



# Performance Analysis and Detection of Microcalcification in Digital Mammograms using Wavelet Features

Dr.R.Harikumar  
Professor  
BIT  
Sathyamangalam.India.

S.R.Sannasi Chakravarthy  
Assistant Professor  
BIT  
Sathyamangalam.India

C.Abirami  
PG Scholar  
BIT  
Sathyamangalam, India.

**Abstract:** Breast cancer has been most persistent form of common cancer in women. It is also the leading cause of fatality in women each year. Breast cancer is much less common in younger women and is most often analyzed when women are over 60. One of the leading methods for interpretation of breast cancer is screening mammography. The appearance of micro-calcification in mammograms is an initial sign of breast cancer. To overcome the issue automated micro-calcification exposure techniques play a vital role in cancer diagnosis and treatment. This paper aims to develop an automatic system to classify the digital mammogram images into Benign or Malignant images. We have proposed artificial neural network based classifier to detect the micro calcification at each location in the mammogram images. The proposed method has been evaluated using Mammogram Image Analysis Society (MIAS) database. Experimental results show that, when compared to several other methods RBF shows 93% micro calcification detection in mammograms.

**Keywords:** mammogram images; wavelet; artificial neural network; classification

## I INTRODUCTION

Breast cancer is the most common cancer that develops from breast tissue in women. Outcomes for breast cancer may depend upon the cancer type, extent of disease and also the person's age. It is reported that it is more common in developed countries [1]. The first prominent symptom of breast cancer is typically a lump that feels different from the rest of breast tissue. Moreover 80% of breast cancer cases are detected when women feels a lump. Cancer starts when abnormal cells grow out of control. Untreated cancer can cause death. A tumor is a group

of abnormal tissue. There are two types of breast cancer tumor. Namely, non cancerous or 'benign' and those that are cancerous or 'malignant'. Benign tumor is a mass of cell that lacks ability to invade neighboring tissues. Malignant tumors are cancerous and combinative because they invade and damage surrounding tissue. When tumor is suspected to be malignant, the doctor will perform a biopsy to determine the severity of the tumor. About 90% of breast cancer are due to the genetic abnormalities and 5-10% are due to abnormality inherited from father or mother[16].

Mammogram is one of the best screening tool to detect the initial breast cancer in women. It uses lower dose x-ray to detect the cancer. There exist two types of mammography. They are screening mammography and diagnostic mammography. Screening is implemented to detect breast cancer in asymptomatic population. Diagnostic mammogram are used after suspicious results which are obtained from the screening mammogram [3].

Presence of micro calcification in a mammogram is a early sign of cancer. Breast calcification is small deposits of calcium in the breast. Micro calcification are scattered through the mammary glands, which is 1-4mm in diameter. They appear in certain patterns and are clustered together, they may be a sign of precancerous cells or early breast cancer.

The following illustration of this paper is organized as follows. Section II describes about the materials and methods Section III describes about the feature extraction Section IV describes about the net classification Section V describes about the performance matrices which are used to calculate the accuracy of the neural net Section VI describes about the result and discussion and Section VII describes about the conclusion of the paper.



## II MATERIALS AND METHODS

The Mammographic Image Analysis Society (MIAS) is an organization of UK research groups which contains a database of digital mammograms. Total number of 322 samples are obtained from MIAS database. These were divide into training and testing sets. The images are 1024\*1024 pixels. These obtained images are in the form of Portable Grey Map (PGM). It includes radiologist's "truth" – markings on the location of any abnormalities that present in the image. It counts 208 normal images, 63 benign, 51 malignant images.[4][15]

## III FEATURE EXTRACTION

Feature extraction is a eccentric form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is presented to be notoriously redundant (much data, but not much information) then the input data will be converted into a reduced representation set of features (also named features vector). Converting the input data into the features is known as feature extraction..

### A. Discrete WaveletTransforms

Wavelets is a well known mathematical tool used fairly in image processing. They have been worn for feature extraction, compression, denoising, face recognition, and image resolution[5]. The decomposition of images into different frequency ranges permits the segregation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into definite sub bands. This results in desolation small changes in an image mainly in high frequency sub band images[6]. Therefore discrete wavelet transform (DWT) is a worthy tool to be used for designing a classification system.

The 2-D wavelet decomposition of an particular image is performed by using 1-D DWT along the rows of the image first, and, their results are decomposed along the columns. This operation has the outcome in four decomposed sub band images referred to as high-low (HL), and high-high(HH), low-low (LL) and low-high (LH).[18].

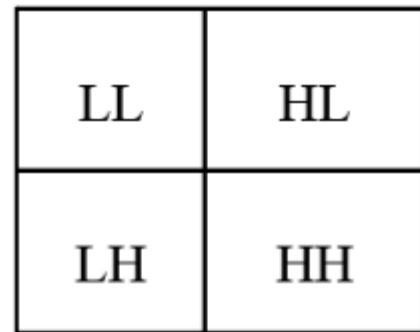


Fig 1. 2D DWT DECOMPOSITION

### B.Prefered Wavelet

The basis of a wavelet transform that is shorten or localized is called the mother wavelet of a wavelet transform. In case of mammogram images, the pixel intensity values vary smoothly, which cannot be handly represented by a Haar wavelet[7]. Christo Ananth et al. [10] proposed a system in which OWT extracts wavelet features which give a good separation of different patterns. Moreover the proposed algorithm uses morphological operators for effective segmentation. From the qualitative and quantitative results, it is concluded that our proposed method has improved segmentation quality and it is reliable, fast and can be used with reduced computational complexity than direct applications of Histogram Clustering. The main advantage of this method is the use of single parameter and also very faster. While comparing with five color spaces, segmentation scheme produces results noticeably better in RGB color space compared to all other color spaces.

## IV NEURAL NET CLASSIFICATION

An artificial neural network(ANN)is a computational tool developed based on the configuration of and functions of biological neural network. Information that is spread through the network consequence the structure of the ANN since a neural network evolves or learns based on the input and output[9].

### A. Multi Layer Perceptron (MLP):

This class of neural network consists of multiple layers of computational unit, usually interconnected in a feed forward way. Each neuron in one layer has conducted connectios to the neurons of the following layer. Multilayer network use a variety of learning techniques, the most prominent being back-propagation[11]. The output values are compared with the correct answer to compute the value of the predicted error function[17]. Equation (1) describes the mathametical form of MLP

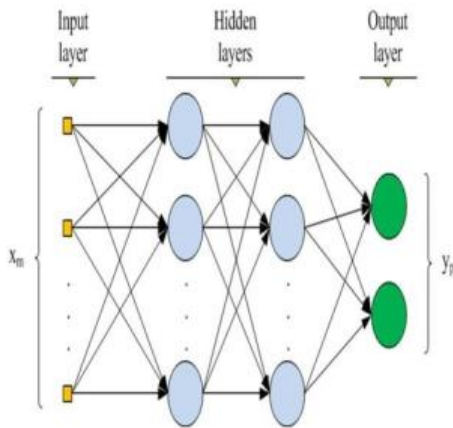


Fig 2 Architecture of MLP

#### B.Radial Basis Function (RBF):

Radial basis function uses radial basis function as activation functions. The output of the network is a linear combination of radial basis function of the inputs and neuron parameters[12]. RBF typically have three layers an input layer,a hidden layer with non linear RBF activation function and a linear output layer[13].

(2)

Where N is number of neurons  $C_i$  is the center vector of neuron i,  $a_i$  is the weight of neuron i.

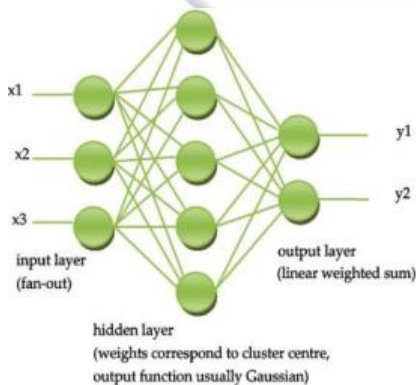


Fig 3 Architecture of RBF

#### V. PERFORMANCE METRICES

The performance analysis of the neural network is carried out using measures like sensitivity(SE), specificity(SP), performance index (PI)and accuracy(AC). All the performance measures are purely based on four metrics namely False Positive (FP), False Negative (FN) True Positive (TP) and True Negative (TN).The normal dataset correctly classified to be normal is called as True Positive, abnormal dataset correctly classified to be abnormal is said to be True Negative, normal dataset wrongly classified to be abnormal is said to be False Positive, and abnormal dataset which is wrongly classified to be normal is said to be False Negative[14].

The performance analysis of a neural net can be calculated using following formula.

$$SE = \frac{TP}{TP + FN} \quad (3)$$

$$SP = \frac{TN}{TN + FP} \quad (4)$$

$$PI = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$AC = \frac{PC}{PC + MC + FA} \quad (6)$$

Where PC=Perfect classification

MC=Missed classification

FA=False alarm

#### VI. RESULTS AND DISCUSSION

In analyzing the mammogram images, it is very important to choose the appropriate wavelet and its decomposition level. In this analysis the Harr wavelet, Daubechies (db4,), at level 4 decomposition was choosen.

The classification accuracy of an neural net is based on the percentage ratio of the number of images correctly classified to the total number of images considered for classification, depends on the type of wave- let chosen and the type of the network architecture. The table I shows the sample representation of extracted features using haar wavelet. The table II shows the classification accuracy of MLP,RBF neural net. It is clearly seen that RBF has the better classification accuracy of mammogram images compared to MLP.[19]





TABLE I REPRESENTATION OF HAAR WAVWLET

IMA GE	MEAN	MEDIAN	MODE	MAX	MN	RANGE	SD	MAD	MEANAD	L1NORM	L2NORM	MAXNORM
1	0.841283	0.173928	0.990528	0.986687	1	0.986632	0.827229	0.151332	0.833457	1.69E-07	1.25E-01	0.986687
2	0.90625	0.259062	0.939162	0.914491	1	0.914139	0.947478	0.238811	0.924907	1.82E-07	1.40E-01	0.914491
3	0.605921	0.050715	1	1	1	1	0.717346	0.024769	0.687361	1.22E-07	1.01E-01	1
4	0.712007	0.104805	0.937705	0.912442	1	0.912082	0.831375	0.080338	0.796283	1.43E-07	1.18E-01	0.912442
5	0.685609	0.120652	0.998543	0.997952	1	0.997943	0.753974	0.096618	0.728996	1.38E-07	1.09E-01	0.997952
6	0.548438	0.026605	0.958652	0.941884	1	0.941645	0.75812	0	0.672119	1.10E-07	1.02E-01	0.941884
7	0.602138	0.026605	0.913843	0.878904	1	0.878406	0.812716	0	0.739033	1.21E-07	1.10E-01	0.878904
8	1	0.197872	0.965938	0.952125	1	0.951928	1	0.175948	1	2.01E-07	1.51E-02	0.952125
9	0.992599	0.24127	0.968124	0.955197	1	0.955013	0.988252	0.220533	0.991078	1.99E-07	1.49E-02	0.955197
10	0.562582	0.112454	0.876685	0.826677	1	0.825964	0.691085	0.088196	0.636877	1.13E-07	9.65E-02	0.826677
11	0.80773	0.241104	0.934608	0.90809	1	0.907712	0.887353	0.220362	0.852045	1.62E-07	1.29E-02	0.90809
12	0.55773	0.026605	0.882514	0.834869	1	0.83419	0.716655	0	0.65026	1.12E-07	9.87E-02	0.834869
13	0.782155	1	0.87377	0.822581	1	0.821851	0.655771	1	0.664312	1.57E-07	1.07E-01	0.822581
14	0.604276	0.026605	0.932787	0.90553	1	0.905141	0.78369	0	0.723048	1.25E-07	1.08E-01	0.90553
15	0.471628	0.030662	0.911658	0.875832	1	0.875321	0.680373	0.004165	0.586914	9.46E-08	9.08E-02	0.875832
16	0.628947	0.053625	0.929144	0.90041	1	0.9	0.78991	0.027759	0.725651	1.26E-07	1.10E-01	0.90041
17	0.46176	0.026605	0.935337	0.909114	1	0.90874	0.672702	0	0.567732	9.27E-08	8.95E-02	0.909114
18	0.926809	0.989358	0.989071	0.984639	1	0.984576	0.822391	0.989067	0.817844	1.86E-07	1.31E-01	0.984639
19	0.732401	0.251413	0.948452	0.927547	1	0.927249	0.816171	0.230953	0.773234	1.47E-07	1.18E-01	0.927547
20	0.898026	0.117858	0.977	0.902	1	0.9653	0.9553	0.093748	0.93829	1.80E-07	1.41E-01	0.963902



TABLE II CLASSIFICATION RESULT OF NEURAL NET

Performance Metrics	MLP		RBF	
	DB4	HAAR	DB4	HAAR
PERFORMANCE INDICES(%)	79	96	78	76
SENSITIVITY(%)	85	96	94	97
SPECIFICITY(%)	95	95	92	87
ACCURACY	90	95.5	93	92

## VII CONCLUSION

In this work, a method for diagnosis of mammogram images with the help of wavelets as feature extractor and machine learning approach was proposed. The neural net such as MLP and RBF are considered for the classification of mammogram images. The feature extraction was accomplished with the help of DWT. The extracted features are fed as the input to the neural net. The better classification results point up the RBF neural net. The accuracy of the classifiers such as GMM, ELM can be studied with the help of the extracted wavelet features.

## REFERENCES

- [1] K. Polat and S. Genes, "Breast cancer diagnosis using least square support vector machine," *Digit. Signal Process.*, vol. 17, no. 4, pp. 694–701, Jul. 2007.
- [2] Pisani et al. "Outcome of screening by Clinical Examination of the Breast in a Trial in the Philippines". *Int. J. Cancer*, 2006.
- [3] J. Suckling, J. Parker, D.R. Dance, S. Astley, I. Hutt, C. Boggis, I. Ricketts, E. Stamatakis, N. Cerneaz, S.L. Kok, P. Taylor, D. Betal, and J. Savage, The mammographic image analysis society digital mammogram database, *Expert Med Int Cong Ser* 1069 (1994), 375–378.
- [4] ACS. (2011, Jul.). Statistics of the American Cancer Society, Washington, DC, USA [Online]. Available: <http://www.cancer.org/cancer/breastcancer/detail/edguide/breast-cancer-key-statistic>
- [5] T. Acharya and A.K. Ray, *Image processing: principles and applications*, Wiley, Hoboken, 2005.
- [6] J. Koenderink, The structure of images, *Biol Cybern* 50 (1984), 363–370.
- [7] Daubechies, The wavelet transform, time-frequency localization and signal analysis, *IEEE Trans Inform Theory* 36 (1990), 961–10051
- [8] M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies, "Image coding using wavelet transform," *IEEE Trans. Image Processing*, vol. 1, pp. 205–220, Apr. 1992.
- [9] SCB Lo, HP Chan, JS Lin, H Li, MT Freedman, and SK Mun, Artificial convolution neural network for medical image pattern recognition, *Neural Networks* 8 (1995), 1201–1214
- [10] Christo Ananth, A.S.Senthilkani, Praghsh.K, Chakka Raja.M., Jerrin John, I.Annadurai, "Overlap Wavelet Transform for Image Segmentation", *International Journal of Electronics Communication and Computer Technology (IJEECT)*, Volume 4, Issue 3 (May 2014), pp-656-658
- [11] M. Arfan Jaffar, Bilal Ahmed, Ayyaz Hussain, Nawazish Naveed, Fauzia Jabeen and Anwar M. Mirza, "Multi domain Features based Classification of Mammogram Images using SVM and MLP", *Fourth International Conference on Innovative Computing, Information and Control*, pp. 1301-1304, 2009.
- [12] T. Kurban and E. Besdok, A comparison of RBF neural network training algorithms for inertial sensor based terrain classification, *Sensors* 9 (2009), 6312–6329.
- [13] X. Fu and L. Wang, Data dimensionality reduction with application to simplifying RBF network structure and improving classification performance, *Syst Man Cybernet Part B: Cybernet IEEE Trans* 33 (2003), 399–409
- [14] RH Nagel, RM Nishikawa, J Papaioannou, and K Doi, Analysis of methods for reducing false positives in the automated detection of clustered microcalcifications in mammograms, *Med Phys* 25 (1998), 1502–1506.
- [15] [www.mias.org](http://www.mias.org).
- [16] Breast Cancer Scenario in India, <http://www.breastcancerindia.net/bc/statistics/stati.htm>
- [17] Sukanesh, R.; Harikumar, R." A Comparison of Genetic Algorithm & Neural Network (MLP) In Patient Specific Classification of Epilepsy Risk Levels from EEG Signals" *Engineering Letters* . 2007, Vol. 14 Issue 1, p96-104. 9p
- [18] Harikumar Rajaguru, Vijayakumar Thangavel" Wavelets and Morphological Operators Based Classification of Epilepsy Risk Levels" *Mathematical Problems in Engineering* Volume 2014 (2014), Article ID813197, 13 pages <http://dx.doi.org/10.1155/2014/813197>
- [19] R.Harikumar, B.Vinothkumar" Performance Analysis of Neural Networks for Classification of Medical Images with Wavelets as a Feature Extractor" *International Journal of Imaging Systems and Technology*, Vol. 25, 33–40 (2015)