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Breast Cancer Detection in Digital Mammograms using Segmentation Techniques

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Abstract: Breast Cancer is one of the major cause of death among women globally. Mammography is the most effective and reliable method for the early diagnosis of the breast cancers through screening and accurate detection of masses, microcalcifications and architectural distortions. The breast cancer detection accuracy and efficiency can be increased by applying various image analysis techniques on digital mammograms on the dense regions of the breasts helping the radiologists to identify suspicious regions preventing unwanted biopsies and traumatic treatments. Accurate detection of breast masses and microcalcifications is a challenging task for the radiologists since they appear similar to the surrounding breast paranchymal. This paper focuses on the various image analysis techniques such as segmentation and edge detection algorithms for the detection breast abnormalities and compares its advantages and disadvantages.

Keywords: Computer Aided Diagnosis (CAD), ROI, Mammography, Microcalcification Clusters (MCC), Segmentation, Receiver operating characteristic (ROC)

1. INTRODUCTION

The second main cause of cancer death in women is due to Breast cancers. Early detection and diagnosis can be done through digital mammography preventing the death rate increase all around the world by identifying the disease in premature stages. Early diagnosis prevents the unwanted growth of malignant cells which saves the life of the patients. The abnormalities in the breast are of various types such as masses, microcalcifications, speculated lesions and architectural distortions. These abnormalities occur in two types called begnin and malignant. The begnin are non-cancerous abnormalities whereas the malignant abnormalities are reported as cancers by the radiologist. The breast masses normally occurs in the dense regions with different shapes which includes shapes such as circumscribed, stellate, lobulated. They are difficult to detect because of the poor contrast, different sizes and shapes and the similarity to other breast muscles, bloodvessels, fibrous tissues and breast parachymal. The microcalcifications occurs in clusters and they are tiny granules of calcium deposits which usually occurs in the size range 0.1 mm to 0.7 mm with irregular shapes.

The extraction of abnormalities from the digital mammograms is the main goal of image segmentation techniques. The segmentation methods consists of the breast regions segmentation and Regions of interest (ROI) segmentation. Segmenting the breast region suppresses the background of the image and separates the breast regions eliminating the surrounding areas which includes the muscles, bloodvessels, fibrous tissues and breast parenchymal. Segmentation of the regions of interest (ROI) is done by extracting the suspicious candidates which are targets of cancers by partitioning the image into non-overlapping regions.

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ROI Segmentation is done on single view mammograms and multi view mammograms. The single view mammogram segmentation consists of the supervised and unsupervised methods which includes region. The multi view mammogram segmentation works on the images of the left and right breasts, multiple views of the same breast and similar views taken at different time intervals. The entire segmentation process also includes the regions with false positives which are eliminated in the classification stages.

The main objective of this paper to bring a complete survey of different segmentation techniques analysing each method using its merits and demerits. The rest of the paper is organised as follows. The section 2 provides the survey of the Image segmentation techniques for single and multi-view mammograms. The section 3 provides thediscussion about the techniques used by comparing its merits and demerits. Section 4 concludes the paper.

2. IMAGE SEGMENTATION TECHNIQUES FOR DIGITAL MAMMOGRAMS

The segmentation is the second step of any computer Aided Diagnosis System(CAD). The CAD scheme for breast cancer detection in Digital mammograms using image segmentation techniques consists of the image pre-processing, image segmentation, feature extraction, classification and evaluation as depicted in Figure 1.

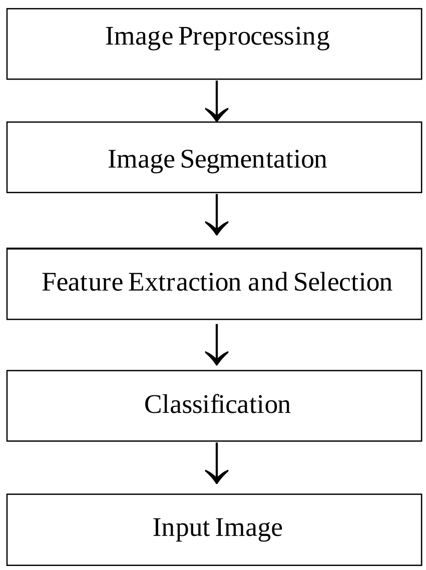

Figure 1: CAD architecture for Breast Cancer Diagnosis

Several researches has been done on the segmentation techniques for digital mammogram breast images. The main objective of the segmentation is to help the radiologists in separating the breast region and the Regions of Interest(ROI) from the mammograms. This section gives a detailed survey of the segmentation methods adapted in single view and multi view mammograms such as clustering, contourbased, regiongrowing, Fuzzy, Variant transformation, Thresholding, Markov Random Model, Stochastic Extraction, Graph technique and Template matching. The input image is the Digital Mammograms collected from the patients who are suspected for breast cancers. The preprocessing stage involves the contrast enhancement which works comparing the intensities of the abnormalities with the background and improves the image quality for easy detection of the cancers. The Image segmentation stage separates the suspicious regions from rest of the image which is named as Regions of interest (ROI) which are targets of cancers. After segmentation the different features are extracted based on the color, shape, density, texture, size, topology and so on. The features extracted are fed in to the classifier which classifies the images as normal and abnormal images. Then the abnormal images are further classified as begnin or malignant abnormality. Some algorithms focus only on breast masses and other focus on single or clustered microcalcifications.

2.1. Clustering Based Segmentation for Digital Mammograms

Clustering is the common method used in the segmentation of digital mammograms. The clustering can be done through nested partitions and single partitions. Clustering uses knowledge about the regions of the image for partitioning and are used for large datasets.

Akshay S. Bharadwaj et al.[1] proposed an algorithm for the detection of microcalcification with top-hattransform and the Gibbs random fields. This algorithm detects the region of interest(ROI) from the mammographic images using Fuzzy C means clustering algorithm and the ROIs are further segmented using top hat transform and they are separated from the images using Gibbs Random Field Algorithm which increases the probability of accurately finding the ROIs from the images. A breast masses detection technique using phase portrait analysis and fuzzy-c-means clustering is proposed by Arianna Mencattini et al.[2]. The preprocessing stage involves the extraction and sizing of regions of interest. The segmentation is done by iterative fuzzy c-means clustering algorithm using an adaptive selection of the optimal size of the regions of interest. The geometric features are extracted for all the segmented regions. A fuzzy inference system(FIS) is used to classify the masses as true masses or normal masses based on human reasoning using rule based inference system which involves the rule based on three agents such as regions of interest, features extracted and the class masses. A method is proposed by Wenda He et al.[3] for segmenting mammograms based on geometric moments. This proposed system involves feature extraction using mammographic patches, deriving local image properties, feature transformation, mammographic building block based model generation by clustering and model driven segmentation. The method is tested against the MIAS database and produced accurate segmentation results for tissue specific areas. Harry Strange et al. [4] proposed Manifold Learning method for Density Segmentation in High Risk Mammograms. The proposed method mainly follows four steps. The first step is to extract the texture features and convert the input matric to feature matrix. The second step is to use the Nystrom principal component analysis algorithm and construct the low dimensional representation of the feature matrix. The third step is the segmentation using the k-means clustering algorithm and the final step is identification of the segmented regions that forms the dense region of the breast. Breast segmentation for a stage mutiscale system is proposed by QaisarAbbasa et al.[5]. The input mammogram is pre-processed using dynamic contrast enhancement(DCE) method using dynamic adaptive histogram equalisation, Gaussian filtering and gamma correction. The background influence correction is done which involves template matching to reduce the noise, gradient magnitude calculation, replacing the noise pixels. Thedetection of candidate points are done by interior and posterior probabilities which involves multiscale decomposition of the image, multi fusion feature of the sub image and segmentation by k means clustering method. Finally the characterisation of the lesions is done by Maximum aposterior method. Patricia B. Ribeiro et al. [6] proposed an algorithm using enhanced independent component analysis for the segmentation of breast masses in mammograms which is based on the concept of statistical mixture model. This involves calculating data log-likelihood for all classes and calculating the probability of all classes and orthogonalising the base matrix and estimation of log-likelihood function. This proposed algorithm segments the data points without the use of labels by calculating the parameters of each class.

2.2. Contours Based Segmentation for Digital Mammograms

Contour based segmentation is used to detect masses in digital mammograms rather than microcalcifications and it is based on mathematical morphology. The snake models are the familiar contours used for two dimensional image segmentation.

A digital Image processing scheme is introduced by R. Guzman-Cabrera et al. [7] which divides the mammogram into several non-intersecting regions and extracts regions of interest and finds the suspicious masses. The proposed technique is based on feature extraction based on texture analysis for the identification and discrimination of suspicious areas related to cancer and benign tumours including microcalcification.

A novel level set active contour model, referred to as MLACMLS was demonstrated by PeymanRahmati et al. [8] which is specialized for the delineation of lesions in digital mammograms. The algorithm estimates the segmentation contour that best separates the lesion from the background using the Gamma Distribution to model the intensity of both regions called foreground and background. This algorithm involves applying the preprocessing filter on the original image, initialising a contour in the domain of the image, calculating the signed distance function U of the initial contour and updating the distance and continued till the convergence. The system is tested against DDSM database and it is proved that the algorithm works well with noisy images without clear edges and with interior and exterior regions. This method provides noise robustness capability by using integrals of the image with good segmentation accuracy. XinHAO et al. [9] proposed a method for the mass segmentation on mammograms combining random walks and active contour methods. First, the images are preprocessed and the background seeds are defined. A method which uses random walks algorithm and Chan-Vese (CV) active contour is used for segmentation of masses. The noises and the unwanted are suppressed. The initial random seeds are generated for initial random walk segmentation which produces initial contour and set of probability masses. This is used to generate the modified energy function which eliminates the contour leakage. The final segmentation is done using multiple random walks.

2.3. Thersholding Based Segmentation for Digital Mammograms

Traditionally, Thresholding is used for the detection of abnormalities in mammography. This can be done either globally or locally. The Global Thresholding is done based on global information collected from histograms. The Local Thresholding method works using the information collected from the surrounding pixels.

A Max-Mean and Least-Variance technique for tumour detection is proposed by Anuj Kumar Singh et al. [10] based on averaging and thresholding which consists of two stages. The first stage is the detection stage in which the original image is applied over an averaging filter and thresholding techniques which finally outputs a malignant region. A rectangular window is created in the output image and a Max-Mean and Least-Variance technique is applied. The next stage is the segmentation phase in which morphological closing operation and image gradient technique is applied to find the region boundary and detect a tumour patch. A vessel detection algorithm is proposed by Francisco L et al. [11] to eliminate the vascular false positive which involves global noise reduction using edge detectors and local noise detection using segmentation process based on a snake. This proposed algorithm performs vessel detection in images with high levels of noise and obtains the highest possible performance both in terms of quality of results and complexity of the algorithm, while maintaining the algorithm as close as possible to real-time processing. Experimental results are evaluated for the database of 13 cases, with four mammograms per case containing 115 vascular false positives and it is proved that this method has an excellent performance level in terms of accuracy, sensitivity and specificity.

Guillaume Kom et al. [12] introduced an automated method for detection of masses in mammograms using adaptive Thresholding. First, A linear transformation filter is applied over the input image and a Symmetric adding of zero is done on the images. An adaptive Thresholding method is done to binarize the image and the noises are suppressed using a median and a high pass filter for smoothening and the location of masses are identified. Mario Mustret all [13] introduced a robust algorithm for the automatic breast and pectoral muscle segmentation from scanned mammograms. This algorithm involves image registration using Hough transform, k–means Thresholding into 10 bins, converting the detected border in to strip, edge detection and conversion of the detected edge in to breast space. The breast images are flipped horizontally by which the top left of the images contains the pectoral muscle region. The boundary detection and segmentation is done through the k-means clustering technique forming about 10 clusters of the aligned images. The pectoral muscle extraction is done through the thresholding and fitting the data points and then doing a cubic polynomial fitting. Thus the pectoral muscle extraction is done by a polynomial estimation. The contrast enhancement is done through the adaptive histogram equalization method. A fully automated breast separation system for breast cancer detection is proposed by LuqmanMahmood Mina et al.[14]. This system aims for preprocessing by separating the background region from the breast profile removing the artifacts and labels from the images. First, the gray scale images are converted into binary images and the largest object is selected eliminating the rest in the binary image. The morphological operation is applied to eliminate the irregularities and they are further expanded and converted to gray scale images. T. Ojala et al.[15] proposed a method for segmentation of mammograms using histogram thresholding, morphological filtering and contour modelling. The method uses thresholding to segment the breast region and further the morphological filtering is applied to smooth the boundary of the segmented region. The segmented artifacts are removed. The location of the final breast boundary is determined using Fourier transform and snake techniques. The method is tested for low-quality Howtek and Pinja images and the best case for boundary detection is achieved by snake technique rather than the B-spline technique. Howard C. Choe et al. [16] proposed an algorithm for detection of microcalcification clusters using multiscale techniques. The digital mammograms are partioned and nonlinear image enhancement is done for each partition. The image decomposition is done by Haar Wavelets pyramidal and reconstruction. All the decomposed images are summed and the dark pixels are removed using histogram thresholdingmethod. The image then undergoes through the adaptive thresholding for false alaram. The false positive discrimination is done through ART2 (continuous-valued adaptive resonance theory) clustering. BalakumaranThangaraju et al. [17] proposed an algorithm for multiscale based fovealsegmentationfor achieving high detection sensitivity using Hessian Matrix and Foveal Segmentation Method on Multiscale Analysis based on global thresholding for Digital Mammograms. This algorithm has three stages. The first stage identifies the regions of interests. In the second stage the regions of interest are detected using the Eigen values of second order partial derivatives that forms the Hessian matrix. Then the suspicious parts are segmented using the foveal segmentation method using multiscaleanalysis. In the third phase, the outputs of the second phase which are the partial derivatives of the images are combined and the microclacifications are detected.

PelinKus et al. [18] proposed an algorithm for a fully automated gradient based breast boundary detection for digitized X-ray mammograms. First, a global threshold value is calculated by using discontinuity and the visibility of the breast border of the image is enhanced by histogram stretching. A gradient vector based border estimation algorithm is used to detect breast border in X-ray mammograms based on the classification of the pixels of the images as border pixels or other pixels. The left and right border pixels are connected further by interpolation.

2.4. Region Growing Based Segmentation for Digital Mammograms

Segmentation using region growing technique is an efficient method for the detection of breast masses and microcalcifications in breast cancer diagnosis. All the pixels with same properties as that of seed pixel are grouped. These techniques works using window size, the processed pixel and the seed pixel. The intensity value of the region grown is calculated and compared with other regions. If the intensity is high then that region is considered as masses or calcifications.

Any Estefany Ruiz Duque et al.[19] introduced a method for breast lesions detection based on region growing techniques. The segmentation is done using a region-based technique and morphological operations such as air area homogenization, breast border segmentation, and pectoral muscle segmentation. Segmentation based on region growing uses clustering of pixels and regions initializing a seed with predetermined parameters for a pixel or group of pixels. The detection is done using split and merge technique which is again based on region growing. The method reached an efficiency level greater than 85% both in the case of segmentation and classification.

An improved technique for preprocessing of mammograms is developed by IndraKantaMaitra et al. [20]. This technique involves three steps such as the contrast enhancement based on contrast enhancement by a adaptive histogram equalization (CLAHE) method. The segmentation region is done from the regions of interest using new modified seeded region growing (SRG) technique which is similar to watershed algorithm by defining a rectangle to isolate the pectoral muscles and by suppressing them which are not the target of cancers. Tolga Berber et al.[21] proposed a breast mass contour segmentation (BMCS) approach for a given ROI in an image based on seeded region growing (SRG) algorithm. A new thresholding approach is adapted to tune the SRG algorithm by adjusting the threshold value to eliminate the need for under and over segmentation. The preprocessing step consists of a median, averaging and Laplacian filters to reduce the noise and increase the contrast. First, an initial threshold value is set based on mass size. If the size of the current segment is less than the threshold then that segment is referred as small segment else its large segment. The proposed segmentation algorithm also segments the region if the size is in a predetermined interval. As the final segmentation, a sphere shaped morphological filter is used to eliminate the artifacts. Chia-Hung Wei et al. [22] proposed amethod for content-based mammogram retrieval to effectively access the mammogram databases based on a similarity measure scheme using the mammographic features and weighting distance measure. In the preprocessing stage a brightness adjustment technique is used along with a median filtering technique to reduce a noise. The segmentation is done through the region growing technique and mass template is created based on the mass boundary. The final segmentation is done by combining the resulting template on the adjusted image. The shape, margin and density features are extracted with the help of Sobel features. Isaac N. Bankman et al.[23] proposed segmentation algorithm for the detection of microcalcifications using region growing techniques and active contours models. The proposed segmentation algorithm is based on the assumption that all the edge pixels of a microcalcification for segmentation is a closed contour. The segmentation is done by growing the edgesby hill climbing and multi tolerance algorithms through finding the labelled pixels which are 4-connected to unlabeled pixels and it is used to compact intensity Hills. The proposed algorithm is segmented using six mammograms with 15 clusters with a total of 124 microcalcifications and it is proved that the hill climbing, active contours method performs better than the multitolerence region growing algorithm. Fei Mao et al. [24] introduced a region growing algorithm based on distance-based and dense-to sparse grouping method. The methodology is based on forming clusters by choosing the microcalcifications which are close to each other so that most closely distributed microcalcifications forms the clusters. The first stage of groping involves initialization of the clusters, calculating the center of the clusters, calculating the distances between the clusters. The second stage calculates the distance between the clusters and arranges in the ascending order and then merging two clusters with the smallest distance.

2.5. Markov Random Field Models (MRF) Based Segmentation for Digital Mammograms

Markov Random field models is a statistical method which works under the principle of finding the Global relationships between the pixels using local information. It is an iterative pixel classification method.

A computer aided diagnosis system is introduced by Sung-Nien Yu et al. [25] based on wavelet filters and Markov random field model for the detection of microcalfications. This system has two stages such as detection of suspicious microcalcifications and recognition of true microcalcifications. The detection of suspicious microcalficationsare done through multiresolution wavelet filters calculating the mean pixel value of the image. The texture feature extraction is done through the Markov random field parameters based on Derin-Elliott model. Two classifiers namely, the Bayes and back propagation neural network is used in the recognition of true microcalcifications. M. Suliga et al. [26] presented an approach for segmentation of masses in mammograms based on a statistical classification method called Markov random field (MRF) clustering which describes the image pixels using statistical and contextual information. The MRF clustering model used in the approach consists of initial labelling in which a class is assigned to each pixel, defining the energy function based on neighbouring system and normalization of the parameters used in the function. Jose Anibal Arias et al.[27] proposed acomputer aided diagnosis system for classification of breast masses. The preprocessing stage involves eliminating the labels, tape and scanning artefacts, and pectoral muscle and enhancing the contrast. The segmentation is done on the regions of interest using Top-hat and Markov Random field method to isolate the suspicious regions as abnormality which is true positive or tissue which is false positive. Several shape and texture features are extracted using the Gray level co-occurrence matrix method (GLCM) which is further fed to a Support vector machine classifier which works on radio basis function kernel to classify the masses as bengin or malignant masses. J.M. Mossi et al. [28] introduced an algorithm for the detection of the clustered microcalcifications using morphological connected operators in digital mammograms. The preprocessing step extracts the bright pixels of the image using mathematical morphology and filters the noise and artifacts. The segmentation of the image is done through labelling by Markov Random Field and by eliminating the small peaks.Veronica Rodrýguez-Lopez et al. [29] introduced a system containing two algorithms, namely, contrast enhancement and mass segmentation. Contrast enhancement uses special filters based on morphological operators in order to enhance the contrast of the possible mass regions in the image mass. The segmentation is done through Gaussian Markov Random Field (MRF) model which involves top-hat transformation, noise removal and normalization in order to segment the images.

2.6. Variant Feature Transformation Based Segmentation for Digital Mammograms

Variant feature transformation is used for the detection of breast masses for single view mammograms. It mainly uses multifractal approach based on the similarity measures from the digital mammograms.

A method for detecting small-sized details in mammograms based on Multifractal (MF) approach, is proposed by TomislavStojic et al. [30]. This analysis works under the principle of self similarity human tissue that is of high degree. The segmentation using this method involves calculation of MF quantities such as Holder exponent and the multifractal spectrum which leads to extraction of isolated light objects from the edge objects in the digital mammograms.

2.7. Stochastic Extraction Based Segmentation for Digital Mammograms

Stochastic extraction is an unsupervised segmentation technique used for breast cancer diagnosis. The segmentation is done through labelling of homogenous regions containing the lesions.

Vladimir A. Krylov et al.[31] proposed an algorithm for extraction of Elongated Curvilinear Structures in mammographic images. This algorithm has two stages through which it extracts the blurry and low contrast curvilinear structures in mammographic images. In the first stage, a Randon transform is applied on the image to find the line segmented data points. In the second stage, the line segments are extracted using a Markov dependency structure on the local square grid. The algorithm is further optimized using Markov chain Monte Carlo algorithm based on simulated annealing.

2.8. Graph Based Segmentation for Digital Mammograms

Graph segmentation is used for the detection of breast masses which occurs in high density areas of the breast. It follows two types of tree structure for the detection. One is the minimum spanning tree and the other is the pyramid tree structure.

Ciro D Elia et al. [32] proposed an algorithm for the automatic detection of clustered microcalcifications based on multi classifier approach. The adaptive segmentation is done on the images using Tree-Structured Markov Random Field based segmentation (TS-MRF) by portioning the images in to sub regions to identify the regions of interest. The geometric and texture features are extracted from the regions of interest and a heuristic filter is used to identify the best features for classification. The regions of the interest are grouped using clustering called Moving Leader Clustering method. The formed clusters are further classified for malignancy using a Gentle AdaBoost classifier for individual clusters and then they are combined to form the final decision for malignancy.

2.9. Fuzzy Based Segmentation for Digital Mammograms

Fuzzy techniques are used for the detection of abnormalities of high density. It works based on fuzzy memembership functions and error calculations. A set of Fuzzy rules are framed based on the properties of the image for the detection.

A Fuzzy rough sets hybrid scheme for breast cancer detection is introduced by AboulElla Hassanien et all[33] based on Fuzzy histogram hyperbolization algorithm. The Fuzzy image preprocessing is done and the Fuzzy c-mean segmentation algorithm is used to segment the objects which are of interest. The statistical features such as Contrast, Inverse different moment, Angular second moment, Entropy are extracted which are further analysed using rough set analysis and fed to a classifier which works on a fuzzy inference kernel which contains the Rough sets for generation of all reductions that contains minimal number of attributes and rules. These rules are used by the fuzzy classifier to discriminate the masses as normal or abnormal accurately.

2.10. Template Matching Based Segmentation for Digital Mammograms

Template matching is simplest and oldest method used in pattern recognition for breast cancer diagnosis.2D templates are matched with the patterns and the Gaussian and two dimensional functions are used for the detection of masses and microcalcifications

A CAD system is proposed by Maciej A. Mazurowski et al. [34] based on mutual information based template scheme to detect breast masses which consists of the following steps: first, the mammographic or breast tomosynthesis image is preprocessed in which the spatial resolution is reduced. Thebreast is segmented and finally the mask for pixels with high intensity is created. The template matching is done which calculates likelihood maps based on template matching using mutual information. The images are postprocessed which involves creating islands from likelihood, creating masks from islands, removing masks that are too close, removes masks that with likelihood<T and the last step is to find the locations of the suspicious regions. The CAD system not only performed well on screen-film mammograms but also on DBT.

A three class study is made for feature extraction and classification for finding the normal, beginin and malignant masses by SemihErgin and OnurKilinc [35]. The Histogram of Oriented Gradients(HOG), Dense Scale Invariant Feature Transform (DSIFT), andLocalConfiguration Pattern(LCP)methods are studied for the feature extraction and SupportVectorMachine (SVM), k-NearestNeighborhood (k-KNN), DecisionTree, and Fisher Linear Discriminant Analysis (FLDA) are studied for classification of the masses. A new pattern recognition feature extraction framework is proposed which consists of wavelet decomposition, noise filtration, time-domain feature generation constructs.

3. DISCUSSION

The survey presented here discusses the existing breast cancer detection and segmentation techniques for digital mammograms including the segmentation using clustering, contours, thresholding, region growing, Markov Random Model, Variant feature, Stochastic Extraction, Graph and Template Matching. The techniques listed out in the survey is applicable for both normal and full field mammograms. Some techniques handles images in both views such as CC and MLO viewsof the both sides of the breast. The techniques of segmentation is evaluated using a receiver operating characteristic (ROC) curve in which a curve is plotted with true positive as a function of false positive. Some techniques also finds the location of the breast tumours along with the existence to help the radiologists to find the exact location and stage of the cancer for easy diagnosis. The survey is only for the digital mammograms and not for the other images take from other diagnosis techniques such as MRI and Ultrasound Images. The paper also discusses some techniques which are fully automated without any manual operations. Some techniques are fully manual whereas some techniques are semi automated techniques where some parameters are generatedautomatically. The survey table presented here lists all the methods, merits, demerits and the accuracy rates achieved during the segmentation process and the databases used for validating the techniques with variable size datasets collected for research purposes.

Table 1 summarizes the Clustering techniques used in breast cancer detection comparing its merits and demerits along with experimental results. The advantages of Clustering methods are: i) Probabilistic Clustering Techniques has better efficiency than Clustering techniques based on hierarchy, ii) Many Fuzzy techniques has been used to take intelligent decisions and iii) It works on both left and right breast images in both CC and MLO views. Currently, the clustering techniques also suffer from the following demerits: i) the accuracy of the clustering techniques are lower than the classification techniques ii) the distance measure of the data points decides the performance of the hierarchical clustering techniques.

Table 2 summarizes the contour based techniques used in breast cancer detection. The Contour based techniques are mainly used for Boundary detection for accurate segmentation of the Digital Mammograms. The Contour based Techniques has the following advantages: i) These methods are automatic which is done during the image storing process, ii)It separates the abnormality region from the rest of the region which are the not targets of cancers. The Disadvantages of Contour based techniques are:i)In some techniques the accuracy is completely dependent on the outcome of filters, ii) There is a chance of misclassification of the background region as breast region and iii) There is a chance forcontour leakage problems.

Table 3 summarizes the thresholding techniques used in breast cancer detection. The thresholding techniques is a classical approach can be done locally and globally. The merits of the thresholding techniques are: i) The thresholdingtechniques works well for segmentation of breast masses rather than microcalcifications, ii) The computational complexity of the thresholding approaches are less when compared to other techniques and iii) These techniques are used as the preprocessing technique for other algorithms. The demerits of the thresholding techniques are: i) Global thresholding techniques are not used to accurately identify the Regions of Interest (ROI), ii) The local based techniques are pixel oriented and it does notpartitions the pixels in to suitable sets and iii) In some cases the thresholding techniques has to be clubbed with some clustering techniques for better accuracy.

Table 4 summarizes the region growing techniques used in breast cancer detection. The region growing techniques is one of the most efficient techniques used in breast cancer detection. This works mainly on selecting the appropriate seed pixels and adding the other pixels with similarities. There are advantages of region growing techniques when compared to other techniques such as i) adaptive region growing techniques are more accurate for segmenting, ii) These implementation complexity of these techniques are less and iii)These techniques works well for when the Gaussian distribution is used in the images. The region growing techniques suffers from following disadvantages: i) These techniques are more sensitive to noise errors, ii)The performance of this technique completely depends on the selection of the seed pixel and iii) The discrete region growing techniques fails in accuracy when compared to probabilistic region growing techniques.

Table 5 summarizes the Markov Random Field (MRF) techniques used in Breast cancer Detection. The experimental results and the databases used for validation of these methods are listed out in the survey. The Markov Random Field techniques is a pixel based segmentation approach. These techniques are statistical based. The advantages of these techniques are: i) Segmentation is good since the it works on the global information which is extracted local neighbor pixels, ii) These techniques are dependent on the statistical properties of each pixels which increase the accuracy of segmentation and iii)The MRF method has the following drawbacks: i)Since it is a statistical method, the time complexity of these methods are high when compared to other techniques, ii)The statistical data computation is high in MRF based segmentation and iii)when compared with discrete wavelet transform the segmentation rate is low in case of MRF based segmentation.

Table 6 summarizes the Other techniques such as Variant Feature, StochasticExtraction, Graph based approach, Fuzzy methods and segmentation based on Template Matching. Some of these techniques are adaptive and are used when the complex decision are to be taken and when the images are of high densities. The advantages of these techniques are listed as follows: i) Variant feature and stochastic extraction techniques works more accurately for segmentation of the breast masses, ii)The Fuzzy methods are best suited when the tumors occurs in high density areas of the image and the segmentation has to be done with the help of radiologist who update the fuzzy rules as required according to the cases they handle, iii) The Fuzzy techniques are more suitable for the images with low quality and also when the boundaries of the breasts are not well defined, iv) Template Matching producesmore accurate results when the prototype selected are appropriate, v) Implementation complexity is high when compared to other techniques, vi)The Stochastic extraction works well when it is used along with some search algorithms such as content based search retrieval techniques and vii) The graph based techniques shows best results in segmentation of the clusters of the microcalcifications appearing in the high intensity areas of the digital mammograms.

The drawbacks of the techniques are: i)The template matching scheme mainly depends on the properties of the image and it can lead to high number of false positives, ii)Difficult to design the fuzzy rules without which the accurate results cannot be achieved, iii) The template matching techniques achieves good results in some cases with similarity matching but only with partial loss, iv)The computation of the parameters in the stochastic extraction techniques is complex v)The time complexity of stochastic extraction techniques are high when it is used in the case of Digital Mammography.

Most of the classical approaches listed in the survey are easy to implement and adapt in case of medical image processing. The Fuzzy techniques are used in tedious decision making process to help the radiologist to find the tumors in the precancerous stages. Some of the statistical approaches listed are more dependent on the statistical properties and are mainly dependent on the local information available among the neighbor pixels. Some schemes are validated using cross fold validation using some public databases such as MIAS and DDSM. Some approaches are used along with the optimization techniques and better results are achieved especially during the segmentation of microcalcifiactions of clusters (MCC) to get better optimization

Table 1
Overview of Clustering Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
Akshay S. Bharadwaj et al. [1]	Top-hat transform and the Gibbs random fields	Algorithm is not dependent on the orientation and size of theMCs, resolution and size of the image	only classical approaches without any fuzzy segment-ation techniques which are more powerful	Detection rate is 94.4%, accuracy is 88.2% and false negative detection rate of 5.6%	322 images from the digital mammo-gram database of the Mammographic Image analysis society
Arianna Mencattini et al.[2]	Phase portrait analysis and fuzzy inference systems	Improves malig-nancy assessment of the identified masses for auto-matic breast cancer diagnosis.	The inference rules framed for this techni-que cannot be adapted for neural or LDA classifiers	For cancer images false positive per image is 0.85, 0.7, 0.55, and 0.45 and for normal images false positive image equal to 0.4, 0.3,	674images from Digital Database for Screening Mammography

(contd...)

(Table 1 contd...)

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
				0.25 and 0.2 is achieved	
Wenda He et al.[3]	Parenchymal patterns and geometric moments	Shows good segmentation accuracy and overall good classification results for BIRADS	No good classification results for the proposed method for Tabar Pattern	Classification accuracies of 71% and 79% in low and high risk categories for Tabár and Breast Imaging Reporting And Data System schemes respectively	The MIAS database containing 322 images digitised at 50 resolution
Harry Strange et al. [4]	Manifold Learning	Good correlation between left and right breasts taken from the samepatient with respect to density estimates	Cannot be adapted for segmenting images with BIRADS classes	Segmentations with average accuracy of 87%	Full field digital mammograms (FFDM) from twelve patients of BIRADS class four and consisting of left and right craniocaudal view
QaisarAbbasa et al. [5]	Region-based and edge-based method	This system eliminates the problem of over and under segmentation. Good segmentation for all type of masses with non smooth boundaries.	Does not identify boundaries of highly speculated masses	The average area overlap measure percentages 91%, 88%, 90%, 89%, 94%, and 92% for circumscribed, spiculated, ill-defined, microlobulated, obscured respectively.	Digital Database for Screening Mammography consisting of 390 mammograms
Patricia B. Ribeiro et al. [6]	ICA mixture model	Good segmentation result is achieved than using classical approaches. It works well for the images which are preprocessed	This enhanced ICA model has not achieved good result in segmenting tumours in dense regions	Segmentation rate of 48.25% of pre processed images and 51.75% of images without preprocessing	443 images from mini mammographic database

Table 2
Overview of Contour Based Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
R. Guzman-Cabrera et al. [7]	Intensity-based segmentation.	Produces the accurate inputparameters and differentiates between microcalcification and mass	Lack of fully automated system to be identified for the feature analysis through texture analysis	The extracted areas using this technique gives 3.5%, 1.41%, and 0.48% from the total image	Digital database for screening mammography for cancer research and diagnosis
PeymanRahmati et al.[8]	Maximum likelihood active contours	Good for noisy images without clear edges and with interior and exterior regions	The algorithm does not use multiple view mammograms	Segmentation accuracy (MLACMLS): 86.85%. (ALSSM): 74.32% and (SSLS): 57.11%)	100 test images including 50 spiculatedtumors and 50 other types of masses selected from the DDSM database.
Xin HAO et al. [9]	Random walks and active contour	Efficiently handle complexshapes or subtle structures of masses.	Does not work well with contour leakage problem. It concentrates only on the core region os masses and discards dimmer or subtle	The average and standard deviation of the segmentation time is 5.143±1.102	Digital Database for Screening Mammography consisting of 1066 mammograms

Table 3
Overview of Thresholding Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
Anuj Kumar Singh et al[10]	Max-Mean and Least-Variance	The technique is simple and fast because of using basic image processing	The manual selection of threshold parameter and size of averaging filetr	Approximate execution time is 4.20 sec exp-eri ment on each image	–
Francisco L et al. [11]	Deformable model	Obtain the highest possible performance both in terms of quality of results and compl-exityof the algorithm	This approach is best suited for mamao-gramsand need to be extended for anigograms	The 82% of the vas-cular false positivesare detected taking an extra one second along with the normal process	Database of 13cases, with four mammograms per case containing 115 vascular false positives.
Guillaume Kom et all [12]	Local Adaptive Thresholding	The algorithm is best suitable for all types of masses and micro-calcifications	The algorithm does not produce good segmentation results for images without preprocessing	The algorithm exhibits formass detection, a sensitivity of 95.91% and 93.87%,	Database consisting of 61 mammograms
Mario Mustr et al. l[13]	k–means thersholding	Segments the pectoral muscles of low cont-rast because it uses lesser value of cont-rast difference when compared to the det-ection threshold	The alignment of segmentation line with actual pectoral skin line is not accurate in some images of varying intensities which gives errors	Successful segment-ation rate is 89.69%	322 images from mini mammographic images
Luqman Mahmood Mina et all [14]	Morphological Operations	The Breast separation is fully automated and various intensities of breast images are used for testing	Lack of computer aided detection system	The segmentation rate is 99.06%.	The MIAS database comprises 322 images
T. Ojala et al. [15]	Histogram Thresholding	Performs well on the low quality images where the breast line is almost not visible	Single thresholding is not essential for some images with poor quality	Standard deviation of the mean error is 6.2	Howtek and Pinja images
Howard C et al. [16]	Multiscale Techniques	Reduction in the false positives when com-pared to other tech-niques	Global threshold analysis is not good when working with large type of databases	Sensitivity is 96.88% Positive predictive value (PPV) is 20.67%	Mammographic Image Analysis Society Mini Mammographic Database of 322 images
Balakumaran Thangaraju et al. [17]	Hessian Matrix and Foveal Segmentation Method	Detection of Variable sized microcalcifi-cation clusters by multiscale filter with-out affecting their shapes.	Fails in the detection of clusters in dense mammograms in young women breast tissues	The detection methodh as a TP ratio of 97.76 % with 0.68 false positives per image	335 mammogram images having both craniocaudal (CC) and mediolateral oblique (MLO) pro-jection view from UCSF, MIAS, and DDSM
PelinKus et al. [18]	Gradient based	Require less comput-ation for iterative processing for feature extraction and also training	Not applied for the objects inside the breast except the boundaries	The segmentation rate of the proposed algorithm is 99%	84 mammograms from the MIAS database

results. The output of these segmentation methods are fed into the suitable classifier and are classified as normal and abnormal images. Some segmentation such as bilateral approaches and multi scaling techniques are used in case of images with two views such as CC and MLO views. Segmentation techniques work well when the images are decomposed with suitable wavelet and Curvelettransforms. Better the quality of

Table 4
Overview of Region Growing Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
Any Estefany Ruiz Duque et al. [19]	Split and merge technique	Good results when embedded with other image processing techniques and all the possible lesions has been successfully labelled	Breast density regions are only focused and other regions are neglected while selecting regions of interest.	The maximum efficiency attained is 85%	Data set of 40 mammograms
Indra Kanta Maitra et al. [20]	Seeded Region Growing Technique	The method has the advantage that it is fairly robust, quick, and parameter free	Its dependency on the order of pixel processing	Segmentation rate is 95.71%	322 mammogram images in MIAS database
Tolga Berber et al. [21]	Seeded region Growing Technique	Gives balanced accuracy, Hausdorrf distance and scalable discrepancy. It has less chances of over and under segmentation problems	Produced false pixels distance in manual selection which is called Yasnoff error	The maximum accuracy attained is 95.09%	DEMS dataset consists of 260 mammograms
Chia-Hung Wei et al. [22]	Seeded Region Growing Technique	The algorithm proved efficient while retrieving round and circumscribed margin masses achieving high precision	A system dow not have a user friendly interface and also the retrieval time of the image has to be reduced more.	Highest precision for round masses 70% and for other shaped masses the precision range from 57% to 45%.	DDSM mammogram dataset consisting of 1919 mammograms
Isaac N. Bankman et al.[23]	Multitolerence region growing	Lower computational complexity when compared to active contours and region growing methods	The hill climbing used may not be suitable for images with complex structures	Roc curve is 0.83, 0.90,0.54,0.85 for contrast, relative contrast, area, sharpness respectively	A set of six mammograms with 15 clusters and 124 microcalcifications
Fei Mao et al. [24]	Region Grouping	It eliminates the under grouping and over grouping problem of the clustering methods	High computational complexity because of two sets of procedures one for clustering other for detection	The detection accuracy is 3 MCC/cm	A set of 30 mammograms containing 40 microcalcification clusters

segmentation the features extracted are more accurate and the classification of the abnormalities in the digital mammograms gave more accuracy rate and the disease can be diagnosed in the pre mature stages. Some of the techniques such as Fuzzy clustering and Fuzzy Region Growing has a good scope for future enhancements.

The CAD schemes for Breast Segmentation and ROI segmentation are usually validated against manual segmentation techniques where a comparative study is done to visualize the effects of the CAD schemes on real time images collected from the clinical laboratories. An effective Implementation of these Segmentation schemes are indeed essential for the successful separation of the ROI and the Breast regions which act as the basement for accurate feature extraction results without which the classification accuracy and the sensitivity rate decreases which aids the radiologist to go through unnecessary biopsies and radiations increasing the chances of death rate all over the world.

4. CONCLUSION

This paper presented a survey and analysis on the classical and fuzzy approaches of the image segmentation techniques used in Digital Mammography. The technique described in paper includes all the segmentation

Table 5
Overview of Markov Random Field Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
Sung-Nien Yu et al. [25]	Wavelet filter and Markov random field model	Accurate detection is high since it uses the features of wavelet filters combined with Markov random field	Not suitable for dense grandular tissues where the microcalci-fications are invisible	Sensitivity is 92%, with only 0.75 false positives per image	20 mammograms containing 25 areas of clustered MCs
M. Suliga et al. [26]	Markov random field -based clustering	Reduces the noise in scanned mammograp hic films and it is simple and easy to implement	No of classes should be mentioned and there is no automated system to calculate the classes needed	Segments the noise range from 10 to 100	Data set of 100 mammograms
Jose Anibal Arias et al.[27]	Multilevel adaptive process	SVM classification produces good accu-rate scores with a minimum set of features	This system is com-pletely available for public	SVM classification results using a RBF kernel and the full set of 63 features 84.18 %	Mammographic Image Analysis Society database set of 278 detected ROIs was randomly divided in 25 masses and 114 normal tissue segments
J.M. Mossi et al. [28]	Morphological connected operator	By keeping the structure constant without changing the shape the noise level is reduced	There is no automated system which performs a chain of morpho-logical operators	92% cluster detection rate with a 1.13 false positive clusters per image	Data set of 40 mammograms

Table 6
Overview of Other Techniques in Breast Cancer Detection

Author	*Method*	*Merits*	*Demerits*	*Accuracy*	*Database*
Tomislav Stojic et al. [30]	Multifractal Analysis	Good detection rate of microcalcifications in dense tissues.	Calculating the multi fractal spectrum is used complex for large images	Nil	Images from Mini Mammographic database
Vladimir A. Krylov et al. [31]	Stochastic Extraction	Accurately extract blurred andlow-contrast elongated continuous curvilinear structures	Does not have a multiscale approach for grid scale independence	Segmentation size of 50 pixels X 30 pixels where I + 0.2N is the segmentation result for N is the noise and I is the image	20 images from Digital Database for Screening Mammo-graphy
Ciro D Elia et al. [32]	Multi Classifier Approach	More efficient for the detection of clusters with varying densities	More features has not been included which indicates the stages of the cancer in the classification stage	Detection rate is 90% with a false positive per image equalto 1.7 in the working point	40 mammographic images from Nijmegen database
Aboul Ella Hassanien et al. [33]	Fuzzy rough sets hybrid scheme	Useful for the classification of breast cancers where the information is incom-plete and in consistent	More decision rules has to be included in the fuzzy scheme	Detection rate is 98% with minimum number of rules 24.8%	Mammography Image Analysis Society (MIAS) with 320 images
Semih Ergin et al. [35]	Feature extraction framework	Features extracted using this technique is more discriminative than classical descriptor	A CAD system has to be coupled with the new framework to help radiologists to find the right diagnosis.	Classification accuracy of maximum 90.60%	Image Retrieval in Medical Applications (IRMA) project database

detection algorithms for both single view and multi view mammograms and these techniques suitable for breast region segmentation and ROI segmentation. However, these segmentation algorithms segment the images including few false positives which will be neglected in the later stages of the classification process. Majority of the techniques included in this paper are from unsupervised segmentation. In future, robust segmentation techniques based on various color models such as RGB, HSV, LUV, CMY will be developed which can help in bothROI segmentation and the Breast abnormality structure segmentation through various color intensity differences. In addition, the feature extraction algorithms based on color space models will be explored which can aid for more accurate color texture analysis for better classification results in classifying the breast masses, Clusters of MicrocalcificationsMCC) and architectural lesions.

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