Enhancement and Classification of Mammographic Images for Breast Cancer Diagnosis using Statistical Algorithms

Muhammad Talha[a], Abdulhameed Al-Elaiwi [b]

[a]Deanship of Scientific Research, King Saud University, Riyadh Saudi Araiba.
[b]Software Engineering Department, College of Computer & Information Sciences, King Saud University, Riyadh, Kingdom of Saudi Arabia
E-mail: aalelaiwi@KSU.EDU.SA

Abstract: Breast cancer is going to be a common health problem in the globe. Although high degree of accuracy is needed in the detection and diagnosis of breast cancer as it is a serious and complicated issue. Apart from skin cancer, breast cancer is the most commonly identified cancer among women in the United States. It is also predicted that breast cancer may be the major source of mortality in upcoming decades. After lung cancer, it is the second leading cause of death through disease. Screening mammograms cannot stop or reduce breast cancer but are helpful in the early detection of breast cancer. Different research has proved that early detection and treatment of breast cancer can reduce mortality. The goal of image enhancement is to improve the image quality so that the processed image is better than the original image for a specific application or a set of objectives. In this paper, we have done the Image enhancement using Histogram Equalization (HE). Haralick Texture Features are used for feature extraction. Artificial Neural Network (ANN) has been used for classification into benign and malignant. It has been observed that outcomes are enough promising. MIAS data set is used for experimentation purpose.
[Muhammad Talha, Abdulhameed Al-Elaiwi. **Enhancement and Classification of Mammographic Images for Breast Cancer Diagnosis using Statistical Algorithms**. *Life Sci J* 2013;10(2):764-772] (ISSN:1097-8135). http://www.lifesciencesite.com. 108

Keywords: Breast Cancer, Mammogram, Histogram Equalization, Enhancement, ANN, Classification

1. Introduction

Excluding cancers of the skin, breast cancer is the most common type of cancer in women in the United States, accounting for 1 of every 3 cancers diagnosed. A woman's chance of developing invasive breast cancer at some time in her life is approximately 1 in 8 (12%). It is one of the leading causes of cancer mortality among women in the United States (American Cancer Society, 2008). Mammography is the recommended examination for breast cancer, especially in women older than 40 years, the age group with the highest incidence. Some studies have shown that mammography may be particularly beneficial for women who are 80 years of age and older (Schonberg MA et al 2006 and Badgwell BD et al, 2008). The earliest sign of breast cancer is an abnormality depicted on a mammogram, before it can be felt by the woman or her physician. When breast cancer has grown to the point where physical signs and symptoms appear, the patient feels a breast lump (usually painless). In November 2009, the U.S. Preventive Services Task Force (USPSTF) updated their recommendations for routine mammography screening for woman aged 40-49 years (Screening for breast cancer, 2009). The USPSTF examined the evidence on the efficacy of 5 screening modalities in reducing mortality from breast cancer:

- Film mammography
- Clinical breast examination
- Breast self-examination
- Digital mammography
- Magnetic resonance imaging

In automatic detection of breast cancer using mammograms, enhancement and segmentation are two demanding handling tasks in automatic detection of breast cancer using mammograms. Mammograms are poor quality images with low-contrast resulting that is a difficult task to detect indirect signs of malignancy like micro calcifications and masses. Because of low contrast results, it becomes difficult to control two main concerns namely; false-positive interpretations and false-negative results. False-positives lead to biopsies performed on women with benign (non-cancerous) conditions. False-negatives allow early stage disease to grow to a more complex stage with less survival rates. The several approaches for improving local contrast, enhancing image details and segmentation have been proposed mostly based on the wavelet transform. Most of these approaches employ either decimated or undecimated (dyadic) wavelet transforms together with statistical modeling. Many screening algorithms have been created until now for different purposes like enhancement, segmentation, classification and detection of masses but they have some drawbacks, e.g. they are fit for restricted numbers of images. This is usually due to the amount of time needed to evaluate, record, and compare the results of the algorithms. Breast cancer considered as acute malignancies that grow in one or both breasts and in developed countries it is the most occurred form of cancer among women. Breast cancer is the most common malignant disease among women (O.Whi-Vin et al, 2009). Most early breast cancer can be diagnosed by detecting microcalcification clusters in mammographic X-ray images. Those clustered microcalcifications are an important indicator for early detection of breast cancer (Global Cancer Facts & Figures 2007). According to American Cancer Society 2007, United States has highest figure in the world about crude and age-standardized breast cancer incidents (F.Eddaoudi et al, 2006). Actually, one in eight women will suffer in breast cancer. Particularly in US, "the threat of breast cancer within five years among 50-year-old women was 0.8% (1 in133) for Hispanic women, 0.9% (one in 107) for Asian/Pacific Island women, 1% (one in 98) for African American women and 1.3% (one in 75) among Caucasian women. Threats increased with age, with the highest rates occurring in Caucasian women (8%, or one in 13) and African-American women (5.5%, or one in 18) at age 60" (American Cancer Society 2001). According to Breast Cancer Statistics-2009, approximately 22,700 Canadian women will be detected with breast cancer and 5,400 will expire from it and approximately 170 men will be diagnosed with breast cancer and 50 will die of it. According to estimation, 1 in 9 women (11%) is expected to develop breast cancer during her lifetime (by age 90) and one in 28 (3.6%) will pass away from it (Canadian Cancer Society, 2009). The particular breast cancer reasons are still not clear. Yet, there are some aspects that may increase the possibilities of growing breast cancer in the women, for example, family history of breast cancer, hormone replacement therapy, early or late onset of menopause, and certain nutritional reasons. However, in over 75% of women with breast cancer none of these risk factors are present (Hutt et al 1996).

The fluctuation was seen in breast cancer mortality rate in different ages. It was increasing 0.4% annually from 1975 and 1990 but reduced by 2.3% from 1990-2002. This reduction in mortality rate is due to enhancement in breast cancer treatment and mammographic screening. Screening mammograms cannot prevent or diminish breast cancer but are helpful in the early diagnosis of breast cancer [6, 7]. Mammography is the most efficient method of screening for breast cancer which can diagnose a malignancy (cancer) up to two years before a lump can be aroused (National Cancer Institute 2006). Process of Mammographic screening has been proved to be reducing factor in deaths by 30% to 70% (Jemal A et al, 2004). This paper presents selected methods for the enhancement of digital images. To improve the appearance of images, to eliminate noise or error, or to highlight certain features in an image, image enhancement techniques are very helpful and useful. These procedures can be enough supportive in the improvement of digital mammogram examination methods.

It has been examined radiologists are unable to detect around 10-30% of breast cancers during routine screening which causes high penalty in the form of unnecessary biopsy (Wallis, 1991). Mammographic image interpretation can be improved using computational advancements to reduce complexity that ultimately may save time and money. Many computer-aided systems are proposed by different researchers to enhance the accuracy of interpretation. Some of them used calcification, some talked about masses (like circumscribed lesion, stellate lesion, speculated lesions, ill-defined masses, etc) in breast. Masses in digital mammograms may be classified into benign or malignant. Cells from benign tumors do not spread to other parts of the body and can be removed if necessary, although benign breast tumors are not risk for life. Malignant tumors can invade and damage nearby tissues and organs, and spread to other parts of the body, a process called metastasis (National Cancer Institute 2006).

(Cheng, 2006) depict only asymmetry because of breast cancer but nobody has taken all these abnormalities of cancer as a complete problem. This paper proposes a novel approach in which efficient classification methods for detection of breast cancer abnormalities is used. The main complexity about digital mammogram diagnosis is the detection of malignant images and its classification on the basis of abnormalities present. This paper investigates the accuracy of a detection methodology that uses Haralick Texture Features as an input to ANN (Artificial Neural Networks) to classify the images into benign or malignant. A very efficient technique for pre-processing the mammograms is used, (Jaffar, M.A., et. al. 2010) which involves the automatic cropping of the mammograms, extracting breast region and remove other spots which are not part of breast. The proposed technique is fully automatic and very robust. The strong automatic abnormality detection method is proposed. The rest of paper is arranged as Section 2 discusses the related work. Section 3 describes the proposed architecture. Section 4 presents the experimental results followed by the conclusions and future work in Section 5.

1.1 Major contributions

1. A fully automatic and robust technique has been proposed.

2. Strong preprocessing technique and automatic abnormality type detection method is used.
3. No prior knowledge of the mammogram is needed about its feature, type and contents.
4. This is a supervised method for diagnosing breast cancer.
5. Proposed system achieved quite good accuracy for the classification of mammograms as malignant and benign.

2. Related Work

Many methods have been used to detect anomaly in medical images such as fractal theory, statistical methods and wavelets using features extraction mechanism from image processing field. (Cahoon, et.al, 2000) have proposed Breast cancer detection using image processing techniques. A computer-aided diagnosis system in which features are extracted using image processing techniques is developed in (M. P. Sampat, 2005) for detection of abnormalities. Tang et al. (2009) gave an overview of recent advances in the development of such tools and related techniques. Kom et al. (2007) proposed a technique for the automated detection of malignant masses in screening mammography. The technique is based on the presence of con-centric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region. Malignant masses were detected with 92, 88 and 81% sensitivity of 5.4, 2.4 and 0.6 false positive per image. Eltonsy et al. (2007) introduced an algorithm for detection of suspicious masses in mammographic images that shows a sensitivity of 95.91% for mass detection, with receiver operating characteristics (ROC) area of 0.946 when the enhancement of the original image was performed before detection and 0.938 otherwise. Histogram equalization (HE) **r**eassigns the intensity values of pixels to make the new distribution of the intensities uniform to the utmost extent (S.H. Nam, 1998), it is effective in enhancing the entire image with low contrast (M. Wilson, 1998), Cannot enhance the textural information and working only for the images having one object (K. Wongsritong, 1998 and H.D. Cheng, 2004). Features extraction and selection is a key step in mass detection and classification. Features are calculated from the region of interest (ROI) characteristics such as size, shape, density and smoothness etc (P. Undrill, 1996). Feature space is very large and complex due to wide diversity of the normal tissues and the variety of the abnormalities. Feature space can be divided into 3 sub-spaces (N. Petrick, 1999)

- Intensity features
- Shape features
- Texture features

The dimension of the texture feature space derived from the SGLD matrices at different pixel distances and directions is very large. It is well known that the presence of ineffective features often degrades classifier performance, especially when the training data set is small (Raudys and Pikelis 1980, Fukunaga and Hayes 1989). Investigators in CAD research have employed different methods for feature selection. Goldberg *et al* (1992) selected features for classifying malignant and benign masses on ultrasound images by evaluation of the discriminatory ability of the individual features. Wu *et al* (1993) selected features based on the difference in the average values of the individual features between the two classes. Lo *et al* (1995) ranked the importance of each feature based on its effect on the classification accuracy, and then eliminated the features, one at a time, from the least important to the most important, to determine the smallest set of features that provided the highest classification accuracy in their data set. (Chan et al., 1995) presented a region-based algorithm in which eight texture features were calculated from spatial gray-level dependence (SGLD) matrices, and stepwise linear discrimination was used to determine the importance of each feature in distinguishing masses from normal tissue. The extracted features are analyzed by linear or non-linear classifiers which are trained for a specific classification task. We have found that texture features are effective for differentiation of masses and normal tissues (Chan *et al* 1995b, Wei *et al* 1995b), and that morphological features can be used to distinguish malignant and benign clustered microcalcifications (Chan *et al* 1995c). Because the tissue texture in regions containing microcalcifications associated with a malignant process may be different from that associated with a benign process, in the present study we analysed texture features from a region of interest (ROI) containing clustered microcalcifications (Chan *et al* 1995d). The effectiveness of these texture features, in combination with a backpropagation neural network classifier (Freeman and Skapura 1991), for the differentiation of malignant and benign microcalcifications was evaluated. The performance of the neural network was analysed with receiver operating characteristic (ROC) methodology (Swets and Pickett 1982, Metz *et al* 1990).

3. The Proposed Method

We have developed a CAD system for the diagnosis and detection of breast cancer based on automated segmentation of masses in mammograms. Biopsy is the other way of diagnosis of all types of breast diseases. The opinion for a biopsy is mainly based on mammography findings in many cases. The indication of biopsy results is that 65-90% of expected cancer identified by mammography turned out to be benign (H.D. Cheng, 2006)

There are some challenges in breast cancer detection like microcalcifications and masses are two important early signs of breast cancer. Masses are often impossible to differentiate from the surrounding parenchyma because their facial appearance can be obscured or similar to the normal inhomogeneous breast tissues. This formulates the automatic mass detection and classification difficult. The proposed method is divided into four major stages as demonstrated in Fig 1.

Major Stages of Breast Cancer Detection

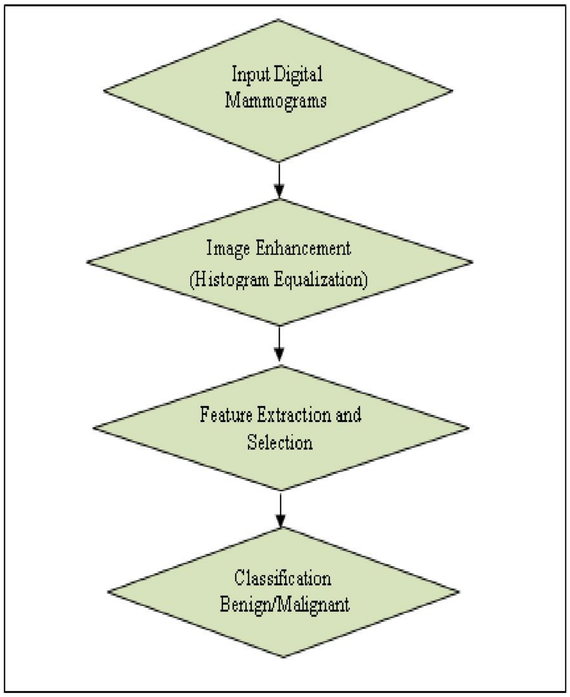


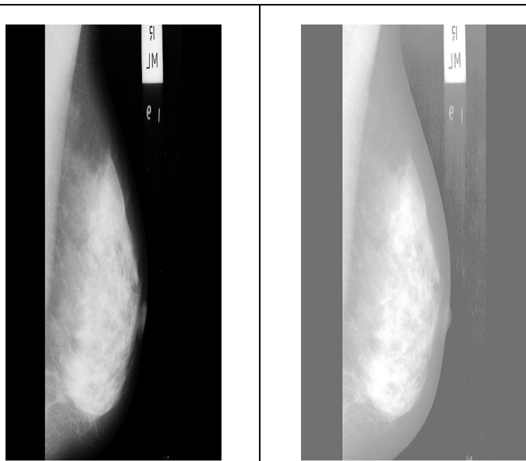
Figure 1: The Proposed Method

First of all, Histogram Equalization (HE) technique will be applied for image enhancement. HE is a procedure used to create a new enhanced image with uniform histogram. This is attained by using a normalized cumulative histogram as a gray scale mapping function.

Features extraction and selection is very significant step in mass detection and classification. Feature selection helps in removing most irrelevant and redundant features from the data or combining data to make a smaller set of features. By reducing the dimensionality of the input set correlated information is removed at the cost of a loss of accuracy (Addison et al 2003). Features are calculated from the region of interest (ROI) characteristics such as size, shape, density and smoothness etc. Feature space is very large and complex due to wide diversity of the normal tissues and the variety of the abnormalities. For classification purpose of masses into benign and malignant, Artificial Neural Network (ANN) technique has been used. ANN is an information processing paradigm inspired by biological nervous systems, such as our brain in which large number of highly interconnected processing elements (neurons) working together. The main purpose for creating neural network is to develop a computation model which work like human brain and be able to solve difficult problems in short time than traditional approach (Duda et al 2001). These are helpful for a specific application, such as pattern recognition or data classification, through a learning process. ANN systems may help when we can't formulate an algorithmic solution or when we need to pick out the structure from existing data. The output of the neuron is determined through an activation function which is sum of the product of inputs with their associated weight to that neuron.

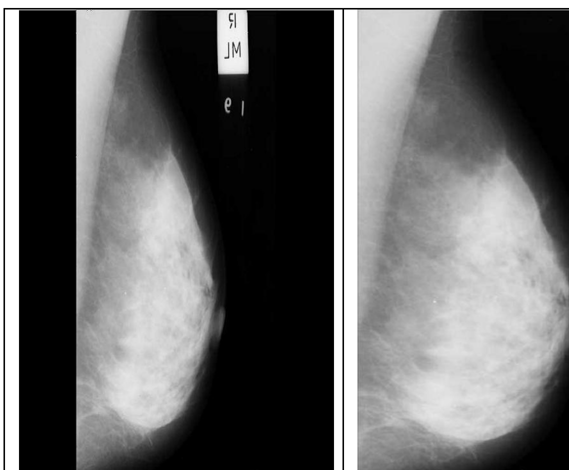
3.1 Preprocessing for Enhancement

Histogram Equalization (HE) is another method to enhance the contrast of an image. A new enhanced image with uniform histogram is created by histogram equalization. This is attained by using a normalized cumulative histogram as a gray scale mapping function. Histogram equalization corresponds to redistribution of gray levels in order to obtain uniform histogram. In this case every pixel is replaced by integral of the histogram of the image in that pixel (Thangavel. K et al, 2009) .Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. Through this adjustment, the intensities can be better distributed on the histogram. It allows for areas of lower local contrast to enhance their contrast. Histogram equalization accomplishes this by efficiently spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed (M. Vasantha et al, 2010). In mammogram images, Histogram equalization is used to make contrast adjustment so that the image abnormalities will be better visible. The visual results of complete preprocessing phase are given in the Fig 2 & Fig 3.



Original Image	**Histogram Equalization**

Figure 2: Enhancement of Breast Mammogram Images



Before Background removal	**After Removal**

Figure 3: Background Removal of Breast Mammogram Images

3.2 Features Extraction

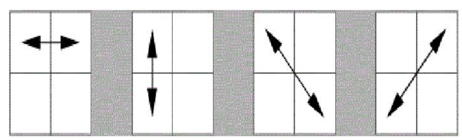
Features play a significant role in CAD (Computer Aided Diagnostic) environment. The transformation of an image into its set of features is known as feature extraction. Useful features of the image are extracted from the image for classification purpose. It is a challenging task to extract good feature set for classification. We have used Haralick's texture features for our proposed system.

3.2.1 Haralick's Texture Features

The basis for Haralick's texture features (Robert M. Haralick et al, 1979) is the gray-level co-occurrence matrix G in Equation 1. This matrix is square with dimension N_g, where N_g is the number of gray levels in the image. Element [*i*,*j*] of the matrix is generated by counting the number of times a pixel with value *i* is adjacent to a pixel with value *j* and then dividing the entire matrix by the total number of such comparisons made. Each entry is therefore considered to be the probability that a pixel with value *i* will be found adjacent to a pixel of value *j*.

$$\mathbf{G} = \begin{bmatrix} p(1,1) & p(1,2) & \cdots & p(1,N_g) \\ p(2,1) & p(2,2) & \cdots & p(2,N_g) \\ \vdots & \vdots & \ddots & \vdots \\ p(N_g,1) & p(N_g,2) & \cdots & p(N_g,N_g) \end{bmatrix} \tag{1}$$

Since adjacency can be defined to occur in each of four directions in a 2D, square pixel image (horizontal, vertical, left and right diagonals - see Figure 4), four such matrices can be calculated. Haralick then described 14 statistics that can be calculated from the co-occurrence matrix with the intent of describing the texture of the image.



(4)

Figure 4 Four directions of adjacency as defined for calculation of the Haralick texture features. The Haralick statistics are calculated for co-occurrence matrices generated using each of these directions of adjacency.

2. Material and Methods

Supervised classification is the process of using samples of known identity to classify samples of unknown identity. The characteristics apply to a supervised classification are that it requires detailed knowledge of the area and input patterns are provided with the labels. But supervised classification is more controlled and directed classification which surly enhances the accuracy. We have used neural network classifier to classify the malignant and benign mammograms. A brief discussion of this classifier is given below.

3.3.1 Artificial Neural Networks

Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. Neural networks are a form of multiprocessor computer system, with

- simple processing elements
- a high degree of interconnection

- simple scalar messages
- adaptive interaction between elements

The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view (Duda, R.O et al, 2001). Good performance (e.g. as measured by good predictive ability, low generalization error), or performance mimicking animal or human error patterns, can then be used as one source of evidence towards supporting the hypothesis that the abstraction really captured something important from the point of view of information processing in the brain. Another incentive for these abstractions is to reduce the amount of computation required to simulate artificial neural networks, so as to allow one to experiment with larger networks and train them on larger data sets (Muhammad Talha et al, 2012). We used neural network to classify benign and malignant. In this problem, neural network consists of one hidden layer with five hidden neurons. As the number of hidden layers increase, the time taken by neural network to train and to generate output also increases. Therefore, in the proposed technique minimum number of hidden layers and neurons, with which neural network gives best performance are used.

In experimentation, a standard back-propagation neural network has been used for classification with the following specifications as shown in the Table 1.

Table 1: Specifications of Neural Networks used for classification

No of input neuron	**7**
No of hidden layers	**3**
No of neurons in hidden layer	**5**
No of ouput neuron	**1**
Activation function at hidden layer	tansig
Activation function at output layer	logsig
Training algorithm	trainlm

4. Results and Discussion

The database used into this work is freely available at internet and is named as the Mammographic Institute Society Analysis (MIAS) (J Suckling et al 1994). The specification of the data is given in the referred site. Six enhancement methods were implemented for enhancement of digital mammograms. The results were evaluated using CNR and PSNR as shown in table 2.

The Experimental results show that the Histogram Equalization yields maximum PSNR as well as CNR values and thus we use this method for enhancement of mammogram. Further it also consumes less time compared to counterlet transform filtering. The result of enhancement using Histogram Equalization is shown in figure 2 and figure 3 is presenting the results of background removal as shown.

Table 2. Evaluation of Enhancement Techniques

S.No	**Enhancement Technique**	**Contrast-to-Noise Ratio (db)**	**Peak Signal-to-noise Ratio (db)**
1	Contourlet Transform Filter	0.0161	14.12
2	Median Filter	0.0239	20.56
3	Hybrid Technique	0.0221	22.35
4	Contrast Stretching	0.0172	37.11
5	Mean Filter	0.0094	38.19
6	**Histogram Equalization**	**0.0701**	**40.91**

We have tested the performance of these classifiers by calculating and analysis of accuracy, sensitivity and specificity for malignancy detection. These are defined as follows:

Accuracy: number of classified mass / number of total mass

(TP+TN) / (TP+TN+FP+FN)

Different classifier results are shown in Table 3 & 4 and Comparison of performance measure of classification is shown in Table 5.

Table 3 Malignancy Detection Results

Dataset	**Accuracy %**
Proposed Method	**97.11**

Table 3 gives a very clear picture of the performance of each classifier we have used and also the improvement in the results which we have achieved using ensemble classifier.

Table 4: Comparison of performance measure of different classifiers

Sr.No	**Techniques**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
1	**KNN**	79.40	79.71	80.34
2	**SVM**	89.13	88	89.84
3	**Bayesian**	90.23	89.2	91.23
4	**Neural Network**	91.20	92.37	93.51

Table 5: Comparison of performance measure of classification

Sr.No	**Technique**	**Accuracy (%)**
1	**Neural Network + Haralick**	91.20
2	Campanini (Campanini R, 2004)	80
3	Guo (Guo Q, 2005)	72.5
4	Miller (Miller P, 1994)	86.7

5. Conclusion and Discussion

We developed the above image processing proposed system for detecting breast cancer from mammograms using Matlab codes and applied over to several images from the MIAS data base. Our algorithm works in multiple phases. Histogram equalization is used to enhance image quality. Haralick Texture Features are used for feature extraction from an ROI containing the microcalcification cluster. Artificial Neural Network (ANN) has been used for classification into benign and malignant. The classifier could correctly identify a significant fraction of benign cases, which had been recommended for surgical biopsy under current clinical criteria, without missing any malignant cases. The results are found to be satisfactory and they have been validated by expert radiologists.

Acknowledgement:

The authors extend their appreciation to the College of Computer & Information Sciences Research Center, Deanship of Scientific Research, King Saud University for funding this research work.

Corresponding Author:
Dr. Abdulhameed Al-Elaiwi
College of Computer & Information Sciences, King Saud University, Riyadh, Kingdom of Saudi Arabia
E-mail: aalelaiwi@KSU.EDU.SA

References

1. Canadian Cancer Society (2009) / National Cancer Institute of Canada; Canadian Cancer Statistics 2009, Toronto, Canada.
2. H.D. Cheng, X.J. Shi, R. Min, L.M. Hu, X.P. Cai, H.N. Du (2006), Approaches for automated detection and classification of masses in mammograms, Pattern recognition, 39, 646-668
3. Hutt, Ian (1996). “Computer aided Detection of Abnormalities in Digital Mammograms. ”Diss. U. of Manchester.
4. National Cancer Institute (2006). Probability of breast cancer in American women. Updated October 2006. Fact Sheet 5.6.
5. Jemal A, Clegg LX, Ward E, Ries LAG, Wu X, Jamison PM, Wingo PA, Howe HL, Anderson RN, Edwards BK (2004): Annual report to the nation on the status of cancer, 1975–2001, with a special feature regarding survival. Cancer 101(1):3–27.
6. M. P. Sampat, M. K. Markey, and A. C. Bovik (2005), “Computer-aided detection and diagnosis in mammography,” in *Handbook of Image and Video Processing*, 2nd ed. New York: Academic, pp. 1195–1217.
7. R. M. Rangayyan, F. J. Ayres, and J. E. L. Desautels (2007), “A reviewof computer-aided diagnosis of breast cancer: Toward the detection of early signs,” *J. Franklin Inst.*, vol. 344, no. 3–4, pp. 312–348.
8. Global Cancer Facts & Figures 2007. Atlanta, GA: American Cancer Society, 2007.
9. American Cancer Society (2001). Breast Cancer Death Rates Continue to Decline. [Online] Available:http://www.cancer.org/docroot/NWS/content/NWS_1_1x_Breast_Cancer_Death_Rates_Continue_to_Decline.asp (October 10, 2001).
10. Addison, J F D, MacIntyre J (editors) 2003 “Intelligent techniques: A review”, Springer Verlag (UK) Publishing Company, 1st Edition, Chapter 9, To appear September 2003.
11. Duda, R.O., Hart, P.E., Stork, D.G (2001). Pattern classification (2nd edition), Wiley, ISBN 0-471-05669-3.
12. P. Undrill, R. Gupta, S. Henry, M. Dowing, Texture analysis and boundary refinement to outline mammography masses, Proceedings of the 1996 IEE colloquium on Digital mammography, 1996, pp. 51-56.
13. N. Petrick, H.P. Chan, B. Sahiner, M.A. Helvie, Combined adaptive enhancement and region growing segmentation of breast masses on digitized mammograms, Med. Phys. 26 (1999) 1642-1654.
14. Wallis, M., Walsh, M., and Lee, J. (1991), “A Review of False Negative Mammography in Asymptomatic Population”, Clinical Radiology, Volume 44, pp. 13.15.
15. Cheng, H., et. al. (2006), “Approaches for Automated Detection and Classification of Masses in Mammograms”, Pattern Recognition, Volume 39, pp. 646.668.
16. Nawazish Naveed, Muhammad Arfan jaffar, Faisal Karim Shaikh, (2011), Malignancy and Abnormality Detection of Mammograms using Classifier Ensembling, Mehran University Research Journal Of Engineering & Technology, Volume 30, NO. 3, pp. 501-510.
17. American Cancer Society (2008). Detailed Guide: Breast Cancer What Are the Key Statistics for Breast Cancer? American Cancer Society Cancer Resource Information. [Online] Available: http://www.cancer.org/docroot/CRI/content/CRI_2_4_1X_What_are_the_key_statistics_for_breast_cancer_5.asp (May 16, 2008).
18. Schonberg MA, Ramanan RA, McCarthy EP, Marcantonio ER (2006). Decision making and counseling around mammography screening for

women aged 80 or older. *J Gen Intern Med*. Sep 2006;21(9):979-85.

19. Badgwell BD, Giordano SH, Duan ZZ, Fang S, Bedrosian I, Kuerer HM, et al (2008). Mammography Before Diagnosis Among Women Age 80 Years and Older With Breast Cancer. *J Clin Oncol*. Apr 21 2008.
20. Screening for breast cancer (2009): U.S. Preventive Services Task Force recommendation statement. *Ann Intern Med*. Nov 17, 2009;151(10):716-26, W-236.
21. Tang J, Rangayyan R, Xu J, El Naqa I, Yang Y (2009). Computer-aided detection and diagnosis of breast cancer with mammography: Recent advances, Information Technology in Biomedicine, IEEE Trans. On, 13(2): 236–251.
22. Eltonsy N, Tourassi G, Elmaghraby A (2007). A concentric morphology model for the detection of masses in mammography, Medical Imaging, IEEE Trans. On, 26(6): 880–889.
23. Kom G, Tiedeu A, Kom M (2007). Automated detection of masses in mammograms by local adaptive thresholding, Comput. Biol. Med., 37(1): 37–48.
24. S.H. Nam, J.Y. Choi, A method of image enhancement and fractal dimension for detection of microcalcifications in mammogram, in: Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 20, vol. 2, 1998, pp.1009–1012.
25. M. Wilson, R. Hargrave, S. Mitra, Y.Y. Shieh, G.H. Roberson, Automated detection of microcalcifications in mammograms through application of image pixel remapping and statistical filter, in: Proceedings of the IEEE Symposium on Computer-based Medical Systems, 1998, pp. 270–274.
26. K. Wongsritong, K. Kittayaruasiriwat, F. Cheevasuvit, K. Dejhan, A. Somboonkaew, Contrast enhancement using multipeak histogram equalization with brightness preserving, in: IEEE Asia-61 Pacific Conference on Circuits and Systems—Proceedings, 1998, pp. 455 –458.
27. H.D. Cheng, X.J. Shi, A simple and effective histogram equalization approach to image enhancement, Digital Signal Process. 14 (2) (2004) 158–170.
28. R.M. Haralick, K. Shanmugam, I.K. Denstein, Textural Features for Image Classification, IEEE transctions on systems, man and cybernatics, vol. 3(6), 610-621, 1973.
29. H. P. Chan, D.Wei, M. A. Helvie, B. Sahiner, D. D. Adler,M.M. Goodsitt, and N. Petrick, “Computer-aided classification of mammographic masses and normal tissue: Linear discriminant analysis in texture feature space,” *Phys. Med. Biol.*, vol. 40, no. 5, pp. 857–876, 1995.
30. O.Whi-Vin, K. Kwang Gi, K. Young-Jae, K. Han Sung, R. JungSil, M. Woo Kyung (2009), Detection of Microcalcifications in Digital Mammograms Using Foveal Method, Journal of Korean Society of Medical Informatics, 15-1, 165:172.
31. F.Eddaoudi, F.Regragui, K.Laraki (2006), Characterization of normal mammograms based on the Statistical Features, Proc. Second International Symposium on Communications, Control and Signal Processing (ISCCSP), Marrakech.
32. Cahoon, T.C. Sutton, (2000); Breast cancer detection using image processing techniques, Ninth IEEE International conference Volume: 2, On page(s): 973-976.
33. Thangavel. K, Roselin. (2009), Mammogram Mining with Genetic Optimization of Ant-Miner Parameters, R, *International Journal of Recent Trends in Engineering, Vol 2, No. 3.*
34. M. Vasantha, Dr. V.Subbiah Bharathi, R. Dhamodhar (2010), An Medical Image Feature, Extraction, Selection and cassification, *International Journal of Engineering Science and Technology, Vol. 2(6)*, 2071-2076.
35. Robert M. Haralick, ``Statistical and structural approaches to texture," *Proc. IEEE*, vol. 67, no. 5, pp. 786-804, 1979.
36. M. G. Fleming, ``Design of a high resolution image cytometer with open software architecture," *Analytical Cellular Pathology*, vol. 10, no. 1, pp. 1-11, 1996.
37. Duda, R.O., Hart, P.E., Stork, D.G., (2001), "Pattern classification" (2nd edition), Wiley, ISBN 0-471-05669-3.
38. Muhammad Talha, Ghazali Solung, Nawazish Naveed, M. Arfan Jaffar (2012). "Malignancy and Abnormality Detection of Mammograms using Discrete Wavelet Transformed Features and Neural Network". International information Institute Vol 15 (2), pp.707-720, 15 February, 2012.
39. Mohammed Jahirul Islam (2009), Computer-Aided Detection and Classification of Masses in Digitized Mammograms. [Online] Available: http://www.vlsi.uwindsor.ca/presentations/2009/ComputerAided%20Detection%20and%20Classification%20of%20Masses%20in%20Digitized%20Mammograms.pdf (November 20, 2009).
40. Raudys S and Pikelis V (1980). On dimensionality, sample size, classification error, and complexity of classification algorithm in

pattern recognition *IEEE Trans. Pattern Anal. Machine Intell.* **2** 242–52.
41. Fukunaga K and Hayes R R (1989). Effects of sample size on classifier design IEEE Trans. Pattern Anal. Machine Intell. 11 873–85.
42. Goldberg V, Manduca A, Ewert D L, Gisvold J J and Greenleaf J F (1992). Improvement in specificity of ultrasonography for diagnosis of breast tumors by means of artificial intelligence *Med. Phys.* **19** 1475–81.
43. Wu Y, Giger M L, Doi K, Vyborny C J, Schmidt R A and Metz C E 1993 Artificial neural networks in mammography: application to decision making in the diagnosis of breast cancer *Radiology* **187** 81–7.
44. Lo J Y, Baker J A, Kornguth P J and Floyd C E 1995 Computer-aided diagnosis of breast cancer: artificial neural network approach for optimized merging of mammographic features *Acad. Radiol.* **2** 841–50.
45. Chan H-P, Wei D, Helvie M A, Sahiner B, Adler D D, Goodsitt M M and Petrick N (1995b). Computer-aided classification of mammographic masses and normal tissue: linear discriminant analysis in texture feature space *Phys. Med. Biol.* **40** 857–76.
46. Wei D, Chan H P, Helvie M A, Sahiner B, Petrick N, Adler D D and Goodsitt M M (1995b). Multiresolution texture analysis for classification of mass and normal breast tissue on digital mammograms *Proc. SPIE* **2434** 606–11.
47. Chan H-P, Wei D, Lam K L, Lo S-C B, Sahiner B, Helvie M A and Adler D D 1995c Computerized detection and classification of microcalcifications on mammograms *Proc. SPIE* **2434** 612–20.
48. Chan H P, Wei D, Lam K L, Sahiner B, Helvie M A, Adler D D and Goodsitt M M 1995d Classification of malignant and benign microcalcifications by texture analysis *Med. Phys.* **22** 938.
49. Freeman J A and Skapura D M 1991 *Neural Networks—Algorithms, Applications, and Programming Techniques* (Reading, MA: Addison-Wesley).
50. Swets J A and Pickett R M 1982 *Evaluation of Diagnostic System: Methods from Signal Detection Theory* (NewYork: Academic).
51. Metz C E, Shen J H and Herman B A 1990 New methods for estimating a binormal ROC curve from continuouslydistributed test results *Annu. Meeting Am. Stat. Assoc. (Anaheim, CA, 1990).*
52. Jaffar, M.A. Nawazish Naveed, Sultan Zia, Bilal Ahmed and Tae-Sun Choi (2010), "Multi Domain Features Based Classification of Mammogram Images Using SVM and MLP", ICIC Express Letters, Volume 4, 5495-5513.
53. J Suckling et al (1994). The Mammographic Image Analysis Society Digital Mammogram Database Exerpta Medica. International Congress Series 1069 pp 375-378.

3/30/2013