Computer-aided mammography techniques for detection and classification of microcalcifications in digital mammograms

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Abstract: Recent techniques that are developed in computer-aided mammography (CAM) produce more accurate results in detection and diagnosis of microcalcifications in its earlier state that can lead to breast cancers among women. These techniques aim at the reduction of false positive rates through which the number of biopsies and surgeries can be greatly reduced. This paper gives a detailed study of the existing techniques available in CAM for the segmentation and classification of the microcalcifications present in the di0067ital mammograms which help the radiologists to take quick and accurate diagnosis decisions.

Keywords: segmentation; classification; CAM; computer aided mammography; MCC; microcalcification clusters; ROC; receiver operating characteristics; ANN; artificial neural networks.

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1 Introduction

Breast calcifications are calcium deposits that occur in the breast area which can lead to breast cancers. These calcifications are considered to be the prime symptom of breast cancer and usually, the digital mammograms are checked for the existence of such calcium stones to diagnose the patients with breast cancer. These calcifications occur as clusters which are called as clusters of microcalcifications (MCC). The severity of microcalcifications is benign and malignant. They appear as high-intensity pixels in digital mammograms which can be visualised by the human eye as bright dots that spread over the breast region. Some calcification occurs as larger stones which are called macrocalcifications that are non-cancerous called benign calcifications. The characteristics of microcalcifications given in Table 1.

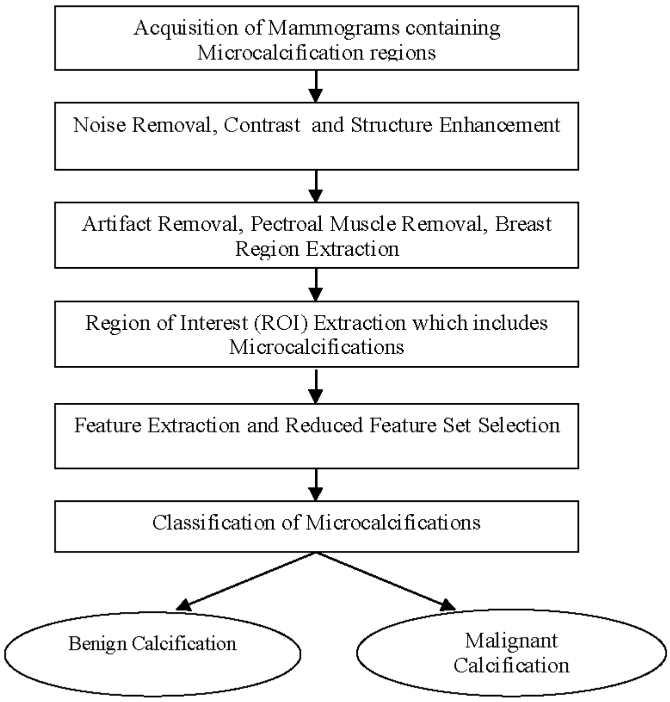
Table 1 Characteristic of microcalcifications in digital mammograms

Features	*Symptoms*	*Severity*
Size	Small, calcifications less than 2 mm	Malignancy
	Large, calcifications larger than 2 mm	Benign
Shape	Angular, heterogeneous and non-uniform	Malignancy
	Round, regular and uniform	Benign
Scattering	Scattered	Benign
	Concentrated at one place	Malignancy
Density	Less or high dense	Benign or malignancy

CAM techniques are used for detection and diagnosis of commonly occurring breast abnormalities in digital mammograms such as masses, lesions, calcifications, architectural distortions and asymmetrical breasts. The CAM detection techniques consist of the pre-processing of the mammogram for noise removal, enhancing the contrast and brightness levels such that the granular calcifications are better visible to the human eye. The main technique used for detection is the segmentation which consists of the breast region extraction which is achieved by partitioning the image into segments and removing the unwanted portions of the image. The segmentation technique also consists of the Region of Interest (ROI) extraction which is the target for diagnosis which usually occurs as high-intensity pixel areas. The CAM techniques used for diagnosis consists of the feature extraction, feature selection and classification of the microcalcifications. The feature extraction is the process of extracting the features such as texture, shape, and intensity characteristics. The extracted features are further processed to obtain a reduced set of features which serves as the input to the classifier. The classification process employs a classifier to categorise the microcalcifications into benign or malignant. Some systems use double classifiers in order to classify the images as normal or abnormal and further the abnormal images are classified as benign or malignant. Figure 1 shows the process of detection and classifications present in digital mammograms.

This paper provides a survey on the existing techniques used in CAM depicting each technique with the performance analysis. The paper is organised as follows. Section 2 gives the review of the preprocessing techniques available for the microcalcifications in CAM Scheme. Section 3 provides the detection techniques used for microcalcifications available in CAM scheme. Section 4 includes the feature selection and feature selection techniques used for microcalcifications. Section 5 reviews the classification techniques used for microcalcifications and Sections 6 and 7 provides the discussion and research direction respectively and Section 8 concludes the paper.

Figure 1 Detection and classification scheme in CAM



2 Preprocessing techniques for microcalcifications in CAM

Preprocessing is the preliminary and primary step for any image processing application through which the image quality gets upgraded and the image can be clearly visualised making a way for correct diagnosis of breast cancer. The denoising techniques play an important role in preprocessing of the digital mammograms. Denoising removes the noise present in the mammograms through which the quality can be improved and the tiny microcalcifications and its clusters are visible to the radiologists. Further, the contrast enhancement technique improves the portions of the image which are not visible and makes the human interpretation easier.

2.1 Denoising techniques

Saad et al. (2016) proposed a method for classifying the microcalcifications present in the digital mammograms. The noise removal in the images is done using Wiener filter. The contrast of the images is enhanced using top hat and button hat transformations. Ostu segmentation is used to segment the suspicious regions and texture analysis is carried out using Law's mask to achieve two-level segmentation where the microcalcifications regions are segmented. The texture features are extracted and fed to the AdaBoost classifier and artificial neural network classifier. It is proved that the AdaBoost classifier achieves a higher accuracy of 98.83 when compared with artificial neural network achieves an accuracy of 97.91% when tested using MIAS database. Bria et al. (2014) presented a system for classification of microcalcifications in Digital mammograms. The images are preprocessed using quantum noise equalisation. The initial detection is done through ranking based cascade detector and the macrocalcifications are removed. The component-based thresholding is done followed by the clusters of microcalcifications. The shape, texture, and topological features are extracted and used for the classification stage to classify the microcalcification as benign or malignant when tested using 1599 digital mammograms.

2.2 Contrast enhancement techniques

Duarte et al. (2015) demonstrated a technique for the segmentation of microcalcifications using Geodesic active contours (GAC) combined with anisotropic texture filtering. The images are preprocessed using Alternating sequential filtering (ASF) and the contrast of the mammograms are enhanced using CLAHE techniques. The image set used for the system was extracted from DDSM database. The technique achieved mean area overlap measure (AOM) of 0.52 ± 0.20, 87.4% of the malignant cases and 86.4% of benign cases. Daul et al. (2005) proposed a system for 3D representation of clusters of microcalcifications from 3D mammograms of two views. The images are represented in three-dimensional view. The 3D views are further preprocessed using grey level differences for enhancing the contrast and Gaussian filters. A local thresholding and labelling algorithm is employed for detection of microcalcifications. The moment based and non-moment based features are extracted for classification. Multi-threshold based on density algorithm is used to reduce the false positives. The mean accuracy gained is 16.25 when the system is tested with a set of 66 images.

3 Segmentation techniques for microcalcification in CAM

The image segmentation plays an important role for accurate and correct identification of the breast calcifications that occurs in and around breast region. The detection of microcalcifications needs the segmentation of breast region from its surrounding area. The most critical part of segmentation deals with finding the exact regions where the tiny calcifications are located as single or with clusters that lead to breast cancer which is called as Region of Interest (ROI) segmentation. Effective segmentation of microcalcification clusters also deal with removing the artifacts present in the mammograms and the pectoral muscle removal, which is present in the top left corner of the mammograms mostly in MLO views.

3.1 Clustering techniques

Estevez et al. (1996) proposed a system with a graphical user interface where the radiologists can select the portions of calcifications in order to reduce the number of false positives. A set of nine image features are extracted and Isaac clustering is used to cluster the Microcalcification occurrences. This system uses 15 mammograms from Hoffitt Cancer Institute at The University of South Florida and it achieved true/false ratio of 2/7 < 0.285 before radiologist interaction. Qian et al. (2002) proposed a microcalcification detection algorithm using distance-based region grouping method. The detection was done using two-stage grouping methods. In the first stage, the closely placed microcalcifications are grouped with each other and clusters are formed. In the second level, the remaining microcalcifications are grouped with clusters with minimum distant cluster centres. The system is tested with 30 mammograms and it achieved a sensitivity of 92.5% with false positive of 2.4 /image.

3.2 Mathematical morphology

Guo et al. (2016) introduced a system for detecting the microcalcifications clusters found in digital mammograms. The artifacts in the mammograms are removed using region growing method. The contrast is enhanced using top-hat transformation and greyscale adjustment methods. The suspicious portions of the mammograms are obtained using contourlet transformation. The clusters of calcifications are detected using non-linking pulse coupled neural networks. The proposed system attains a good accuracy of 95.8%, sensitivity of 96.3% and specificity of 94.7% when tested using MIAS and JSMIT databases respectively. Yang et al. (2016) used an approach which uses an improved pulse coupled neural network for the detection of microcalcification clusters. The breast region is extracted using Ostu thresholding. The contrast is enhanced using mathematical morphology and non-linear transformation. The biorthogonal wavelet is used to retain the high-frequency components in the image. The microcalcification clusters are detected using simplified pulse coupled neural network. The method achieves an accuracy of 93.182% when tested with MIAS database.

3.3 Thresholding techniques

Ogiela and Krzyworzeka (2016) presented a system for the detection of clusters of microcalcifications. This system uses MIAS database and the artefacts are removed using a threshold-based segmentation. The breast area is separated using linear function algorithm. Two heuristic approaches were performed in the first approach a pixel-based segmentation technique is used. Each pixel is checked for the range of calcifications. The second approach uses a thresholding technique to detect the calcifications. The accuracy of the proposed approaches was obtained up to 80–100%. Mehdi et al. (2017) demonstrated a hybrid computer-aided detection system for the detection of microcalcifications by combining two approaches called spatial automatic nonlinear stretching and Shannon Entropy-based wavelet coefficient thresholding. The images used in this system are the mammograms from MIAS database where the contrast of the mammogram is improved using a Second Derivative-Like measure of enhancement (SDME) algorithm. The algorithm yields a SDME value of 78.8db, the true positive rate of 97.14 % for 0 and 48 false positives per image. Mohanalin and Beenamol (2014) introduced a method for the enhancement and segmentation of microcalcifications. The mammograms are enhanced for contrast using wavelet thresholding based enhancement. The detection of microcalcifications in mammograms is done using Ostu thresholding method. The threshold used for the detection is computed based on the entropy-based Shannon and Tsallis methods. The system is tested with MIAS and UCSF database and the true positive rate is 95.97%.

3.4 Region growing techniques

Liu et al. (2015) proposed a system for the detection of microcalcification clusters in full field mammograms. This system uses region growing and active contour segmentation method techniques for the detection of clusters of microcalcifications. The geometric and texture features are extracted from the suspicious regions. These features are fed as input to a trained Support Vector Machine Classifier that classifies the regions as with microcalcifications and without calcifications. The image set for testing and training purposes are collected from the INbreast database. This system achieves a sensitivity of 92 % and false positive rate of 2.3 clusters per image. Malek et al. (2010) presented a method for the segmentation of microcalcifications in digital mammograms using seeded region growing method. The initial seed selection is fully automatic which uses regional maximum and local maximum methods. The boundary segmentation is done using mathematical morphology. The accuracy of image segmentation is 0.94 where the method used images from National Cancer Society in Malaysia consisting of 50 mammograms.

3.5 Wavelet-based techniques

Al-Qdaha et al. (2005) compared and evaluated the detection rate of microcalcifications in digital mammograms between Indian, Chinese and Malaysian races in Malaysia. The detection of microcalcifications is done by decomposing the images into wavelets using db4 wavelets to find the region of interest (ROI). The thresholding is applied in the region of interest to identify the microcalcifications that appear as bright spots and they are separated from the background. Graphical user interface is provided for the radiologist to test the system for the detection rate. The detection rate for Indian women is more than Chinese and Malaysian women which is 85–90.5%. Razek et al. (2013) used a Computer Aided Detection (CAD) system for the detection of microcalcifications clusters. An LIBCAD software is created which consists of all the computing functions that can be used in an image viewer. This CAD system identifies the clusters of microcalcifications in digital mammograms and classifies it as True Positive image and True Negative image. The detection results of the LIBCAD is compared with radiologists detection results and this CAD system achieved a detection rate of 97.4% at a threshold level of 4 foci per cluster and 92.1% at a threshold level of 8 foci per cluster.

3.6 Contour based detection techniques

Arikidis et al. (2010) proposed an algorithm for the image segmentation based on the size of the microcalcifications in the breast region. The segmentation algorithm is based on multiscale active contour model where a robust selection algorithm is employed for the selection of scales to initialise the active contour model. The system is tested with image set of DDSM database and attained an area overlap of 0.61 ± 0.15.

3.7 Fuzzy detection techniques

Touil and Kalti (2016) proposed a system for the segmentation of breast region from its background which is the first step in detecting any abnormalities such as microcalcification and masses. This system utilises a region-based method and the estimation of breast region extracted using a fuzzy method for segmentation which increases the precision of the extracted region using Fuzzy C-means clustering algorithm. The system is tested with MIAS database and attained 95.45% completeness and 59.05% correctness.

3.8 Three dimensional detection techniques

Yam et al. (2001) demonstrated a method for three-dimensional representation of the breast region and microcalcification clusters from a two-dimensional mammogram. The method concentrates on both the CC and MLO views. The reconstruction of microcalcification in three dimensions is done considering the geometric constraints and matching criteria. The preprocessing is done through Linear approximation, Hough transform, dynamic programming. The system is tested with a set of 30 mammograms. The microcalcification segmentation is done through iso-contours and normalised methods. Yang et al. (2005) introduced a system for registering the microcalcification clusters, 3D localisation of the clustered microcalcifications and 3D visualisation of clustered microcalcifications. Three features such as gradient, energy, and local entropy codes are used for the registration of the microcalcifications in two views such as CC and MLO as decision trees. The localisation is performed using nipple as a control point and changing the coordinates of the breast region. The 3D visualisation is performed using virtual reality modelling language viewer (VRMLV) to view the breast calcifications. Huang et al. (2006) proposed an approach using 3D Modified Projective Grid Space algorithm for reconstructing the microcalcifications from two views such as CC and MLO views. The reconstruction model is created using the uncompressed scheme to exactly replicate the real mammogram taken from patients. The distance is calculated from the reconstruction model to the real model and the microcalcification shapes are reconstructed. The system is tested with 15 pairs of CC and MLO views and the registration accuracy was 96.7%. C. Dromaina et al. (2013) reviewed the computer-aided diagnosis system that works with both h screen-film mammography and full field digital mammography. It discusses the various abnormalities that lead to breast cancer such as masses and microcalcifications and the role of computer-aided diagnosis system in providing guidance for decisions. The paper makes understand that the CAD system should never be the final decision for patients.

4 Feature extraction techniques for microcalcification in CAM

The feature extraction is the fundamental step that extracts the characteristics of the breast microcalcifications present in the Region of Interest (ROI) that are segmented. The shape, colour, texture and size are the most important features to be extracted from the segmented abnormalities and these are used as the input to the next stage, which is classification. Some systems also find the topological features when the microcalcification clusters are classified.

4.1 Texture feature extraction

Peng et al. (2016) used a system for the detection and classification of microcalcifications in Digital mammograms. The images are preprocessed using 2D median filtering and the pectoral muscles region is segmented using seeded region growing method. The resultant segmented images if further used for the feature extraction where the Haralick and Tamura features are extracted using grey level Cooccurrence matrix. The classification system used is the feedforward back propagation neural network where the learning is done through the back propagation algorithm. This system uses a reduced set of features where reduction is done using rough set methods. The classifier classifies the features as malignant or benign. The classification accuracy is 96% when tested on MIAS and BancoWeb database.

4.2 Shape feature extraction

Soltanian-Zadeh et al. (2004) evaluated and compared four shape and texture feature extraction methods. Four methods such as conventional shape quantifiers, a cooccurrence-based method of Haralick, wavelet transformations and multi-wavelet transformations were used to extract the features. The feature set selection is done using real-valued genetic algorithms and binary genetic algorithms. The testing is done using 103 microcalcification regions extracted from Nijmegen database where the shape features performed well when compared to texture and wavelet features if they are classified using KNN classifier. When it is tested, the ROC curve ranges from 0.84–0.89 for real-valued GA and 0.83-0.88 for binary genetic algorithms. Pak et al. (2015) proposed an algorithm for the detection and classification of breast cancer such as microcalcifications and masses. The images are preprocessed for enhancing the contrast using NonSampled Contourlet Transform and Super-resolution methods. The microcalcifications are detected using thresholding and morphological operators. The regional, boundary and density features are further extracted and are fed into the AdaBoost classifier obtaining the accuracy of 91.43% and false positive rate of 6.42%, when they are tested with MIAS database.

5 Classification techniques for microcalcifications in CAM

Classification is the final step in diagnosing the breast cancer which categorises the digital mammograms as normal or abnormal. Further the abnormal mammograms are categorised as benign and malignant based on the severity which is calculated using the features that are fed as the input to the classifier. Some classifiers works on the basis of supervised learning and the rest works on unsupervised methods.

5.1 Neural network classifiers

Khehra and Pharwaha (2016) presented a system for the classification of microcalcification clusters using Levenberg-Marquardt multilayer feed-forward backpropagation ANN and sequential minimal optimisation (SMO) based SVM. A comparative study has been performed which proved that the classification accuracy of SMO-SVM is better than the LM-MLFFB-ANN classifier. A set of 23 suitable feature set is selected from a set of 50 features using particle swarm optimisation. These features are fed to LM-MLFFB-ANN and SMO-SVM classifier to classify the ROIs as benign or malignant. The overall accuracy of LM-MLFFB-ANN is 0.8651 and SMO-SVM are 0.9016 when tested using image set extracted from DDSM database. Dócusse et al. (2013) proposed a system for the detection and classification of microcalcifications using region growing and multilayer neural networks. The images are preprocessed using wavelets and the detection of the microcalcifications are done using modified region growing. A set of for image features is extracted and fed to the classifier as input. The classifier employed is the Multilayer ANN trained using backpropagation network which classifies it as benign or malignant. The classification accuracy gained is 96.67% when it is tested using an image set of 210 mammograms.

5.2 K-nearest neighbour (KNN) classifiers

Amjath Ali and Janet (2013) used a system for the classification of microcalcifications using KNN classifiers. The system uses the Shearlet transformation to calculate the energy features. The features that are extracted are fed into the KNN classifier for the classification where it is decided as benign or malignant. The system is tested using MIAS database and attained classification rate of 100%, 91.67% for malignant and benign cases.

5.3 Support vector machine classifiers

Zyout et al. (2015) presented techniques for the reduction of false positives in the detection of calcifications and masses in digital mammograms. For this, multiscale textural parameters are extracted using wavelet and grey level cooccurrence matrix. Further important parameters are selected using a model developed using particle optimisation algorithm. The selected feature set is given as the input to the trained SVM classifier for classifying the abnormalities as benign or malignant. The digital database for screening mammography is used for training and testing purposes. The accuracy of the proposed system reaches up to 0.85 ± 0.007 for DDSM database. Gedik (2016) proposed a feature extraction method in order to classify all types of abnormalities including calcifications in the mammograms. Using a finite Shearlet transformation, feature vectors are constructed. The ranking of features is done using a t-test. The ranked features are fed to Support Vector Machine Classifier (SVM). A 5 cross-validation was applied using the MIAS and DDSM databases over the optimal feature set. The system achieved a classification accuracy of 98.29% for MIAS and 96.89% respectively for DDSM images to classify the abnormalities as benign or malignant.

5.4 Fuzzy classifiers

Pawar and Talbar (2016) introduced a technique for the classification of breast calcifications as benign or malignant based on genetic fuzzy classification method. The GFS classifier uses texture based Wavelet Cooccurrence features calculated from GLCM matrix. The MIAS database images are used for testing purposes and the images are cropped to 128×128 pixels to reduce the background noise. The classifier uses 16 features from the 76 features set, which attained the highest classification accuracy of 89.47%.

5.5 Extreme machine classifiers

Malar et al. (2012) introduced a system for the detection and classification of microcalcifications in digital mammograms using extreme learning machine. The preprocessing is done using morphological operations and grey level slicing methods. The region of interests is extracted using manual cropping. The texture features are further extracted using orthogonal wavelet transforms, GLSDM and Gabor filters. These features are further fed to the extreme learning machine classifiers to classify the features as benign and malignant. This system achieves a classification accuracy of 94% when tested using MIAS database image set and it is compared with Bayes, Naive and SVM classifiers.

5.6 Data mining classifiers

Diz et al. (2016) analysed and compared two classification techniques such as Nave Bayes and random forest classifiers for the classification of various abnormalities including microcalcifications. These classifications are tested on two datasets such as Breast Cancer Digital Repository (BCDR) and In breast database. The features extracted are the texture features using GLCM and GLRM techniques. The experimental results show that random forest classifier achieves the best results for microcalcifications reaching up to 75.8% for Inbreast and 78.3% for BCDR datasets respectively. Karabatak (2015) proposed an approach for the classification of breast abnormalities as masses and microcalcifications using weighted Naïve Bayesian. The database used for testing is the Wisconsin breast cancer database and this approach when tested achieves a sensitivity of 99.11%, specificity of 98.25% and accuracy of 98.54% respectively. The weighted features are fed to the Naive Bayesian classifier which classifies the features as benign or malignant in a decision space.

5.7 Deep learning classifiers

Abdel-Zaher and Eldeib (2016) demonstrated a classification technique for breast abnormalities including calcifications using deep belief networks. This system combines both the supervised and unsupervised training methods using deep belief neural network in unsupervised training phase and supervised back-propagation training phase. The Wisconsin Breast Cancer Dataset (WBCD) is used for testing and training the proposed classifier. The proposed system achieves a classification accuracy of 99.68%.

5.8 Expectation logarithmic classifiers

Bekker et al. (2015) proposed a system using expectation maximisation logistic regression for classifying the microcalcifications of fatty and dense breast regions. The rotation invariant features are extracted using curvelet transforms and classified using Expectation maximisation logistic regression model as benign and malignant. The system is tested with the image set extracted from DDSM database and the accuracy gained is 73.19 for fatty breast regions and 69.5 for dense breast regions.

6 Discussion

Accurate detection and classification of the presented algorithms in this paper depend on how much the false positives are rejected and the true positives are encouraged. Some algorithms incorporate the knowledge of the radiologist as the final stage of detection and classification for rejecting the false positives. Table 2 shows the preprocessing algorithms that are involved in the microcalcification detection in CAM scheme. Since the microcalcifications appear as very small spots and occur as clusters, the preprocessing plays an important role in the good detection of microcalcification clusters (MCC) from its background area. The advantages of these preprocessing techniques are:

- it removes the unwanted noise present in the mammograms, to enhance the contrast of the grey scale mammogram so that the tiny calcifications have much visibility than its surrounding area
- it makes the data manipulation easier
- it performs various smoothening and correcting of the background area of the mammograms.

Tables 3 and 5 provide the review of the segmentation techniques present in the microcalcification detection in CAM scheme. The advantages of these techniques are:

- it partitions the mammogram to remove the pectoral muscle region which is not the targets of detection
- it identifies the breast area from its background
- it exactly separates the regions of interest (ROI) in which the cancerous calcifications occur
- it converts the grey scale mammogram image into a binary image for easy manipulation using a technique called thresholding
- it partitions the image based on discontinuities and similarities using region growing, region grouping, splitting and merging.

The segmentation also deals with finding the exact microcalcification spots by incorporating edge detection techniques such as Canny edge detection methods and some edge filters such as Gabor and Laplacian filters. Sometimes segmentation techniques used for the microcalcification detection also involve some artificial neural networks along with optimisation techniques to optimise its parameters. Table 4 shows the feature extraction of the microcalcifications in the CAM scheme. These techniques concentrate on the intensity features as the calcification appears as bright spots in the mammograms. They also extract the topological features since the calcifications occur as clusters and the connectivity between these spots play an important role in their classification. Almost majority of the systems extract the texture of the ROIs since the texture differences are useful in increasing the classification accuracy. The microcalcification clusters can also be classified based on its scattering on the surface. Table 6 presents the classification techniques available for microcalcifications in CAM scheme. They are useful in identifying the severity such as benign that are non-cancerous and malignant is cancerous. Fuzzy classifiers make an intelligent decision by framing rules based on the radiologist's knowledge base. The ANN classifiers give the accurate severity of the stages of the malignant classification. Some systems use a two-level classification where the output of the first classifier is given as the input to the second classifier. The Linear Discriminate Analysis classifier gives the classification based on linear functions and they are suitable for microcalcification classification. The support vector machines can be combined with the fuzzy techniques to form fuzzy support vector machines Suresh et al. (2011) constructed based on some fuzzy rules can obtain good classification accuracy and improve efficiency.

Table 2 Review of preprocessing techniques for microcalcifications in CAM

Author	*Pre-processing*	*Segmentation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Saad et al. (2016)	Wiener filter	OSTU segmentation	Good detection using two-level segmentation	No shape and intensity features	Classification accuracy of 98.83	MIAS
Bria et al. (2014)	Quantum noise equalisation	Ranking based cascade detector, component-based thresholding	Uses a good set of features such as shape, texture and topology	No optimisation techniques employed	ROC curve malignant lesions 0.97	Images from the Netherlands
Duarte et al. (2015)	Alternating sequential filtering ASF, CLAHE	Geodesic active contours combined with Anisotropic texture filtering	Good detection accuracy and the usage of radiologists knowledge	Does not produce a good performance for smaller calcifications	87.4% for malignant 86.4% for benign	DDSM database
Daul et al. (2005)	Gaussian filters	Thresholding algorithm and a labelling technique	This system is hardware independent	Works for some viewpoints reconstruction is not fully automatic	16.25-mean accuracy	66 images

Table 3 Review of segmentation techniques for microcalcifications in CAM

Author	*Segmentation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Estevez et al. (1996)	Isaac clustering algorithm	The good graphical user interfaces	Masses have not been detected	True/false ratio of 2/7 < 0.285	15 mammograms
Qian et al. (2002)	Distance spaced and dense to sparse region grouping	Better than kernel-based region grouping	No classification of detected microcalcifications	Sensitivity of 92.5% with false positive of 2.4 /image.	30 mammograms
Guo et al. (2016)	Contourlet transformation and non-linking pulse coupled neural networks	The good detection rate of microcalcifications	No feature extraction and classification	93.182%	MIAS and JSMIT database
Yang et al. (2016)	OSTU thresholding method and improved pulse coupled neural network	Good detection of microcalcifications	No feature extraction and classification	Detection accuracy: 93.1 82%	MIAS database
Ogiela and Krzyworzeka (2016)	Pixel based segmentation, linear functions	Simple and easy to implement	No severity identification	Detection accuracy: 80%–100%	MIAS database
Mehdi et al. (2017)	Spatial automatic non-linear stretching Shannon entropy-based wavelet	–	No optimisation of techniques	The true positive rate of 97.14 % for 0,48 FP/per image	MIAS database
Mohanalin and Beenamol (2014)	Ostu method	Good threshold selection using SE and TE methods	No classification	True positive rate 95.97%	MIAS, UCSF database
Liu et al. (2015)	Region growing active contour segmentation method	Good and easy detection	Limited set of features used	Sensitivity of 92 % and FPR of 2.3 cluster/image	In breast database
Malek et al. (2010)	Seeded region growing, boundary segmentation using morphology	Automatic initial seed selection for region growing	The proposed method is not tested for masses	87.4% of the malignant 86.4% for benign	National cancer society in Malaysia

Table 4 Review of feature extraction for microcalcifications in CAM

Author	*Features*	*Classification*	*Merits*	*Demerits*	*Accuracy*	*Database*
Peng et al. (2016)	Haralick and Tamura features Texture features using GLCM and rough set feature selection	Feed Forward back propagation neural network	Good testing with two benchmark databases	Not been tested for masses	Classification accuracy 96%	MIAS database, BancoWeb database
Soltanian-Zadeh et al. (2004)	Shape, wavelet and Haralick features	KNN classifier	Good feature set selection using genetic algorithms	Topological and Intensity features has not been compared	0.84 to 0.89 when using real-valued GA, 0.83 to 0.88 when using binary GA	Nijmegen database
Pak et al. (2015)	regional, boundary and density	AdaBoost algorithm	BIRADS standard has been followed	No use of any optimisation	91.43% and 6.42% as a mean accuracy and FPR	MIAS database

Table 5 Review of segmentation techniques for microcalcifications in CAM

Author	*Segmentation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Al-Qdaha et al. (2005)	db4 wavelets and thresholding	Good graphical user interfaces for radiologists	No classification or feature extraction	Acc Indian 85–90.5% Malaysia-85–88.5% Chinese-85–87%	25 mammograms
Razek et al. (2013)	LIBCAD which is a Dynamic Linked Library (DLL)	The LIBCAD system can be embedded into any image viewer	No optimisation techniques employed	ACC of 97.4% at a threshold level of 4 foci	Images from two institutions
Arikidis et al. (2010)	Multiscale active contour algorithm using scale selection algorithm	Good detection range	Only single expert is involved in generating ground truth images	Area overlap of 0.61 ± 0.15	DDSM
Touil and Kalti (2016)	Region growing, fuzzy segmentation, fuzzy c-means clustering	Increasing the Precision of initially segmented breast region	Has not been applied and tested for various abnormalities	95.45% for completeness and 59.05% for correctness	MIAS
Yam et al. (2001)	Iso-contours, normalised mammographic methods	Three-dimensional view gives more accuracy in finding the microcalcifications	The severity of the microcalcifications are not identified	–	30 set of mammograms

Table 5 Review of segmentation techniques for microcalcifications in CAM (continued)

Author	*Segmentation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Yang et al. (2005)	Registering calcification clusters, 3D and 3D visualisation	Tested with Mammograms, MRI and Phantom cases	The severity of the microcalcifications are not identified	–	10 pairs of mammograms from
Huang et al. (2006)	3D modified projective grid space	The radiologists can adjust for final refinement	This method has not been applied for clinically	Registration accuracy 96.7%	15 pairs of CC and MLO view
Dromaina et al. (2013)	Computer-aided diagnosis system	Provides a good study about the computer-aided system	No new techniques introduced	–	–

Table 6 Review of classification techniques for microcalcifications in CAM

Author	*Features*	*Classifier*	*Merits*	*Demerits*	*Accuracy*	*Database*
Khehra and Pharwaha (2016)	Texture features	Multilayer FeedForward ANN and sequential minimal optimisation based SVM	Provides a good comparative analysis on ANN and SVM. Demerits	Does not incorporate metaheuristic approaches to find the optimal hyperplane	98.29% for MIAS and 96.89% for DDSM	DDSM database
Dócusse et al. (2013)	A set of four image features	Multilayer ANN with backpropagation	Does both detection and classification of calcifications	Classification is done only based on few features	Classification accuracy 96.67%	210 images
Amjath Ali and Janet (2013)	Energy features	KNN classifier	Simple and easy implementation	No optimisation techniques involved	100% and 91.67% classification rate	MIAS database
Zyout et al. (2015)	Texture features	SVM classifier	Optimised feature set selection		ACC 0.85 ± 0.007	DDSM database
Gedik (2016)	Fast finite shearlet transform (FFST) coefficients	SVM classifier	The use of *s*-FFST, *t*-test statistics, and dynamic thresholding. increases classification accuracy	Does not incorporate any optimisation technique for classification	98.29% for MIAS and 96.89% for DDSM	MIAS and DDSM
Pawar and Talbar (2016)	Texture features	Genetic fuzzy classification method	Good optimisation using genetic	No other features like shape or intensity	Accuracy of 89.47%.	MIAS

Table 6 Review of classification techniques for microcalcifications in CAM (continued)

Author	*Features*	*Classifier*	*Merits*	*Demerits*	*Accuracy*	*Database*
Malar et al. (2012)	Orthogonal wavelet transform, GLSDM, Gabor filters	Extreme Machine Learning	The use of EML gives more accuracy than normal FFNN	Has not been tested with different wavelet feature methods	Classification accuracy (94%)	MIAS
Diz et al. (2016)	Texture using GLCM	Nave Bayes and random forest classifiers	Simple and easy to implement	No use of the reduced feature set	Random Forest 75.8% for Inbreast and 78.3% for BCDR	Breast Cancer Digital Repository, Inbreast
Karabatak (2015)	A set of nine features that includes cell and nuclei related features	Weighted Naïve Bayesian classifier	Weighted Naive Bayesian classifier works well	Grid search is more expensive for the selection of optimum weights	Sensitivity of 99.11%, and accuracy of 98.54%	Wisconsin breast cancer database
Abdel-Zaher and Eldeib (2016)	Texture features	Deep belief neural network	Good classification using deep belief networks	No optimisation of neural network parameters	Classification accuracy of 99.68%.	Wisconsin breast cancer dataset
Bekker et al. (2015)	Rotation invariant feature using the Curvelet	Expectation maximisation logistic regression	Two stage classification model	Severity of masses has not been classified.	73.19 for fatty breast 69.5 for dense breast	DDSM database

7 Limitations and research direction

As breast cancer is the second common cancer worldwide and it is a life threatening disease. The necessity for mammogram manipulation by the radiologists becomes necessary. Since the availability of the experienced radiologists is less and the mammograms that need their decisions are more the necessity of developing a fully automatic detection and decision system without the interventions of the doctors plays an important role. The research direction could be incorporating optimisation techniques for the optimisation of the parameters of the detection algorithms, creating an optimised set of features and optimising the parameters of classification techniques. The use of deep learning neural networks in the classification of microcalcifications is also an interesting direction to pursue.

8 Conclusion

This paper brings out the recent CAM techniques employed for pre-processing, segmentation, feature extraction and classification of microcalcifications that are benign or malignant. Some of the approaches work for multiview mammograms such as CC views and MLO views and others work only for single view mammograms. The development of an accurate fully automatic detection and classification systems are challenging and they act as a second opinion for the radiologists to cross-validate their decisions in complex decision-making situations.

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