Analysis of Framelets for the Microcalcification

K.S. Thivya and P. Sakthivel

Abstract Mammography is used commonly to detect the cancer in breast at the early stage. The early stage of breast cancer detection helps in avoiding the removal of breast in women and even the death caused due to breast cancer. There are many computer aided softwares that are designed to detect breast cancer but still only biopsy method is effective in predicting the exact scenario. This biopsy technique is a painful one. To avoid this, a novel classification approach for classifying microcalcification clusters based on framelet transform is proposed. The real -time mammography images were collected from Sri Ramachandra Medical Centre, Chennai, India in order to evaluate the performance of the proposed system. The GLCM features (contrast, energy and homogeneity) are extracted from the framelet decomposed mammograms with different resolution levels and support vector machine classifier is used to classify the unknown mammograms into normal or abnormal initially and then further classifies it as benign or malignant if detected as abnormal. The result shows that framelet transform-based classification provides considerable classification accuracy.

Keywords Framelet transform · Support vector machine · GLCM features (contrast, energy and homogeneity) · Microcalcifications and Mammography

1 Introduction

As per the medical research reports, one of the important criterion for death in women, is due to breast cancer. Microcalcification which is a major indicator of breast malignancy is classified by many methods. A matrix consisting of wavelet

K.S. Thivya (✉)
Department of Electronics and Communication Engineering,
Easwari Enginnering College, Chennai 600 089, India
e-mail: grss_dew@yahoo.co.in

P. Sakthivel
Department of Electronics and Communication Engineering,
Anna University, Chennai, India

© Springer Science+Business Media Singapore 2017

B. Raman et al. (eds.), *Proceedings of International Conference on Computer Vision and Image Processing*, Advances in Intelligent Systems and Computing 459,
DOI 10.1007/978-981-10-2104-6_2

coefficients of each image is used; then by selecting the threshold the Euclidian distance is maximized by the columns and the classification is done by using the features which are nothing but the selected columns [1]. DT CWT is used for decomposing the mammograms for different levels and SVM is used for the classification of breast cancer [2]. Two-stage wavelet transforms is applied for detecting and segmenting the granular microcalcifications [3]. Skewness and kurtosis property is used for detecting the microcalcification [4]. Texture features were extracted and the SVM is used for classification purpose [5].

Curvelet transform is employed in extracting the features of texture [6]. The Split Bregman method is used to sort out the resulting minimization problem [7]. Linearized Bregman iteration is proposed and analyzed for image deblurring in tight frame domains [8]. For image fusion, framelet transform is used [9]. Segmentation and surface reconstruction is done by using wavelet frame models [10].

Neural network is used as a classifier and the equivalent regularization properties has been discussed [11]. For detecting microcalcification automatically several state-of-the-art machine learning methods are discussed [12]. An automatic detection method for both the microcalcification and masscalcification is explained by using a feed forward neural network [13]. Different textural features are extracted and neural network is employed to classify the mass automatically [14]. Gabor wavelet features of textural analysis are discussed [15].

The scheme proposed for the classification of mammogram as normal/abnormal and benign/malignant for microcalcification is shown in Fig. 1. The GLCM features from framelet decomposed mammogram are extracted and fed to SVM classifier linear kernel. The flow of the paper is as follows. The explanation of the flow

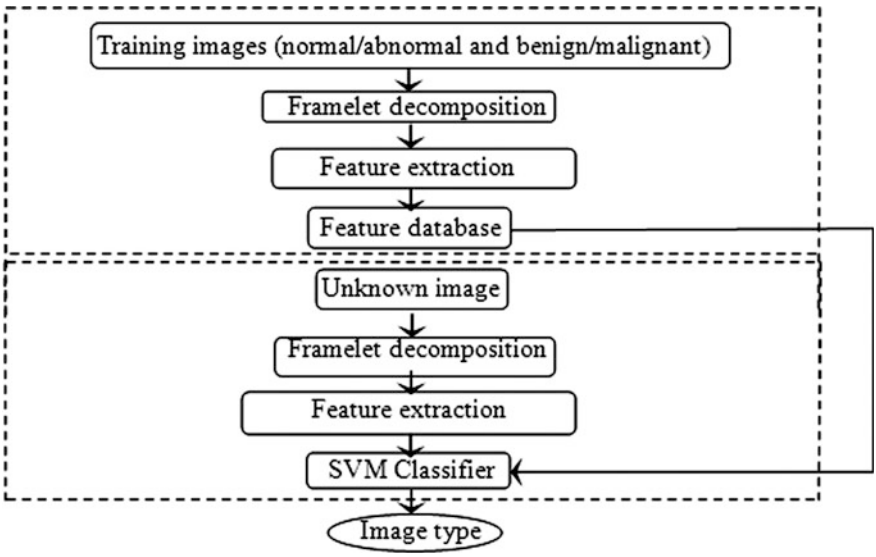


Fig. 1 Flow chart of analysis of framelets for the microcalcification

diagram of the proposed system is discussed in Sect. 2. An explanation of material used in the propose system and the ROI extraction from the mammograms is discussed in Sect. 2.1. The details of feature extraction using framelet transform are given in Sect. 2.2. Section 3 deals with the demonstration of the proposed system and Sect. 5 gives the classification rate results and concludes the proposed system.

2 Methodology

The proposed method is used to classify whether the given mammogram is a normal or abnormal one. If any abnormality is detected, then the second stage of classification is done to identify whether it is benign or malignant. To do this, a two-phase operation is involved. In the first phase, the system is trained with the images to detect whether it is normal or abnormal, for processing this, a framelet transform is applied. Framelet transform is used because it can be much more directionally selective for image processing and has shift invariant property. It is also less sensitive to corruption.

At various levels of decomposed framelets the GLCM features are extracted. The feature that shows the similarity is grouped to a same class and is used as reference for classification. In the second phase the similar steps are repeated to construct another database for classifying benign and malignant. For both the stages, separate SVM linear kernel is used to classify by making use of the two different databases created for the two phases mentioned above.

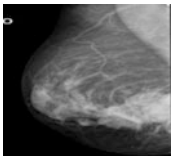
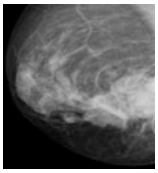
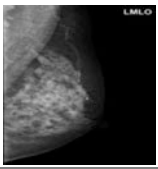
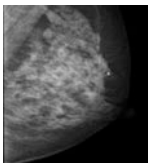
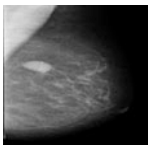
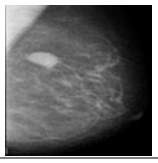
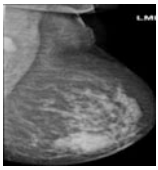
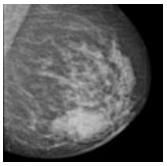
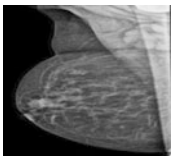
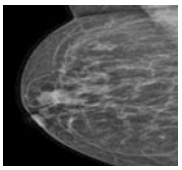
2.1 Material Used

The real-time digital mammogram images were collected from Sri Ramachandra Medical Centre, Chennai. The size of the image is 1024*1024. Half of the image contains only the background information; therefore, a manual cropping is done to remove the background information. This is done by aligning the centre of ROI with the given centre of abnormality by the database provided. The cropped ROI size is 256*256. Generally, a mammogram can be filmed in four different angles. In the proposed system, the MLO view images are only considered because it covers most of the upper quadrant breast and also the arm pit area. The training set images for benign and malignant classification is presented as a tabular column below for an overview of how the database was constructed from the collected data (Table 1).

2.2 Framelet Feature Extraction

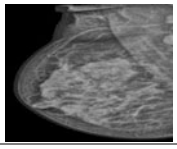
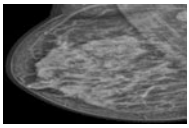
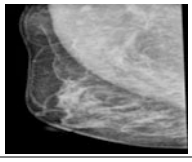
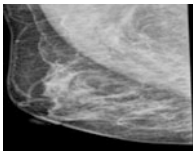
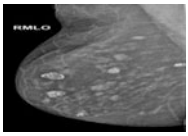
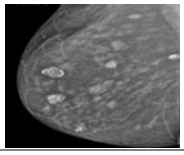
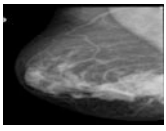
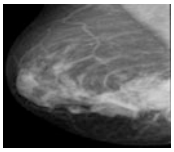
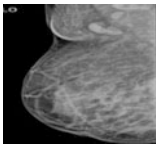
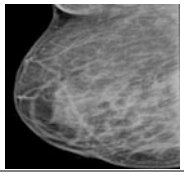
The framelet transform is applied for the images which will in turn provide us the framelet decomposition. For different levels of decomposed framelets feature extraction is done. In this proposed method, GLCM features are classified.

Table 1 Tabular column of the collected database to train the proposed system

No	MLO	Zoomed MLO	Us report	Histopathology report
1			Spiculated, microlobulated masses with nipple retraction and probable malignant right axillary lymphadenopathy—right breast (BIRADS VI)	Positive for malignant cells
2			Focal macro calcification left breast {BIRADS II)	Cytology is suggestive of a benign breast lesion
3			Fibroadenoma with cystic degeneration and calcific foci in the left breast—BIRADS III	Features are that of benign lesion
4			Hypo echoic lesion in left breast subareolar region at 8–9 o'clock position. The lateral aspect of the lesion appears well defined, while the medial aspect appears ill-defined with speculated margins. Calcific specks noted within.-f/s/o malignant mass	Cytology is positive for malignant cells suggestive of invasive ductal carcinoma
5			Irregular spiculated mass lesion with group of microcalcification within the mass—right breast with multiple right axillary lypmh nodes showing loss of fatty hilum. (birads v)	Positive for malignant cells

(continued)

Table 1 (continued)

No	MLO	Zoomed MLO	Us report	Histopathology report
6			Features are suggestive of multicentric breast carcinoma—right breast (birads 5)	Positive for malignant cells
7			Cyst with thin septa —left breast (u -3)	Benign breast tissue
8			Hypoechoic lesion at 12'o clock position in the right breast—birads iii	Histology shows features of a benign breast lesion
9			Spiculated, microlobulated masses with nipple retraction and probable malignant right axillary lymphadenopathy—right breast (birads vi)	Positive for malignant cells
10			Simple cyst in right breast-birads ii	Features are in favour of benign proliferative breast disease

The GLCM features are contrast, energy and homogeneity. These features are calculated by the formulae given below in [16].

$$\text{(i) Homogeneity (angular second moment)} - \text{ASM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}\text{\^{}}2 \tag{1}$$

$$\text{(ii) Contrast} = \sum_{n=0}^{G-1} n\text{\^{}}2\left\{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,\ j)\right\}, |i-j| = n \tag{2}$$

$$\text{(iii) Energy} = \sum_{i=0}^{2G-2} iP_{x+y}(i) \tag{3}$$

The extracted features are used for reference and are created as a database. Two sets of databases are created, one for normal and abnormal and the second one is for benign and malignant. Using the database, the two-stage SVM classifier classifies the image type at each level.

3 Demonstration of the Proposed System

The prototype of proposed breast cancer diagnosis system discussed in the previous section is established in this section. It allows the radiologists to have easy access to the system and helps them in diagnosing breast cancer using digital mammograms. A PC platform is required to run the proposed system. Figure 2 shows the complete generalized frame of the proposed system.

In order to display the acquired digital mammogram, a larger window is designed inside the frame. Also, a small window is designed for displaying the ROI region. The right side of the frame contains a toolbar for accessing the various functions of the proposed system such as selection of input images, ROI extraction, saving the extracted ROI and classification processes. Initially, only the "Input Image" pushbutton is enabled for selecting the mammogram for diagnosis. All other functions are disabled. The "Input Image" pushbutton allows the user to select the digital mammogram for diagnosis. As soon as the mammogram is selected, it will

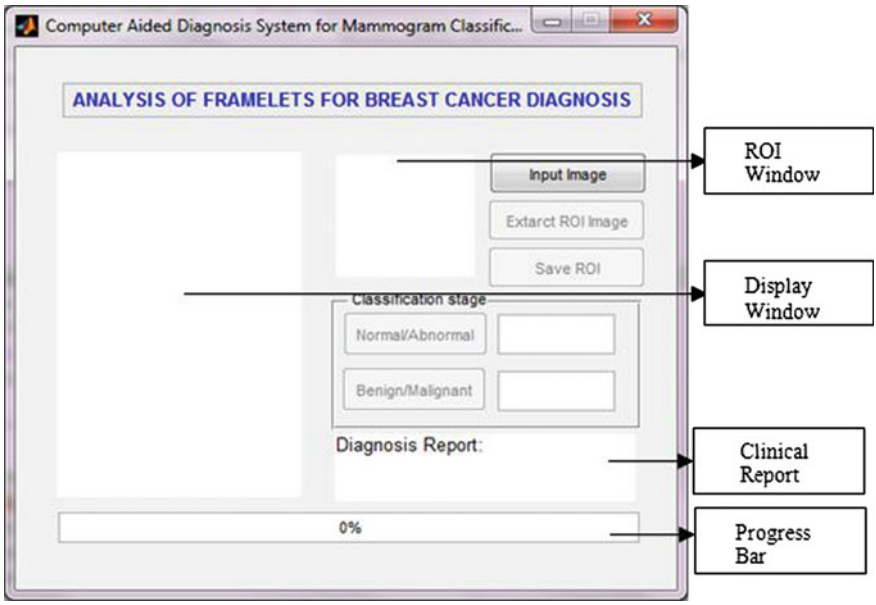


Fig. 2 A complete generalized frame window of the proposed system

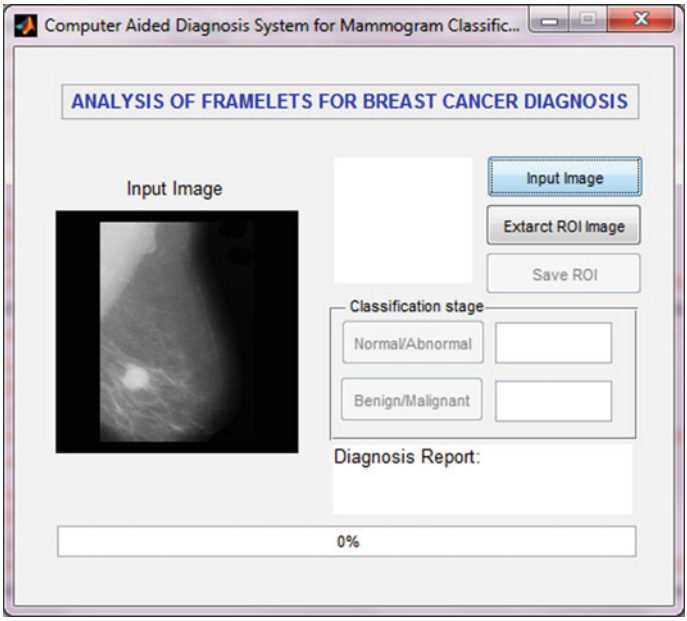


Fig. 3 A selected mammogram in the larger window

be displayed in the larger window of the frame which is shown in Fig. 3. Also the "Extract ROI Image" pushbutton is enabled.

When the "Extract ROI Image" pushbutton is clicked, the first module of the system, i.e. ROI extraction is executed that allows the user for selecting the suspicious region from original mammogram image. Figure 4 shows the screenshot of the ROI extraction module. The user has to click the approximate centre of the abnormality or the ROI that has to be diagnosed. This produces an ROI of size 256×256 pixels around the centre of abnormality as shown in Fig. 5. The "save ROI" pushbutton enables the user to save the extracted ROI for further analysis. After ROI extraction, the system is ready to analyze the abnormality in the ROI. To ease the analysis, the other modules of the proposed system such as feature extraction and classification stages are integrated into a single step.

To execute the stage I classification 'Normal/Abnormal' pushbutton and for stage II classification, "Benign/Malignant" pushbutton is designed. If the diagnosis of the given ROI is abnormal then only the stage II classification is enabled and the user has to click the "Benign/Malignant" pushbutton to find the abnormality of the ROI. Finally, the diagnosis report is also generated in the "Diagnosis Report" page. The progress bar in the frame visualizes the progression of the proposed cancer diagnosis system. Figures 6 and 7 show the entire system output for normal and abnormal cases, respectively.

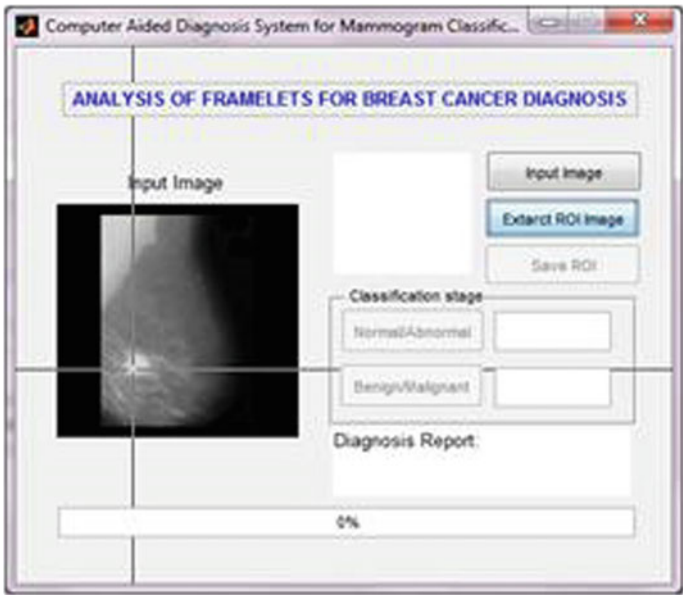


Fig. 4 Screenshot of ROI extraction process

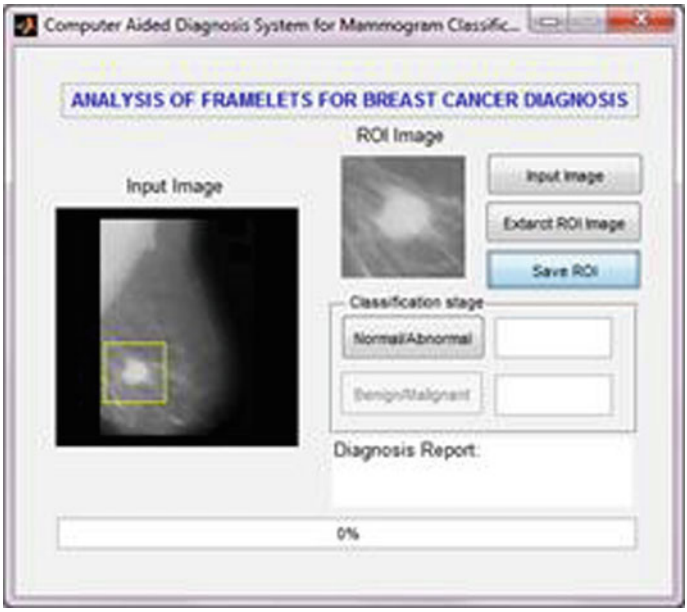


Fig. 5 Acquired digital mammogram and the selected ROI in the respective windows

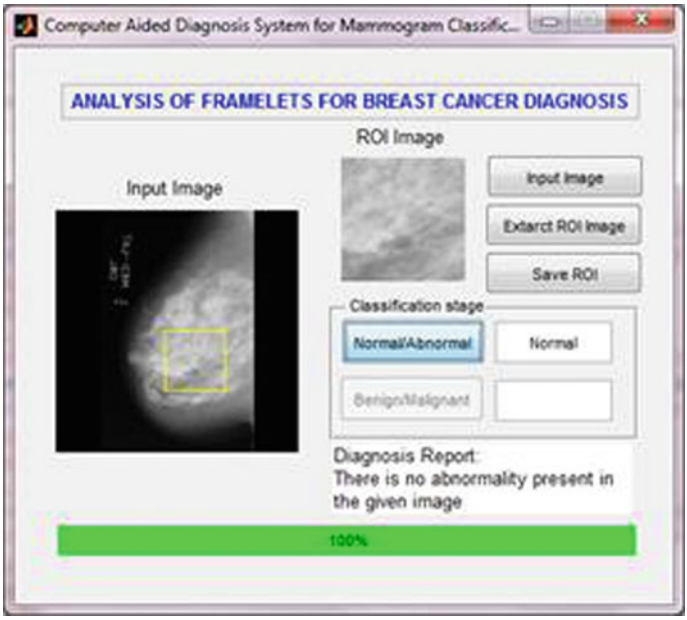


Fig. 6 Entire system output: normal mammogram

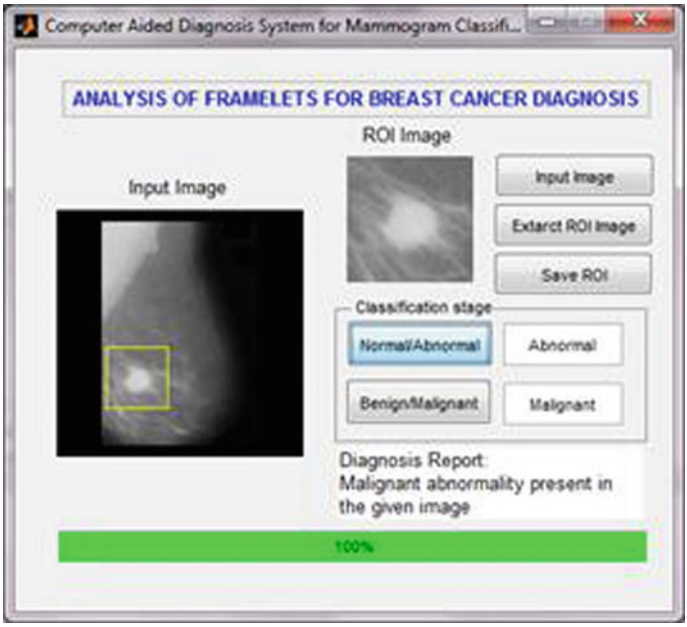


Fig. 7 Entire system output: abnormal mammogram

Table 2 Classification accuracy of the proposed microcalcification system using ROI

Framelet filter	Stage	Classification rate (%)							
		Decomposition level							
		1	2	3	4	5	6	7	8
Haar	I	81	81	85.13	85.54	87	88.53	86	93
	II	85	85	90.12	91	93	93	95.16	96.17
Piecewise linear	I	93	90	89.76	93	96	94	90	90
	II	96.83	100	100	100	97	97	94.31	94.31
Piecewise cubic	I	93	95.84	98	98	97	98	93.41	91
	II	100	100	100	95	94	93.24	91	91.32

4 Classification Accuracy Based on Framelet Transform

The framelet transform is used to represent the mammogram in multi-scale representation. The size of ROI extracted from the original mammogram image is 256*256. Up to eighth level the decomposition is available for the given image. In each level, the GLCM features extracted from each subbands are used as the feature vector of the corresponding mammogram (Table 2).

5 Conclusion

The proposed system performs well with the real time data collected from the hospital. In each fold, two-third of the total images are randomly selected to train the classifier while the remaining images are employed for testing. It can be concluded from the table that the extracted features based on piecewise cubic framelet produces higher accuracies than Haar and piecewise linear. The satisfying highest classification accuracies obtained are 98 % and 100 % for stage 1 and 2 classifier, respectively.

In order to take the work to next level, the application of the proposed system on all the four views of mammographic images can be done. In the feature extraction stage, other multiresolution and multidirectional analyses such as Shearlet transform, Contourlet transform can be used. In addition to GLCM feature extraction, other features such as statistical features, geometry features, etc., can also be calculated to create a more accurate database for reference thereby increasing the classification accuracy. By employing the above-mentioned changes, the biopsy method can be fully eliminated through helping the patients from pain and mental stress.

References

1. Ibrahima Faye and Brahim Belhaouari Samir, "Digital mammograms Classification Using a Wavelet Based Feature Extraction Method", IEEE conference on Computer and Electrical Engineering, 2009, pp 318–322.
2. Andy Tirtajaya and Diaz D. Santika, "Classification of Micro calcification Using Dual-Tree Complex Wavelet Transform and Support Vector Machine", IEEE International Conference on Advances in Computing, Control and Telecommunication Technologies, December 2010, pp 164–166.
3. R.N. Strickland & H.I. Hahn, "Wavelet Transform for detecting micro calcification in Mammograms", IEEE Transactions on Medical Imaging, Vol. 15, April 1996, pp 218–229.
4. K. Prabhu Shetty, Dr. V. R. Udupi, "Wavelet Based Microcalcification Detection on Mammographic Images", IJCSNS International Journal of Computer Science and Network Security, vol. 9 No. 7, July 2009, pp. 213–217.
5. Sara Dehghani and Mashallah Abbasi Dezfooli, "Breast Cancer Diagnosis System Based on Contourlet Analysis and Support Vector Machine", World Applied Sciences Journal, vol. 13 (5), 2011, pp 1067–1076.
6. Mohamed Meselhy Eltoukhy and Ibrahima Faye, "Curvelet Based Feature Extraction Method for Breast Cancer Diagnosis in Digital Mammogram", IEEE International Conference on Intelligent and Advanced Systems, June 2010, pp 1–5.
7. Jian-Feng Cai, Hui Ji, Chaoqiang Liu and Zuowei Shen, "Framelet-Based Blind Motion Deblurring From a Single Image", IEEE Transactions on Image Processing, vol. 21, no. 2, February 2012.
8. Jian-Feng Cai, Stanley Osher and Zuowei Shen, "Linearized Bregman Iterations for Frame Based Image Deblurring", SIAM Journal on Imaging Sciences vol. 2, no. 1, January 2009.
9. M. J. Choi, D. H. Lee and H. S. Lim, "Framelet-Based Multi Resolution Image Fusion with an Improved Intensity-Hue-Saturation Transform", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 37, Part B7, 2008.
10. Bin Dong and Zuowei Shen, "MRA Based Wavelet Frames and Applications: Image Segmentation and Surface Reconstruction", Proceedings of the International Society of Optics and Photonics", 2012.
11. Smola A. J., Scholkopf B., and Muller K. R., "The connection between regularization operators and support vector kernels", Neural Networks New York, vol. 11, November 1998, pg 637–649.
12. Liyang Wei, Yongyi Yang, Robert M. Nishikawa and Yulei Jiang," A Study on Several Machine –Learning Methods for Classification of Malignant and Benign Clustered Microcalcifications", IEEE Transactions on Medical Imaging, vol 24, No. 3, March 2005.
13. De Melo, C. L., Costa Filho, C. F., Costa, M. G & Pereira, W. C, "Matching input variables sets and feed forward neural network architectures in automatic classification of microcalcifications and microcalcification clusters", 3rd International Conference on Biomedical Engineering and Informatics (BMEI), Vol. 1, pp. 358–362, 2010.
14. Cascio, D. O. N. A. T. O., Fauci, F., Magro, R., Raso, G., Bellotti, R., De Carlo, F & Torres, E. L, "Mammogram segmentation by contour searching and mass lesions classification with neural network", IEEE Transactions on Nuclear Science, Vol. 53, No. 5, pp. 2827–2833, 2006.
15. B. S. Manjunath & W. Y. Ma (1996), "Texture feature for browsing and retrieval of image data", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. No. 18(8), pp: 837–842.
16. Steve R. Gunn,"Support Vector Machines for Classification and Regression", Technical report, University of Southampton, 10 May 1998.

http://www.springer.com/978-981-10-2103-9

Proceedings of International Conference on Computer Vision and Image Processing
CVIP 2016, Volume 1
Raman, B.; Kumar, S.; Roy, P.P.; Sen, D. (Eds.)
2017, XIV, 645 p. 308 illus., Softcover
ISBN: 978-981-10-2103-9