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Breast Cancer Detection using Classification Techniques in Digital Mammography

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ABSTRACT

Early breast cancer diagnosis is a challenging task for the radiologists without which the cancer death rate can be increased among women globally.Digitital mammography is the powerful technique which helps diagnosing breast cancers in premature stages preventing unnecessary biopsies and radiation treatments by proper screening and abnormality detection. The malignancy can be found in patients in the presence of masses and microcalcifications in the breast region. Successful analysis of the breast tumor relies on features extracted from the cancer suspicious areas and classification of features using classifier or combinations of the classifier. This paper summarizes all the existing classification techniques used in digital mammography for classifying the detected masses and microcalcifications as normal or begnin or malignant.

Keywords: Classification; Segmentation; Clusters of Micorcalcification (MMC); Free Response Operating Curve (FROC); Receiver Operating Charatersitics (ROC)

1. INTRODUCTION

Breast cancer isa life killing disease through the existence of debilitating growths influencing ladies mostly after the age of 30 all over the world. Early diagnosis of the breast cancers by the radiologist reduces the death rate globally. Many techniques are available for the detection of breast cancers among which digital mammography is the familiar and successful technique currently used by the radiology people. Mammograms are collected from patients who are suspected for breast cancers mostly as full field mammograms where the image detection and classification is high due to the high image quality. The main sign of breast cancers in Digital Mammograms is the existence of abnormalities such as breast masses, single or clustered microcalcification, lesions, nodules and architectural changes in the breast and the nipples.

The Computer Aided Diagnosis (CAD) mainly has four stages for classification of the abnormalities using Digital Mammograms. The input image is pre-processed which involves contrast enhancement using some filters. The segmentation is done by extracting the regions of interest (ROI) from the background. Thenthe features such as shape, size, color, texture, density, topology and morphological features are derived from the image. Finally, the derived features are fed into an appropriate classifiers to classify the images as normal or abnormal. Some approaches used multiple classifiers, where the output of the first classifier is fed as the input to second classifier to classify the abnormal tumors as begnin or malignant. Fig. 1 depicts the classification scheme for breast cancer findingin digital mammograms. The evaluation of the classification scheme for digital mammograms is done by testing the schemes using different databases and plotted as Receiver Operating Curve (ROC) using true positive and false positive

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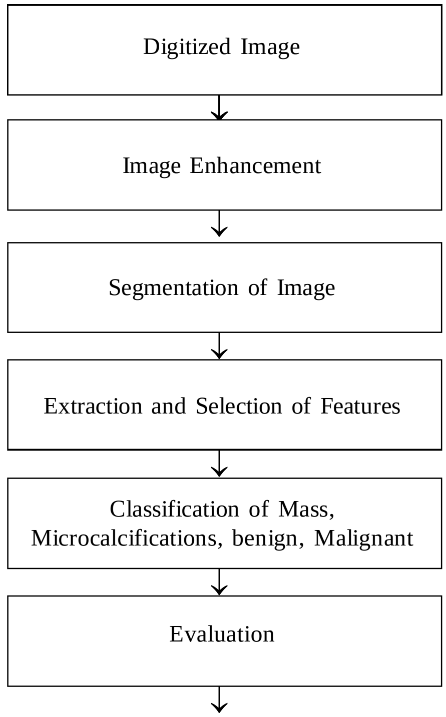

Figure 1: Classification Scheme for Breast Cancer Detection

as parameters. Higher the ROC area indicates that the classification performance is accurate. Another metric used for the evaluation is the FROC where the curve is plotted for true positive as a function of average number of false positives.

This paper summarizes majority of the currently used techniques for the classification used in breast cancer detection. The section 2 of the paper includes classification schemes based on the training data involving two types such as supervised and unsupervised classifiers. The section 3 involves classification schemes based on pixel information which includes pixel based andsub pixelclassifiers. The section 4 involves the classification schemes based on parametersused called parametric and nonparametric classifiers. The section 4 and 5 includes the discussion and conclusion of the paper.

2. CLASSIFICATION TECHNOIUES FOR BREAST CANCER DETECTION BASED ON TRAINING DATA

2.1. Supervised Classification

The supervised classification are conventional techniques in which the system is trained with a known set of pixels and then the classifier classifies the images as normal or abnormal.Examples are Distance based, AdaBoost, Decision Tree, Random forest classifiers.

Wei Qian et al. [1] introduced a detection algorithm by involving two challenges finding the presence of MCC in mammograms and classification using CAD for differentiating between the benign and malignant tumors.Chun-Chu Jen [2] proposed an automatic detection system for the classification of abnormal mammograms from the mammographic dataset. The textural features are derived from the images using binary level quantization and the suspicious mass regions are identified. Thepreprocessing of this system consists of noise elimination, binary conversion, breast extraction, Orientation finding and the pectoral muscle elimination. Then an automatic detection classifier is based on principal component analysis and Euclidean distances among the images that are tested and the centroids of the images in the entire mammographic dataset. Agood learningalgorithm is proposed by BrijeshVerma et al. [3]. The algorithm uses additional neurons for benign and malignant classification in the hidden layer for each output class for improving memorization ability. The network is trained by combining weightsof minimum distance and estimation of direct outputs.

An automatic system is introduced by Arnau et al. [4] based on derivation of local features for detecting MCC and masses. The initial training set learns and selects salient features at each round. Then these features are finally tested to detect the individual microcalcificationsusing Adaboost classifier. An approach is defined for accurately estimating the contour of abnormalities in mammograms by Mario Molinara et al. [5]. This approach is defined on the assumption that the location of the center of the mass and an external contour is available. This approach incorporates a classifier based on boosting method which is trained on the core and the external contour so that the classifier classifies Tomasz Arodz et al. [6]proposed two pattern recognition methods relied on AdaBoost and SVM based technique and evaluated based on different circumstances. The AdaBoost based method perfectly identifies majority of the malignant masses and lesion types where as SVM based technique does not find the indication of abnormal tissues novel method is proposed by DaeHoeKim et al. [7] in which the images are first pre-processed to extract the region of interest(ROI). The stellate features are further extracted from three sub regions such as the core, inner and outerparts based on the statistical characteristics for individual sub regions. The classification is done through AdaBoost learning for classifying the masses as normal benign and malignant masses.Ciro D Elia et al. [8] introduced an automatic detection of clustered MCC based on multi classifier approach. The geometric and texture features are derived from the regions of interest and heuristic filter is used to identify the best features for classification. 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.

D. Brzakovic et al. [9] proposed tumor detection in mammograms which involves two steps. Then the pixel groupings are fed to the classifier based on four level hierarchical structure which uses Bayes classifier for decision according to certain measurements such as shape and intensity in order to classify benign and malignant tumors. N. Karssemeijer et al. [10] gives amethod for the detection of stellate patterns in mammograms. The classification uses a classifier which uses the pixel orientation map by constructing new operators that varies according to the straight lines radial patterns.H.D. Li, M. Kallergi et al. [11] derived a technique for the detection through segmentation and discrimination of breast tumors. The classification is done classifying the masses as normal and malignant based on a binary tree for decision.An artificial intelligence algorithm is designed by L. Zhen et al. [12] which involves extraction of the regions of interests using the fractal dimension analysis. The segmentation of the images are done through dogs-and-rabbits clustering algorithm. Classification of the useful portion of images are done through three level tree type classifier which uses variance and inside gradient, compactness and edge variance at each level for classifying the masses as normal and malignant.Rodrigo Pereira Ramos et al. [13] proposed a computer aided method of masse detection and false positive reduction for the classification of breast tumors in x ray mammograms. The texture features are derived using the gray level co co-occurrence matrix, wavelets, rigdelets transforms. The best features are selected using a genetic algorithm. The segmentation in the regions of interest are done through the Random Forest algorithm which is a data mining method divides the data into segments without overlapping.This algorithm works on a collection of classification tress with bootstrap samples used for training the classifier with random features.

2.2. Unsupervised Classification

The unsupervised classification techniques analyses large set of pixels which are not known before and then group them according to the natural properties of the pixels. Examples of unsupervised classifiers include cluster based, association rule mining and extreme machine learning classifiers. The Unsupervised classification consumes major amount of time for execution when compared to supervised classification techniques. This section presents some of the techniques used for digital mammograms in past and recent researches.

A detection algorithm is demonstrated by Murk J. Bottema et al. [14] which consists of primary detection of candidate calcifications, model fitting, and estimation of parametersafter which finally finding if the candidate is a true calcification or not by clustered classification technique. Best fit model parameters are used for detection and classification. Xi-Zhao Li et al. [15] proposed an algorithm for classification of breast masses using high order textons.The segmentation is through k means method of clustering and the clusters are identified in the feature vector space which forms the higher order textons.The first order texton maps are identified using Euclidean distance method.Vipul Sharma Sukhwinder Singh [16] presented the correlation-based feature selection (CFS) and sequential minimal optimization (SMO) based on kernels for the classification of fatty and dense mammogram. Texture analysis is done to quantify the texture of parenchyma patterns of breast on the regions of interest. To minimize the dimensionality and to differentiate between breast tissue densities the correlation based feature selection is used. The classification is done through sequential minimal optimization SMO.

Aswini Kumar Mohanty et al. [17] proposed a system that has three stages. First, the region of interest (ROI) is calculated with 256 × 256 pixels size sets. Next stage is the feature extraction for finding twenty six features which is capable of finding the difference between normal and cancerous tissues, maximizing the classification rate. The third stage is classifying the extracted features based on association rule mining to classify the normal and cancer developing tissues. An algorithm for texture based classification using associative mining for rules used for classification for medical image analysis is introduced by Deepa S. Deshpande et al. [18]. The algorithm uses GLCM algorithm to find out the texture features from the mammographic images. From the features extracted associative rules are formed.Aswini Kumar Mohanty et al. [19] proposes a method for classification of breast masses using correlated rule mining. The images are preprocessed by resizing and finding out the regions of interest. The Statistical and texture features are formed using the gray level co occurrence matrix method (GLCM).The classification is done through the Correlated association rule mining which takes association framed using the features extracted. The purning is done using the CorClass algorithm. The classification is done based on the decision list and the weighted combination of the association rules based on which the best rule is selected for classification.Zhiqiong Wang et al. [20] demonstrated an algorithm for breast tumor detection along with classification using extreme machine learning. The images are preprocessed using a median filter through which the noises are reduced and the images are enhanced in contrast. The breast edge segmentation is done through the wavelet modulus maxima transform method, region growing techniques and morphological operation. Then five texture features and five geometrical features are extracted and a two dimensional input vector is formed and fed in to the Extreme Machine Learning classifier for the classification of breast masses.

3. CLASSIFICATION TECHNIIQUES FOR BREAST CANCER DETECTION BASED ON PIXEL INFORMATION

3.1. Per pixel classification

Per pixel classification where each data points in the image is processed individually.Example of these type of classification are K–Nearest Neighbour Classifier.

An automatic mammographic risk classification system is proposed by Zhili Chen1et al. [21] based on the breast density by using a hierarchical structure drawn from the higher sets of the images.A shape tree and a density tree is drawn which gives the saliency and independency measures based on which the shapes of interest which are dense regions are derived and further they are used in classification. Zhili Chen et al. [22] presented an algorithm for Topological modelling for the detection coupled classification of the groups of microcalcifications using K-Nearest Neighbour classifier.This extracts the topological features based on multiscalemorphology.A group of topological based features are formed from the graph which is build based on the connectivity of the clusters of microcalcifications.After which features are fed into the KNN based classifier to classify the cluster as benign or malignant Xingwei Wang et al. [23] developed an interactive computer aided diagnosis for detection with classification of masses using content based retrieval based on K nearest neighborclassifier. This system consists of the user interface that contains the options to the user to query an image, displaying the classification score, displaying the reference images. A region growing algorithm based on many layers topographic regiongrowth and an approach based on contours is used for segmentation of the masses. CBIR algorithm compares and retrieves a group of K reference images that are equal to the queried image.

3.2. Sub Pixel classification

The Sub Pixel Classification works by extracting the information regarding different classes of the same pixel. Examples include Fuzzy logic and pixel based Classifiers.

Arnau Oliver et al. [24] introduced a method for automatic detection of microcalcification along with cluster detection based on a boosting classifier. A word dictionary is created using a bank of filters for a set of patches that contain the microcalcifications which helps in the classification of images containing clusters of microcalcifications. This dictionary and the patches which contain positive and negative tissues of breast cancer are fed as the input to the Gentleboostclassifier. These patches are classified pixel by pixel using a dictionary trained classifier. Gisele Helena et al. [25] introduced a Fuzzy logic based computer aided system for the grouping of breast masses in mammograms.Animage set of 40 from DDSM database are described using the image descriptor constructed on BI-RADS classification standard.The classification is done through fuzzy modelling in two steps.In the first step, the nodules and calcifications are classified using the visual attributes. The second step builds a fuzzy inference system with three input parameters such as shape coefficient; contour coefficient and density coefficient. The Mamdani method is used as an inference model. The rules are framed using different combinations of the input coefficients.A machine learning algorithm called Fuzzy Omega algorithm is used to represent the experts knowledge by generating the membership function based on statistical analysis of data. A fuzzy rule method for the discrimination of breast masses dependent on BI-RADS categories for shapes is developed by A.Vadivel et al. [26].The images are preprocessed using gray threshold based approach. A set of 17 shape and margin features are extracted using a set of mathematical functions.The rules are then constructed based on the features using Mamdani based fuzzy inference model.The best rules are selected using Decision tree algorithm based on the depth of the tree which is usually set as 1.Based on the fuzzy rules framed the fuzzy membership functions are generated and the breast masses are classified as bengin or malignant.

4. CLASSIFICATION TECHNIIQUES FOR BREAST CANCER DETECTION BASED ON PARAMETRS USED

4.1. Parametric Classification

The parametric classification mainly works under the data distribution assumptions. Linear Discriminant Analysis Classifier is one of the best examples for Parametric Classification.

B. Sahiner et al. [27] studied the impact of the accuracy for classificationby the automatic mass segmentation technique by comparing the automated segmentation technique by the manual methods involving two radiologists on a group of 100 masses using distance measures of the data set of six tests based on statistical properties were performed and the classification is done for two feature sets extracted using linear discriminate analysis and the stepwise feature selection. An algorithm is introduced by L.M. Bruce et al. [28] for classification of the shapes of the masses in the mammographic images using linear discriminant analysis classifier to classify masses as round masses, nodular and stellate masses. The feature extraction is done through the shape analysis and the multiresoultion and uniresolution shape features are extracted. These shape features of the manually segmented masses are fed to the LDA classifier

4.2. Non Parametric Classification

These type of Classification Techniques does not rely on the probability density of the images. Examples include Support Vector Machine, Maximum Likelihood Classifiers and Expert System Classifiers.

Daniel RodriguesEriceira et al. [29] introduced an sequence of steps for detection of the breast masses in the asymmetric regions by using different functions formed using spatial description with variogram and cross-variogram.The cross variogram functions identifies the asymmetric regions using structural variations done using bilateral registration of left and right breasts pairs of patients waiting for diagnosis. Then on those asymmetric regions the varogram functions are applied to classify the masses as normal or abnormal.Defeng Wang et al. [30] proposed a Structured SVM(s-SVM) model to determine if the region of the mammogram which are doubted for cancers is normal or cancerous by considering the patterns of clusters oftrainingset involved. Many features including curvilinear features, features based on texture, Gabor features along with multi-resolution features are formed from the images which are taken as the sample set after which, the salient features are derived from recursive feature elimination algorithm. An algorithm is framed by Alfonso Rojas Domínguez and Asoke K Nandi [31] to find out the group of six features framed for differentiation of mass margins.Three famous classifiers namely Bayesian classifier, Fisher's linear discriminant analysis classifier and a support vector machine classifier are used for prediction on each of features extracted. T.S. Subashini et al. [32] proposed a method for assessment of breast tissue density which involves preprocessing, feature extraction and classification. Statistical features that imply the texture are given as the input to the support vector machine classifier to classify it into any of the three classes namely, fatty, glandular and dense tissues. De Vito et al. [33] developed an algorithm for the classification of microcalcifications in breast images using a multi expert system. This algorithm combines the decision of multiple exerts system in order to find the malignancy of the microcalcifications.For the classification of single micro calcification the algorithm uses mC-EXPERT system and for the classification of the clustered microcalcification.

5. DISCUSSION

The table 1 summarizes of the Supervised Classification techniques for breast cancer detection for mammograms. The supervised classification techniques are one in which the classifier is trained using a training set and then these knowledge is used for classification of the medical images.The main advantage is that the training sets are reusable and these techniques have self assessment. The main disadvantage of these techniques is the appropriate selection of suitable training sets and the cost of training the classifier.

The Table 2 lists the Unsupervised Classification techniques for breast cancer in which the natural properties are considered for classification. The advantage of the unsupervised techniques is the low cost and its suitable for the unknown pixel classification.The disadvantages of the these techniques is the time complexity if these techniques are high and the results cannot be of expected.

The Table 3 summarizes of the classification techniques based on pixel information. The main advantage of pixel based classification is that the cost of pixel based classification is low when compared to object based classification and the disadvantage is that it does not take the spatial properties of the pixels in to account.

The Table 4 summarizes the classification techniques based on parameter used. The advantage of these techniques is it gives more accuracy when it is used for recognition applications due to its high computational capacity. The demerit is that the parameters selection is of tedious job without which the classification accuracy will be reduced. The Digital mammograms used in many techniques are the x ray images which are digitized.

Table 1
The analysis of Supervised classification techquies for breast cancer detection

Author	*Classifier*	*Abnormality*	*Features Extracted*	*Segmentation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Wei Qian et al. [1]	Distance based classifier	Microcalcification clusters (MCC)	Average contrast, greylevel deviation	An Adaptive Segmentation method	Overcomes the problems of the Kernel based region grouping by using grouping	No cluster oriented analysis for discovering new features	Sensitivity 92.5%, 2.4 FP per image	Set of 30 full mammograms
Chun-Chu Jen et al. [2]	Abnormality detection classifier (ADC)	Abnormal and normal breast masses	The textural ,geometric and shape features	Gray Level Quantisation	Useful for large data sets of images with various abnormalities	Lack of automated system with changing parameters	Sensitivity 88%	322 images from Digital Database for Screening Mammography
Brijesh Verma [3]	Trained neural classfier	Beginin and malignant breast masses	BI-RADS features, Grey level-based features	–	Capacity for new training patterns learning	Not fully automatic	Classification rate 100% and 94% on training and test set.	DDSM and other benchmark Databases
Arnau Oliver et al. [4]	Boosted Classifier	Microcalcification clusters (MCC)	Local features	Bank of Filters	It also detects clusters of microcalcifications	No tested with large databases	80% sensitivity at 1 false positive cluster	322 imaegs of the MIAS database
Mario Molinara et al. [5]	Boosting-Based Classifier	Begnin, malignant and normal masses	Gray level and spatial features	Region and edge based	Accurate segmentation of masses of mammograms	Need for two contours	–	Digital Database for Screening mammography
Tomasz Arodz et al. [6]	Improved AdaBoost Classifier	Malignant masses and lesions	Intensity features	Set of Gabor Filters	Identifies majority of the malignant masses and lesion types	No image feature identification	Classifier accuracy is 90% for masses	Set of 40 masses and 720 non-lesions
Dae Hoe Kim et al. [7]	Variable selection using Ada Boost learning	Normal, begnin and malignant masses	Region based stellate features	Multi Thersholding	Encoding of the physical characteristics of the stellate patterns	stellate patterns has not been included	ROC is 9187 0.929, 0.9567 for Decision tree, LDA, SVM	DDSM consisting of 140 mammograms
Ciro D Elia et al. [8]	Multi-Classifier Approach	(MCC) as positive or negative	Mean, Area, Aspect Ratio, Gradient	Tree Structured MRF	Efficient for clusters with large variations	Not many features has been analysed	Cluster detection rate is 90 % with one falser positive per image	40 images from Nijmegen database
D. Brzakovic et al. [9]	Deterministic Classifiers	Malignant-cancerous lesions	Edge distance variation , Edge intensity variation	Fuzzy Pyrramid Linking	This system is good in detecting the regions which need further biopsy.	Does not accurately help for actual recognition	Classification accuracy 85% detection accuracy was 95%	25 samples of mammograms
N. Karssemeijer et al. [10]	Classifier using Gaussian derivative operators	Speculated lesions and architectural distortions	Stellate features	Wavelets	The abnormality can be detected at a high specificity level	High computation time	The detection accuracy is 90% one false positive	50 images from MIAS database
H.D. L.M.	*Fuzzy*	*Suspicious*	Radio-	MRF	Classification	Has not been	Sensitivity is	90 images

(*contd...*)

(*Table 1 contd...*)

Author	*Classifier*	*Abnorm-ality*	*Features Extracted*	*Segment-ation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Kallergi et al. [11]	*Binary Decision Tree*	and normal breast masses	graphic, Density related features.		of abnormality breast masses < 10mm	used for large databases	90%	
L. Zhen, A.K. Chan et al. [12]	Binary tree Classifier	Suspicious Unsuspicious breast masses	*Gradient within current region*, area, compactness,	Dog and Rabbit Clustering	Low false alarm rate with high detection	Less gray level value matched with the background.	Sensitivity level of 97.3% FP 3.92	MIAS database of 322 images
Rodrigo et al. [13]	Data Mining Classifier	Breast masses	Texture features	Wavelets	Reduced set of features with high classification rate	Not generalizable	ROC curve AUC = 0.90	DDSM consisting of 120 images

Table 2
Performance analysis of UNSupervised classification techniues for breast cancer detection

Author	*Classifier*	*Abnorm-ality*	*Features Extracted*	*Segment-ation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Murk J. Bottema et al. [14]	Cluster based Classifier	Lobular and DCIS (small cell)	Radius, size and circumference	–	Detects points in the image for correct classification of the image identifying the maligi-nant cluster	Cannot be used for the detection of other abnormalities	Fraction of true positive detection is 60%. Classification is 69%.	Film mammograms from archives of Breast Screen SA in Adelaide, SA, Australia.
Xi-Zhao Li et al. [15]	Higher order texton classifier	Begnin and malignant breast tumors in both sides	BI-RADS features	–	Great increase in classification performance	Increase in computational complexity	Classification rate is 96.19%	320 images from Digital Database of Screening Mammograms
Vipul Sharma Sukhwinder Singh et al. [16]	CFS–SMO based classifier	Fatty and dense breast masses	BI-RADS features	K means Clustering	Effectively differentiates between the texture patterns.	BI-RADS standard has to be used for more accuracy	Accuracy 96.46% with 100% sensitivity and 88.23% specificity	Mini-MIAS The database contains 322 images in mediolateral-oblique (MLO) view
Aswini Kumar Mohanty et al. [17]	Data mining classifier	Cancerous and non-cancerous abnormalities	First-order statistics features, second order statistics	–	The large potential for cancer detection	Only eight features are used	Sensitivity of 96.5% and a specificity of 96.88%	DDSM database
Deepa S. Deshpande et al. [18]	Association rule mining classifier	Normal, benign, and malignant breast masses	Texture features	Wavelets	More time efficient compared to Apriori algorithm	Less number of association rules decreasing the accuracy	Classification rate obtained is Normal masses 100% Malignant masses 84% Benign 100%	322 images from Mammo graphic Image Analysis Society (MISA)

(*contd...*)

(*Table 2 contd...*)

Author	*Classifier*	*Abnorm-ality*	*Features Extracted*	*Segment-ation*	*Merits*	*Demerits*	*Accuracy*	*Database*
Aswini Kumar Mohanty et al. [19]	Correlated association rule mining classifier	Begnin and malignant breast masses	Mean, standard deviation, Entropy, skewness	Object Based Segment-ation.	Enhanced feature set such as topological features	The proposed method works well for both images with or without deno-ising	The method yields 98.6% sensitivity and 97.4% speci-ficity	DDSM Con-sisting of 402 images
Zhiqiong Wang et al. [20]	Extreme Learning machine Classifier	Normal and abno-rmal breast tumors	Five text-ural eat-ures and five mor-phological features	Mor-phological operations and region based	High Accuracy	High com-putational complexity	Receiver operating curve is 0.1 -1	482 images from Tumor Hospital of Liao Ning Province

Table 3
Performance analysis of classificationtechniques based on pixel information

Author	*Classifier*	*Abnorm-ality*	*Features Extracted*	*Segment-ation*	*Merits*	*Demerits*	*Accuracy*	*Database*
				PER PIXEL CLASSIFICATION				
Zhili Chen et al. [21]	KNN	MCC breast as begnin and malignant	Topologi-cal features	K means Clustering	Highly effective in reducing the region of interest	Shape and texture features has not been included for classification	Classification 96% and the ROC curve reached up to 0.96	MIAS, DDSM and full field Datasets
Zhili Chen et al. [22]	Density map	Breast masses classified using BIRADS classes	Shape and density features	MRF	Quantifies the density and tracks the changes in breast density	Lack of a fully automated system using density map classification	Classification rate for MIAS and DDSM databases are 76.01% and 81.22%	Full MIAS database and DDSM database
Xingwei Wang et al. [23]	CBIR based KNN	Normal and sus-picious mass regions	Local and global image features	Region growth and active contour	User friendly Functions	No BIRADS classification	(ROC)curve increased from 0.865 ±0.006 to 0.897±0.005	Dataset with database with 1800 images
				SUBPIXEL CLASSIFICATION				
Arnau Oliver et al. [24]	Gentle boost	Positive or negative microcal-cification patches	Local image features	Thers holding	The approach is fully automatic	The approach has not been tested for large databases	Sensitivity of 80% with 1 FP/image	232 images form MIAS database
Gisele Helena et al. [25]	Fuzzy rule	Contour, shape and density features	Nodules and mic-rocalci-fications	Fuzzy Modelling	The input co efficient are selected by semantically and friendly way	Does not con-firm to BIRADS classification standard	Accuracy of 76.67% for nodules and 83.34% for calcifications is achieved	(DDSM) consisting of 40 images
A. Vadivel et al. [26]	Fuzzy rule	Bi-RADS Shape features	Breast Mases and Calci-fications	Thers-holding	Combination of oval and round masses with 100% accuracy	This approach has not been used for 3D images	ILOR 87.76%, RO 100%, RL 95.45%	Total of 224 DDSM mamm-ogram masses

Table 4
Performance analysis of classification btechniues based on PARAMETERS USED

Author	*Classifier*	*Abnormality*	*Features Extracted*	*Merits*	*Demerits*	*Accuracy*	*Segmentation*	*Database*
B. Sahiner et al. [27]	Linear discriminant analysis and stepwise selection classifier	Texture, morphological, and speculation features	Normal, begnin and malignant breast masses	Robust to both hand segmentation and automated segmentation	Only less features have been extracted in order to classify	ROC was 0.89 for classification and 0.88 ROC for the segmentation	Active Contour Model	A set of 249 films from 102 patients
L.M. Bruce et al. [28]	LDA Classifier	Multi resolution Shape Features	Nodular masses lymphomas, and stellate masses.	Not only classifies a single shape mass but concentrates on all types of shapes	The system is not fully automated	Classification rates are 83% and 80%	The Wavelet transform modulus-maxima method	Data set containing 60 digitized mammographic images
Daniel Rodrigues Ericeira et al. [29]	Trained SVM Classifier	Tissue texture features	Mass and Non Mass	Handles both the left and right breast in multi views	No detailed Classification	Sensitivity 100% Specificity 67.56%	Cross-variogram function.	100 mammograms form DDSM database
Defeng Wang et al. [30]	Structured support vector machine Classifier	Curvilinear features, texture features, Gabor features and multi-resolution features	Normal and Cancerous masses	Structured SVM has good detection performance in comparison to SVM	Kernel parameter selection is not automatic	Classification rate is 95.4%	Edge detection using Gabor Filters	DDSM.
Alfonso Rojas Domínguez et al. [31]	Support vector machine classifier	Contrast, edge strength, edge-signature information, relative gradient orientation	Benign or malignant breast masses microcalcifications	Design of classification features with more discriminative power.	Only limited feature set	Sensitivity & specificity values of. 0.6 and 0.8, respectively	Dynamic-programming-based method and region-growing method	MIAS database
T.S. Subashini, et al. [32]	Radial basis function kernel SVM	Fatty, glandular and dense tissue	Statistical features	More accurate Classification	More features have not been added	Classifier accuracy of 95.44%.	Gray level thresholding and connected component labelling	Mini-MIAS digital database
S.De Vito et al. [33]	Multiple Expert Classifier	Malignant clusters and masses	Shape and texture	Use of two Expert classifiers	Not fully automatic	75.37% classification	Nil	40 image set

6. CONCLUSION

The paper lists out the survey of major existing classifiers used in the image Classification techniques used in Digital Mammography.The classifiers described in this survey classifies all the abnormalities which occurs in the high and low density areas of the breast such as distortions, lesions, nodules, masses, microcalicifcation clusters.Some techniques also gives the classification indicating the stages of the cancers to give an effective assistance to the radiologists.

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