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Comparative Analysis of Different Techniques Used for Detection and Classification of Micro-calcifications in Mammogram

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Abstract-Breast cancer is the primary and the most common disease found among women. Due to this the mortality rate has increased a lot as compare to other cancers found in women. Mammography is found to be most powerfuldetection technique which is been helpful to detect earlier cancerous tumor and increase success rate of treatment. Classification is a machine learning procedure thatclassify the data into predefined class labels which are used to predict the data according to those Classes.With this objective, a survey on mammogram classification is done by considering various feature extraction and classification methods used for classification of mammogram images. We compare the results of classification obtained from various feature extraction and classification techniques.

Index Terms: BPNN, Bayesian network, random forest network, k-means clustering, Multiscale Features, Co-occurrence, CWT, DWT, Mammogram.

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1. INTRODUCTION

Breast cancer is nothing but a malignant tumor that initiates in the cells of the breast.A group of cancer cells is acancerous tumor which that can infect surrounding tissues or spread to distant areas of the body. The disease is most common and occurs almost entirely in women, but men can pick it up, too. Breast cancer, the most common type of cancer is one of the leading causes of cancer deaths in women [2]. Breast cancer is caused by cancer cells that expand after the cells have grown uncontrollably. The cells combine to produce a mass or lump called a tumor which can be benign or malignant. It is imperative to remove the malignant tumors from the body once developed in order to keep the disease from spreading to the surrounding part around the breast. The solemnity of breast cancer depends on the stage of detection. Thus, early detection of cancer is the major concern for cancer treatment. Breast cancer percentage among all cancers is very high in women especially in urban areas in India. The moderate age of developing the breast cancer has been shifted to 30-40 years from 50-70 years, the earlier the cancer detected the better treatment can be provided [5], [6].

One of the most dependable methods for early detection of breast carcinomas is Mammography. However, it is difficult for radiologists to provide both uniform and accurate evaluation for the massive number of mammograms generated in widespread screening. Human observers consist of limitations: 10 –30% of breast lesions are missed during routine screening [5]. With the approach of pattern recognition, digital image processing and artificial intelligence,Radiologists have a chance to improve their diagnosis with the assist of computer systems on average, the readers' quality can be increased by 10% with the help of Computer Aided Diagnosis (CAD) systems the presence of micro-calcification clusters (MCCs) is acrucial sign for the detection of early breast carcinoma [1], [3]. The high correlation between the appearance of the micro-calcification clusters and the diseases exhibit that the auto-mated detection/classification of MCCs can be very helpful for breast cancer control [16], [18], [23].

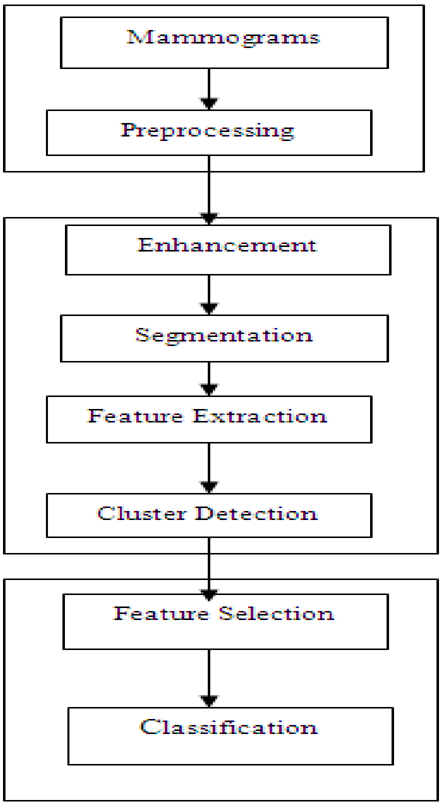

Fig-1: Block diagram of mammography CAD system [5]

2. PREPROCESSING OF IMAGE

Image enhancement increases the quality of the image. Here we try to curtail the over brightness or over darkness in the mammogram image. This is done using "Histogram Equalization" [5]. It enhances the specific features in an image, by increasing the contrast range in the image. Image enhancement includes intensity and noise reduction, contrast manipulation, edges sharpening, background removal [2], [5]. The task of mammogram enhancement is to acuminate the edges or boundaries of ROIs, or to increase the contrast between ROIs and background.

3. FEATURE EXTRACTION

3.1 Gray Level Co-Occurrences Matrix (GLCM)

The amount of gray levels in the image is used to determine size of the GLCM. By default, gray co-matrix uses scaling to reduce the amount of intensity values in an image to eight, properties of spatial distribution of the gray levels in the texture image are acknowledged by the gray-level co-occurrence matrix. Several statistical measures can be derived from the GLCM [21].
To illustrate, the following figure shows the concept of how graycomatrix calculates the first three values in a GLCM. The output of the GLCM, element (1, 1) holds the value 1 because there is only one occurrence in the input image where both the horizontally adjacent pixels, holds the value as 1, respectively [24]. Element (1, 2) holds the value 2 since there are two occurrences where two horizontally adjacent pixels holds the values 1 and 2. Element (1, 3) in the GLCM holds the value 0 as there are no occurrence of two horizontally adjacent pixels holding the values 1 and 3. Graycomatrix continues processing the input image, scanning the image for other pixel pairs (*i,j*) and maintains the sums in the corresponding elements of the GLCM.

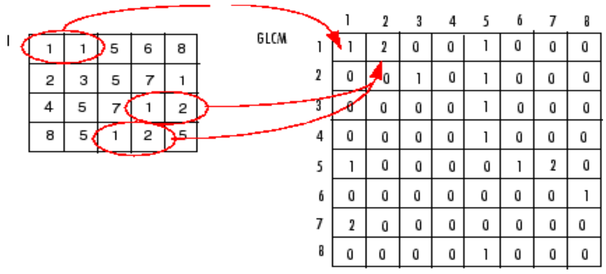

Fig-2: Process Used to Create the GLCM

First order grey-level histogram is the distribution of the probability of occurrence of a grey-level in the image. The second-order histogram, or grey-level co-occurrence matrix, H (yqyr, d, B), represents the distribution of probability of occurrence of a pair of grey level values separated by a given displacement vector, d, at an angle of 0. In other words, $H(y_q y_r, d, \theta)$ indicates the frequency with which particular grey-level pairsyq and yr, at an angle of 9, are separated by the vector d [6]. This is computed for all grey-level pairs in the image, for various displacement vectors and for all angles (usually 0 ^{0,} 45 ^{0,} 90 ^{0} and 135 ^{0,} around a central pixel). For each displacement vector used four co-occurrence matrices are calculated. Typically, these angularly dependent matrices are not used directly, rather the mean of the four co-occurrence matrices are used, insuring rotational invariance [30]. The elements of H(yqyr, d, 9) are normalized by dividing each entry by the total number of pixel pairs enabling the co-occurrence matrix to be treated as a probability mass function.

3.2 Wavelets

Wavelet decomposition was performed on all the ROI's used for the analysis. Daubechies wavelets [6] are orthonormal, regular wavelets having compact support and can be suitable for the analysis of signals with finite support. A separate feature is extracted from each scale (level), of the wavelet transform so it gives the features that reflect scale-dependent properties. For each the approximation and detail coefficients at each level of the decomposition the wavelet texture signatures are obtained. The wavelet transform was computed

to 4 levels of decomposition [22]. For each level or scale of the decomposition, the energy, entropy and root texture signatures were computed for the approximation and detail wavelet coefficients.
The Gabor transform [37] are the classical approach for the analysis of no stationary signals. Wavelet transform (WT) approach provide better signal resolution than the STFT, for bothshort windows at high frequencies and long windows at low frequencies [35]
Waveletsare a set of basic functions obtained by decomposition of signal and are also the core of wavelet analysis. There are different types of wavelet transforms that can be chosen depending on the various application available [11], [34]. The continuous wavelet transform (CWT) is used only for continuous signals. Time and scale are both continuous.

3.3 Multiscale Features

Multiresolution techniques are an important aspect of texture analysis [17]. Wavelets used for the analysis of image texture features along with the multiscale statistical texture features are used in this study [31]. The continuous wavelet transform (CWT) of a I-D signal f (c) is defined as ca,b $= \int f(x)\psi_{a,b}(x)dx$
Where the wavelet computed from the mother wavelet by translation and dilation, i.e.

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right)$$

The transform may be discretized by restraining a and b to a discrete lattice (a = '2 ^{n} ,b e Z). The mother wavelet then becomes

$$\psi_{n,m}(x) = 2^{-n/2}\psi(2^{-n}x - m)$$

To construct a mother wavelet, we must first determine a scaling function

40) = $\sqrt{2}\sum_k h(k)\phi(2x$ - k)

The mother wavelet in is constructed using the scaling function as follows

$$\psi(x) = \sqrt{2}\sum_k g(k)\phi(2x-k)$$

Where

g(k) $= (-1)^k h(1-k)$

Thus, the decomposition is obtained by passing the signal through a pair of filters H and G, with impulse responses h(n) and g(n) [25], [19] and down sampling the filtered signals by two. The h(n)and g(n)are the impulse responses that are defined as h(n) = h(—n), g(n) = g(—n)
The pair of filters H and G correspond to the half band low pass and high pass filters respectively, and are called quadrature mirror filters. Product of I-D filters is used to perform the extension to the 2-D case.

Ln(j) — H_x $[H_y \star L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}$ (j)

Dn2(j) = $[G_y \star L_{n-}$ I-Ic(j) J2,1

Dn2(j) -$G_x [H_y \star L_{n-}$1 J2,1

Dn3(j) = $\left[G_x [G_y \star L_{n-1}]_{\downarrow 2,1}\right.$11 2 (j) (8)

Where * denotes convolution, .1 2, 1 denotes subsampling along rows and 1, 2 denotes subsampling along columns. By low pass filtering Ln is obtained, and is therefore referred to as the low pass residue at scale nA specific direction the Dnisub images are obtained byapplying high pass filtering and thus contemn directional detail information at scale n, and are referred to as the detail images, providing horizontal, vertical and diagonal details [27], [28]. A set of sub images at several scales represented by the original image; {Ld, Dnili$= 1,2,3, n = 1..d\}$which is a multiresolution representation of depth d of the original image [32], [33].

3.4 Features representing size of micro calcifications

One of the characteristics of a micro calcification, which can be a sign of their malignancy, is their sizes [26]. A measure of its size in each micro calcification is determined by number of pixels [6], [7]. The features are: maximum size of micro calcifications in a cluster, standard deviation of size of micro calcifications in a cluster and sum of areas of micro calcifications in a cluster.

3.4.1 Compactness

Compactness is one of the feature that has proven to be a good measure for classifying micro calcifications by their shape. The ratio of the squared perimeter (P) to the area (A) is defined as Compactness (C), i.e., C=A (1) [14], [15].
The roughness of an object's boundary relative to its area is represented by Compactness. The smallest value of compactness is 12.56, which is for circle [29]. Compactness for circle becomes larger as circle deviates towards a more complicated shape. After upscaling the segmented micro calcification clusters,Compactness is calculated for each particle by separating the isolated calcifications in each cluster. The further step is marking the contour of each micro calcification. For doing this, we convolve the binary micro calcification image with four filters: [i — ii, [—1 ii, [], [ii] and store the results in four separate matrices. The following features are calculated: maximum value of compactness; and average compactness in each cluster after calculating the compactness for each of the micro calcifications [8].

3.4.2 Moments

Other shape features, which have proved effective for classifying micro calcifications, are moments.

The moments of the boundaries are used [10]. Moments are boundaries that are characterized by an ordered sequence, which represents the Euclidian distances between the centroid of the region and all contour pixels.

3.4.3. Features related to entire cluster

The size of the micro calcification cluster is one of the important specifications, it is always considered by radiologists for diagnosing mammograms. This parameter can be represented by using the radius of the circle that best fits the cluster, as a feature [13], [9]. We have is the standard deviation of the distances of the micro calcifications in each cluster to the center of the fitting circle is another feature extracted for every cluster. The scattering of the Micro calcifications, an important factor for classifying them is represented by using this feature. Another feature, number of micro calcifications in a cluster is another is obtained in the labeling procedure [12].

Table-1: study of various Feature Extraction techniques

Features	Details	References
Multiscale statistical features	The original mammogram is decomposed and its gray level dependency matrix is calculated to extract the features.	[39]
Wavelet features	Wavelet transform is applied on the mammogram images and energy, entropy and homogeneity features are extracted from various scale images.	[6],[11], [22],[34], [35],[37]
Co-occurrence features	Spatial gray level dependency matrix used to extract features such as Energy measure, correlation, inertia, entropy, difference moment, inverse difference moment, sum average, sum entropy, difference entropy, sum variance, difference variance, difference average, information measure of correlation, information measure of correlation.	[6],[21], [30],[24]
Individual Micro calcification features	Features such as moments, compactness, cluster features, etc. are directly extracted from the mammogram.	[6],[7],[8],[9],[10], [12],[13], [14],[15], [29]

4. CLASSIFIER

The implementation of computer-aided detection of mammography is mainly based on classifier. The features or a subset of these features are employed to train the classifiers and further during testing the classifier classify into micro-calcifications into benign and malignant. Training is any approach to classification assuming some knowledge about the data. Sample input data, domain facility, and a classification assignment to the data is required for Training Data. Classification accuracy is used to measure the Classification performance. The outcome of classification can be described as [3]

- True positive (TP): A tuple xi predicted to be in classckand is actually in it.
- False positive (FP): A tuple xi predicted to be in classck, but is actually not in it.
- True negative (TN): A tuple xi not predicted to be in class ck, and is actually not in it.
- False negative (FN): A tuple xi not predicted to be in class ck, but is actually in it.

To determine the accuracy of the classifier the precision and recall are used and it is calculated as [3].

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Accuracy is indicated by a confusion matrix. When classifying a class with m classes, the confusion matrix is a m*m matrix. An entry $C_{i,k}$ indicates the number of tuples assigned to a class C_k but the correct classification is C_i. A general confusion matrix for two classes is as shown in [3]

Table-2: General Confusion Matrix for Two Classes

Category		Predicted assignment	
		Positive	Negative
Actual assignment	Positive	TP	FP
	Negative	FN	TN

4.1 Random Forest

Random forest a composite classifier is built from a collection of tree classifiers. It is the concept of unpruned classification induced from bootstrap samples of training data, using random feature selection in tree induction process [4].

Construction of a tree:

Step 1: Random sampling procedure, with bootstrap is used for training the data, creation of tree is done by using two-third of data.

Step 2: from the above feature set random number of attributes are selected, and the ones with most information gain to comprise each node is identified.

Step 3: Stop the work due to information loss which result in of creating no more nodes.

Step 4: By running the remaining one-third of dataset through the tree error estimate is determined and correctness is computed.

Algorithm [7**]**

Random Forest Decision Classifier (RFDC):

A collection of individual tree classifier is a Random forest decision classifier. The concept of a general Random forest is as follows:

1. Select m the number of trees to grow, and n a number no larger than the number of variables.
2. for i = 1 to Nm
   Call T Forest ():
3. Draw a bootstrap sample from the data, term those not in the bootstrap sample as outside data.
4. A random tree is grown; the best set is chosen among m randomly selected variables eat each node.
5. Use the tree to predict outside data.
6. In the end use the predictions on outside data to form majority votes.
7. Anticipationof test data is done by maximum votes from predictions from the ensemble of trees.

Function T forest is used to train the Random forest. Here Random forest classifier is used to classify the database objects as benign or malignant

4.2 Feed-Forward Back Propagation and Cascade-Forward BackPropagation Artificial Neural Network

Feed-forward back propagation Network and Cascade-Feed-forward back propagation Network and Cascade-forward back propagation network were trained for classification of mammogram images into benign and malignant. The performance is measured by Mean Square Error (MSE) [43]. In training phase, the features extracted from training set of images are saved in a dedicated database and used to train the Artificial Neural Network. The extracted features from the unknown (or tested) mammogram images are passed through the trained ANN for classification in the Recognition phase [38]. Hit and trial method is used to compute the optimum number of nodes and layers. The predictive accuracy of detection for different number of neurons and then for different number of layers is persuaded by using ANN model for testing of detection [42].

4.3 K-nearest neighbor

In pattern recognition, the k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression Here, the output is a class membership, a majority vote of its neighbors is used to classify an object, with the object being attached to the class most routine among its k nearest[34],[36]. This value is the average of the values of its k nearest neighbors.

The length from an unknown pattern is calculated KNN algorithm to every sample and the base for classification is selected by the K nearest samples. The class containing the most samples among the K-nearest samples is assigned the unknown pattern. Kramer and Aghdasi[29],[12] used co-occurrence features and wavelet features as the inputs of a KNN classifier. Classification accuracy achieved was 100% when classifying 40 images of Nijmegen database. Kramer and Aghdasi compared the performances of KNN classifier and NN [39]. The performance of NN is better than KNN classifier by validating their results. Zadeh et al. used a set of shape features and co-occurrence features as the inputs of a KNN classifier. 40 mammograms of Nijmegen database were used, it could only get an area of 0.82 under the ROC curves [12], [40].

4.4 Bayesian belief network

An optimal pattern recognition method, which uses a probabilistic approach to determine an optimal segmentation given a distinct database is Bayesian belief network (BBN) [20]. In BBN an “acyclic” graph is built in which nodes represent feature variables, and direct probabilistic imminences between the variables is represented connections between nodes. For each node the probabilistic independence of two variables is indicated by the total of probability values for all states which is equal if there is no path between any two nodes [7], it indicates Bayesian classifier was used to merge extracted features. The Bayesian techniques and ANN are able to produce many ROC points. The performance of CAD system might be more dependent on feature selection and training database [41].

Table-3: Comparative Analysis of various classification techniques

Classifier	Results	References
Random Forest	Average accuracy computedwas90.45 % over 10 different sets of data from MIAS dataset. Area A_z = 0.764 under the receiver operating characteristic.	[7],[4]
Bayesian belief network	ROC of 0:873 ± 0:009 for 433 images with 12 features from Washington University Medical School in St. Louis About 84% accuracy for 70 images from source N/A	[14],[37]
K-nearest network	More than 80% accuracy for a set of 180 images from NijmegenLLNL/UCSF database. 80% TP for set of 40 images from Nijmegen database.	[34],[24],[12], [36], [29],[7], [38]
Back propagation Neural Network	88.9% classification accuracy for 40 images fr4om the Nijmegen database. Back propagation network has accuracy of 87.5% for set of 42 verified patient cases from source N/A	[42],[38], [43]

Table-4: Study of various classification techniques

Classifier	Details	References
Random Forest	Unpruned classification or regression trees, induced from bootstrap samples of training data, using random feature selection in tree induction process.	[7],[4]
Bayesian belief network	The extracted features are merged with a variable from each node in the “acyclic’ graph.	[41],[7]
K-nearest network	For classification co-occurrence features, wavelet features and shape features are used.	[40],[39]
Back propagation Neural Network	A multi stage neural network with back propagation.	[42],[38]

5. CONCLUSION

Mammography has proven to be a significant way to detect breast cancer. In this paper, classification and categorization of digital mammograms are performed.

This Paper presents a brief knowledge about classification of mammogram images using various feature extraction and classification techniques. Basicallythe system is trained by extracting features of mammogram images by applying various extraction techniques and testing the accuracy by using various classifiers to classify the mammogram images into benign or malignant. Through our survey it is observed and analyzed that for each extraction technique and classification technique, accuracy varies, which is described in the result table.

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REFERENCES

[1] Beura S, Majhi B, Dash R. Mammogram classification using two dimensional discrete wavelet Transform and gray-level co-occurrence matrix for detection of breast cancer. ELSEVIER Neurocomputing 2014.

[2] Strickland RN, Hahn H. Wavelet transform for detecting microcalcifications in mammograms. IEEE Trans Med Imaging 1996.

[3] Wang TC, Karayiannis NB. Detection of microcalcifications in digital mammograms using wavelets. IEEE Trans Med Imaging 1998.
[4] Zheng B, Qian W, Clarke LP. Digital mammography: mixed feature neural network with spectral entopy decision for decision of microcalcifications. IEEE Trans Med Imaging 1996.
[5] Yu S Guan L. A CAD system for the automatic detection of clustered microcalcifications in digitized mammograms films. IEEE Trans Med Imaging 2000.
[6] S. Lahmiri and M. Boukadoum. Discrete Cosine and Radon Transform-based image pre-processing system for digital mammogram classification with SVM. IEEE Engineering in Medicine and Biology Society Conference, Boston, MA, USA, August 30-September 3,2011. In press.
[7] K.S. Woods, C.C. Doss, K.W. Bowyer, J.L. Solka, C.E.Priebe, W.P. Kegelmeyer, Comparative evaluation of pattern recognition techniques for detection of microcalcifications in mammography, Int. J. Pattern Recognition Artif. Intell. 7 (1993) 1417-1436.
[8] B. Zheng, W. Qian, L.P. Clarke, Digital mammography: mixed feature neural network with spectral entropy decision for detection of microcalcifications, IEEE Trans. Med. Imag.15 (5) (1996) 589–597.
[9] D.H. Davies, D.R. Dance, Automatic computer detection of clustered calcifications in digital mammograms, Phys. Med. Biol. 35 (1990) 1111 -1118.
[10] R.M. Nishikawa, Y. Jiang, M.L. Giger, K. Doi, C.J. Vyborny,R.A. Schmidt, Computer-aided detection of clusteredmicrocalcifications, Proceedings of the IEEE InternationalConference on Systems, Man and Cybernetics, 1992, pp.1375–1378.
[11] R.N. Strickland, H.I. Hahn, L.J. Baig, Wavelet methodsfor combining CAD with enhancement of mammograms,Medical Imaging 1996: Image Processing, SPIE Proceedings,Vol. 2710, 1996, pp. 888–903.
[12] W.J.H. Veldkamp, N. Karssemeijer, An improved method for detection of microcalcification clusters in digitalmammograms, The SPIE Conference on Image Processing,Vol. 3661, February 1999, pp. 512–522.
[13] S. Bothorel, B.B. Meunier, S. Muller, A fuzzy logic basedapproach for semiological analysis of microcalcifications in mammographic images, Int. J. Intelligent Systems 12 (1997)819–848.
[14] N. Karssemeijer, Recognition of micro calcification clustersin mammograms, Int. J. Pattern Recognition Artif. Intell. 7(6) (1993) 1357–1376.
[15] L. Zhang, W. Qian, R. Sankar, D. Song, R. Clark, A newfalse positive reduction method for MCCs detection in digitalmammography, IEEE International Conference on Acoustics, Speech and Signal Processing, May 7–11, 2001, pp. 1033–1036.
[16] D.H. Davies, D.R. Dance, C.H. Jones, Automatic detection of clusters of calcifications in digital mammograms, SPIE Med. Imag. IV: Image Process. 1233 (1990) 185–191.
[17] C.H. Chen, G.G. Lee, Image segmentation using multiresolutionwavelet analysis and expectation-maximization(EM) algorithm for digital mammography, J. Digital Imag.8 (1997) 491–504.
[18] S. Sehad, S. Desarnaud, A. Strauss, Artificial neural classification of clustered microcalcifications on digitizedmammograms, Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Vol. 5, 1997, pp. 4217–4222.
[19] K. Woods, C. Doss, K. Bowyer, L. Clarke, R. Clark, A neural network approach to microcalcification detection, IEEE1992 Nuclear Science Symposium and Medical ImagingConference, Orlando, FL (October 1992), 1992, pp. 1273–1275.
[20] Bankman, J. Tsai, D. Kim, O. Gatewood, W. Brody, Detection of microcalcification clusters using neuralnetworks, Annual International Conference of the IEEEEngineering in Medicine and Biology Society—Proceedings, Vol. 16, 1994, pp. 590–591.
[21] J.S. DaPonte, P. Sherman, Classi"cation of ultrasonicimage texture by statistical discriminated analysis and neuralnetworks, Comput. Med. Imag. Graphics 15 (1) (1991) 3–9.
[22] S. Yu, L. Guan, S. Brown, Automatic detection of clustered microcalcifications in digitized mammogram "lms,J. Electron. Imag. 8 (1) (1999) 76–82.
[23] R.M. Nishikawa, M.L. Giger, K. Dol, C.J. Vyborny,R.A. Schmidt, Computer-aided detection of clustered microcalcifications on digital mammograms, Med. Biol. Eng.Comput. 33 (2), March, (1995) 174–178.
[24] S.A. Hojjatoleslami, J. Kittler, Detection of clusters of microcalcification using a K-nearest neighbor classifier,Proceedings of the 1996 IEE Colloquium on DigitalMammography, May 1996, pp. 1–6.
[25] W. Spiesberger, Mammogram inspection by computer, IEEETrans. Biol. Eng. BMF-26 (4) (1979) 213–219.

[26] J. Marti, J. Batle, X. Cu", J. Espanol, Microcalcificationevaluation in computer assisted diagnosis for digitalmammography, Proceedings of the 1999 EE Colloquium onDigital Mammography, 1999, pp. 1–6.
[27] R.M. Nishikawa, Y. Jiang, M.L. Giger, C.J. Vyborny, R.A.Schmidt, R. Bick, Characterization of the mammographic appearance of microcalcifications: applications incomputer-aided diagnosis, SPIE Image Process. 1898 (1993)422–429.
[28] J. Marti, X. Cu", J. Rgincos, J. Espanol, J. Pont, C. Barcelo,Shape-based features selection for microcalcificationevaluation, SPIE 3338 (1998) 1215–1224.
[29] T. Bhangale, U.B. Desai, U. Sharma, An unsupervised scheme for detection of microcalcifications on mammograms, IEEE International Conference on Image Processing,September 10–13, 2000, pp. 184–187.
[30] C.Y. Enderwich, E.M. Tzanakou, Classification of mammographictissue using shape and texture features, Proceedings of the 19th International Conference-IEEE/EMBS, 1997, pp.810–813.
[31] R.J. Ferrari, A.C.P.L.F. de Carvalho, P.M.A. Marques,A.F.Frere, Computerized classification of breast lesions: shape and texture analysis using an artificial neural network, Image Process. Appl. (1999) 517–521.
[32] A.P. Dhawan, Y. Chitre, M. Moskowitz, Artificial neural network based classification of mammographicmicrocalcifications using image structure features, Proc.SPIE 1905 (1993) 820–831.
[33] D. Meersman, P. Scheunders, D.V. Dyck, Classification of microcalcifications using texture-based features, DigitalMammography Nijmegen 1998 (1998) 233–236.
[34] A.P. Dhawan, Y. Chitre, C. Kaiser-Bonasso, M. Moskowita,Analysis of mammographic micro calcifications usinggrey-level image structure features, IEEE Trans. Med. Imag.15 (3) (1996) 246–259.
[35] L. Gagnon, J.M. Lina, B. Goulard, Sharpening enhancement of digitized mammograms with complex symmetricDaubechies wavelets, Annual International Conference of theIEEE Engineering in Medicine and Biology—Proceedings, Vol. 17(1), 1995, pp. 543–544.
[36] F. Rafiee-Rad, H. Soltanina-Zadeh, M. Rahmati, S. Pour-Abdollah, Microcalcification classification inmammograms using multiwavelet features, Proceedings of the 1999 Wavelet Applications in Signal and Image Processing, 1999, pp. 832–841.
[37] H.S. Zadeh, S.P. Nezhad, F.R. Rad, Texture featureextraction methods for microcalcification classificationin mammograms, Proc. SPIE 3979 (2000) 982–989.
[38] Dani Kramer, FarzinAghdasi, Texture analysis techniques for the classification of microcalcifications in digitizedmammograms, Proceedings of the 1999 Fifth IEEEAFRICON Conference Electro Technical Service for Africa, September 28–October 1, 1999, pp. 395–400.
[39] D. Kramer, F. Aghdasi, Classification of microcalcifications indigitized mammograms using multiscale statistical texture analysis, Proceedings of the South African Symposium on Communications and Signal Processing, September 7–8,1998, pp. 121–126.
[40] H.S. Zadeh, S.P. Nezhad, F.R. Rad, Shape-based andtexture-based feature extraction for classification of microcalcification in mammograms, Proc. SPIE 4322 (2001)301–310.
[41] B. Zheng, Y.H. Chang, X.H. Wang, W.F. Good, D. Gur, Application of a Bayesian belief network in a computer-assisted diagnosis scheme for mass detection, SPIEConference on Image Processing, Vol. 3661, San Diego, CA,February 1999, pp. 1553–1560.
[42] P. Deshmukh and U. Bhosle, “A Survey of Image Registration,” International Journal of Image Processing (IJIP), vol.5(3), 2011, pp. 1-6.
[43] F. Keivanfard, M. Teshnehlab, M. A. Shoorehdeli, K. Nie, M. Y. Su, “Feature selection and classification of breast cancer on dynamic Magnetic Resonance Imaging by using artificial neural networks,” 17th Iranian Conference of Biomedical Engineering, Nov.2010, pp. 1-4, DOI 10.1109/ICBME.2010.5704942