Feature Selection in Computer Aided Diagnostic System for Microcalcification Detection in Digital Mammograms

Mohamed A. Alolfe[1], Wael A. Mohamed[2], Abo-Bakr M. Youssef[1], Yasser M. Kadah[1,3], and Ahmed S. Mohamed[1]

[1] *System & Biomedical Engineering Department, Cairo University, Giza, Egypt*

[2] *Department of Electrical Engineering, Benha High Institute of Technology, Benha University, Benha, Egypt*

[3] *Center for Informatics Science, Nile University, Egypt*

E-mail: al_olfe2001@k-space.org

Abstract

In this paper an approach is proposed to develop a computer-aided diagnosis (CAD) system that can be very helpful for radiologist in diagnosing microcalcifications' patterns in digitized mammograms earlier and faster than typical screening programs and showed the efficiency of feature selection on the CAD system. The proposed method has been implemented in four stages: (a) the region of interest (ROI) selection of 32×32 pixels size which identifies clusters of microcalcifications, (b) the feature extraction stage is based on the wavelet decomposition of locally processed image (region of interest) to compute the important features of each cluster, (c) the feature selection stage, which select the most significant features to be used in next stage, and (d) the classification stage, which classify between normal and microcalcifications' patterns and then classify between benign and malignant microcalcifications. In classification stage, two methods were used, the voting K-Nearest Neighbor classifier, and support vector machine classifier. The proposed method was evaluated using the Mammographic Image Analysis Society (MIAS) mammographic databases. The proposed system was shown to have the large potential for microcalcifications detection in digital mammograms.

1. Introduction

Mammography is the most effective diagnostic technique for early breast cancer detection available today. However, not all breast cancer can be detected by mammograms such that microcalcifications (MCCs) [1]. MCCs are calcium deposits of very small dimension and appear as a group of granular bright spots in a mammogram, masses, architectural distortion, asymmetry between breasts, breast edema and lymphadenopathy, the interpretations of their presence are very difficult because of its morphological features. For example, the sizes of MCCs are very tiny, typically in the range of 0.1mm- 1.0mm and the average is about 0.3mm, implying it can easily be overlooked by a radiologist. While in some dense tissues, and/ or skin thickening, MCCs areas are almost invisible to be seen by examining radiologist. The dense tissues especially in younger women may easily be misinterpreted as MCCs due to film emulsion error, digitization artifacts or anatomical structures such as fibrous strands, breast borders or hypertrophied lobules that almost similar to MCCs. Other factors that contribute to the difficulty of MCCs detection are due to their fuzzy nature, low contrast and low distinguish ability from their surroundings [2].

In the literature, various numbers of techniques are described to detect and classify the presence of microcalcifications in digital mammograms as benign or malignant. Yu *et al.* [3] presented a CAD system for the automatic detection of clustered microcalcifications through two steps. The first one is to segment potential microcalcification pixels by using wavelet and gray level statistical features and to connect them into potential individual microcalcification objects. The second step is to check these potential objects by using 31 statistical features. Neural network classifiers were used. Mascio *et al.* [4] developed a microcalcification detection algorithm, which operates on digital mammograms by combining morphological image processing with arithmetic processing. Netch [5] proposed a detection scheme for the automatic detection of clustered microcalcifications using multiscale analysis based on the Laplacian-of-Gaussian filter and a mathematical model describing a microcalcification as a bright spot of certain size and contrast. Barman *et al.* [6] used a low-pass filter to detect microcalcification by analyzing digital mammogram. Although the system based on their

algorithm is still under development, good preliminary results have been produced with further modifications still to be made. Karssemeijer [7]–[9] developed a statistical method for detection of microcalcifications in digital mammograms. The method is based on the use of statistical models and the general framework of Bayesian image analysis. Chan *et al.* [10]–[12] investigated a computer-based method for the detection of microcalcification in digital mammograms. The method is based on a difference image technique in which a signal suppressed image is subtracted from a signal enhanced image to remove structured background in the mammogram. Zheng *et al.* [13]–[15] proposed a method for the detection of microcalcifications clusters in digitized mammograms using mixed feature-based neural networks. Zaiane et al. [16] used neural network and data mining techniques for detection and classification of digital mammograms. Cheng *et al.* [17] proposed an approach using fuzzy logic for the detection of microcalcifications. Pfrench *et al.* [18] presented a two–dimensional adaptive lattice algorithm to predict correlated clutters in the mammogram. Li *et al.* [19] proposed using fractal background modeling, taking the difference between the original and the modeled image, which results in enhanced MC detection.

Strickland *et al.* [20], [21] used a discrete wavelet transform (DWT) with biorthogonal spline filters to detect microcalcifications. Yoshida *et al.* [22], [23] applied a DWT. They multiplied every scale by a weight factor and reconstructed an image by applying the inverse transform. The weights were determined by supervised learning, using a set of training cases. Clarke *et al.* [24] and Qian *et al.* [25], [26] applied a denoising to the image and then took the high-pass scale of a DWT using spline wavelets. This resulted in a general edge detector that could locate not only microcalcifications but also several other structures, such as film artifacts or lines. Bazzani *et al.* [27] proposed a method for MC detection based on multiresolution filtering analysis and statistical testing, in which an SVM classifier was used to reduce the false detection rate. Essam *et al.* [28] investigated an approach based on SVM for detection of microcalcification clusters in digital mammograms, and the sensitivity as high as 94% was achieved by the SVM. Wei *et al.* [29] investigated several state-of-the-art machine-learning methods for automated classification of clustered microcalcifications in mammograms.

The remainder of the paper is organized as follows. Section 2 provides detailed information about the proposed system. Experiments performed and the results achieved are discussed in Section 3. Conclusions are drawn in Section 4.

2. Materials & Methods

The proposed system has four stages: preprocessing, feature extraction, feature selection, and classification process.

2.1. Preprocessing stage

2.1.1. Mammogram image data source: It is difficult to access real medical images for experimentation due to privacy issue. The data collection that was used in our experiments was taken from the Mammographic Image Analysis Society (MIAS) [30]. It consists of 322 images, which belong to three categories: normal, benign and malign, which are considered abnormal. In addition, the abnormal cases are further divided into six categories: circumscribed masses, spiculated masses, microcalcifications, ill-defined masses, architectural distortion and asymmetry. All images are digitized at a resolution of 1024×1024 pixels and eight-bit accuracy (gray level). They also include the locations of any abnormalities that may be present. The existing data in the collection consists of the location of the abnormality (like the center of a circle surrounding the tumor), its radius, breast position (left or right), type of breast tissues (fatty, fatty-glandular and dense) and tumor type if exists (benign or malign).

2.1.2. ROI Selection: Using the locations of any abnormalities supplied by the MIAS for each mammogram, the ROI of size 32×32 pixels is extracted with microcalcification centered in the window, and divided into two sets: the training set and the testing set. We used 100 images for normal cases, and 25 images for microcalcification cases (13 benign images and 12 malignant images).

2.2. Feature Extraction

Features are extracted from the ROI based on the wavelet decomposition process. These features are passed to the feature selection stage. There are four processing steps in the features extraction stage. Features, in our system, are extracted from the coefficients that were produced by the wavelet analysis decomposition. In this section we discuss these steps.

2.2.1. Wavelet decomposition: In this work, the wavelet decomposition applied on the region of interest using the matlab toolbox. The output of wavelet analysis are the decomposition vector C and corresponding book keeping matrix S, The vector C consist from horizontal, vertical, and diagonal detail coefficients and one approximation.

2.2.2. Coefficients extraction: The horizontal, vertical and diagonal detail was extracted from the wavelet decomposition structure [C, S]. These vectors were extracted at each scale.

2.2.3. Normalization: The coefficients vectors for scales 1 to 3 are normalized after extracted. The normalization process is achieved by dividing each vector by its maximum value. The results of this operation is that all vectors values become less than or equal one. The normalization process is used to simplify the coefficients value.

2.2.4. Energy computation: We compute the energy for each vector by squaring every element in the vector. The produced values are considered as features for the classification process. Finally, we obtain matrix of features contain 136 columns, each column be represent one feature.

2.3. Feature selection

Feature selection is an important part before any classification scheme. The success of a classification scheme largely depends on the features selected and the extent of their role in the model. The objective of performing feature selection is three fold: (a) improving the prediction performance of the predictors, (b) providing faster and more cost effective predictors and (c) providing a better understanding of the processes that generated the data [31]. There are many benefits of variable and feature selection: it facilitates data visualization and understanding, reduces the storage requirements, reduces training times and improves prediction performance.

Feature selection algorithms designed with different evaluation criteria broadly fall into three categories: the filter model [32]-[35], the wrapper model [36]-[39], and the hybrid model [40], and [41]. The filter model relies on general characteristics of the data to evaluate and select feature subsets without involving any mining algorithm. The wrapper model requires one predetermined mining algorithm and uses its performance as the evaluation criterion. It searches for features better suited to the mining algorithm aiming to improve mining performance, but it also tends to be more computationally expensive than the filter model [39], and [42]. Methods like Forward Selection and Backward Elimination come under this category. The hybrid model attempts to take advantage of the two models by exploiting their different evaluation criteria in different search stages.

In this work, the filter model, and wrapper model are used to feature selection by applied these models on the features matrix which obtained from previous step and show the efficient of feature selection on the CAD system. In Filter model, the features are selected using the Feature Selection Tool v0501 software package [43]. The Feature Selection Tool was designed to make it easy to perform feature selection and to check the effect of the selection on classification accuracy. Some criteria such as correlation coefficients, information gain, log ratio, entropy measures, and margin based feature selection methods such as relief, Iterative Search Margin Based Algorithm (Simba), and Greedy Feature Flip Algorithm (G-flip) are used to feature selection. In wrapper model, the features are selected using sequential forward selection method, and stepwise forward linear regression method from the matlab toolbox.

2.4. Classification

The classification process is divided into the training phase and the testing phase. In the training phase, known data are given. Separately, the data on a candidate region which has already been decided as a microcalcification or as normal are given, and the classifier is trained. In the testing phase, unknown data are given and the classification is performed using the classifier after training. The number of images which used in training and testing sets see in Table 1.

Table 1. Number of training and testing sets

Category	No. of image	No. of training set	No. of testing sets
Normal	100	75	25
Microcalcification	25	18	7
Benign	13	9	4

Malignant	12	8	4

We used two classification techniques, the voting K-Nearest Neighbor (K-NN) classifier, and Support Vector Machine (SVM) classifier to classify between normal and microcalcification tissues, and then to classify between benign and malignant microcalcification tissues.

2.4.1. Voting K-Nearest Neighbor (K-NN) classifier: The Voting k-Nearest Neighbor (k-NN) classifier is nonparametric technique, it assigns a test sample to the class of the majority of its K-neighbors; that is, assuming that the number of voting neighbors is $k=k_1+k_2+k_3$ (where k_i is the number of samples from class i in the k-sample neighborhood of the test sample), the test sample is assigned to class m if $k_m = \max\{k_i, i=1, 2, 3\}$ [44]. Through this study, the results are computed at $k=1$.

2.4.2. Support Vector Machine (SVM) classifier: SVM has the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not has as distinct an influence on the performance of SVM as it has on the performance of conventional classifier. That is why it is noticed to be especially efficient in large classification problem. This will also benefit in faults classification, because the number of features to be the basis of fault diagnosis may not have to be limited. Also, SVM-based classifier is claimed to have good generalization properties compared to conventional classifiers, because in training SVM classifier the so-called structural misclassification risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized. The performance of SVM in various classification tasks is reviewed, e.g., in Christiani and Shawe-Taylor [45], through this study, we used radial basis function (rbf) kernel function.

We measured, quantitatively, the detection accuracy of the classifiers in equation (1) by computing the sensitivity and specificity on the data. Sensitivity is the conditional probability of detecting cancer while there is really cancer in the image. Specificity is the conditional probability of detecting normal breast while the true state of the breast is normal.

$$\text{Accuracy} = (\text{Sensitivity} + \text{Specificity}) / 2 \quad (1)$$

3. Results & Discussions

The previously mentioned 136 features obtained from feature extraction step, the discriminate powers for these features are tested by using the feature selection methods, and then check the effect of the feature selection on classification accuracy. We used two categories for feature selection, filter category, and wrapper category. In filter category, by using the feature selection toolbox 0v501 seven evaluation criteria (information gain, conditional entropy, correlation coefficient, log ratio, simba, relief, and G-flip) are used to feature selection. In wrapper category, by using matlab toolbox two evaluation criteria (sequential forward feature selection, and stepwise forward feature selection) are used.

Results of the proposed system obtain from test set in two steps; first we obtained results of classification between normal and microcalcification images from feature selection and two classifiers shown in tables (2, and 3) and figures (1, and 2). Second we obtained results of classification between benign and malignant microcalcifications images from feature selection and two classifiers shown in tables (4, 5, 6, and 7) and figures (3, and 4).

Table 2. K-NN classifier accuracy (%) for classification between normal and microcalcification

Feature selection (filter category)	No. of feature selection												
	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**136**
Information gain	100	100	100	100	100	100	100	100	100	100	100	100	100
Cond. Entropy	81.25	90.63	93.75	96.88	83.5	90.63	87.5	90.63	90.63	90.63	90.63	90.6	100
Releif	93.75	100	100	100	100	100	100	100	100	100	100	100	100
Simba	100	100	100	100	100	100	100	100	100	100	100	100	100
G-flip	100	100	100	100	100	100	100	100	100	100	100	100	100
Log ratio	100	100	100	100	100	100	100	100	100	100	100	100	100

Corr. coeff	100	100	100	100	100	100	100	100	100	100	100	100	100

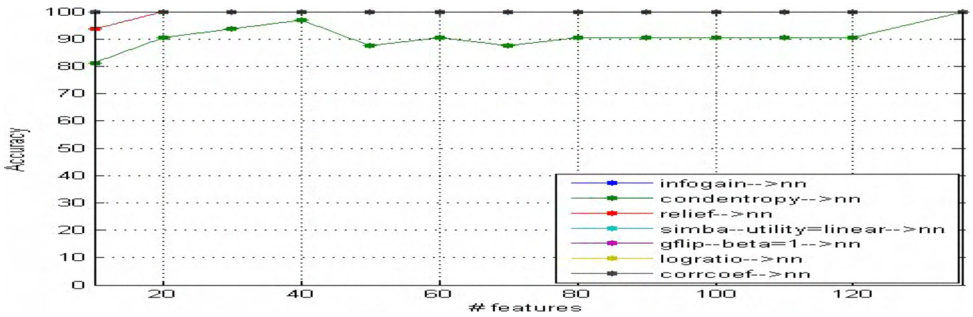

Figure 1. K-NN classifier accuracy vice no. of feature selection in table 2

Table 3. SVM classifier accuracy (%) for classification between normal and microcalcification

Feature selection (filter category)	No. of feature selection												
	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**136**
Information gain	100	100	100	100	100	100	100	100	100	100	100	100	100
Cond. Entropy	83.5	87.5	93.75	96.88	93.75	93.75	93.75	93.75	96.88	93.75	96.88	96.88	100
Releif	93.75	100	100	100	100	100	100	100	100	100	100	100	100
Simba	100	100	100	100	100	100	100	100	100	100	100	100	100
G-flip	100	100	100	100	100	100	100	100	100	100	100	100	100
Log ratio	100	100	100	100	100	100	100	100	100	100	100	100	100
Corr. coeff	100	100	100	100	100	100	100	100	100	100	100	100	100

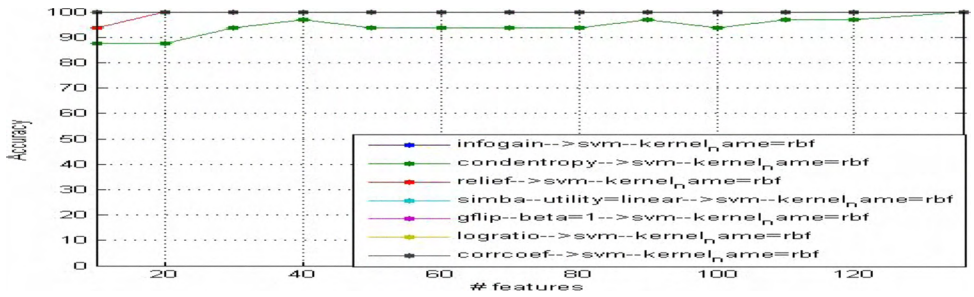

Figure 2. SVM classifier accuracy vice no. of feature selection in table 3

Table 4. K-NN classifier accuracy (%) for classification between benign and malignant

Feature selection (filter category)	No. of feature selection												
	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**136**
Information gain	50	75	62.5	50	37.5	37.5	50	50	50	50	50	50	50
Cond. Entropy	75	75	62.5	62.5	50	62.5	50	50	50	50	50	50	50
Releif	50	50	50	50	75	75	75	75	75	75	75	75	75
Simba	50	50	50	50	50	50	50	50	50	50	50	50	50
G-flip	75	75	75	75	75	75	75	75	75	75	75	75	62.5
Log ratio	75	75	62.5	50	37.5	37.5	50	50	50	50	50	50	50
Corr. coeff	62.5	62.5	37.5	62.5	62.5	62.5	50	50	50	50	50	50	50

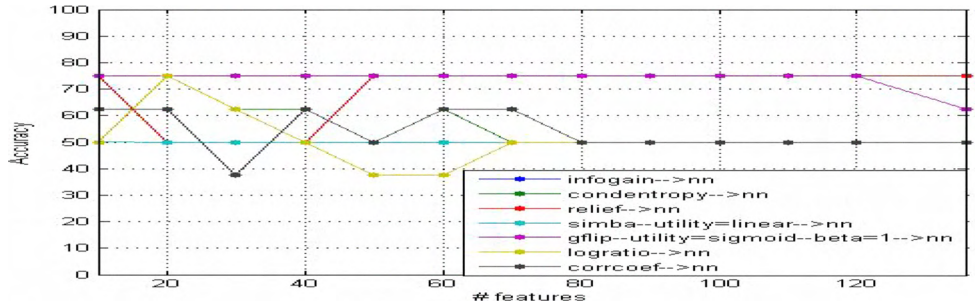

Figure 3. K-NN classifier accuracy vice no. of feature selection in table 4

Table 5. SVM classifier accuracy (%) for classification between benign and malignant

Feature selection (filter category)	No. of feature selection												
	10	20	30	40	50	60	70	80	90	100	110	120	136
Information gain	75	62.5	75	62.5	87.5	75	75	75	75	75	75	75	75
Cond. Entropy	75	62.5	75	87.5	87.5	75	75	75	75	75	75	75	75
Releif	50	50.	75	62.5	62.5	62.5	50	62.5	62.5	75	62.5	62.5	50
Simba	50	50	50	50	50	50	50	50	50	50	50	50	50
G-flip	75	62.5	75	75	87.5	750	75	62.5	75	87.5	75	75	75
Log ratio	75	62.5	75	62.5	87.5	75	75	75	75	75	75	75	75
Corr. Coeff	62.5	87.5	87.5	87.5	87.5	87.5	75	87.5	87.5	75	87.5	87.5	75

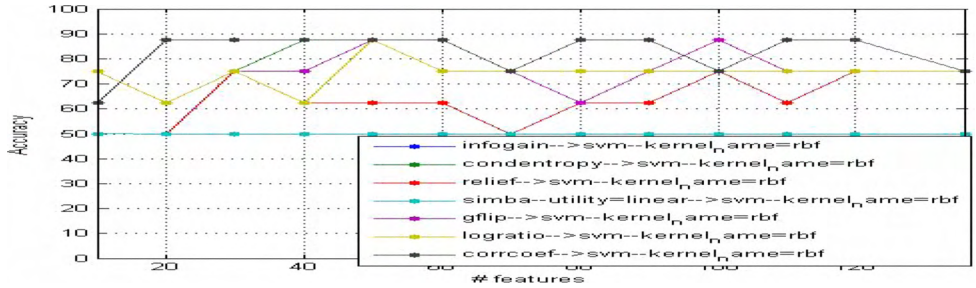

Figure 4. SVM classifier accuracy vice No. of feature selection in table 5

Table 6. K-NN and SVM classifier accuracy (%) for classification between benign and malignant

Feature selection (wrapper category)		No. of feature selection											
		10	20	30	40	50	60	70	80	90	100	110	120	136
Sequential Forward Feature Selection	K-NN	62.5	75	50	62.5	75	75	75	75	75	75	75	62.5	62.5
	SVM	75	37.5	50	75	87.5	75	100	100	87.5	100	87.5	87.5	87.5

Table 7. K-NN and SVM classifier accuracy (%) for classification between benign and malignant

Feature selection (wrapper category)	No. of feature selection	
	5 features (K-NN)	5 features (SVM)
Stepwise Forward Feature Selection	75	100

In the first step we classify between normal and microcalcification, and we use the filter method only for feature selection, these results demonstrate that two classifiers accuracy with seven evaluation criteria of feature selection give the best results other than conditional entropy along different number of feature selection. And also these results prove that proposed system with feature selection methods give the best results with select 10 features, and then we can reduce the computation time for processing CAD system with used only one of feature selection methods.

The results collect for classification between benign and malignant microcalcification in the second step with use the filter method and wrapper method for feature selection. In the filter method, the results in table

(4) and figure (3) prove that the best accuracy of K-NN classifier (75%) with G-flip feature selection method, and the results in table (5) and figure (4) prove that the best accuracy of SVM classifier (87.5%) with correlation coefficient feature selection method. and then we can reduce the computation time for processing CAD system with used only one of feature selection methods and also obtained the best result of classifier accuracy.

In table (6), and (7) show results of two classifiers accuracy obtained by using two wrapper methods for feature selection, these results demonstrate the wrapper method is better than filter method, and also show the best result (100%) obtain from sequential forward feature selection at number of feature selection (70, 80, and 100). The results of stepwise forward feature selection give the best results (100%) for two classifiers at small number of feature selection (5 features). From all results mentioned above, we conclude the wrapper method is better than filter method for feature selection, and the SVM classifier gives results better than K-NN classifier.

4. Conclusions

In this study, a computer-aided diagnostic system for microcalcification detection in the digitized mammograms of the breast has been presented. This system depends on selecting some features and using them in the classification process. Experiments were conducted on the MIAS dataset to diagnose microcalcification in a fully automatic manner using wavelet analysis, feature selection method, and two classifiers.

The feature selection method that we have used in proposed CAD system had given a promise results in classify between normal and microcalcification, and also had gives a promise results in classify between benign and malignant. In the research reported in this paper, a medical decision making system based on wavelet analysis, feature selection, and two classifiers were applied on the task of microcalcification detection and classification in digital mammograms and the most accurate learning methods was evaluated.

The results suggest that proposed system can aid in the microcalcification detection and classification in digital mammograms. It is hoped that more interesting results will follow on further exploration of data. Although developed method is built as an offline diagnosing system, it can be rebuilt as an online diagnosing system in the future.

References

[1] Mousa R., Q. Munib, and A. Moussa, "Breast Cancer Diagnosis System based on Wavelet Analysis and Fuzzy-Neural," Expert *Systems with Applications*, *Volume* (28), pp. 713-723, 2005.

[2] Cheng H. D., and M. Cui, "Mass Lesion Detection with a Fuzzy Neural Network," *Pattern Recognition, Volume* (37), pp. 1189-1200, 2004.

[3] Yu S., and L. Guan, "A CAD System for the Automatic Detection of Clustered Microcalcifications in Digitized Mammogram Films," *IEEE transactions on medical imaging*, *Volume* (19), no. 2, February 2000.

[4] Mascio L., M. Hernandez, and L. Clinton, "Automated analysis for microcalcifications in high resolution mammograms," Proc. SPIE—Int. Soc. Opt. Eng., Volume (1898), pp. 472–479, 1993.

[5] Netsch T., "A scale-space approach for the detection of clustered microcalcifications in digital mammograms," in Digital Mammography 96, Proc. 3rd Int.Workshop Digital Mammography, IL, pp. 301–306, Chicago, June 1996.

[6] Barman H., G. Granlund, and L. Haglund, "Feature extraction for computer- aided analysis of mammograms," in *State of the Art of Digital Mammographic Image Analysis*, *Volume* (7), pp. 128–147, 1994.

[7] Karssemeijer N., "A stochastic model for automated detection of calcifications in digital mammograms," in Proc. 12th Int. Conf. Information Processing Medical Imaging, pp. 227–238, Wye, U.K., July 1991.

[8] Karssemeijer N., "Recognition of clustered microcalcifications using a random field model, biomedical image processing and biomedical visualization," in SPIE Proc., vol. 1905, pp. 776–786, San Jose, CA, 1993.

[9] Karssemeijer N., "Adaptive noise equalization and recognition of microcalcification clusters in mammograms," *Int. J. Pattern Recognit. Artificial Intell.*, *Volume* (7), no. 6, pp. 1357–1376, 1993.

[10] Chan H. P., K. Doi, S. Galhotra, C. J. Vyborny, H. MacMahon, and P. M. Jokich, "Image feature analysis and computer-aided diagnosis in digital radiography, 1. Automatic detection of microcalcifications in mammography," *Med. Phys.*, *Volume* (14), no. 4, pp. 538–548, July/Aug. 1987.

[11] Chan H. P., K. Doi, C. J. Vyborny, K. L. Lam, and R. A. Schmidt, "Computer-aided detection of microcalcifications in mammograms methodology and preliminary clinical study," *Investigative Radiol.*, *Volume* (23), pp. 664–671, 1988.

[12] Chan H. P., K. Doi, C. J. Vyborny, R. A. Schmidt, C. Metz, K. L. Lam, T. Ogura, Y. Wu, and H. Maxmahon, "Improvement in radiologists' detection of clustered microcalcifications on mammogram: The potential of computer aided diagnosis," *Investigative Radiol.*, *Volume* (25), pp. 1102–1110, 1990.
[13] Zheng B., W. Qian, and L. P. Clarke, "Artificial neural network for pattern recognition in mammography," in Proc. World Congress Neural Networks, pp. I-57–I-62, San Diego, CA, June 1994.
[14] Zheng B., W. Qian, and L. P. Clarke, "Multistage neural network for pattern recognition in mammography," in Proc. IEEE World Conf. Computational Intelligence, pp. 3437–3441, Orlando, FL, July 1994.
[15] Zheng B., W. Qian, and L. P. Clarke, "Digital mammography: Mixed feature neural network with spectral entropy decision for detection of microcalcifications," *IEEE Trans. Med. Imag.*, *Volume* (15), pp. 589–597, Oct. 1996.
[16] Zaiane O., A. Maria, C. Alexandru, "Application o data mining techniques for medical image classification." In Proceedings of second international workshop on multimedia data mining (MDM/KDD') in conjunction with seventh ACM SIGKDDS, USA.
[17] Cheng H., Y. M. Lui, and R. I. Feiimanis, "A novel approach to microcalcification detection using fuzzy logic techniques," *IEEE Trans. Med. Imag.*, *Volume* (17), pp. 442–450, June 1998.
[18] Pfrench P. A., J. R. Zeidler, and W. H. Ku, "Enhanced detectability of small objects in correlated clutter using an improved 2-D adaptive lattice algorithm," *IEEE Trans. Image Processing*, *Volume* (6), pp. 383–397, Mar. 1997.
[19] Li H., K. J. Liu, and S. Lo, "Fractal modeling and segmentation for the enhancement of microcalcifications in digital mammograms," *IEEE Trans. Med. Imag.*, *Volume* (16), pp. 785–798, Dec. 1997.
[20] R. N. Strickland and H. I. Hahn, "Wavelet transform for detecting microcalcifications in mammograms," *IEEE Trans. Med. Imag.*, *Volume* (15), no. 2, pp. 218–229, Apr. 1996.
[21] Strickland R. N. and H. I. Hahn, "Wavelet transform methods for objects detection and recovery," *IEEE Trans. Image Process.*, *Volume* (6), no. 5, pp. 724 735, May 1997.
[22] Yoshida H., K. Doi, and R. M. Nishikawa, "Automated detection of clustered microcalcifications," *Proc. SPIE (Digital Mammograms Using Wavelet Transform Tech., Med. Imag. 1994: Image Process.)*, *Volume* (2167), pp. 868–886, Feb. 1994.
[23] Yoshida H., K. Doi, R. M. Nishikawa, M. L. Giger, and R. A. Schmidt, "An improved computer-assisted diagnostic scheme using wavelet transform for detecting clustered microcalcifications in digital mammograms," *Acad. Radiol.*, *Volume* (3), pp. 621–627, 1996.
[24] Clarke L. P., M. Kallergi, W. Qian, H. D. Li, R. A. Clark, and M. L. Silbiger, "Three-structured nonlinear filter and wavelet transform for microcalcification segmentation in digital mammography," *Cancer Lett.*, *Volume* (77), pp. 173–181, 1994.
[25] Qian W., L. P. Clarke, M. Kallergi, and R. A. Clark, "Tree-structured nonlinear filters in digital mammography," *IEEE Trans. Med. Imag.*, *Volume* (13), no. 1, pp. 25–36, Mar. 1994.
[26] Qian W., L. P. Clarke, B. Zheng, M. Kallergi, and R. A. Clark, "Computer assisted diagnosis for digital mammography," *IEEE Eng. Med. Biol. Mag.*, *Volume* (14), no. 5, pp. 561–569, Sep.-Oct. 1995.
[27] Bazzani A., A. Bevilacqua, D. Bollini, R. Brancaccio, R. Campanini, N. Lanconelli, A. Riccardi, and D. Romani, "An SVM classifier to separate false signals from microcalcifications in digital mammograms," *Phys. Med. Biol.*, *Volume* (46), pp. 1651–1663, 2001.
[28] Issam E., Y. Yongyi, and W. Mile, "A Support Vector machine for detection of microcalcifications," *IEEE transactions on medical imaging*, *Volume* (21), No. 12, December 2002.
[29] liyang W., Y. Yongyi, N. Robert, and J. Yulei, "A study on Several machine-Learning Methods for Classification of Malignant and Benign Clustered microcalcifications," *IEEE transactions on medical imaging*, *Volume* (24), No. 3, March 2005.
[30] http://peipa.essex.ac.uk/info/mias.html.
[31] Guyon I., A. E., "An introduction to variable and feature selection," *Journal of Machine Learning Research*, *Volume* (3), pp. 1157–11182, 2003.
[32] Dash M., K. Choi, P. Scheuermann, and H. Liu., "Feature selection for clustering – a filter solution," Proceedings of the Second International Conference on Data Mining, pp. 115–122, 2002.
[33] Hall M.A.., "Correlation-based feature selection for discrete and numeric class machine learning," Proceedings of the Seventeenth International Conference on Machine Learning, pp. 359–366, 2000.
[34] Liu H. and R. Setiono., "A probabilistic approach to feature selection - a filter solution," Proceedings of the Thirteenth International Conference on Machine Learning, pp. 319– 327, 1996.
[35] Yu L. and H. Liu., "Feature selection for high-dimensional data: a fast correlation-based filter solution," Proceedings of the twentieth International Conference on Machine Learning, pp. 856–863, 2003.
[36] Caruana R. and D. Freitag., "Greedy attribute selection," Proceedings of the Eleventh International Conference on Machine Learning, pp. 28–36, 1994.

[37] Dy J. G. and C. E. Brodley., "Feature subset selection and order identification for unsupervised learning," Proceedings of the Seventeenth International Conference on Machine Learning, pp. 247–254, 2000.
[38] Kim Y., W. Street, and F. Menczer., "Feature selection for unsupervised learning via evolutionary search," Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 365–369, 2000.
[39] Kohavi R. and G.H. John., "Wrappers for feature subset selection," *Artificial Intelligence*, *Volume* (97), pp. 273–324, 1997.
[40] Ng A. Y., "On feature selection: learning with exponentially many irrelevant features as training examples," Proceedings of the Fifteenth International Conference on Machine Learning, pp. 404–412, 1998.
[41] Xing E., M. Jordan, and R. Karp., "Feature selection for high-dimensional genomic microarray data," Proceedings of the Eighteenth International Conference on Machine Learning, pp. 601–608, 2001.
[42] Langley P., "Selection of relevant features in machine learning," Proceedings of the AAAI Fall Symposium on Relevance, pp. 140–144, 1994.
[43] http://www.cs.huji.ac.ill/~anavot/feature_selection_tool/fst.html.
[44] Kadah Y. M., A. A. farag, A. M. badawy, and A. M. Youssef, "Classification algorithm for quantitative tissue characterization of diffuse liver disease from ultrasound," *IEEE transactions on medical imaging*, *Volume* (15), no. 4, August 1996.
[45] Cristianini N., N.J. Shawe-Taylor, *an Introduction to Support Vector Machines*, Cambridge University Press, Cambridge, 2000.