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A Survey on Breast Cancer Segmentation and Classification Using Several Methods

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***Abstract* — The early detection of breast cancer is an important factor in a medical field to control the disease as well as increase the success of treatment. In a present day, a mammogram is a most important and frequently used tool to diagnose and detect the breast cancer. The most common abnormalities of breast cancer are mass and microcalcification. These abnormalities are missed or misinterpreted by radiologist in times of the large number of screening programs. To overcome this problem, computer aided diagnosis (CAD) system is introduced to analysis the medical image and provide accurate results. The CAD system helps the radiologist and reduces the number of false positive in their results. The overview of a CAD system is preprocessing, segmentation, feature extraction and classification. The above stages are summarized and discussed in this paper.**

***Keywords* — ANN Classifier, SVM, Fuzzy C Means, Digital mammography, micro calcification, Linear Discriminant analysis**

I. INTRODUCTION

The Breast malignant growth is the second driving reason for death for ladies from around the world. In the lifetime of women, entirely 9% of women can have an effect on by this illness. In the year of 2008, the United States offers the report that 182,460 new analyzed cases and 40,480 women are passing because of this bosom malignant growth [1]. The 40% or more death rate of breast cancer is reduced or decreased by the early stage of detection [2]. In the year of 2013, the report is given by world health organization international agency for research on cancer (IARC); 1.7 million women affected by breast cancer in which 11.9% are diagnosed with 522,000 women are death. They also reported, 19.3 million new cancers will be caused around the year of 2025 [3, 4]. If the breast cancer is earlier detected than proper treatment is provided to the respective affected women. The earlier detection should be an effective one and it's able detects the breast cancer into benign and malignant tumors.

A mammogram is the effective method to detect the early stages of breast cancer. Even though, the accurate detection is difficult for the radiologist because of the large number of mammogram images for screening. In the screening method, totally, 10%-30% of lesions are missed is obtained by a human observer due to routing screening process. To alleviate the problem or reduce the workload of radiologist by the introduction of computer aided diagnosis system where digital image processing advance techniques, pattern recognition and artificial intelligence methods are used to improve the diagnosis of breast cancer identification [4-14].

There are several forms of abnormality affect the brain tissue and is divided into two types are microcalcification and mass.

The mass is also called as opacity is a localized sign of breast cancer and it is seen in two different locations. The masses are differentiating or characterized by their shape, size and margin. The mass can be benign and malignant. The shape of the mass is round, oval, lobular and irregular. The benign mass is defined by circumscribed oval and round. The malignancy is representing by irregular shape. The illustration of a breast mass is illustrated in figure 1.

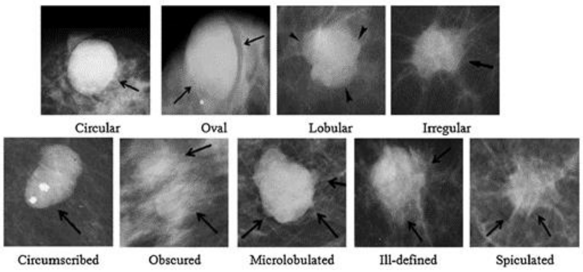

Figure 1: The illustration of breast mass

The microcalcification is very small and their range is from 0.1-1.0mm. It is characterized by various sizes, shapes and distribution due to the template matching is impossible. The microcalcification is seen by low contrast, their intensity is quite slim between their suspicious area and surrounding tissue. The clustered calcification is illustrated in figure 2.

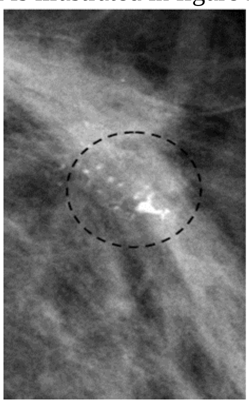

Figure 2: Clustered calcification

II. Computer Aided Diagnosis System

The CAD system reduces the false positive rate, operator dependency and it reduces the expensive of medical complementary [15-17].

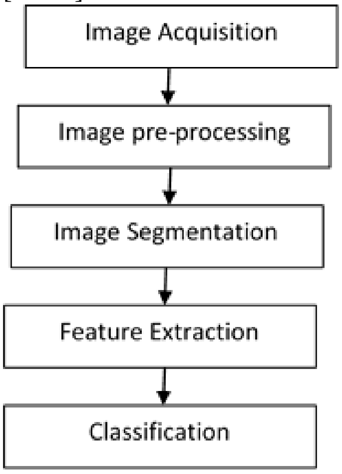

Figure 3: Block Diagram of CAD system

Image Acquisition: In image acquisition the images are captured; the captured images are transformed into digital form by converting the image into the signal.

Image Preprocessing: The image preprocessing steps are to improve the image through noise removal, contrast enhancement, edge detection. Through these all method the input images are improved and it's helpful to extract the information of the given image.

Image segmentation: In this process the images are divided into several parts or regions in which the pixels of each region have similar characteristics. The effective image segmentation process provides the best results or success in image analysis. The image segmentation is done by different approaches [18]. The following two segmentation processes are done by several researchers are Texture segmentation and Region segmentation.

The texture segmentation is done by the partition of images through different modes within the estimated empirical distribution using extracted the region of interest in the image [19-22]. The region segmentation provides the important information about the object in the given image [23-25].

Other techniques used for the image segmentation are Non-contextual segmentation and Contextual segmentation techniques. The non-contextual segmentation is performed by the global attributes of the given image. This process is done by thresholding technique. The gray or color image is given as the input of thresholding process and the output of this process is a binary image. The binary output is one and zero pixel; if the pixel intensity is higher than the threshold, then it's considered as white pixel or one; whereas if the pixel intensity is lower than threshold value then it represent as zero or black pixel. The two types of thresholding techniques are adaptive or color thresholding technique.

The contextual segmentation processes are performed by the features of the given image. The spatial analyses are included in contextual segmentation. The contextual segmentation methods are region growing and merging or splitting techniques [26].

The region growing methods segment the image the pixel has similar properties are grouped into regions. The opposite of region growing method is region splitting and region merging technique. The region splitting technique divides the whole image into sub - regions until it satisfies the homogeneity condition. The merging techniques are merging the regions have a similar characteristics.

The tradition image segmentation processes are pixel based segmentation, edge based segmentation and region based segmentation process. The pixel based segmentation process is similar to the threshold segmentation process. The edge based segmentation processes detect the edges of the regions.

Feature Extraction: The feature extraction technique is an important task in the image processing and pattern recognition. The images appear with different properties such as color, size and shape. For an automated system to differentiate between normal and abnormal image is determined, feature vector is generated for each segmented region. The feature vector is generated by extracting the image characteristics.

Classification: The obtained feature vector is given to the classifier to classify the image into normal or abnormal image. The two basic types of classifiers are supervised and unsupervised classification.

Supervised classification: The supervised algorithm needs training set for each time to test the testing data and provide results. Examples of supervised classifier are multidimensional thresholding; Minimum-distance classification; maximum likelihood classification; and support vector machine.

Unsupervised classifier: The unsupervised classifier does not need any training data each time for testing performance. Examples of unsupervised classifier are K-means, fuzzy K-means, hierarchical, and histogram-based clustering.

TABLE I

THE PERFORMANCE OF DIFFERENT IMAGE MODALITIES OF BREAST TUMOR CLASSIFICATION TECHNIQUES

Image modality	Techniques	Additional features	Results	Database
Digital mammography [27]	KNN	This method classifies the ROI of breast cancer into normal or abnormal	Sensitivity=92.85% Accuracy=92.815	The breast images are collected from IRMA dataset
Digital Mammography [28]	SVM technique	Classify the breast tissue into normal and masses; classify the breast tumor into benign and malignant	The accuracy of this method from 68% to 100%	The images are taken from MIAS 109 cases
Digital Mammography [29]	Combination of associative classifier with Fuzzy Artificial Neural network classifier	This combination technique classifies the breast images into breast tissue and masses	They obtained the results of Sen=92.22% Sp=96.39, Acc=95.11%	The breast images are collected from DDSM database, it consist of 170 benign and 130 malignant breast images

Digital Mammography [30]	Three types of classifier such as SVM, NB and RF	These three classifiers used to find three different scopes are predicting benign/malignant, finds the breast tissues into dense or fatty tissue and identify the mass and microcalcification in breast tissue	They obtained individual evaluation results for these scopes that: Acc=89.3% for benign and malignant; 758% for density or fatty tissue; 71% for mass and microcalcification identification	The breast images are taken from the INbreast BCDR database
Digital Mammography [31]	SVM technique	The abnormalities are classified based on SVM technique using fusion features	They obtained the evaluation results Acc=93.17%; Sen=92.71%; Sp=93.46%	They collect the breast images from MIAS database
Digital Mammography [32]	Combination of adaptive differential Evolution wavelet technique with Artificial Neural Network	This combined technique classifies the breast tumor into benign and malignant	They obtained the results of two databases: MIAS; Acc=89.38% Sen=83.58% Sp=93.43% DDSM; Acc=87.27% Sen=82.5% Sp=90.33%	They collect the images from two databases are MIAS and DDSM database
Digital Mammography [33]	Two techniques such as SVM and ANN classifier is used	The comparison between two classifiers are done and it classifies the masses from breast images	The results for SVM; Acc=93.2% ANN; Acc=92.5%	They have taken the breast images from DDSM database, it has 303 images
Digital Mammography [34]	SVM technique	This method is used to detect or classify the masses from breast image	The results of this approach; Acc=83.53%; Sen=92.31%; Sp=98%	They have taken the breast images from DDSM database
Digital Mammography [35]	RF	The automatic segmentation of breast tumor and classify the tumor	They obtained the results of Acc=87% Sen=92.5% Sp=98%	They collect the taken from two databases are DDSM and MIAS
Digital Mammography [36]	The clustering method of Fuzzy C-Means is used	This clustering method classifies the ROI into benign, malignant	They obtained the results of Acc=87% Sen=90% Sp=84%	They collect the images from DDM database
Digital Mammography [37]	SVM technique is used	This approach detects the microcalcification in breast images	They obtained the results of Sen=92% Acc=86.76	They collect the images from INbreast it consist of 410 images
Digital Mammography [38]	SVM technique is used	The feature vector is given to an SVM classifier to classify the breast tumor images into malignant or nonmalignant	They obtained the results for two databases: IRMA database; Sen=99%, Sp=99%; DDSM; Sen=97%, Sp=96%	They collect the images from IRMA and DDSM database
Digital mammography [39]	SVM technique	This approach used to classify the breast cancer	They obtained the results of Acc=97% Sen=98.24% Sp=95.08%	They collect the images from WBC database, it consists of 458 benign images and 241 malignant images
Digital Mammography [40]	SVM technique	This approach classifies the breast images into the malignant and benign tumor	They obtained the results of Acc=99%	They collect the images from MIAS database
Digital Mammography [41]	Fuzzy C Means clustering method	The cluster enhances the microcalcification in breast tissue	They obtained Acc=95% and Sen=93% for private database Acc=94% and Sen=82% for MIAS database	They collect the images from private and MIAS database
Digital Mammography [42]	SVM technique	This classifier used to classify the breast mass from breast tissue	They obtained the results of Acc=80.5%	They collect the breast images from DDSM database, it has 600 benign and 600 malignant images
Digital Mammography [43]	Decision tree classifier	In this method three types of decision tree classifier are used to classify the breast cancer	They obtained the results of Acc=97.51%	They collect the images from WBC database, it has 458 benign and 241 malignant images
Digital Mammography [44]	ANN technique is used	Breast cancer is detected and classified	They obtained the results of Acc=97.66% Sen=98.65% Sp=95.82%	They have taken the images from WBC database
Digital Mammography [45]	The SVM and ANN of two classifiers is used	The both classifiers are used to detect and classify the masses from breast images	The accuracy of SVM classifier is 93.7% and 92.5% for ANN classifier	They collect the images from DDSM database
Ultrasound image [46]	KNN classifier is used	The non-mass lesion in breast tissues are diagnosed	They obtained the results of Sen=87.8% Sp=89.5%	They collect he breast images from private database, it consist of 97 images
Ultrasound image [47]	SVM classifier is used	It distinguishes the breast tumor into benign and malignant tumor	The results of this approach are Acc=86.9% Sen=86.96% sp=86.96%	They collect the images from private database, it consist of 138 images

Ultrasound images [48]	SVM technique	The breast masses are detected from breast tissue and its diagnosis	The results of this approach are Acc=95.855 Sen=96% Sp=91.46%	They collect the images from private database, it consists of 70 benign and 50 malignant images
Ultrasound images [49]	SVM technique is used	The breast tumor is evaluated using this approach	They predicted Acc=96.67%, Sen=96.67% Sp=96.67%	They collect the breast images from private database, it consists of 120 benign and 90 malignant images
Ultrasound images [50]	Linear Discriminant Analysis	This method discriminates the positive and negative lymph node from breast tissue	They obtained an accuracy of 85%	They collect 90 breast images from private databases
Ultrasound images [51]	SVM technique is used	This technique classifies the breast tumor into benign and malignant	They obtained an accuracy of 91.07%	The breast images are collected from a private database and it has 77 malignant and 96 benign images
Ultrasound images [52]	RF	This approach classifies the breast tumor into benign and malignant	They obtained an ROC Accuracy of 99%	The images are taken from private database, it has 31 malignant and 28 benign images
Ultrasound images [53]	Three techniques such as NB, LR and Adaboost are used	The three techniques are used to discriminant the breast tissue into benign and malignant masses	The result of this approach is Sen=905 Sp=97.5%	They collect the images from 246 patients
Magnetic Resonance Images (MRI) [54]	KNN classifier is used	It classifies the non-invasive lesions from breast images	The result of this approach is Acc=74.7%	The images are collected from 200 patients
MRI [55]	Three types of techniques such as SVM, KNN and RF are used	The three methods are used to classify and discriminant the brain lesions into malignant and benign	The SVM technique obtained an Acc=82.8% Sen=94% Sp=77.8%	The breast images are collected from private database, it consist of 327 breast images
MRI [56]	The Fuzzy C Means clustering method is used	The breast masses are detected from breast images	The detection rate of this approach is high	The images are collected from private it consists of 61 biopsy lesions
MRI (54)	SVM technique is used	The non-mass enhancing lesions are diagnosed	This approach obtained their results through AUC figures	The breast images are collected from private it consists of 61 malignant and 23 benign images
MRI [57]	SVM technique is used	This technique classifies the breast images into normal or abnormal	It obtained an accuracy of 98%	The images are collected from private it consist of 70 normal and 50 abnormal images
MRI [58]	SVM technique is used	Suspicious malignancy is classified	It obtained an accuracy of 94%	The images are collected from private database, it consist of 70 breast images
MRI [59]	RF technique is used	This technique differentiates the mass and non-mass of breast images	It obtained an Sen=100% Sp=77%	The images are collected from 240 patients
MRI [60]	Fuzzy C-means clustering approach is used	It discriminant the breast images into malignant and benign lesions from breast images	It obtained an AUC=0.88	The breast images are collected from private database, it consists of 15 malignant and 8 benign images
Microscopic images [61]	Two classifiers such as ANN and SVM technique is used	It is graded the cancer malignancy	ANN technique obtained an Acc=87.1 whereas SVM technique obtained 77.23%	The images are collected from private database, it has 202 breast images
Microscopic images [62]	Three techniques such as KNN, NB and DT are used	The three techniques are used to classify the breast tumor into benign and malignant	The three techniques obtained and accuracy of 96% and above	The images are taken from private it consists of 50 images in which 25 benign and 25 malignant images
Microscopic images [63]	Four techniques such as KNN, SVM, RF and Quadratic Linear analysis are used	These techniques are used to classify the breast tumor into normal and abnormal breast images	In this approach quadratic Linear analysis method obtained 100% accuracy	The images are collected from 82 patients
Microscopic images [64]	SVM technique is used	This technique is used to classify the breast cancer	It obtained a classification accuracy of 825	The images are collected from private databases
Microscopic images [65]	DL technique is used	This method is used to detect the breast cancer from breast images	It obtained a result, in terms of mean and standard value	The images are collected from private databases
Microscopic images [66]	The RF and SVM technique is used	The breast cancer is diagnosed from breast images	It obtained a result of Acc=90% Sen=94.59% Sp=96.72%	The breast images are collected from private database, it consists of 228 breast images

Microscopic images [67]	Three techniques such as KNN, ANN and SVM classifiers are used	The breast malignancy is classified and graded	The SVM technique obtained an accuracy of 96.9%	The breast images are collected from private databases
Infrared Thermography [68]	Ant Colony Optimization (ACO) technique is used	It classifies the breast tumor into benign and malignant from breast images	It obtained an Acc=79.52%	The images are collected from Private database, it consists of 29 malignant and 117 benign images
Infrared Thermography [69]	SVM technique is used	The breast cancer is detected	It obtained an Acc=88.10%, Sen=85.71% Sp=90.48%	The images are collected from private database, it consists of 25 normal images and 25 malignant images
Infrared Thermography [70]	Decision Tree classifier is used	The breast cancer is classified	It obtained an Acc=90.01% Sen=81.02% Sp=92.35%	The images are collected from private database, it consists of 150 breast images
Infrared Thermography [71]	Fuzzy classifier is used	It classifies the breast images into normal and abnormal breast images	It obtained a result of Sen=82.35% Sp=92.15%	The breast images are collected from private databases
Infrared Thermography [72]	The combination of sequential minimum optimization technique with SVM classifier	The malignant breast conditions are detected and classified	It obtained an Acc=61.8% Sen=61.72% Sp=62.9%	The images are collected from private databases

III. PREPROCESSING

The preprocessing step is an important task in the image processing and pattern recognition. The task of preprocessing is to sharpen the edges and to increase the contrast level between the background image and suspicious region. The preprocessing consists of noise removal, sharpen the edges and contrast enhancement.

In the year of 1989, modified median filter was used to enhance the sharpness of mammogram images [73]. In the year of 1994, a nonlinear filter was developed to remove the noise from a mammogram image and it also preserves the edges of the mammogram image [74]. In the year of 1999, iris filter was applied to mammogram image for the removal of noise. The feature of this filter is the tumor region is well isolated from its background [75].

In the same year, region based enhancement method was applied to the mammogram image to enhance the structure of breast tissue. The feature of this enhancement method was it used each pixel as a seed to grow a region as well it enhances the region and background [76]. In the year of 2000, the unsharp masking of Sobel operation was given to mammogram image to reduce the low frequency information of the mammogram image [77]. The accurate adaptive approach was applied to the mammogram image to equalize the noise [78]. The recursive Gaussian low pass filtering and sub-sampling operation was employed in the mammogram image to smooth the breast tissue [79]. In the year of 2004, matched filter was applied to mammogram image. This method was used to enhance the breast tissue in the mammogram image [80].

In the year of 2006, wavelet based method such as wavelet shrinkage and the scale space analysis was applied to mammogram image for noise reduction and image enhancement. This approach was used two level detail image such as horizontal and vertical. The feature of this approach was preserving the edges of the mammogram image [81].

IV. SEGMENTATION

The local adaptive thresholding technique was proposed in [82] to segment the breast cancer mammogram image into different parts based on their class. Finally, adaptive clustering is applied to the image to refine the results.

An adaptive threshold technique was developed in [83] where histogram analysis was used to discriminate the mammogram image into three categories depends on their breast tissue density ranges from fatty to dense. The breast mass in ROI was detected by multiple threshold value depends on the category of breast mammogram image. The segmentation of various regions of breast tissue was performed in [84] where binary conversion was performed based on multiple threshold levels.

An adaptive threshold level was used to segment the affected region of breast tissue was presented in [85]. The adaptive grey-level threshold technique was applied on breast tissue for initial segmentation of suspicious regions [86].

The initial contour boundary of mass region was segmented by adaptive topographic region growth algorithm. After this initial process, an active contour was applied to segment the final mass region from breast tissue [87]. The initial mass within the ROI was detected by K-means clustering followed by the object selection method. The experience radiologist extracted the ROI depends on their biopsied mass in the breast tissue [88].

The combination of the Laplacian of Gaussian filter with density weighted contrast enhancement was applied to mammogram image. The enhancement technique combined with an edge detection algorithm for enhancing the structures of mammogram image and it's easy to detect the boundaries of the affected region in breast tissue by edge detection algorithm [89].

The combination of gradient vector flow filed with adaptive histogram equalization enhancement technique was applied to mammogram image. In this approach, the histogram equalization enhancement technique was used to enhance the structure of the brain tissue. After this process the ROI is extracted from the mammogram image through gradient vector flow field method [90].

The dual stage method was used on the mammogram image to extract the mass from breast tissue. The dual-stage segmentation methods were radial gradient index and region based active contour model. The initial contour near to the lesion boundary was segmented by radial gradient index method and then a lesion boundary of breast tissue was segmented by region based active contour model [91].

The hybrid technique was applied to mammogram image for the segmentation of breast masses. In this approach the combination of finite generalized Gaussian mixture model with contextual Bayesian relaxation labeling method was used. The finite generalized Gaussian mixture model was used to enhance the structure of breast tissue and extract the mass lesions from breast image. The contextual Bayesian relaxation labelling model was used to detect the suspected masses from the extracted mass from breast tissue [92].

The speculated mass of breast tissue was segmented from breast tissue was adopted by hybrid technique of pulse coupled neural network with fuzzy set theory [93].

TABLE II
SEVERAL SEGMENTATION METHODS AND THEIR REMARKS

Methods	**Remarks**
The combination of Gaussian filter, morphological filter and conditional thickening [94]	This method detected the approximate size of the spots.
Region growing approach [95]	This technique is easy to define the region depends on the seed selected and the condition on of their termination. In computing time and memory space, this approach is expensive.
The morphological filter such as top-hat filter with multi-scale element	Due to multi-scale element use, the segmented results are not affected by distortion and background noise. However the resolution level is needed to determine the size and shape of mammogram [96].
Histogram Thresholding	This method works well with low computation complexity. There is no requirement prior information for the histogram thresholding for the breast image segmentation [97].
Fuzzy logic	In this approach microcalcification was detected in breast tissue. This approach uses fuzzy rule to detect the various shapes of microcalcification. But the determination of fuzzy member is hard [98]
Multi channel wavelet transform	This method preserves the resolution of ROI due to discrimination of different frequencies. This method does not require the shape and size of the mammogram image [99].

V. FEATURE EXTRACTION

It is the important step in breast cancer detection and classification. The important features used in image processing or pattern recognition is given in below table.

TABLE III
SEVERAL FEATURES FOR MAMMOGRAM IMAGE

Features	**Feature Description**
Texture features	TF1: Auto-covariance coefficients [100] TF2: Block Difference of inverse probabilities [100] TF3: Block Variance of local correlation coefficients [100] TF4: auto-correlation, variance [101] TF5: Wavelet coefficient distortion distribution [102] TF6: Order statistics with their mean and variance [103] TF7: The contrast of the grey values [104] TF8: The correlation is defined from co-occurrence matrix [105] TF9: Dissimilarity of the given image [106] TF10: The relative frequency is obtained from the edges of the given image [105] TF11: Auto-correlation [107] TF12: Minimum side difference is obtained [108] TF13: The homogeneity of breast lesion [109] TF14: Standard deviation of gray value [110] TF15: The features are obtained from SGLD matrix [110] TF16: The features are obtained from a GLD matrix [110]
Morphological features	MF1: Spiculation [101] MF2: Find the ratio of depth to width [111] MF3: Branch pattern [112] MF4: Features of the lobulation [113] MF5: Features of the margin sharpness [114] MF6: Features of the margin echogenicity [115] MF7: Features of the angular variance [116] MF8: Number of substantial protuberances and depressions (NSPD) [111] MF9: Features of the lobulation index are find [111] MF10: Features of the Elliptic-normalized circumference [111] MF11: Features of the Elliptic-normalized skeleton [111] MF12: Features of ratio between long axis to short axis [111] MF13: Features of area lesion [111] MF14: Features of the normalized radial gradient [117] MF15: Features of the margin circularity [82] MF16: Degree of abrupt interface across the lesion boundary [118] MF17: Features of the angular characteristic [119]
Model based features	TF1: Auto-covariance coefficients [100] TF2: Block Difference of inverse probabilities [100] TF3: Block Variance of local correlation coefficients [100] TF4: auto-correlation, variance [101] TF5: Wavelet coefficient distortion distribution [102] TF6: Order statistics with their mean and variance [103] TF7: The contrast of the grey values [104] TF8: The correlation is defined from co-occurrence matrix [105] TF9: Dissimilarity of the given image [106] TF10: The relative frequency is obtained from the edges of the given image [105] TF11: Auto-correlation [107] TF12: Minimum side difference is obtained [108]

	TF13: The homogeneity of breast lesion [109] TF14: Standard deviation of gray value [110] TF15: The features are obtained from SGLD matrix [110] TF16: The features are obtained from a GLD matrix [110]
Descriptor features	MF1: Spiculation [101] MF2: Find the ratio of depth to width [111] MF3: Branch pattern [112] MF4: Features of the lobulation [113] MF5: Features of the margin sharpness [114] MF6: Features of the margin echogenicity [115] MF7: Features of the angular variance [116] MF8: Number of substantial protuberances and depressions (NSPD) [111] MF9: Features of the lobulation index are find [111] MF10: Features of the Elliptic-normalized circumference [111] MF11: Features of the Elliptic-normalized skeleton [111] MF12: Features of ratio between long axis to short axis [111] MF13: Features of area lesion [111] MF14: Features of the normalized radial gradient [117] MF15: Features of the margin circularity [82] MF16: Degree of abrupt interface across the lesion boundary [118] MF17: Features of the angular characteristic [119]

A. Features for microcalcification detection of breast cancer

This section describes about the extraction of feature for the detection of microcalcification in breast cancer.

Individual microcalcification features are directly extracted from a mammogram image such as area, perimeter, compactness, elongation, eccentricity, thickness, orientation, direction, line, background, foreground, distance and contrast. The well - developed radiologist can easily extract these individual characteristics from the mammogram image [128-130].

The spatial gray level dependence matrix provides the co-occurrence features [131].

The surrounding region dependence features are used to detect the microcalcification in breast tissue, it is obtained by a weighted sum of four directions [132].

The microcalcifications are detected by the extraction of features from Gray Level run length (GLRL) [133].

The microcalcification also detected from extraction of features from Gray Level difference (GLD) [134].

The wavelet features are used to detect the microcalcification such features are energy, entropy and norm extracted from wavelet transform sub images [135].

The features are extracted from Gabor filter bank are used for the detection of microcalcification [136].

The fractal mode of the breast image provides the features of fractal dimension [137].

The cluster features are extracted from the number of microcalcification in an area [138].

The classification of mammogram image into normal and abnormal using multiresolution texture features were presented by (Wei et al., 1997). In their method, they used wavelet transform to decompose the mammogram region of interest. The multiresolution texture features were extracted from the wavelet decomposes coefficients [139].

In the year of 1998, Kim et al., implement the statistical texture analysis method for the detection of cluster microcalcification in mammogram image. The statistical texture analysis method is called as a surrounding region Dependence method (SRDM). This feature extraction with back propagation neural network classifier provides the sensitivity of 90% [140].

A set of statistical features was extracted from the wavelet coefficients were developed by (Liu et al., 2001). The extracted statistical features with binary classifier provide the accuracy rate of 84.2% [141].

The shape, texture and margin sharpness features were extracted from the mammogram image to descript the mass lesions was implemented by (Alto et al., 2005). In this approach shape feature were extracted based on compactness, fractional concavity and speculation index. Totally 14 GLCM texture features were extracted from mass lesions. The acutance features derive the margin sharpness features [142].

The computer aided diagnosis system was developed by (Retico et al., 2006) to distinguish the malignant from benign masses. This method consists of three stage approach are segmentation, feature extraction and classification. In feature extraction, 16 different features were extracted based on shape, size of the mammogram lesions. The data set consists of 226 lesions in which 109 malignant and 117 benign cases. The feature extraction with classifier provides 78.1% for sensitivity and 79.1% for specificity [143].

A set of five different features was extracted from the mammogram image to detect the mass lesions was presented by (Kinoshita et al., 2007). The five sets of features were shape features, texture features, moment features, Gray-level histogram features, random features and Granulometric features [144].

The four different features were developed by (Alfonso, 2009) for the detection of mass in breast cancer image. The four features provide the degree of Spiculation of a mass, relative gradient orientation of pixels, the other two features provides the local fuzziness of the mass margins. These features were extracted from a set of 319 masses. These features produce the results of 89% correct classification [145].

(Yu et al., 2010) combined model-based and statistical textural features for clustered microcalcification detection. Firstly, suspicious regions containing microcalcification were detected using a wavelet filter and two thresholds. Secondly, textural features based on Markov random fields and statistical textural features with fractal models were extracted from each suspicious region and were classified by a back propagated neural network [146].

A research group of (Velayutham and Thangavel, 2012) used different features such as GLCM, Grey Level Difference Matrix (GLDM) and surrounding region dependency matrix (SRDM) was used to extract the features of the segmented microcalcification region. On their approach, a relevant feature was selected based on unsupervised method of rough set-based entropy to remove the redundant features [147].

The detection of individual microcalcification and cluster was presented by (Arnau Oliver et al., 2012) based on feature extraction and classifier. In their approach, local features were extracted from Gabor filter to predict the relevant information on the morphology of microcalcification. The features were extracted from MIAS database. The feature extraction with boosted classifier provides the sensitivity of 80% [148].

In the year of 2013, (do Nascimento et al.,) extract the multiresolution analysis features of the DDSM database mammogram image. These features were calculated using three distinct wavelet functions. The obtained feature with polynomial classification algorithm detects the mammogram image as normal or abnormal [149].

A set of features were extracted from the mammogram image was developed by (Diaz-Huerta et al., 2014). In their approach, a set of features were spatial, texture and spectral domain feature was extracted to reduce the number of false positive. The set of feature with SVM classifier provides the results of 85.9% sensitivity [150].

The discovery of breast cancer was created by (Shradhananda et al., 2015) in view of highlight feature extraction and classification. In this technique, the GLCM strategy was utilized to extract the features from 2D-DWT of region of interest (ROI) of a mammogram. From the feature matrix, the relevant features were obtained through t-test and f-test method. The features are extracted from MIAS database and DDSM database mammogram image. The feature extraction with classifier provides the results of 98% sensitivity and 94.2% specificity for MIAS database, whereas 98.8% and 97.4% for DDSM database [151].

The co-authors (Mohamed Abdel-Nasser et al., 2015) proposed uniform local directional pattern (ULDP) was used to extract the features from the breast tissue in mammogram image. The ULDP feature was based on the edge response of local neighborhood pixels. The features were extracted from mini-MIAS and In-breast database [152].

For the purpose of classification, features were extracted from the mammogram mass lesions. The two different types of features such as GLCM_sparse-ROI and (gray level aura matrix) GLAM_sparse-ROI were extracted on the sparse matrix was implemented by (Karteeka and Srinivasa, 2016). The purpose of sparse-ROI is to model the irregular shaped mass to facilitate the accurate diagnosis by a radiologist. The results are performed on MIAS database and obtained accuracy of 97.2% [153].

The significant features were presented by (Xie et al., 2016) to detect the mass as benign or malignant. In this approach, the features were extracted from mass region, background of the mass and the boundary of the mass region. The above features with a combination of SVM and Extreme learning machine method detect the mass as normal or abnormal [154].

Two different features were used by (Simara et al., 2016) to detect the different lesions in the mammogram image. The features were extracted from ROI of the mammogram image using GLCM and Gray-level run-length matrices (GLRMs). These features fed in to an SVM classifier to classify the mammogram image into benign or malignant. The above two features provides the results of 88.31% of accuracy, 85% of sensitivity, 91.89% of specificity [155].

The correlation based structural similarity features were developed by (Casti et al., 2017) to discriminant the malignant from benign lesions. The performance was evaluated on 94 mammogram images were collected from two publicly available datasets. The sensitivity, specificity and accuracy of the proposed features with classification were 86%, 65% and 75% [156].

VI. MAMMOGRAM CLASSIFICATION SYSTEM

The lesions were identified through computerized image analysis was implemented by (Judy Kilday et al., 1993). In this approach the interactive segmentation was used to segment the lesions from mammogram image. Next, seven features were extracted based on the shape of the segmented region. The obtained seven features were given into classifier of Linear Discriminant Analysis classification to classify the mammogram image [157].

The Markov random field was used to segment the lesion region from the mammogram image was applied by (Li et al., 1995). Then fuzzy binary decision classifier was used to classify the mammogram into normal and abnormal region [158].

The texture analysis method for the detection of microcalcification was developed by (Jong Kook Kim and Hyun, 1999). The texture features were extracted from the mammogram image was obtained through spatial gray-level dependence method, gray-level run-length method, and the gray-level difference method. The obtained features are fed into the classifier of back propagation neural network to classify the mammogram image into microcalcification and non-microcalcification [159].

The computer aided diagnosis system was developed by (Songyang Yu and Ling Guan, 2000) for the detection of clustered microcalcification. In this approach, first the mammogram image was segmented; then individual segmented microcalcification are applied into wavelet features, gray level and texture features. Totally 31 features were extracted from these features. The obtained 31 features were fed into the general regression neural network classifier using forward and sequential backward selection techniques to classify the mammogram image into microcalcification and non-microcalcification [160].

The grey level, shape and gradient features were extracted from the mammogram image was presented by (Naga Mudigonda et al., 2001). The obtained feature from the mammogram image was given the classifier of Linear Discriminant analysis classifier method was used as a pattern classification [161]. In the same year, Sahiner et al., extract the texture, morphological and Spiculation features from the mammogram image. The selective features were selected based on the stepwise feature selection method. The obtained selected features were fed into the Linear Discriminant classifier to classify the mammogram image [162].

The detection of cancer in the breast mammogram image was implemented by (Lei Zheng and Andrew Chan, 2001). In this method, first wavelet transform is used to decompose the mammogram image in which Dogs-and-Rabbit clustering algorithm was applied on three levels wavelet decomposition to segment the suspicious region. Finally, binary tree-type classification was used to classify the segmented region into normal or cancer region [163].

The computer aided diagnosis system was implemented by (Christoyianni et al., 2002) consists of feature extraction and classification system. The features were extracted from the region of interest from a mammogram image through gray level and texture features. The both features were given into the classifier of Radial Basis Function Neural Network classifier to classify the mammogram image into normal and abnormal mammogram image [164].

The detection of microcalcification in digital mammogram was developed by (Papadopoulos et al., 2002). This system consisted of feature extraction, feature reduction and classification system. Totally 22 features were extracted from the individual microcalcification system. The correct or relative features are selected based on feature reduction method of principle component analysis (PCA) method. The obtained selected features were given into classifier of neural network sub-system classifier to classify the mammogram image into normal and abnormal mammogram image [165].

The same author in the year of 2005, detect the microcalcification cluster in the digitized mammogram image using rule based classifier and support vector machine classifier. The detected results are evaluated using receiver operating characteristic (ROC) system [166].

The Gabor filters were extracted from the mammogram image was developed by (Tomasz Arodz et al., 2005). The features were given to the classifier of support vector machine (SVM) classifier to classify the mammogram image [167].

In the same year, three different types of features were extracted from the mammogram image was given by (Fu et al., 2005). The obtained three different features set was fed into Support vector machine classifier to classify the mammogram image into normal and abnormal image [168]. The machine learning approach of the relevance vector machine was used by (Liyang Wei et al., 2005) to detect the microcalcification in the mammogram image [169].

The detection of microcalcification was developed by (Sung-Nien Yu et al., 2006). The suspicious microcalcification was segmented by thresholding technique. The texture features were extracted from the segmented mammogram image. The obtained texture features were fed into classifier of the Bayesian classifier to classify the mammogram image into microcalcification and non-microcalcification [170].

The number of false positive in the identification of mammogram image was researched by (Celia Varela et al., 2007). This framework consists of preprocessing, segmentation, feature extraction and classification. In preprocessing, iris filter was applied on various sizes of the mammogram image. The affected or suspicious regions are segmented using the adaptive threshold method. The four distinct types of features such as gray level, texture, contour-related and morphological features were extracted from the segmented region [171].

The detection of mass lesions in digital mammogram image was developed by (Pasquale et al., 2007). First, the mass lesions were segmented, then extract the features of the segmented region. The features were extracted based on the shape, size and intensity of the lesions. Finally, the obtained sixteen features were fed into a multi-layered perceptron neural network classifier to classify the mammogram image into mass lesions and non-mass lesion [172].

The detection of clustered microcalcification was implemented by (Stelios Halkiotis et al., 2007). The detection was obtained by feature extraction and classification method. The features were extracted from individual microcalcification was based on mathematical morphology. The obtained features were fed into the classifier of artificial neural network of multi-layer perception and radial basis function to classify the mammogram image into microcalcification and non-microcalcification [173].

The detection of microcalcification cluster was presented by (Anna Karahaliou et al., 2008) in which the microcalcification was identified by wavelet method. The gray level texture and wavelet coefficient texture features were extracted from three level decomposition of wavelet image. The extracted features were fed into a probabilistic neural network to identify or classify the mammogram image into malignant and benign tissue [174].

The integration of Bayesian classifier and pattern synthesizing methods was developed by (Imad Zyout et al., 2009) to detect the microcalcification cluster. This method extracts the texture, spectral and statistical features from each input mammogram image. The obtained features were fed into the integration classifier to classify or segment the mammogram image into healthy tissue and non-healthy tissue [175].

The mammogram image was detected as normal and abnormal image was introduced by (Defeng Wang et al., 2009). In this approach different types of feature were extracted based on curvilinear features, texture features, Gabor features and multiresolution features. The features were selected based on elimination algorithm. The obtained selected features were fed into Support vector machine to classify the mammogram image into normal and abnormal image [176].

The detection of mass of mammogram image was developed by (Llado et al., 2009). The features were extracted using local binary patterns of the texture features from the segmented mass region. The obtained features were given into classifier of support vector machine to classify the mammogram image into mass lesion and non-mass lesion region [177].

The detection of microcalcification was developed by the association rule mining approach given by (Thangavel and Kaja Mohidee, 2009). In this method, shape based features were extracted from the mammogram image. The obtained features were given into a rule based system of association rule mining approach classifier to classify the mammogram image [178].

The assessment of breast tissue density in digital mammogram image was developed by (Subashini et al., 2010). The artifacts in the mammogram image were eliminated using gray level thresholding and connected component labelling method. The statistical features were extracted from the brain tissue. The obtained features were fed into support vector machine classifier to classify the mammogram image into a fatty, glandular and dense tissue [179].

The early detection of breast cancer was proposed by (Jinchang Ren et al., 2011) through the identification of microcalcification clusters from mammogram image. The

Artificial neural network classifier was used to classify the mammogram image [180].

The detection of the mammogram image comprises of preprocessing, feature extraction, feature reduction and classification was implemented by (Ioan Buciu and Alexandru Gacsadi, 2011). In this approach, Gabor wavelet was used to filter the mammogram image and directional features were extracted from the filtered mammogram image. The respective features were selected based on the principal component analysis method. Finally, proximal support vector machine was used to classify the mammogram image into normal and abnormal image [181].

The detection of breast cancer based on computational methodology was developed by (Wener Borges Sampaio et al., 2011). In this method, first remove the noise and improve the mammogram image. Second, segment the mass region from the mammogram image was obtained through cellular neural networks. Third, shape and texture features were extracted from the mammogram image. These features were given into the classifier of support vector machine to classify the mammogram into mass region or non-mass region [182].

VII. Conclusion

In this paper, computer aided diagnosis systems for breast cancer detection and classification using various techniques are given in the literature. The above procedures comprise of four phases are preprocessing, segmentation; feature extraction and classification are summarized. This survey paper will be helpful for the explorers in computer vision, image processing and radiology.

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