# A Review of Breast Tissue Classification in Mammograms

Gensheng Zhang, Wei Wang, Jucheol Moon
Department of Electrical Engineering and Computer Science, South Dakota State University
Brookings, SD, 57006, USA
gensheng.zhang@jacks.sdstate.edu
wei.wang@sdstate.edu
jucheolmoon@jacks.sdstate.edu

Jeong K. Pack[1], Soon Ik Jeon[2]
[1]Dept of Radio Science Engineering
Chungnam National University, Korea
jkpack@cnu.ac.kr
[2]Radio Technology Research Department
ETRI
Daejeon, Korea
sijeon@etri.re.kr

## ABSTRACT

For women in the U.S. breast cancer is the most commonly diagnosed cancer besides skin cancer and has become one of the major health issues in recent decades. Early detection through screening is one of key factors to reduce the death rates. The strong correlation between abnormality of breast tissues presented in mammograms and breast cancer shows that radiologists could benefit from Computer-Aided Diagnosis (CAD) systems with abilities of automated breast tissueclassification. This paper reviews recent advances in classification technologies of breast tissues. The major contribution of this paper is thatwe extensivelydiscuss recent breast tissue classification technologiesandcomparethree different types of approaches. According to our survey, we found that machine learning approaches could be chosen as anappropriate classification technology for a CAD system,considering efficiency and compatibility.

## Categories and Subject Descriptors

A.1 [**INTRODUCTORY AND SURVEY**]: a survey of automated classification of breast tissues in mammograms.

## General Terms

Algorithms, Performance.

## Keywords

Breast cancer, computer-aided diagnosis system, classification of breast tissues.

## 1. INTRODUCTION

For women in the U.S. breast cancer death rates are higher than those for any other cancer besides lung cancer [1]. About 1 in 8 women in the United States (i.e.12%) develop invasive breast cancer over the course of their lifetime. According to an estimation study in 2010, a total of 207,090 new cases of invasive breast cancer were expected to be diagnosed in women in the U.S., along with 54,010 new cases of non-invasive (in situ) breast cancer. About 39,840 women in the U.S. were expected to die in 2010 from breast cancer, though death rates have been decreasing since 1990. These decreases are deemed to be the result of treatment advances, earlier detection through screening, and increased awareness.



RACS '11, November 2-5, 2011 Miami, Florida, USA



Diagnostic Mammograms can be used to check breast cancer after a lump or other disease symptomshave been found. Signs of breast cancer include pain, skin thickening, nipple discharge, or a change in breast size or shape [2]. It is well known that there is a strong correlation between breast cancer and abnormalities of breast tissues presented in mammograms. It is valuable if a CAD system could classify the breast tissues into regions of interest(ROIs), such as calcifications, macro-calcifications, cysts and fibroadenomas. Thus, radiologists could benefit from CAD systems with abilities of automated classification of breast tissues. These systems act as anassistant, and the final decision is made by the radiologist [3]. CAD systems have been shown to improve radiologists' accuracy of diagnosis of breast cancer in previous studies [4-7].

The low contrast of mammograms makes it difficult for radiologists to detect the breast cancer. Diagnoses based on mammograms have been shown to have a high rate of false positives (identify normal breast changes as potential cancers) as well as false negatives (a true abnormality was not detected) [8-9]. To measure the performance of a diagnostic system, sensitivity and specificity indices are widely used which are defined as follows, respectively [10]:

$$sensitivity = \frac{TPs}{TPs + FNs} \quad (1)$$

$$specificity = \frac{TNs}{TNs + FPs} \quad (2)$$

where TP is for true positive, FN for false negative, TN for true negative and FP for false positive. Receiver operating characteristic (ROC) analysis is a well-accepted method of evaluation for detection tasks. The area under the curve, usually referred as the $A_z$ index, is an accepted way of evaluating diagnostic performance. A ROC curve with an $A_z$ of 1.0 means perfect diagnostic accuracy.

Breast cancer is difficult to diagnose by examining mammograms, even for radiologists. CAD systems strive to emulate the process of radiologists discriminating between benign and malignant breast tissues. Generally speaking, there are three categories of approaches to classify breast tissues: texture feature analysis, statistical modeling, and machine learning. Usually, machine learning approaches are based on the other two approaches.

There are already several papers in theliterature that have reviewed classification technologies, such as [11] and [12]. This paper extends them to recent advances,but focuses on breast tissue classification only. Through the comparison of three types of approaches, we try to find out an appropriate choice for CAD systems. The organization of the rest of this paper is as follows. Section 2 discusses classification of breast tissues using approaches mentioned. Discussion about the classification issues and future works will be included in Section 3.

# 2. BREAST TISSUE CLASSIFICATION

## 2.1 Texture feature analysis

Approaches based on texture feature analysis typically analyze the instinct characteristics of texture features extracted from regions of interest (ROIs) to classify ROIs into well-known knowledge categories. Measures of the skewness of the image brightness histogram, and measures of image texture characterized by the fractal dimension were investigated by Byng *et al.* [13] to analyze film-screen mammograms. Both measures were found to be strongly correlated with radiologists' subjective classifications of mammographic parenchyma (Spearman correlation coefficients, $R_s$ = -0.88 and -0.76 for skewness and fractal dimension measurements, respectively). Wavelet transform was investigated by Docusse *et al.* [14] to classify microcalcification borders and the results showed Symmlets wavelet family presented the best results with a 94% efficacy in their tests, and a curvelet transform based texture analysis was presented by Eltoukhy *et al.* [15] for the classification of tissues. A discrimination of breast density implemented by Bovis and Singh [16] was based on the underlying texture contained within the breast tissue apparent on a digital mammogram and realized by utilizing four approaches to quantify the texture. The testing data set was split into four categories: (a) predominantly fat; (b) fat with some fibroglandular tissue; (c) heterogeneously dense; (d) extremely dense. To discriminate lesions from normal tissues characteristics such as intensity, contrast, isodensity, location and texturewere defined and tested by Brake *et al.* in [17].Oliver *et al.* [18] segmented the breast area into fatty versus dense mammo-graphic tissue, extracted morphological and texture features from the segmented breast areas and then used a Bayesian combination of a number of classifiers. The evaluation showed a strong correlation ($\kappa$ = 0.81 and 0.67 for the two different data sets) between automatic and expert-based Breast Imaging Report and Data System (BIRADS) mammographic density assessment. Wei *et al.* [19] investigated a linear discriminant classifier using the multi-resolution texture features to effectively classify masses from normal tissue on mammograms. With texture features based on the wavelet coefficients and variable distances, the average area, $A_z$, under the ROC curve, reached 0.89 and 0.86 for the training and test groups, respectively. Wei *et al.* [20] also investigated the application of multi-resolution global and local texture features to reduce false-positive detection in a computerized mass detection program.The results of that investigation indicated the effectiveness of the combined global and local features in the classification of masses and normal tissue for false-positive reduction. With both global and local features, the area,$A_z$, under the test ROC curve, reached 0.92 for the manual dataset and 0.96 for the hybrid dataset, demonstrating statistically significant improvement over those obtained with global or local features alone. Saidin*et al.* [21] applied graph cut technologies to segment a mammogram into different mammographic densities and extended their work using seed based region growing techniques in [22] to evaluate the graph cut techniques in the segmentation of the mammogram. Panchal*et al.* [23] used grey-level based image features and BI-RADS lesion descriptors along with patient age and a subtlety value (radiologists' interpretation) for the reliable classification of calcification and mass type breast abnormalities into malignant and benign classes.

## 2.2 Statistical modeling

To identify different types of breast tissues, statistical appearance of ROIs' features could be a candidate measurement. A commonly employed statistical model is Linear Discriminant Analysis (LDA). Stepwise feature selection and LDA were applied by Li *et al.* [24] to identify features that differentiate between the low-risk women and the BRCA1/BRCA2 gene-mutation carriers.Their extended study showed that computerized texture analysis of mammograms provided radiographic descriptors of mammographic parenchymal patterns [25]. The computer-extracted features may be useful for identifying women at high risk for breast cancer and for monitoring the treatment of breast cancer patients. As an alternative to LDA, an approach based on generalized additive models (GAMs) was introduced by Lado*et al.* [26] to deal with a broad variety of variables and to reduce the number of false detections. The results showed the GAMs approach had better performance than LDAs.

Petroudi*et al.* [27] presented a statistical approach for breast parenchymal patternclassification. The proposed scheme uses texture models to capture the mammographic appearance within the breast area: parenchymal density patterns are modeled as a statistical distribution of clustered, rotationally invariant filter responses in a low dimensional space. A physical model of image acquisition was presented by Engeland*et al.* [28] to determine the thickness of dense tissue mapping to a pixel for estimation of dense breast tissue volume from mammograms obtained with full-field digital mammography (FFDM). Miller and Astley [29] performed a series of experiments investigating the use of granulometry and texture energy to classify breast tissue. Results of automatic classifications were compared with a consensus annotation provided by two expert breast radiologists. For a set of 40 mammograms, a correct classification rate of 80% was achieved using texture energy analysis. Gong *et al.* [30] subsequently showed that textures canbe classified using the joint distribution of intensity values over extremely compact neighborhoods and combined the so-called image patch method with a HMRF (Hidden Markov Random Field) to achieve mammogram texture classification and segmentation. Ferrari *et al.* [31] presented a Gaussian mixture modeling for the segmentation of the fibro-glandular disc in mammograms based upon a statistical model of breast density. The density function of the model was represented by a mixture of up to four weighted Gaussians, each one corresponding to a specific density class in the breast. An example is shown in Figure 1. Aylward*et al.* [32] devised a mammogram modeling system which segmented the five major components of a mammogram: background, uncompressed-fat, fat, dense, and muscle. Via segmentation, the corresponding variations are isolated. Automated algorithms can consider the components independently or adapt their parameters based on component-specific statistics. After constructing a finite generalized Gaussian mixture (FGGM) model, Selvan*et al.* [33] proposed a heuristic optimization approach to estimate the model parameter set more accurately by particle swarm optimization (PSO) and evolutionary programming (EP) techniques.

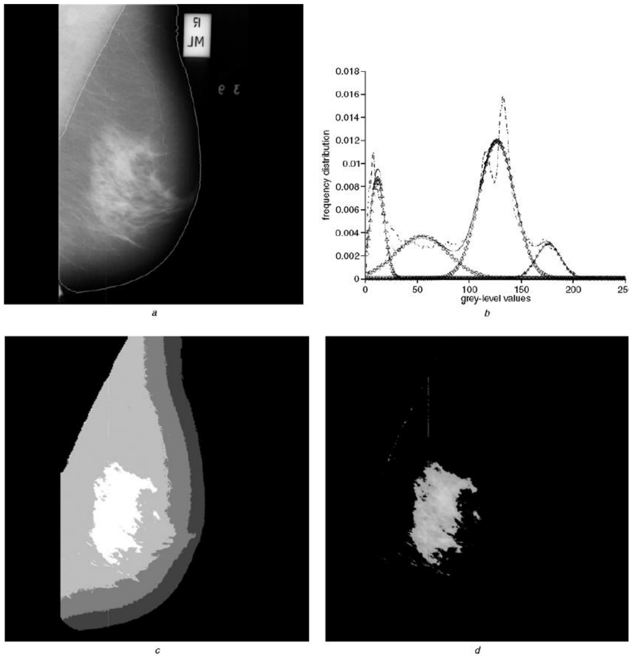


**Figure 1. (a) Breast contour and pectoral muscle edge superimposed on original image mdb042. (b) Image histogram of effective area of mammogram and mixture of Gaussian components. ()Image histogram; () uncompressed fat; ()fat; ()non-uniform density; () high density; (---) mixture summation. (c) Four-level image resulting from EM algorithm. (d) Fibro-glandular disc obtained after thresholding**[31]**.**

## 2.3 Machine learning

As there are many mammograms, technologies which can utilize huge amounts of data are attracting researchers from other fields.Since a machine learner can take advantage of examples to capture unknown underlying characteristics, classification techniques based on machine learning are very popular currently. Machine learning classifiers aim to automatically learn to recognize complex patterns and classify data intelligently. However, the performance of different machine learning methods may vary. Wei *et al.* [34] demonstrated that the kernel based methods (i.e., SVM (support vector machine), KFD (kernel Fisher discriminant), and RVM (relevance vector machine)) yielded the best performance, outperforming that of FFNN (feed forward neural network) and AdaBoost (Figure 2). Furthermore, these methods were also computationally advantageous both in training and in testing. A SVM classifier based on features extracted by dual-tree complex wavelet transform (DT CWT) was proposed by Tirtajaya*et al.* [35], however, they believed other approaches would show better performance. To improve the classification rate of SVM, Dheeba*et al.* [36] suggested taking Law's texture energy measures from the image ROIs. Petroudi and Brady [37] described an algorithm to segment mammographic images into regions corresponding to different densities. The breast parenchymal segmentation adopted information extracted for statistical texture based classification, which was incorporated into multi-vector Markov Random Fields. Aconvolution neural network (CNN) was proposed for the discrimination by Sahiner*et al.* in [38]. With the best combination of CNN architecture and texture feature parameters, the area under the test ROC curve reached 0.87, which corresponded to a true-positive fraction of

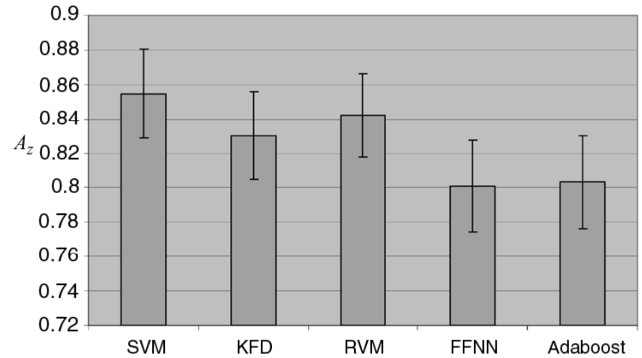


**Figure 2. Classification results obtained with different classifier models** [34]**.**

90% at a false positive fraction of 31%. Their results demonstrated the feasibility of using a CNN for classification of masses and normal tissue on mammograms. An approach for mass classification in digital mammograms based on contourlet texture features and support-vector-based fuzzy neural network (SVFNN) classifier was presented in [39]. Each mammogram was segmented into regions of interest and features were extracted in frequency domain by contourlet coefficients. Kupinski*et al.* [40] developed a regularized neural network for breast tissues classification. They extracted geometry intensity and the gradients of potential lesion features. The effectiveness of regularization was evaluated as a technique to minimize over-training in the paper. Baydush*et al.* [41] investigated the use of the subregionHotelling observer for the basis of a computer aided detection scheme for masses inmammography. A total of 255 features were generated and narrowed down to a reduced subset of 37 features, whichwere then analyzed using a linear discriminant (LD). Preliminary results suggested that using subregionHotelling observers in combination with LDs could provide a strong backbone for a CAD scheme to help radiologists with detection. The empirical results of Normwave (normalized weighted average) algorithm, proposed by Wu *et al.* [42], showed the algorithm may improve the performance of the RBF-based (Radial Basis Function) multiple classifier system, and also reliablyoutperformed some widely used fusion methods, in particular the simple average and adaptive mixture of experts. Karahaliou*et al.* [43] investigated texture properties of the tissue surrounding microcalcification (MC) clusters and employed a probabilistic neural network to differentiate malignant from benign tissue. The majority voting rule based scheme achieved a high $A_z$ value of 0.989. Dheeba*et al.* [44] used Gabor features extracted from the image ROIs as input to the supervised Radial Basis Function Neural Networks (RBFNN) to determine the given ROI was cancer tissue or not and the result showed the scheme had a sensitivity of 85.2%.

## 3. DISCUSSION

The procedure radiologists use to diagnose breast cancer by mammograms is very complicated and is based on experience. It is difficult to simulate the procedure due to the many variants. Researchers have devoted major efforts to automated classification of breast tissues for more than 20 years and have made remarkable achievements.

As classification technologies play an important role in CAD systems, accuracy, efficiency, stability and scalability are the prominent measures of these technologies. Normally, accuracy of classification depends on accuracy of mammographic feature extraction. Deriving a compact quantitative description is one of the major objectives of texture feature analysis. The efficiency of these approaches can benefit from compactness of feature descriptions. However,with compactness, there is also the possibility of losing some significant information,which would affect the sensitivity or specificity. Thusthe performance of texture feature analysis approaches may vary when applied in different circumstances. Statistics modeling tries to build one or more statistical models to interpret and simulate mammographic features, and these models may carry the risk of over fitting. Over-fittingcouldbe a major factor in loweringthe classification sensitivity. Therefore, selection of analytical techniques and verification of hypothesis are crucial and should be carefullydesigned in statistical modeling. Machine learning techniques are outperforming most other approaches. This, combined with the need to overcome shortages of conventional techniques, is attracting more researchers' attention. As shown in Table 1, texture feature analysis approaches can achieve a satisfactory sensitivity when the approaches are tested in particular datasets, such as an efficacy of 94% made by wavelet transform [14]. In the meantime, statistical models demonstrate their performancecompetitively even in general cases, e.g. MR8 [27] and Gaussian mixture modeling [31]. Instead ofdirectly analyzing specific characteristicsof image features, machine learning approaches usually aim to find intrinsic dependencies among these features and learn from existing examples to retrieve an accurate discrimination.It has been demonstrated that machine learning approaches can generate powerful classifiers. Compared to the other two approaches, machine learning methods usually achieve similarcapacity and gain morescalability and stability.However, accuracy of machine learning approaches depends on the quality of training data. This is because machine learning algorithms are usually data driven. A poor, obscured training dataset would not lead to a proper validation. Furthermore, complicated theories and algorithms are usually involved in a machine learning method, which means a large amount of computation cannot be avoided and the complexity of CAD systems may increase dramatically. As a result, it is important for researchers to find more efficient, reliable and scalablemethods to develop CAD systems in future research.

## 4. CONCLUSION

As discussed in this paper, different categories of classification technologieshave different advantages and disadvantages. Texture feature analysis approaches are sensitive to different mammogram machines, and statistics modeling could be inaccurate in some specific situations. With little or no loss of performance compared to the other two approaches, machine learning approaches take the advantage of its compatibility to make it more feasible to develop a universal CAD system.

## 5. ACKNOWLEDGMENTS

This research was supported by the KCC(Korea Communications Commission), Korea, under the R&D program supervised by the KCA(Korea Communications Agency)(KCA-2011-11911-01108).

**Table 1. Performances of typical classification methods**

| Category | Method | Performance |
|---|---|---|
| **Texture Feature analysis** | Wavlet Transform [14] | efficacy = 94% using Symmlets wavelet family |
| | Curvelet transform [15] | 91.68% average successful classification rate |
| | Multi-resolution texture features [19] | $A_z$ = 0.86 |
| | Multi-resolution global and local texture features [20] | $A_z$ = 0.96 |
| **Statistical modeling** | LDA [26] | $A_z$ = 0.86<br>Sensitivity = 0.8052 |
| | GAM [26] | $A_z$ = 0.906<br>Sensitivity = 0.8312 |
| | MR8 filter bank [27] | accuracy = 91% for BI-RADS I<br>accuracy = 78% for BI-RADS IV |
| | Gaussian mixture modeling [31] | 81% of cases satisfactory agreement of evaluation result between expert radiologists and proposed procedure |
| **Machine learning** | SVM based on DT CWT [35] | overall accuracy = 88.64% |
| | SVM based on Law's texture energy measures [36] | Sensitivity = 0.861 |
| | CNN [38] | $A_z$ = 0.87 |
| | RBFNN [44] | Sensitivity = 0.852 |

## 6. REFERENCES


[1] U.S. Breast Cancer Statistics. (2011). [Online]. Available: http://www.breastcancer.org/symptoms/understand_bc/statistics.jsp

[2] NCI Cancer Fact Sheets. (2010). [Online]. Available: http://www.cancer.gov/cancertopics/factsheet/detection/mammograms.

[3] M. P. Sampat, M. K. Markey, and A. C. Bovik, "Computer-aided detection and diagnosis in mammography", in Handbook of Image and Video Processing, A.C. Bovik, Ed., 2nd ed. New York: Academic, 2005, pp. 1195–1217.

[4] M. L. Giger, N. Karssemeijer, and S. G. Armato, III, "Computer-aided diagnosis in medical imaging," IEEE Transactions on Medical Imaging, vol. 20, pp. 1205-1208, 2001.

[5] M. L. Giger, "Computer-aided diagnosis of breast lesions in medical images," Computing in Science & Engineering, vol. 2, pp. 39-45, 2000.

[6] K. Doi, H. MacMahon, S. Katsuragawa, R. M. Nishikawa, and Y. Jiang, "Computer-aided diagnosis in radiology: potential and pitfalls," European Journal of Radiology., vol. 31, pp. 97-109, 1999.

[7] C. J. Vyborny, M. L. Giger, and R. M. Nishikawa, "Computer-aided detection and diagnosis of breast cancer," Radiologic Clinics of North America., vol. 38, pp. 725-40, 2000.

[8] R. Bird, T. Wallace, and B. Yankaskas, "Analysis of cancers missed at screening mammography," Radiology, vol. 184, no. 3, pp. 613–617, 1992.

[9] K. Kerlikowske, P. Carney, B. Geller, M. Mandelson, S. Taplin, K. Malvin, V. Ernster, N. Urban, G. Cutter, R. Rosenberg, and R. Ballard-Barbash, "Performance of screening mammography among women with and without a first-degree relative with breast cancer," Ann. Internal Med., vol. 133, no. 11, pp. 855–863, 2000.

[10] K. Woods, M.Y. Sallam and K.W. Bowyer, "Evaluating detection algorithms" In: "Image-Processing Techniques for Tumor Detection," R.N. Strickland, Marcel Dekker, Inc. pp. 27-28, 2002.

[11] E. SAKKA, A. PRENTZA and D. KOUTSOURIS, "Classification algorithms for microcalcifications in mammograms (Review)," ONCOLOGY REPORTS 15, pp. 1049-1055, 2006

[12] J. Tang, R. M. Rangayyan, J. Xu, I. E. Naqa, Y. Yang, "Computer-Aided Detection and Diagnosis of Breast Cancer With Mammography: Recent Advances," IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 13, NO. 2, pp. 236-251, MARCH 2009

[13] J.W. Byng, N. F. Boyd, E. Fishell, R. A. Jong, and M. J.Yaffe, "Automated analysis of mammographic densities," Phys. Med. Biol., vol. 41, pp. 909– 923, 1996.

[14] Docusse, T.A.; Pereira, A.S.; Marranghello, N.; , "Microcalcification border characterization," Engineering in Medicine and Biology Magazine, IEEE , vol.28, no.5, pp.41-43, September-October 2009

[15] Eltoukhy, M.M.; Faye, I.; Samir, B.B.; , "Curvelet based feature extraction method for breast cancer diagnosis in digital mammogram," Intelligent and Advanced Systems (ICIAS), 2010 International Conference on , vol., no., pp.1-5, 15-17 June 2010

[16] K. Bovis and S. Singh, "Classification of mammographic breast density using a combined classifier paradigm," in Proc. Med. Image Understanding Anal. Conf., 2002, pp. 177–180.

[17] G. M. te Brake, N. Karssemeijer, and J. H. Hendriks, "An automatic method to discriminate malignant masses from normal tissue in digital mammograms," Physics in Medicine & Biology., vol. 45, pp. 2843-2857, 2000.

[18] A. Oliver, J. Freixenet, R. Marti, J. Pont, E. Perez, E. R. E. Denton, and R. Zwiggelaar, "A Novel Breast Tissue Density Classification Methodology," IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 12, NO. 1, p.p. 55-65 JAN. 2008

[19] D. Wei, H. P. Chan, M. A. Helvie, B. Sahiner, N. Petrick, D. D. Adler, and M. M. Goodsitt, "Classification of mass and normal breast tissue on digital mammograms: multiresolution texture analysis," Medical Physics., vol. 22, pp. 1501-13, 1995.

[20] D. Wei, H. P. Chan, N. Petrick, B. Sahiner, M. A. Helvie, D. D. Adler, and M. M. Goodsitt, "False-positive reduction technique for detection of masses on digital mammograms: global and local multiresolution texture analysis," Medical Physics., vol. 24, pp. 903-14, 1997.

[21] Saidin, N.; Ngah, U.K.; Sakim, H.; Ding NikSiong; Mok Kim Hoe; , "Density based breast segmentation for mammograms using graph cut techniques," TENCON 2009 - 2009 IEEE Region 10 Conference , vol., no., pp.1-5, 23-26 Jan. 2009

[22] Saidin, N.; Ngah, U.K.; Sakim, H.A.M.; Ding NikSiong; Mok Kim Hoe; Shuaib, I.L.; , "Density Based Breast Segmentation for Mammograms Using Graph Cut and Seed Based Region Growing Techniques," Computer Research and Development, 2010 Second International Conference on , vol., no., pp.246-250, 7-10 May 2010

[23] Panchal, R.; Verma, B.; , "Classification of breast abnormalities in digital mammograms using image and BI-RADS features in conjunction with neural network," Neural Networks, 2005. IJCNN '05. Proceedings. 2005 IEEE International Joint Conference on , vol.4, no., pp.2487-2492 vol. 4, July 31 2005-Aug. 4 2005

[24] H. Li, M. L. Giger, Z. M. Huo, O. I. Olopade, L. Lan, B. L. Weber, and I. Bonta, "Computerized analysis of mammographic parenchymal patterns for assessing breast cancer risk: Effect of ROI size and location," Med. Phys., vol. 31, pp. 549–555, 2004.

[25] H. Li, M. L. Giger, O. I. Olopade, A. Margolis, and M. R. Chinander, "Computerized texture analysis of mammographic parenchymal patterns of digitized mammograms," Acad. Radiol., vol. 12, pp. 863–873, 2005.

[26] Lado, M.J.; Cadarso-Suarez, C.; Roca-Pardinas, J.; Tahoces, P.G.; , "Using generalized additive models for construction of nonlinear classifiers in computer-aided diagnosis systems," Information Technology in Biomedicine, IEEE Transactions on , vol.10, no.2, pp.246-253, April 2006

[27] S. Petroudi, T. Kadir, and M. Brady, “Automatic classification of mammographic parenchymal patterns: A statistical approach,” in Proc. IEEE Conf. Eng. Med. Biol. Soc., 2003, vol. 1, pp. 798–801.

[28] S. van Engeland, P. R. Snoeren, H. Huisman, C. Boetes, and N. Karssemeijer, “Volumetric breast density estimation from full-field digital mammograms,” IEEE Trans. Med. Imag., vol. 25, no. 3, pp. 273–282, Mar. 2006.

[29] P. Miller and S. M. Astley, “Classification of breast tissue by texture analysis,” Image Vision Comput., vol. 10, pp. 277–282, 1992.

[30] Y. C. Gong, M. Brady, and S. Petroudi, “Texture based mammogram classification and segmentation,” Lect. Notes Comput. Sci., vol. 4046, pp. 616–625, 2006.

[31] R. J. Ferrari, R. M. Rangayyan, R. A. Borges, and A. F. Frere, “Segmentation of the fibro-glandular disc in mammograms via Gaussian mixture modelling,” Med. Biol. Eng. Comput., vol. 42, pp. 378–387, 2004.

[32] S. R. Aylward, B. H. Hemminger, and E. D. Pisano, “Mixture modelling for digital mammogram display and analysis,” in Proc. Int.Workshop Dig. Mammography, 1998, pp. 305–312.

[33] S. E. Selvan, C. C. Xavier, N. Karssemeijer, J. Sequeira, R. A. Cherian, and B. Y. Dhala, “Parameter estimation in stochastic mammogram model by heuristic optimization techniques,” IEEE Trans. Inf. Technol. Biomed., vol. 10, no. 4, pp. 685–695, Oct. 2006.

[34] Liyang Wei; Yongyi Yang; Nishikawa, R.M.; Yulei Jiang; , "A study on several Machine-learning methods for classification of Malignant and benign clustered microcalcifications," Medical Imaging, IEEE Transactions on , vol.24, no.3, pp.371-380, March 2005

[35] Tirtajaya, A.; Santika, D.D.; , "Classification of Microcalcification Using Dual-Tree Complex Wavelet Transform and Support Vector Machine," Advances in Computing, Control and Telecommunication Technologies (ACT), 2010 Second International Conference on , vol., no., pp.164-166, 2-3 Dec. 2010

[36] Dheeba, J.; Selvi, S.T.; , "Classification of malignant and benign microcalcification using SVM classifier," Emerging Trends in Electrical and Computer Technology (ICETECT), 2011 International Conference on , vol., no., pp.686-690, 23-24 March 2011

[37] S. Petroudi and M. Brady, “Breast density segmentation using texture,” Lect. Notes Comput. Sci., vol. 4046, pp. 609–615, 2006.

[38] B. Sahiner, H.-P. Chan, N. Petrick, D. Wei, M. A. Helvie, D. D. Adler, and M. M. Goodsitt, "Classification of mass and normal breast tissue: a convolution neural network classifier with spatial domain and texture images," Medical Imaging, IEEE Transactions on, vol. 15, pp. 598-610, 1996.

[39] Moayedi, F.; Boostani, R.; Azimifar, Z.; Katebi, S.; , "A Support Vector Based Fuzzy Neural Network Approach for Mass Classification in Mammography," Digital Signal Processing, 2007 15th International Conference on , vol., no., pp.240-243, 1-4 July 2007

[40] M. A. Kupinski and M. L. Giger, "Investigation of regularized neural networks for the computerized detection of mass lesions in digital mammograms," presented at Engineering in Medicine and Biology society, 1997. Proceedings of the 19th Annual International Conference of the IEEE, 1997.

[41] A. H. Baydush, D. M. Catarious, C. K. Abbey, and C. E. Floyd, "Computer aided detection of masses in mammography using subregionHotelling observers," Medical Physics, vol. 30, pp. 1781-7, 2003.

[42] Yunfeng Wu; Ng, S.C.; , "Breast Tissue Classification Based on Unbiased Linear Fusion of Neural Networks with Normalized Weighted Average Algorithm," Neural Networks, 2007. IJCNN 2007. International Joint Conference on , vol., no., pp.2846-2850, 12-17 Aug. 2007

[43] Karahaliou, A.N.; Boniatis, I.S.; Skiadopoulos, S.G.; Sakellaropoulos, F.N.; Arikidis, N.S.; Likaki, E.A.; Panayiotakis, G.S.; Costaridou, L.I.; , "Breast Cancer Diagnosis: Analyzing Texture of Tissue Surrounding Microcalcifications," Information Technology in Biomedicine, IEEE Transactions on , vol.12, no.6, pp.731-738, Nov. 2008

[44] Dheeba, J.; Tamil Selvi, S.; , "Screening mammogram images for abnormalities using radial basis Function Neural Network," Communication Control and Computing Technologies (ICCCCT), 2010 IEEE International Conference on , vol., no., pp.554-559, 7-9 Oct. 2010