Biohouse, Volume 2: Issue 2, Mar-Apr 2016

Biohouse Journal of Computer Science

ISSN 2379-1500

The Ensemble technique uses variable hidden neurons hierarchical fusion and ten-fold cross validation for Detection of Breast masses

Dr. J.Subash Chandra Bose
Assistant Professor
College of Computer Science
Department of Computer Engineering
King Khalid University
Aseer, Saudi Arabia.
jsubashme@gmail.com

Dr. Ahmed Said Badawy
Vice Dean
College of Computer Science,
Department of Computer Engineering
King Khalid University
Aseer, Saudi Arabia.

Dr. Mehrez Marzougui
Assistant Professor
College of Computer Science
Department of Computer Engineering
King Khalid University
Aseer, Saudi Arabia.

Dr. Suresh Babu Changalasetty
Associate Professor
College of Computer Science
Department of Computer Engineering
King Khalid University
Aseer, Saudi Arabia.

Dr. Wade Ghribi
Assistant Professor
College of Computer Science
Department of Computer Engineering
King Khalid University
Aseer, Saudi Arabia.

Dr. Lalitha Saroja Thota
Lecturer
College of Arts and Science
Department of Computer Science
Khamis Mushayt
King Khalid University
Saudi Arabia.

Abstract: *Early stage detection of breast cancer using image processing methods in digital mammograms is the best method. Enhancement of the variable hidden neural network for detecting the spot of breast mass is presented. It can be done in several stages, first the preprocessing methods have been done over digital mammogram image. Second stage the Region of Interest - ROI is extracted from the processed image. Third stage the region Growing Segmentation is implemented to separate the part of the image that having the identical pixel values from the mammogram. Fourth stage the features extracted such as density, mass shape, mass margin, patient age, subtlety, and abnormality assessment rank value. Fifth the neural networks by varying the number of neurons in the hidden layer. According to the classification of accuracy these are then trained, tested and ranked. To create an ensemble network, the Ten-Fold cross validation which produces the classifiers, is used. The Artificial neural network classifiers are then fused together using majority vote algorithm to create the final ensemble network which reveals whether the image is malignant or benign. The classification is done using the Digital Database for Screening Mammography (DDSM).The DDSM is organized into "cases" and "volumes". A "case" is a collection of images and information corresponding to one mammography exam of one patient. A "volume" is simply a collection of cases collected together for the purpose of ease of distribution. This database contains 2620 cases in 43 volumes. The Experimental results were discussed using MATLAB.*

Keywords: *Breast cancer, Mammogram, Ensemble neural network, region growing segmentation, ten-fold cross validation.*

1. INTRODUCTION

Cancer is the foremost reason of death in economically developed countries and the second most important reason of death in developing countries. Cancer recognized medically as malignant neoplasm, is an extensive mixture of diseases, all concerning unregulated cell growth. In cancer, cells break up and breed widely, forming malignant tumors, and raid nearby parts of the body. The cancer may also expand to more distant parts of the body through the lymphatic system or bloodstream. Not all tumors are cancerous. Benign tumors do not produce uncontrollably, do not attack neighboring tissues, and do not spread throughout the body.

According to the results of the breast cancer screening programme was conducted in the Eastern Province of Saudi Arabia, October 2009 to February 2014, No. of women screened 8061 Uptake rate (%) 15.0 No. of women recalled 636 Recall rate (%) 7.9 No. of biopsies done 63 [No. of ultrasound-guided biopsies] [53] [No. of stereotactic biopsies] [8] No. of benign biopsies 16 No. of cancers detected 47.

National Cancer Institute statistical report says, 232240 females and 2240 males In USA every year affected by breast cancer. Among them 39620 were died. In Australia, one Women among nine is diagnosed with the breast cancer in their lifetime.

Several methods such as examining the breast, breast ultrasound, breast MRI, biopsy, mammograms, 2D combined with 3D mammograms are used to detect the breast cancer. The mammogram is taking an X-ray by compressing the breast between the two plastic plates.

A mammogram is a special kind of X-ray that allows the doctor to see into the breast tissue to gives confidence in results.

The medical image processing paves a means to detect the breast cancer. Most of the breast cancer detection methods provide compound information about the breast and they lack in providing an accurate result on existence of tumor. As a result, a formal consultation with a radiologist is mandatory, which becomes an unwanted expenditure in case of a non-cancer patient. Therefore, the problem here is to develop a system that provides an automatic result on the survival of Mass calcification and if the cancer exists, the system elaborates the area being affected.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

Ensemble techniques have been applied and shown that they have achieved higher accuracy than a single neural network. Based on the different base classifiers which produces better result. The performance of the ensemble technique is improved by the diversity by varying the number of neurons in the hidden layer of the neural network. The ensemble technique also differentiate the similar characteristics of benign and malignant breast masses.

1.1 OBJECTIVE

Finding the breast cancer in the early stage which includes following methods such as

- The pre-processing method includes importing the image, scaling the image, removal of noise, deleting the small objects, Adaptive Histogram Equalization (AHE).
- Region growing segmentation.
- Ensemble neural network.

1.2 OVERVIEW OF THE PROJECT

This paper proposes a technique called Region Growing Segmentation for segmenting the breast mass from the digital mammogram and the variable hidden neuron ensemble technique for the mass classification. The pre-processing methods and the Region Growing Segmentation are applied to the digital mammogram. The Region of Interest and the features are extracted from the pre-processed image. The ensemble network is created by training the neural network with varying the number of neurons in the hidden layer, choosing the best performers, fusing all the results together and determining whether it is malignant or benign.

2 LITERATURE REVIEW

J. Liu et al [10] correct mass diagnosis in mammogram can reduce the unnecessary biopsy without increasing false negatives. In this paper, we investigated the usage of random forest classifier for the classification of masses with geometry and texture features. Before extracting features, the mass regions need to be extracted. Based on the initial contour guided by radiologist, level set segmentation is used to deform the contour and achieves the final segmentation.

The proposed level set method integrated both region information and boundary information, and with a level regularization term, it can achieve accurate segmentation. Modified Hu moments were used for shape characteristics, and GLCM (Gray Level Co-occurrence Matrix) features are used for texture characteristics.

Random forest, a recently proposed ensemble learning method, for the first time, is investigated for the mass classification, and is compared with SVM (Support Vector Machine).

Mammography images from DDSM were used for experiment. The new method based on the level set segmentation and the features achieved an A_z value of 0.86 with SVM and 0.83 with random forest. The experimental result shows that random forest is a promising method for the diagnosis of masses.

Y. Meena et al [12] classification is a major problem of study that involves formulation of decision boundaries based on the training data samples. The limitations of the single neural network approaches motivate the use of multiple neural networks for solving the problem in the form of ensembles and modular neural networks.

While the ensembles solve the problem redundantly, the modular neural networks divide the computation into multiple modules. The modular neural network approach is used where a Self-Organizing Map (SOM) selects the module which would perform the computation of the output, whenever any input is given. In the proposed architecture, the SOM selects multiple modules for problem solving, each of which is a neural network. Then the multiple selected neural networks are used redundantly for computing the output.

Each of the outputs is integrated using an integrator. The proposed model is applied to the problem of Breast Cancer diagnosis, whose database is made available from the UCI Machine Learning Repository. Experimental results show that the proposed model performs better than the conventional approaches.

Y. Huang et al [7] clustering ensembles can combine multiple partitions generated by different clustering methods into a final superior clustering result. Compared to single clustering algorithm, it can provide better solutions in terms of robustness, novelty and stability. In this paper, a new method named CEMF, i.e., Clustering Ensembles Based on Multi-classifier Fusion is proposed.

It combines the clustering ensembles method and multi-classifier method to deal with the clustering consensus problem. CEMF generates multiple partitions and creates subspaces which can be used to constructs the local optimum classifiers.

CEMF makes use of the advantage of multi-classifiers to assist clustering ensemblesin different subspaces of data set. Experiments carried out on some public data sets show that CEMF is comparable or better than classical clustering algorithms and traditional clustering ensembles methods. It's an effective and feasible method.

D. Costa et al [4] Female breast cancer is the major cause of death in western countries. Efforts in computer vision have been made in order to help improving the diagnostic accuracy by radiologists. In this paper, we present a methodology that uses Independent Component Analysis (ICA) along with Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) to distinguish between Mass or Non-Mass and Benign or Malign tissues from mammograms. As a result, we found the following: LDA reaches 89,5% of accuracy to discriminate Mass or Non-Mass and 95,2% to discriminate Benign or Malignant in DDSM database and in MIAS database we obtained 85 % to discriminate Mass or Non-Mass and 88% of to discriminate Benign or Malignant.

SVM reaches 99,6% of accuracy to discriminate Mass or Non-Mass and 99,5% to discriminate Benign or Malignant in DDSM database and in MIAS database we obtained 97% to discriminate Mass or Non-Mass and 100% to discriminate Benign or Malignant.

Amatia V. Destounis, Renee Morgan and Andrea Areieno, [23] Digital breast to mosynthesis (DBT) is a recent imaging technology that was developed to address the limitations of conventional 2D mammography. It includes reduced sensitivity in dense breasts.

Some methods of lesion diagnosis in mammogram images were developed based in the technique of principal component analysis which has been used in efficient coding of signals and 2D Gabor wavelets used for computer vision applications and modeling biological vision.

3. EXISTING SYTEM

The foundation of the ensemble technique is based on the concept that changing the internal architecture of a neural network and input data can produce diverse neural network classifiers which are combined using hierarchical fusion. If the internal architecture and parameters of each neural network classifier are different then each classifier will represent that knowledge in a slightly different way and that will create diversity. The classifiers with such diversity will allow for the learning of different characteristics of masses in digital mammograms.

3.1. LIMITATIONS OF EXISTING METHOD

- There is no segmentation is proposed in this method. So we cannot identify the location of breast mass.

4. PROPOSED SYSTEM

The region growing segmentation technique is introduced for segmentation purpose. In this proposed system both ensemble and region growing segmentation techniques are used. The main goal of segmentation is to partition an image into regions. Some segmentation methods such as thresholding achieve this goal by looking for the boundaries between regions based on discontinuities in gray levels or color properties. Region-based segmentation is a technique for determining the region directly. The user identifies different regions in an image. These identification tags are called a seed mark. The algorithm starts at the seed marks and increases iteratively the size of the seed mark area.

While the region expands, the algorithm has to decide which pixels are incorporated into the given seed mark region and which not. This decision is based on a similarity measure. The result is dependent on the choice of seeds, too. Region growing is a simple region-based image segmentation method. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. This approach to segmentation examines neighboring pixels of initial "seed points" and determines whether the pixel neighbors should be added to the region. The process is iterated on, in the same manner as general data clustering algorithms.

Region growing methods can correctly separate the regions that have the same properties we define. It can provide the original images which have clear edges with good segmentation results. The concept is simple. We only need a small number of seed points to represent the property we want, then grow the region. We can determine the seed points and the criteria we want to make. We can choose the multiple criteria at the same time. It performs well with respect to noise.

We can conquer the noise problem easily by using some mask to filter the holes or outlier. Therefore, the problem of noise actually does not exist.

4.1. ADVANTAGE OF PROPOSED SYSTEM

- The location of the breast mass can be found.
- The proposed system gives accurate result.

5. OVERALL DATA FLOW DIAGRAM

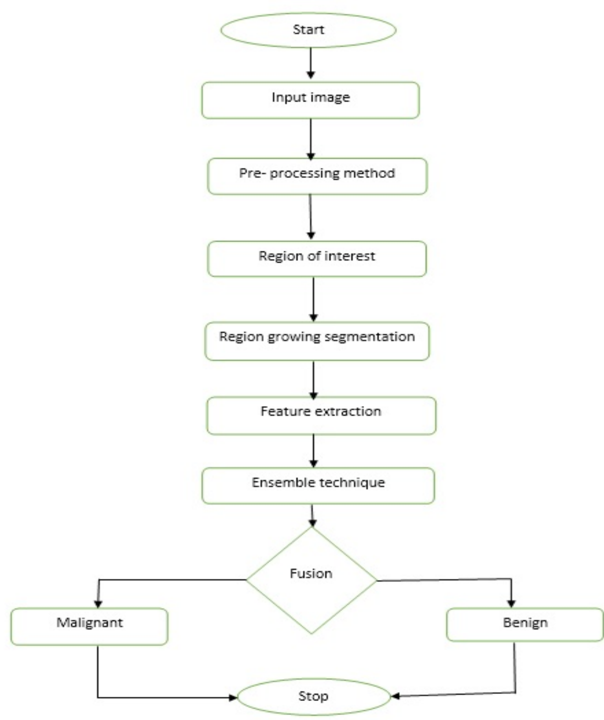

Fig 1 Overall data flow diagram.

Now we are going to discuss a brief about the overall diagram as shown in the figure 1.

5.1. ACQUIRING OF DIGITAL MAMMOGRAMS

The data were obtained from Digital Database of Screening Mammography [DDSM]. The Digital Database for Screening Mammography (DDSM) is a resource for use by the mammographic image analysis research community. The database contains approximately 2,500 studies.

5.2. PREPROCESSING METHODS

5.2.1. Image Reading

The MATLAB environment represents the binary image as one dimensional array, grayscale image as two dimensional array and the color image [RGB] as three dimensional array (one 2-dimensional array for each of the color plane). The size of the image is represented by two factors such as height (number of rows of the array) and width (number of columns of the array). By pointing the z-axis to the front of the image, the x and y co-ordinates are chosen. A pixel is the single point in the image [15].

5.2.2 Image scaling

Image scaling is processing the image and analyzing the image. Processing like resizing the digital image smoothness and sharpness. Various scaling methods are nearest neighbor interpolation, bilinear interpolation and super sampling.

5.2.3. Removing noise

Images acquired through modern sensors may be contaminated by a variety of noise sources. By noise we refer to stochastic variations as opposed to deterministic distortions such as shading or lack of focus. The noise in the image is normally due to the environment conditions, sensor quality and human interference. While modern technology has made it possible to reduce the noise levels associated with various electro-optical devices to almost negligible levels, one noise source can never be eliminated and thus forms the limiting case when all other noise sources are “eliminated”.

A median filter is based upon moving a window over an image (as in a convolution) and computing the output pixel as the median value of the brightness within the input window. If the window is J ´ Kin size we can order the J•K pixels in brightness value from smallest to largest. If J•K is odd then the median will be the (J•K+1)/2 entry in the list of ordered brightness.

5.2.4. Deleting the small objects

It works with one main object and filter out all the remaining objects. This is done through deleting any object that has a size below the size of the largest object in the image (after sorting). Deleting an object essentially makes all of its pixels in image matrix given a value of false is shown in fig 2.

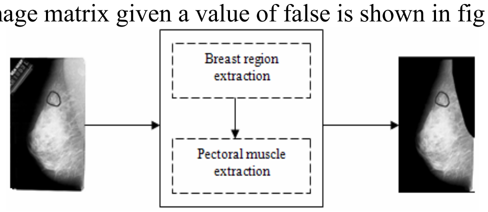

Fig 2. Deleting small objects

5.3. REGION GROWING SEGMENTATION

ALGORITHM

The region is iteratively grown by comparing all unallocated neighbouring pixels to the region. The difference between a pixel's intensity value and the region's mean is used as a measure of similarity.

The pixel with the smallest difference measured this way is allocated to the respective region. This process stops when the intensity difference between region mean and new pixel become larger than a certain threshold (t).

The function performs "region growing" in an image from a specified seedpoint(x,y).

J = regiongrowing(I,x,y,t)

I : input image

J : logical output image of region

x,y : the position of the seedpoint (if not given uses function getpts)

t : maximum intensity distance (defaults to 0.2)

Calculate the mean of the segmented region and number of pixels in region

Free the memory to store neighbors of the (segmented) region

neg_list = zeros(neg_free,3);

Find the distance of the region which is the nearest pixel to the region mean

Neighbor locations (footprint)

Start region growing until distance between region and possible new pixels become higher than a certain threshold

Add new neighbors pixels

Calculate the neighbor coordinate

Check if neighbor is inside or outside the image

Add neighbor if inside and not already part of the segmented area

Add a new block of free memory

Add pixel with intensity nearest to the mean of the region, to the region

Calculate the new mean of the region

Save the x and y coordinates of the pixel (for the neighbor add process)

Remove the pixel from the neighbor (check) list

Return the segmented area as logical matrix

5.4. FEATURE EXTRACTION

An anomaly cannot be readily mapped to a diagnosis without utilizing certain features to facilitate a mapping in feature space to the diagnosis. This research utilizes the same types of features that a radiologist would utilize so that it could be used as a training tool since this facilitates a conceptual understanding from a diagnostic perspective. If a single feature could be used to create a diagnosis then this would be a simple process.

The problem is that no single feature is a good discriminant so a number of features need to be utilized to obtain a minimal degree of accuracy. This situation is compounded, as the similarity between the benign and malignant classes is not clear cut complicating the mapping in feature space that provides a highly accurate diagnosis.

Six features have been chosen for the purpose of this research. These features were chosen as they have been proven to be good discriminants.
These features are as follows :

- Density
- Mass Shape
- Mass Margin
- Abnormality Assessment Rank
- Patient Age
- Subtlety Value

A description of each feature follows below.

Density

The density of a mass anomaly is measured according to the BI-RADS® reporting system and is rated according to the density of surrounding tissues. From a detection perspective, masses of a density that are equivalent to surrounding tissue are harder to identify.

Mass Shape

The shape of a mass can be important for a diagnosis. Benign masses tend to have distinct margins and are more compact in nature. Masses that tend to be more irregular in shape with hard to define margins have a much higher chance of being malignant.

Mass Margin

The margin has a bearing on the likelihood of a mass being benign or malignant. If a margin is distinct and rounded then the likelihood of malignancy is low. Highly suggestive margins are indistinct and tend to blend with surrounding tissue with speculated processes.

Abnormality Assessment Rank

This is an assessment of how serious the anomaly is on a one to five category rating where one indicates that it is not likely to be malignant and five is highly suggestive of malignancy.

Patient Age

The frequency of breast cancer increases with age. The highest survival rate for women in the 45–49 year old age bracket the lowest in the 75 year and above bracket. Some researchers note that more aggressive cancers occur in younger women where the cancer is harder to detect and diagnose.

Subtlety Value

Represents how difficult a lesion is to find. The higher the value the easier a lesion is to locate.

5.5. ENSEMBLE NEURAL NETWORK

ALGORITHM

TrainAdaBoost(D, BaseLearn)

For each example d_i in D let its weight w_i=1/|D|

Let H be an empty set of hypotheses

For t from 1 to T do:

Learn a hypothesis, h_t, from the weighted examples: h_t=BaseLearn(D)

Add h_t to H

Calculate the error, ε_t, of the hypothesis h_t as the total sum weight of the
examples that it classifies incorrectly.

If $\varepsilon_t > 0.5$ then exit loop, else continue.

Let $\beta_t = \varepsilon_t \ / (1 - \varepsilon_t)$

Multiply the weights of the examples that h_t classifies correctly by β_t

Rescale the weights of all of the examples so the total sum weight remains 1.

Return H

TestAdaBoost(ex, H)

Let each hypothesis, h_t, in H vote for ex's classification with weight log(1/ β_t)

Return the class with the highest weighted vote total.

6. EXPERIMENTAL RESULTS

The images are taken from the DDSM database for using an experiments. In DDSM database, the database contains approximately 2,500 studies. Everything is involved for the classification test. The proposed ensemble technique uses variable hidden neurons hierarchical fusion and ten-fold cross validation for detection of breast masses produced 98% of the classification accuracy is show in the table 1 and figure3. Also the simulation results using MATLAB is shown below.

Table 1.Performance Analysis Comparison

Authors	Methods	Classification accuracy
Gou et al, 2010.	Partition Based Network - boosting technique	96.50%.
Liu et al,2010	Random forest – ensemble technique.	79.00%.
Roselin et al,2002	Meta-heuristic ensemble classifier technique	83.00%
Meena et al,2010.	Modular neural network technique	96.87%.
Huang et al,2010	Clustering ensembles based on multi classifiers fusion	89.50%.
Kinnard et al,2002.	Region growing with the analysis for segmentation contours and a multiple circular path convolution neural network	90.07%
Costa et al, 2011	Tenfold cross validation.	90.07%
The proposed technique	The ensemble technique uses variable hidden neurons hierarchical fusion and ten-fold cross validation.	98.00%

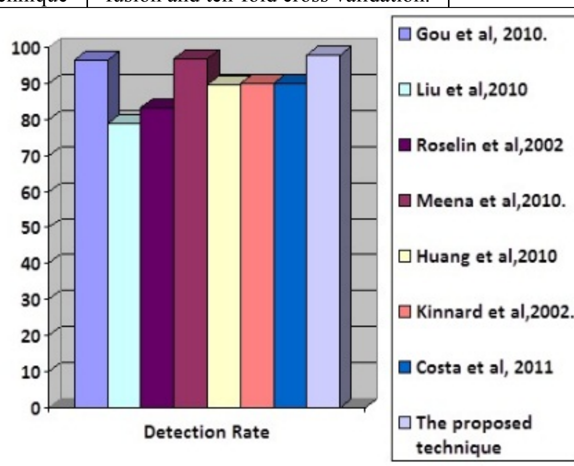

Fig 3.Performance Analysis Comparison

ISSN 2379-1500

Fig: 4 Input Image

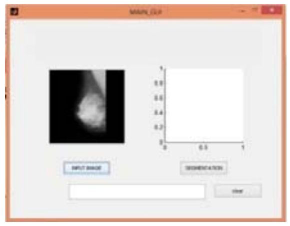

Fig: 5 Selecting the input image

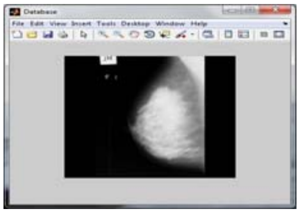

Fig: 6 Input image.

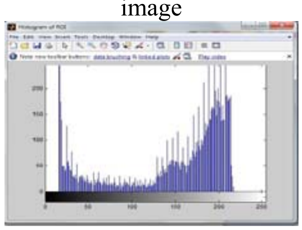

Fig: 7 Adaptive Histogram Equalization

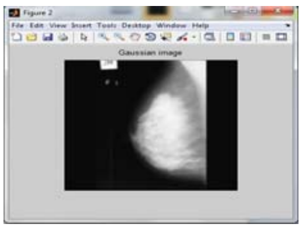

Fig: 8 Gaussian image.

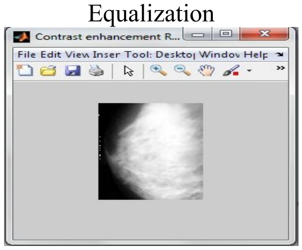

Fig: 9 Contrast Enhancement.

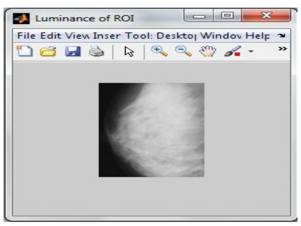

Fig: 10 Luminance of ROI.

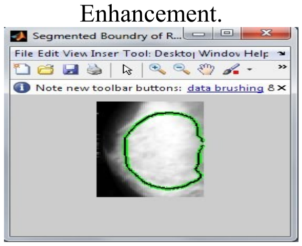

Fig: 11 Region Growing Segmentation

Fig: 12 Output Image

7. CONCLUSION

A new approach has been used for analyzing and classifying masses in digital mammograms. The ensemble technique uses variable hidden neurons hierarchical fusion and ten-fold cross validation and it is evaluated on a subset of DDSM benchmark database. The experimental result has shown classification accuracy over single neural networks. Many comparative analyses have been conducted in which ensemble technique provides better results than the existing techniques for the purpose of classification of masses in digital mammograms. The region growing segmentation is used to find the accurate location affected by cancer.

REFERENCES

[1] Peter McLeod and BrijeshVerma "Variable hidden neuron ensemble for mass classification in digital mammogram" IEEE - 2013.

[2] M. Abdelaal, H. Sena, M. Farouq, and A. Salem, "Using pattern recognition approach for providing second opinion of breast cancer diagnosis," in Proc. 2010 7th Int.Conf. Informatics Systems, pp.1–7

[3] T. Andre and R. Rangayyan, "Classification of breast masses in mammograms using neural networks with shape, edge sharpness, and texture features," J. Electron. Imag, vol. 15, no. 1, p. 013019, 2005.

[4] D. Costa, L. Campos, and A. Barros, "Classification of breast tissue in mammograms using efficient coding," BioMed. Eng. Online, vol. 10, no. 55, 2011.

[5] Gonzalez R, Woods R and Eddins S (2004) Digital images processing. 2nd edition, Prentice-Hall, Inc. NJ, 07458, ISBN 0-13-008519

[6] S. Gou, H Yang, L. Jiao, and X. Zhuang, "Algorithm of partition based network boosting for imbalanced data classification," in Proc. 2010 Int. Joint Conf. Neural Networks, pp. 1–6.

[7] Y. Huang, D. Monekosso, and H. Wang "Clustering ensemble based on multi-classifier fusion," in Proc. 2010 IEEE Int. Conf. Intelligent Computing Intelligent Systems, pp. 393–397.

[8] L.M. Kinnard, S.C.B. Lo, P.C. Wang, M.T. Freedman, M.F. Chouikha, "Separation of malignant and benign masses uses maximum-likelihood modeling and neural networks," in Medical Imaging 2002: Image Processing, San Diego, CA, 2002, pp. 733-741.

[9] Y. Li, S. Gao, and S. Chen, "Ensemble feature weighting based on local learning and diversity," in Proc. 26th AAAI Conf. Artificial Intelligence, 2012, pp. 1019–1025.

[10] J. Liu, J. Chen, X. Liu, and J Tang, "An investigation of mass diagnosis in mammogram with random forest," in IEEE Proc. 4th Int. Workshop Advanced Computational Intelligence, 2011, pp. 638–641.

[11] S. Luo and B. Cheng, "Diagnosing breast masses in digital mammography using feature selection and ensemble methods," J. Med. Syst., vol. 36, no. 2, pp. 569–577, Apr. 2012.

[12] Y. Meena, K. Arya, and R. Kala, "Classification using redundant mapping in modular neural networks," in Proc. IEEE 2nd World Congr. Nature Biologically Inspired Computing, 2010, pp. 554–559.

[13] R. Panchal, "Significance of features in classification of breast abnormality patterns in digital mammography," Ph.D. Dissertation, Central Queensland Univ., Brisbane, Australia, 2006.

[14] U. Rani, "Parallel approach for diagnosis of breast cancer using neural network technique", Int. J. Comput. Applicat, vol. 10, no. 3, pp. 1–5, Nov. 2010.

[15] Robin J and Mason P (2002) Handbook of pharmacy healthcare (diseases and patient advice). *Pharmaceutical Press*, London, UK. ISBN 0- 85369-507-5.

[16] R. Roselin and K. Thangavel, "Classification ensemble for mammograms using ant-miner," in Proc. IEEE 2nd Int. conf. Computing, Communication Networking Technologies, 2010, pp. 1–6.

[17] E. Santos, R. Sbourin, and P. Maupin, "Pareto analysis for the selection of classifier ensembles," in Proc. 10th Annu. Conf. Genetic Evolutionary Computation, 2008, pp. 681–688.

[18] M. Skurichina and R. Duin, "Bagging, boosting and the random subspace method for linear classifiers," Pattern Anal. Applicat., vol. 5, no. 2, pp. 121–135, 2002.

[19] SohaEkrima K. Yousuf ,Sahar Haj Ali A. Mohammed Department of Engineering, Faculty of Biomedical Engineering University of Medical Sciences and Technology "A Parallel Computer System for the Detection and Classification of Breast Masses".

[20] South Jersey Radiology Associates. (2012, Sept. 29). *Women's Imaging. PA.*[Online]. Available: http://v002-dt. wwwcomm.com/imaging/serv-digital.asp

[21] Thaler M and Hochreutener H (2008) Image processing basics using MATLAB.

[22] http://www.emro.who.int/emhj-volume-21-2015/volume-21-issue-2/breast-cancer-screening-programme-experience-from-eastern-province-saudi-arabia.html

[23] Stamatia V. Destounis, Renee Morgan and Andrea Areieno, " Screening for Dense Breasts : Digital Breast Tomosynthesis" American journal of roentgenology , February 2015, Volume 204, Number 2.

Biodata for the Authors

Dr. J. Subash Chandra Bose was born in Erode (India) in October 1977. He did his Diploma in Electrical & Electronics Engineering, Bachelor of Engineering in Electrical & Electronics Engineering from Anna University, Chennai, Master of Engineering in Computer Science & Engineering from Anna University, Chennai, Ph. D in Computer Science & Engineering from Anna University, Chennai, India. He is having more than 13 years engineering teaching and Industry experience, also having good inclination towards research in Medical Image Processing, Wireless network Stenography & Cellular Automata Techniques. He has published more than 40 scientific papers in various National and International Journals and Conference proceedings. He has received a **"BEST COMPUTER SCIENCE FACULTY"** Award by Association of Scientists, Developers and Faculties, Bangkok, Thailand. He Acted as a Key note Speaker and Chair for the International Conference on Cryptography and Security 2014 conducted by ASDF, Bangkok, Kingdom of Thailand.

Dr.Ahmed Said Badawy received Ph.D in Communication Engineering from Alexandria University, Egypt. He has 21 years of teaching experience. His research areas of interest include Digital Signal Processing, Signal separation, CDMA and Embedded systems. He is currently Assistant Professor in Dept of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia

Dr. Wade Ghribi received Ph.D degree from Computer Engineering Faculty, Kharkov National University of Radio electronics, Kharkov, Ukraine. He is currently Assistant Professor in Dept of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia

Dr.Suresh Babu Changalasetty received Ph.D in Computer Science and Engineering from Acharya Nagarjuna Univeristy, Guntur, India. He has 15 years of teaching experience. His research interests are bioinformatics, image processing and data mining. He is currently Associate Professor in Dept of Computer Engineering, College of Computer Science, King Khalid University, Abha, Saudi Arabia.

Dr. Mehrez Marzougui received the B.Sc. degree in Electronics from Tunis University in 1996, the M.Sc. degree and the Doctorate in Electronics from Monastir University in 1998 and 2005 respectively.

Since this date he has been Assistant professor in computer and electronics engineering with the physics department, Faculty of Sciences of Monastir. His research interests include Hardware/Software co-simulation, image processing, Multiprocessor System on Chip (MPSoC). He is currently Assistant professor in the Department of computer engineering, college of computer science, King Khalid University, Abha, Saudi Arabia.

Dr.Lalitha Saroja Thota received Ph.D in Computer Science and Engineering from Acharya Nagarjuna Univeristy, Guntur, India. She has 8 years of teaching experience. Her research interests are bioinformatics and data mining. She is currently Lecturer in Dept of Computer Science, College of Arts and Science, King Khalid University, Khamees Mushyat-1, Abha, Saudi Arabia