Journal of Medical Systems (2019) 43: 183
https://doi.org/10.1007/s10916-019-1316-3

IMAGE & SIGNAL PROCESSING

A Hybridized ELM for Automatic Micro Calcification Detection in Mammogram Images Based on Multi-Scale Features

Jayesh George Melekoodappattu [1] · Perumal Sankar Subbian [2]

Received: 12 March 2019 / Accepted: 25 April 2019 / Published online: 15 May 2019

Abstract

Detection of masses and micro calcifications are a stimulating task for radiologists in digital mammogram images. Radiologists using Computer Aided Detection (CAD) frameworks to find the breast lesion. Micro calcification may be the early sign of breast cancer. There are different kinds of methods used to detect and recognize micro calcification from mammogram images. This paper presents an ELM (Extreme Learning Machine) algorithm for micro calcification detection in digital mammogram images. The interference of mammographic image is removed at the pre-processing stages. A multi-scale features are extracted by a feature generation model. The performance did not improve by all extracted feature, therefore feature selection is performed by nature-inspired optimization algorithm. At last, the hybridized ELM classifier taken the selected optimal features to classify malignant from benign micro calcifications. The proposed work is compared with various classifiers and it shown better performance in training time, sensitivity, specificity and accuracy. The existing approaches considered here are SVM (Support Vector Machine) and NB (Naïve Bayes classifier). The proposed detection system provides 99.04% accuracy which is the better performance than the existing approaches. The optimal selection of feature vectors and the efficient classifier improves the performance of proposed system. Results illustrate the classification performance is better when compared with several other classification approaches.

Keywords Mammography · Micro calcification · Extreme Learning Machine · Feature selection · Classification · FOA

Introduction

Mammography is an X-ray based imaging model which is mostly used for breast cancer detection [1, 2], micro-calcification treatment [3] and image classification [4]. Breast cancer is ranked first amongst the principal reasons of cancer affecting females, and very rarely i.e. 1 out of 10 women in their lifetime are prone to this disease. For the initial detection of masses and defects for breast cancer, the mammogram is considered to be the main method which can sense 85 to 90% of all breast cancers [5]. The milk gland is the main origin of growth of malicious cells [6, 7]. The breast cancer caused malicious cells can be characterised into many classes based on abnormal growth and ability of cells to affect the ordinary cells. The reason for spreading malicious cells all over the body is also identified as metastasis [6].

This can be prevented by identifying the presence of breast cancer in the initial stage with the help of more advanced equipment's and methods [8, 9]. Effective analysis in mammography is determined by sensing cancer in its initial and most curable stage [10–12]. The image classification could be considered as vital for efficiently monitoring large populations. For efficiently monitoring large populations, the automatic classification of such images could be considered as vital. Tumours require different treatment procedures which are found in different types of tissues. So there is a need for automatic breast tissue evaluation taken by mammograms with the help of exact segmentation into known classes is necessary for fast detection. Also, there are several blends of modalities present in mammograms named as ultrasound-CAD-mammograms-infrared [13], MRI-

This article is part of the Topical Collection on *Image & Signal Processing*

✉ Jayesh George Melekoodappattu
jayeshg1988@gmail.com

[1] Department of Electronics and Communication Engineering, Vimal Jyothi Engineering College, Kannur, Kerala, India

[2] Department of Electronics and Communication Engineering, Toc H Institute of Science and Technology, Ernakulam, Kerala, India

mammogram [14] and MR Mammogram X mammogram [15, 16]. For the radiologists reading mammograms is a very difficult job. Radiologist's false impression of the lesion leads to more number of false positive cases [17]. Restrictions in the eye-brain visual system of human, reader exhaustion, disturbance, and the immense number of usual cases seen in screening programs makes that radiologists at all times do not properly describe abnormalities in the medical images [18–20]. The diagnostic accuracy of radiologists can be improved by A CAD tool, lessen the burden of increasing the workload [21, 22].

Al-Najdawi*et al* [3] investigated on merging various algorithms with image enhancement capability to improvebreast region segmentation. The optimal combination of few augmentation methods was obtained,and it split the region of breast attaining better visual clarification for radiologists. Singh et al. 2015 [23] introduced an easy way to detect the cancerous tissues from mammogram images. Tumour region segmentation followed the detection phase in the mammogram. This concept was based on averaging and thresholding of simple image processing technique. For tumour detection, they used Least Variance technique and Max-Mean technique. E Raghavendra et al. 2016 [24] presented an automated classification of breast cancer with benign and malignant using digital mammogram images. Feature extraction and data reduction was done in this work using Gabor wavelet and locality sensitive Discriminant Analysis. The F-values were used to rank the reduced features and fed various classifiers such as Decision tree, K-Nearest Neighbour and so on. Then, the highest performing classifier is selected based on the minimum number of features. KB Soulami*et al* 2017 [25] proposed an efficient method for suspicious region detection and classification. Pectoral muscle was removed using entropy thresholding and ROI had been extracted using Particle Swarm Optimization. Fourier transform and GLCM (Gray Level Co-Occurrence Matrix) features extracts the shape and texture features. The normal and abnormal features are classified using SVM. Chakraborty et al. 2018 [26] proposed an automatic detection and diagnosis approach in mammogram masses which is an iterative method. The radial region growing controls the high-to-low intensity thresholding for the mass detection.

In the literature, a few systems have been proposed to detect micro calcifications presence utilizing different approaches. Specification of regions of interest (ROIs), image segmentation and several methods are used for this purpose. The classification approaches have been used for the identification of ROI such as fuzzy logic system, rule-based system, statistical methods and machine learning. The most of the work done in literature is using neural networks for cluster identification. The concept of neural network is it reads the input features for a particular ROI and produces an output which characterizes the ROI has micro calcification or not. ELM is a new approach which is used to find micro calcification classification as malignant or benign. We use an intelligent system for micro calcification diagnosis in digital mammogram images which is fast and accurate in the detection of ROIs. The important contribution followed in this research is,

- We develop a micro calcification detection system in digital mammogram images efficiently and accurately.
- To enhance the prediction model with the general idea of ELM (Extreme Learning Machine) hybridized with fruitfly optimization algorithm (FOA).
- To improve the prediction model performance, pre-processing steps are included.
- To compare the proposed work with relevant existing papers to highlight the proposed performance.

The rest of the paper is constructed as follows: The proposed model for detection system explained in section 2. The database and simulation set up used in this research are explained in section 3 and finally section 4 concludes the research.

Proposed Methodology

The classification of benign and malignant micro-calcification, we have presented an ELM-FOA it is a new approach which has been proposed with the support of the hybridized learning algorithm. Our proposed approach involves four processes, and they are a) pre-processing b) ROI extraction c) feature extraction and d) classification. In this article, using the ELM network, we have exhibited a new approach for finding the micro calcified areas. The ELM network is chosen for its advantage such as fast training time and it works on the basis of the single hidden layer neural network classifier. The population based FOA algorithm updates the weights to reach the termination condition. Given below in Fig. 1 is the diagrammatic representation of proposed methodology.

Basic preliminaries

Pre-processing and ROI extraction

Pre-processing approaches are used in digital mammograms for identifying the spot of the mammogram, to decrease the noise and to increase the image quality. In several applications of image filtering includes smoothing, sharpening, noise removal and edge detection approaches. The filter can be said as a kernel, which is denoted as small array and is concerned to every pixel and its neighbors in an image. The optimal calculation of the original image is carried out by the Wiener filter by using a least mean square error (MSE) limit between the estimated image and original image. The best Wiener filter reduces the MSE and it has the ability to accomplish both degradation function and also the noise. The degradation

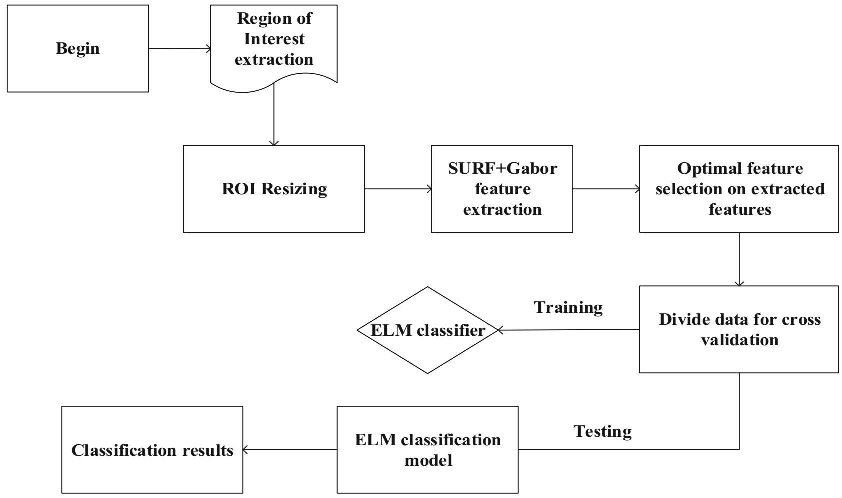


Fig. 1 Process flow of proposed methodology

paradigm the error between the input signal $g(p,q)$ and the expected signal $h(p,q)$ is represented by,

$$E(p,q) = g(p,q) - h(p,q) \tag{1}$$

The square error specification is illustrated in condition (2),

$$[g(p,q) - h(p,q)]^2 \tag{2}$$

The condition (3) defines the Mean square error,

$$E\left\{[g(p,q) - h(p,q)]^2\right\} \tag{3}$$

This Wiener filter [27] really helps to find the difference between a raw image and smoothed image from the pre-processed output the Region of interest (ROI) can be obtained. The ROI should possess high accuracy in order to find the risks in micro calcification and also for accurate analysis. The subsequent part is to obtain proper features from the ROIs.

Detection and removal of pectoral muscle

The pectoral muscle (PM) is located in one side of the mammogram whether it is left or right top corner which is triangle shape region. This triangle shaped region contains the brightest pixels of image. An accurate identification and removal of PM are necessary role for tumor cell detection. The filtered image is used with the segmentation of two image regions for PM detection. Background region and pectoral muscle region are the two regions used in the segmentation. This segmentation process is called as binarization. Gray level thresholding and global thresholding are used for binarization which alters the gray image into binary image. The PM region is completely made by white and the other background region is completely made by black.

CLAHE (Contrast Limited Adaptive Histogram Equalization)

The local histogram mapping function selection has more flexible in CLAHE [28]. The histogram selection of clipping level reduces the undesired noise amplification. Histogram equalization is applied on CLAHE for the contextual region. The input image consists of number of pixels and these pixels are called contextual region centre. Clipping is done in the original pixel, and the clipped pixels are reallocated to each gray level. The new histogram has fluctuated with standard histogram, on the grounds that every pixel power is confined to a client selectable most extreme. So CLAHE can restrict the noise improvement.

Feature extraction

The SURF [29], Gabor filter (GFs) [30] and GLCM [31] are utilized on ROI in the feature extraction process. SURF is said to be a new approach which is to be expected to suitable for the resulting feature detector approaches. And the local robust features are extracted by the SURF by means of the Hessian matrix built portion for the detector and a distribution-built descriptor. SURF with the utility of with Box Filter approaches Laplacian of Gaussian (LoG). The feature extraction principle which is based on the Gabor filter. It is divided into four consecutive sections:

- Process and put on multi-directional (GFS) to obtain the stroke information from the feeding shape standardized eccentric image.
- Gabor filters output are regulated adaptively attaining better performance in contradiction of noise and non-uniform illumination.
- Histogram features are extracted including the positive and negative outputs from the GFs distinctly, from which the histogram features can be significantly upgraded.

- By means of Principal Component Analysis and Linear Discriminant Analysis for compressing the histogram features with the aim to obtain dominant classification features. When the classification features are attained, glow worm optimization (GWO) used on the extracted features in order to choose the feature subset.

Gray-Level Co-occurrence Matrix (GLCM) is an important characteristics of texture of an image. This will be get from the gray level dimensionality in its neighbourhood. The neighbourhood and each pixel value properties are presented in the texture feature. It is a well-known statistical approach to extract features. The height and width of the GLCM matrix are equal to the total number of gray levels of image intensity for an image. 22 features are generated after creating GLCM such as entropy, contrast, energy, correlation, dissimilarity, autocorrelation, inverse difference, homogeneity.

Applying GWO to select optimal feature subset

There is a graph representation is needed to reconstruct the feature selection into a GWO optimization problem. The nodes in the graph are represented as features and the edges between nodes represent the next feature choice. The optimal feature subset is obtained by glow worm traversal through the graph. When a minimum number of nodes visited in the glow worm traversal, the traversal stopping condition is satisfied.

In the search space, the GWO [32] is initiated by dispensing a group of agents randomly. Agents are displayed next glow worms and, henceforth, they will be so-called glow worms. Additionally, they are gifted with added interactive appliances that are not initiated in their natural counterparts. A function of subset evaluation is selected trusted on entropy to assess the heuristic interest of navigating amid the features. For the specific application based on how optimality is well-defined, the pheromone may be updated in view of that. Considering the subset minimality and "goodness" as the two key factors irrespective of the pheromone update must be related to "goodness" and inversely related to size. To evaluate the "goodness" for the subset, the finite mixture model analysis has been applied. A dynamic decision space is held by every glow worm, which comprises its neighbors with greater luciferin values larger than its own value and the distance concerning them contained by the decision space radius. $g_i(t)$ is the set of neighbourhoods of glow worm 'i' at the iteration 't'.

$g_{ij}(t)$ is believed to be the possibility of glow worm at feature 'i' moving toward feature 'j' in the "t" iteration, considered by the below condition,

$$g_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in g_i(t)} l_k(t) - l_i(t)} \tag{4}$$

$l_j(t)$ is the set of glow worm k's unvisited features after the phase of probabilistic mechanism in the 't' iteration. With the group of a number of glow worm, k the GWO feature selection process is started, which are then positioned randomly on the graph (i.e. all glow worm initiates with one random feature). To place on the graph the number of glow worm (k) was matched proportional to the number of features contained by the data; path construction is started by each glow worm at a different feature. There are 12 features are optimally selected from the 24 features. For each iteration process, the optimal features may vary.

Feature classification

The micro calcification analysis is the two-category classifying problem nearly that points to categorize the micro calcification clusters into benign and malignant cases. For the micro calcification diagnosis, we have utilized the ELM as the classifier and for the single hidden layer feed forward neural networks, utilizes the ELM as a fast learning algorithm. The ELM randomly creates hidden node parameters and later, the output weights are systematically decided by the ELM rather than the iterative tuning. As a result, the ELM can quickly run which is very easy to execute and that is more significant for the online intelligent discovery. For training and testing, the leave-one-out cross authentication technique is applied. The test sample is fixed from the S samples and the remaining S-1 samples are considered as training samples. Figure 2 represents the extreme learning structure.

Training with ELM

The suggested feature extraction algorithm creates the feature matrix (FM) on the micro calcification ROI images. The algorithm 1 describes the ELM training. Initially, arbitrarily allocates input weights w_i and biasesb_i for every hidden node. Then, on the basis of w_i and b_i, calculate H. Eventually, with

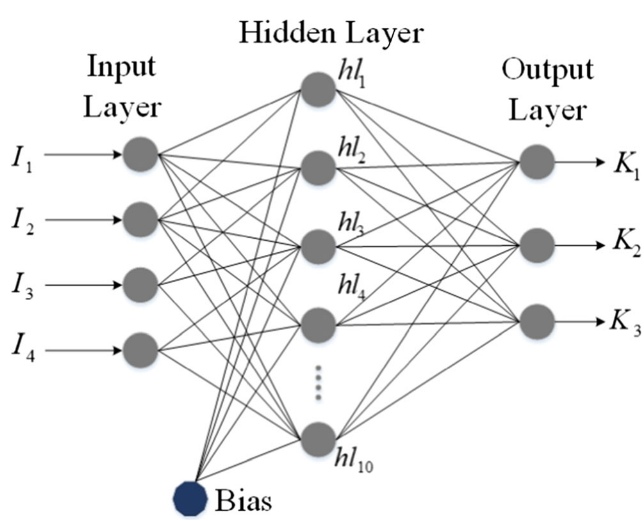


Fig. 2 Structure of Extreme learning

the use of matrix M can calculate the output weight and the ground truth label set G of the micro calcification ROI images to complete the training. In the second section, by utilizing the altered fruit fly optimization algorithm, the weight values are updated.

Algorithm of ELM-FOA

The ELM generalization property depends on the input weights and bias and the random initialization of these parameters in ELM creates two critical issues. First one is, the ELM required number of hidden neurons when compared to the gradient based algorithms and the performance of ELM is slow when a new test sample ism given. Low generalization performance is the problem which occurs due to the ill-conditioned output matrix of the hidden layer. There are many swarm intelligence and evolutionary based have been applied to rectify these issues. The optimization issues are resolved by these algorithms because of their global searching ability. There are several attempts made by the researchers for parameter optimization but the performance of above-mentioned approaches are affected by their specific parameters. So there is a need to set the proper values for parameters for better performance. The proper parameter tuning is important to avoid high computational complexity and getting stuck in local optima. So here we propose an ELM with fruitfly to obtain optimum values of ELM's hidden node parameters to obtain the solution analytically. The optimization of FOA depends on the function of fitness in which, ELM uses G-Mean as a fitness. For ach iteration, weight values and fitness values are generated and finally it produce optimal value.

Notations of classification Consider the training data X which exists to binary classes which is denoted as (x, C). Where, feature is x and target is C and the range of target is +1 or − 1. Inputs (N), hidden nodes (L), every sample features (f),the bias value for every hidden layer represented as (b). (y) and (H) represents the actual output and hidden layer output. (w) represents the input weight among input and hidden node and (β) represents output weight among hidden node and output node. $W(N \times N)$ is the weight matrix, population size (m), number of generation (k), Random matrix size (R). H_T_1 is output of hidden layer for testing and Y_T_1 is the actual output for testing.

Algorithm 1

Input: Training data (x_j, f_j); $x_j = (x_{j1}, x_{j2}, \ldots x_{jn})^T \in R^n$, $f_j = (f_{j1}, f_{j2}, \ldots f_{jn})^T \in R^v, n$

Output: Type of sample
Initialize FOA parameters population size, max_gen;
Set index_generation i=1;
Create 'm' initial population for w_1 is of size $1 \times Number\_of\_classes$;
Do
{
Compute fitness value for every individual by FOA-ELM using below steps:
(A) Conclude W of $N \times N$ size by the below steps:
For j=1 to X
    if X(j) =1
        W (j, j)= W_1 (1)
            else
W (j, j)= W_2 (1)
        end
    end
(B) Create w and b which are hidden node parameter by below steps:
(i) w = R (L ∗ Number_Of_Classes)
(ii) b = R (L ∗ 1)
(C) Compute Weight of output by below steps:
(i) Compute H = $\frac{1}{1+\exp(-(w.x+b))}$
(ii) compute weights for output:

$$\beta = \begin{cases} H^X(1+C+WHH^X)WX & when\ N\ is\ small \\ (1/C+H^XWH)H^XWX & when\ N\ is\ l\arg e \end{cases}$$

(iii) Compute $Y = H * \beta$
Compute FP, TP, FN, TN for X by the comparison of Y and T for training sample
Compute $X\_G-mean = \sqrt{\frac{TP}{TP+FN} * \frac{TN}{TN+FP}}$
Return X_G-mean
fitness value ranking for each individuals
individual fitness for high fitness value
j=j+1
}
While (j ≤ k)
Output is an optimal solution

ELM for testing After completing the training procedure, the ELM parameters are obtained and these obtained parameters are moved to testing process. The algorithm 2 describes the procedure of FOA-ELM testing procedure.

Algorithm 2

Generate w and b using the following:

w = R (L ∗ Number_Of_Classes)

b = R (L ∗ 1)

H_Test= $\frac{1}{(1+\exp(-(w.x'+b)))}$

Compute $Y\_Test = H\_Test * \beta$

Compute TP, FP, TN, FN for T_1 by the comparison of Y and T

Compute $T_1\_G-mean = \sqrt{\frac{TP}{TP+FN} * \frac{TN}{TN+FP}}$

Return T_1_G-mean ;

Simulation

The proposed detection system is based on machine learning which identifies the abnormal regions accurately. The goal of proposed system is to enhance the detection rate using digital image processing technique.

Mammogram database

The database collected from mammogram screening center consist of 184 images of 46 patients. The real-time databases are hard to classify due to the comprehensive spectrum of cases. Screening provides clinical mammograms which were positive for abnormality presence. The dataset collected from 46 patients are agreed to use their mammogram for research studies. Four mammograms were taken for each patient in two different views such as Mediolateral Oblique (MLO) view and Craniocaudal (CC) view. Each breast contains two projections (left and right) which were taken for every case. The detection system identifies the suspicious region based on multiple ML algorithm and which was verified by many radiologists. A total of 184 mammograms was taken for this study, and all the mammograms were digitized to a resolution of 256 × 256 Dots per Inch (DPI).

Experimental results

We evaluate the proposed work using real-world database and MIAS database in this section.

Clinical mammograms collected from 46 patients were used for proposed ELM-FOAclassifier evaluation. MATLAB 2017a used for implementing the proposed model which detects the micro calcification. SURF features and Gabor filter features are extracted from each pixel of the ROI image after pre-processing the clinical mammograms. The data are taken from 20 × 20 pixels from the ROI and is subjected to further analysis. Table 1 shows Deep Neural Network (DNN) and ELM classifiers performance by hidden layer neurons variation with the parameters learning rate of 0.01 and momentum constant as 0.9 respectively.

The accuracy on classification gets increased by increasing the hidden layer neurons. However, the performance gets started to degrade at the 140th hidden layer neurons. It describes that, for increasing the classification performance it is essential to select the optimal network parameters. The momentum factor and rate of learning is differed from 0 to 1 and the hidden neurons differed from 41 to 200 while performing the classifier optimization. The training

Table 1 classification accuracy for hidden layer neuron variation

Hidden neurons	Classification accuracy	
	DNN	ELM
90	75.38	81.05
110	78.01	84.82
130	79.95	86.23
140	77.46	85.01
150	77.01	84.20

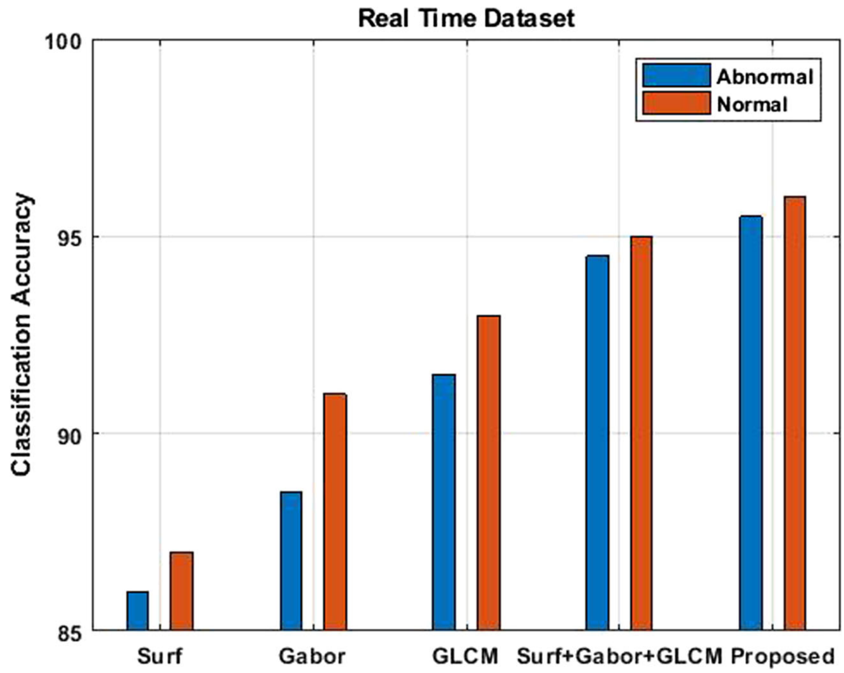


Fig. 3 Classification accuracy for Real time dataset

process is carried out with population size $N = 50$ and performed up to 100 generations along with 1000 training epochs. The benign and malignant micro calcification was included in this pattern. All the utilized real time clinical images (184 images) were tested and the accuracy obtained on both database (real time and MIAS) along with feature extraction technique is shown in fig. 3 and 4.

Performance analysis and discussion

In the discovery of the micro calcifications, the execution of the ELM is detected as the best by contrasting its investigational outcomes with the additional present popular classifiers like Bayes net classifier, Naive Bayes classifier and Support Vector Machine, for three different feature vectors extricated

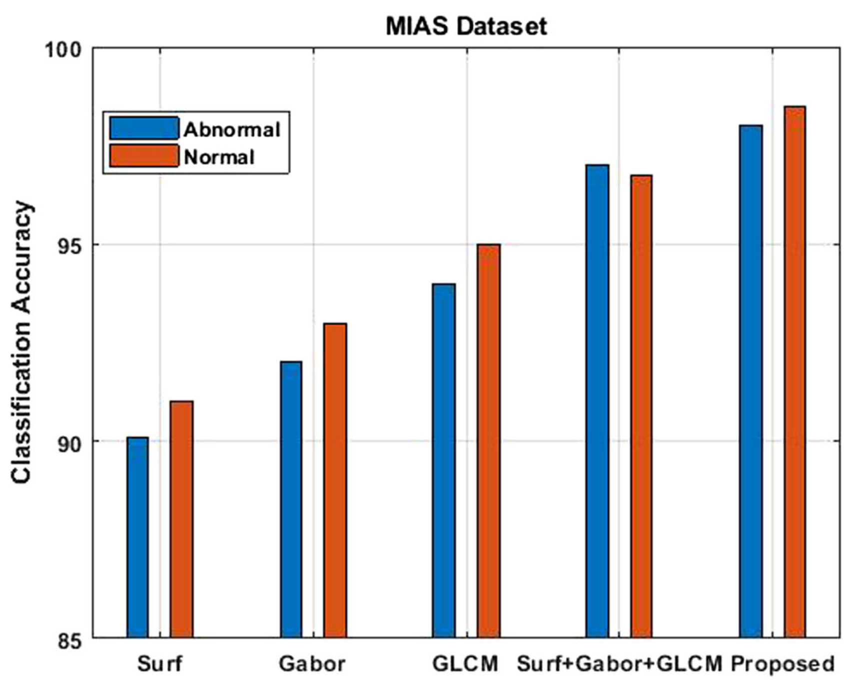


Fig. 4 Classification accuracy for MIAS dataset

by GLSDM and the wavelet methods. For backing the contrast, classification accuracy, true positive rate, false positive rate, F-measure, precision, and Area under the curve (AUC) are utilized. The performance metrics are given below. These methods are applied for the examination assessment termed as: Precision, sensitivity, specificity, fall-out, negative predictive value, accuracy, False Discovery Rate and Rate of convergence (iterations before convergence).

The input image 5 (a) is pre-processed by applying noise removal method. The noise removal method is especially doing for ultrasound, MRI medical images. The noise removed images is shown in Fig. 5(b). The image gets more clarity, quality and it is enhanced by wiener filter algorithm, for improving the detection accuracy. Once the image noise removed and enhanced, the ROI process is applied on the image. Region of the image is shown in Fig. 5(c). Pectoral muscles are removed in fig. 5(d) and the image is enhanced in fig. 5(e). From the quality image features are generated using Gabor filter and the features are shown in fig. 5(f). Figure 5 (g) shows the detected location of calcification.

The input image of real time data is represented in fig. 6(a),(b) shows the ROI image 6(c), 6 (d), 6 (e) represents the denoised image, contrast enhanced image, pectoral muscle removed image respectively and finally resulting image shown in fig. 6(f).

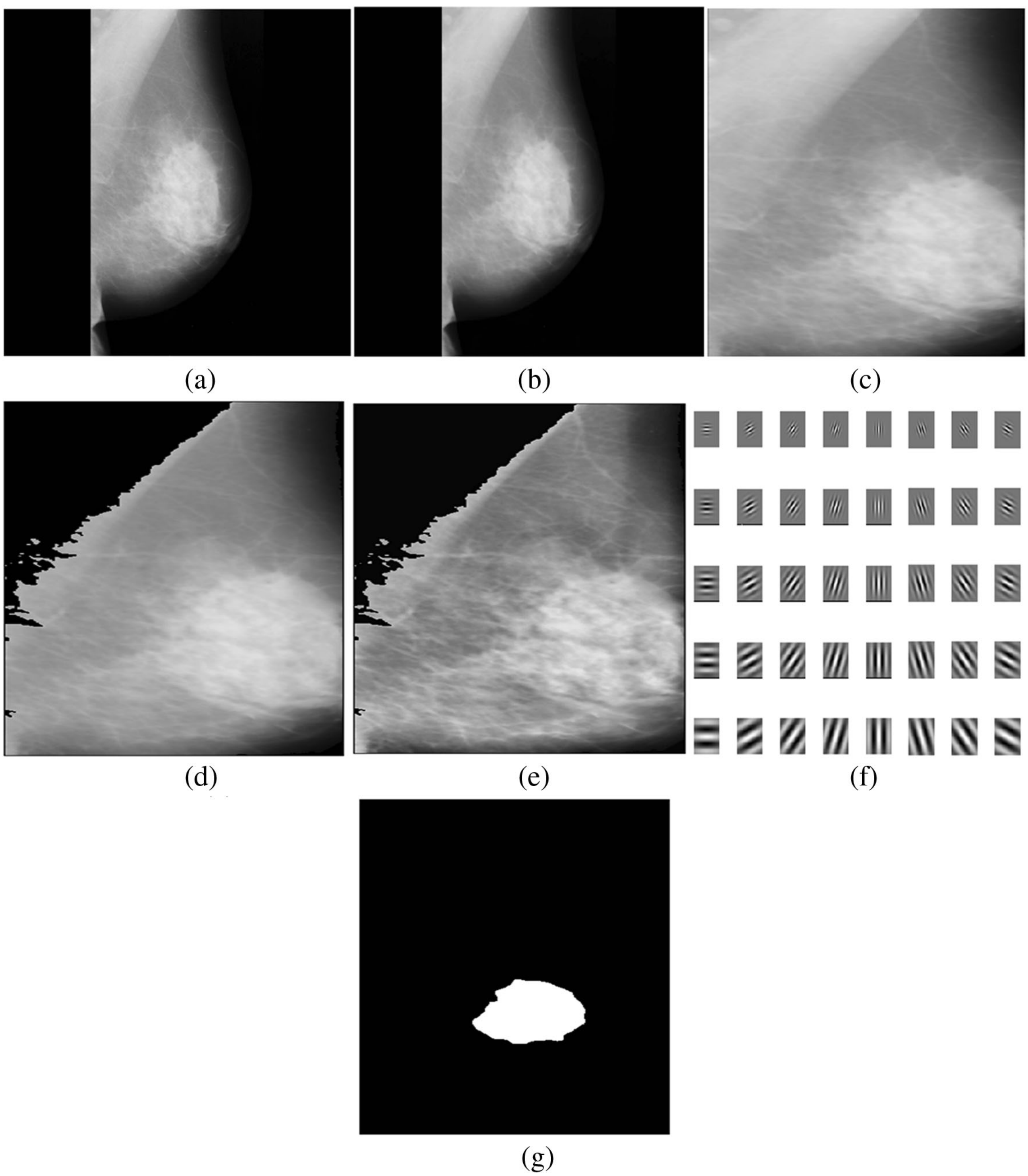
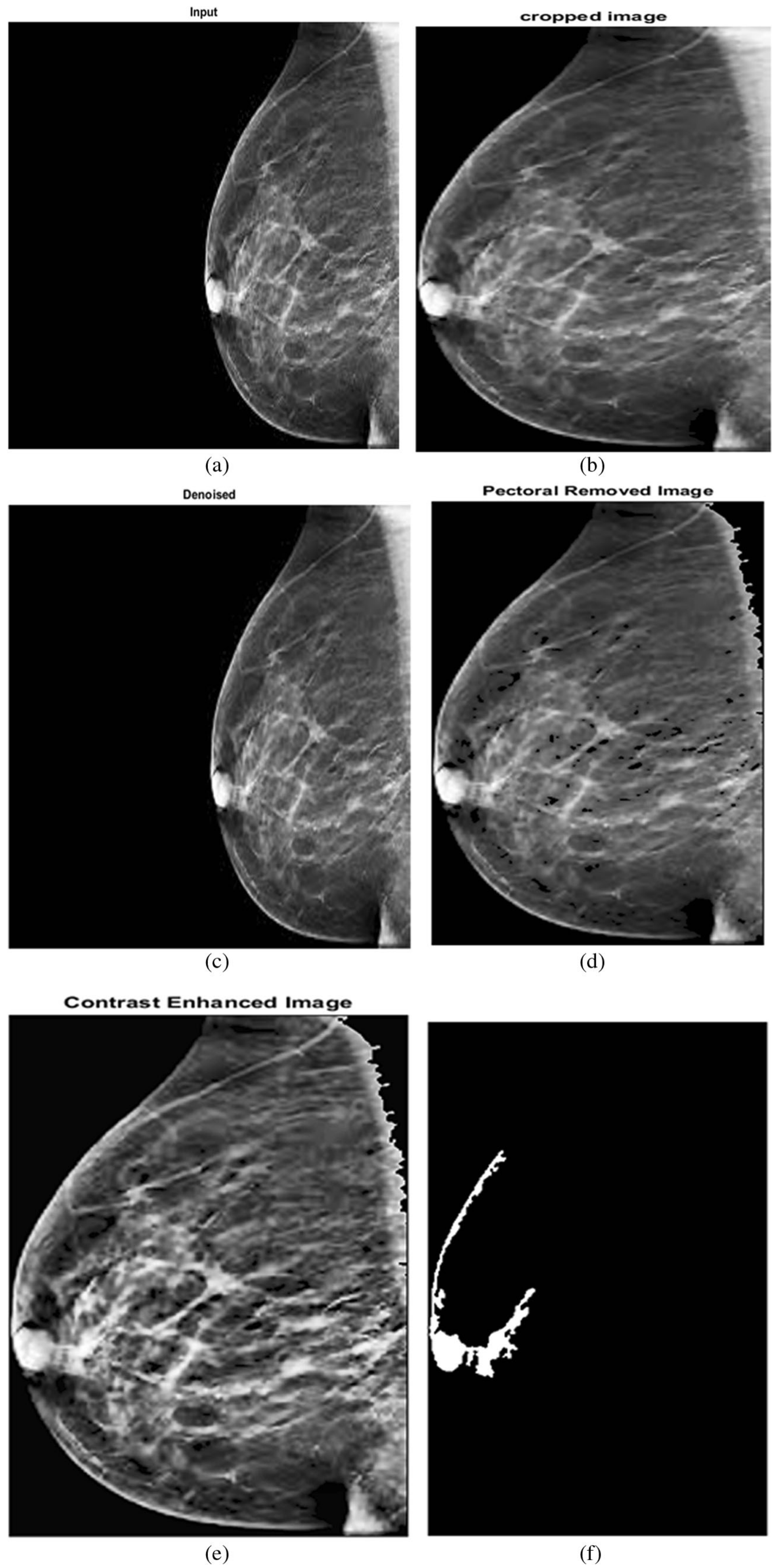


Fig. 5 Simulation results of MIAS database

Fig. 6 Simulation results for Real time database



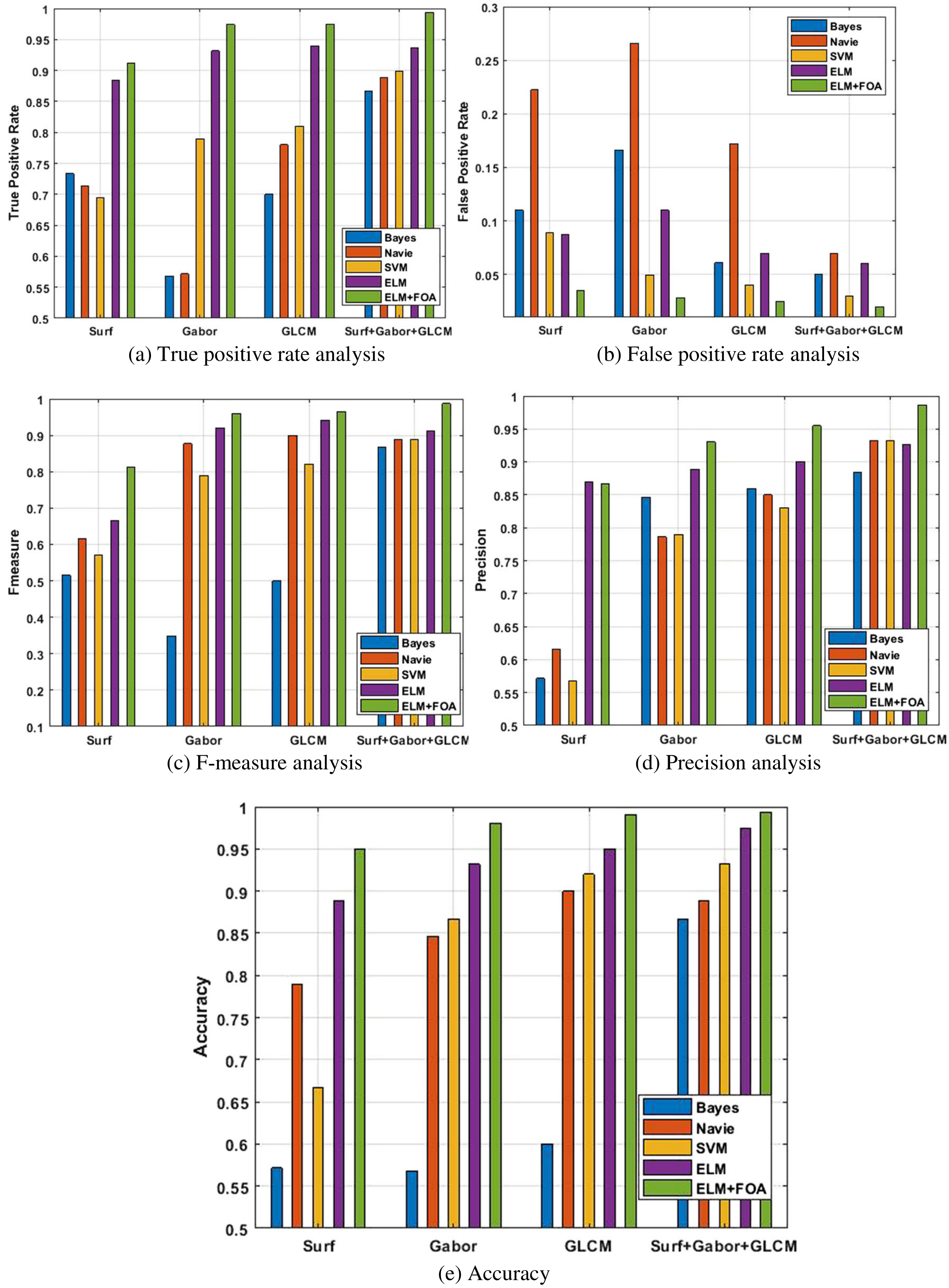


Fig. 7 Performance Comparison

Different classifier results are shown in fig. 7. In MIAS, 25 images are noted as 'CALC'. 25 recognized calcifications in the analysis had correct positions as the rundown, with five more identified calcifications which were not recorded in the presentation of the dataset. Contrasting with a large portion of the current mammogram image processing techniques, the proposed strategy executes numerous errands progressively to gain great execution in each progression. In a grasp assessment methodology, four measurements were characterized to produce the thorough exactness of segmentation, including true positive, true negative, false positive and false negative separately. Every one of the four measurements were joined for the precision count.

The accuracy of classification based on the percentage of the number of images correctly classified to the total number of images taken for classification. The fig. 4 represents the classification accuracy and various performances. It is apparently viewed that the ELM-FOA has better classification accuracy of mammogram images compared to Naïve bayes, SVM, ELM. The SVM classifier achieved 86.1% for the MIAS database in [20]. Because of the low level features used in the SVM it got low accuracy. ELM classifier used for micro calcification classification achieved 94% in []. In our proposed approach, the weight values are updated using FOA algorithm to minimize the error function and tune the classification accuracy. So it achive high accuracy when compared to the other approaches. Figure 8 shows the training time comparison for proposed ELM with two other SVM and Naïve bayes classifier.

In this study, input and output parameters for features ELM classifier based on image segmentation of the mammogram were determined. Benign and malignant classification was performed with ELM. Multi scale features are extracted from the pre-processed image which is optimized by GWO. Initially 24 features got from SURF, Gabor and GLCM as 1, 1, 22. From that 12 features are optimally selected for classification which enhnaces the classification accuracy and minimizes the error rate. Performance and speed were measured, and a comparison with other methods of classification was performed. The performances of the ELM method and other machine learning allowed showing not only the results of ELM method, but also a comparison with other methods,

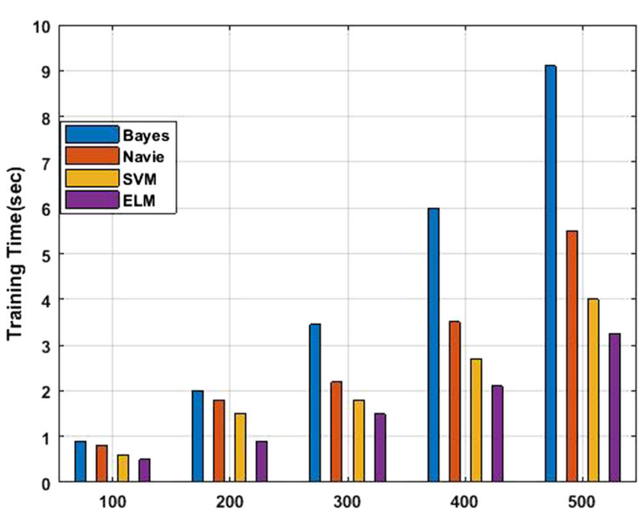


Fig. 8 Training time comparison

and this helps pathologist to use and choose the fastest method with best performance.

Conclusion and Future Work

In the breast cancer detection, the mammography plays a significant role but in certain situations the radiologists cannot identify the tumors even though they have a lot of experiences. In this paper, some computer assisted techniques are introduced that would help the medical staff and also develop the accuracy rate of detection. We have introduced a categorization of mammograms in this paper by utilizing the FOA-ELM classifier. The suggested categorization system is applied to the MIAS database image. The Investigational outcomes display that, when contrasted to the numerous additional techniques the FOA-ELM displays 99% micro calcification detection in the mammograms. With the suggested FOA-ELM classifier, the high precision of the categorization of the MCCs is attained that can assist the radiologists to make the correct diagnostic decision and diminish the redundant biopsies. Our upcoming work is to strengthen the numerous dissimilar features and also the additional categorization of the mammogram. It could be very supportive if a detectioncould be done in real-time at the screening.

Compliance with Ethical Standards

Conflict of Interest The authors has no conflict of interest in submitting the manuscript to this journal.

Ethical Approval This article does not contain any studies with human participants performed by any of the authors.

References

1. Greenspan, H., Ginneken, B., and Summers, R. M., Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique. IEEE Transactions on Medical Imaging 35(5):1153–1159, 2016.
2. Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., and Liang, J., Convolutional neural networks for medical image analysis: Full training or fine tuning? IEEE transactions on medical imaging 35(5):1299–1312, 2016.
3. Al-Najdawi, N., Biltawi, M., and Tedmori, S., Mammogram image visual enhancement, mass segmentation and classification. Applied Soft Computing 35:175–185, 2015.
4. Zhang, X., Liu, W., Dundar, M., Badve, S., and Zhang, S., Towards large-scale histopathological image analysis: Hashing-based image retrieval. IEEE Transactions on Medical Imaging 34(2):496–506, 2015.
5. Sharma, S., and Khanna, P., Computer-aided diagnosis of malignant mammograms using Zernike moments and SVM. Journal of digital imaging 28(1):77–90, 2015.

6. Lee, H., and YPP, C., Image based computer aided diagnosis system for cancer detection. Expert Systems with Applications 42(12): 5356–5365, 2015.
7. Jen, C.-C., and Yu, S.-S., Automatic detection of abnormal mammograms in mammographic images. Expert Systems with Applications 42(6):3048–3055, 2015.
8. Beura, S., Majhi, B., and Dash, R., Mammogram classification using two dimensional discrete wavelet transform and gray-level co-occurrence matrix for detection of breast cancer. Neurocomputing 154:1–14, 2015.
9. Pak, F., Kanan, H. R., and Alikhassi, A., Breast cancer detection and classification in digital mammography based on Non-Subsampled Contourlet Transform (NSCT) and Super Resolution. Computer methods and programs in biomedicine 122(2):89–107, 2015.
10. Carneiro, G., Nascimento, J., Bradley, A. P., Deep Learning Models for Classifying Mammogram Exams Containing Unregistered Multi-View Images and Segmentation Maps of Lesions. In Deep Learning for Medical Image Analysis 321-339, (2017).
11. Pereira, C. D., Ramos, R. P., and Nascimento, M. Z. D., Segmentation and detection of breast cancer in mammograms combining wavelet analysis and genetic algorithm. Computer methods and programs in biomedicine 114(1):88–101, 2014.
12. Summers, R. M., Deep Learning and Computer-Aided Diagnosis for Medical Image Processing: A Personal Perspective. In Deep Learning and Convolutional Neural Networks for Medical Image Computing, Springer, Cham3-10, (2017).
13. Oliver, A., Tortajada, M., Lladó, X., Freixenet, J., Ganau, S., Tortajada, L., Vilagran, M., Sentís, M., and Martí, R., Breast density analysis using an automatic density segmentation algorithm. Journal of digital imaging 28(5):604–612, 2015.
14. Abdel-Nasser, M., Rashwan, H. A., Puig, D., and Moreno, A., Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern. Expert Systems with Applications 42(24):9499–9511, 2015.
15. Kallenberg, M., Petersen, K., Nielsen, M., Ng, A. Y., Diao, P., Igel, C., Vachon, C. M. et al., Unsupervised deep learning applied to breast density segmentation and mammographic risk scoring. IEEE transactions on medical imaging 35(5):1322–1331, 2016.
16. Torres, G. F., Pertuz, S., Automatic Detection of the Retroareolar Region in X-Ray Mammography Images. In VII Latin American Congress on Biomedical Engineering CLAIB 2016, Bucaramanga, Santander, Colombia, October 26th-28th, 2016, Springer, Singapore157-160, 2017.
17. Dheeba, J., Singh, N. A., and Selvi, S. T., Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. Journal of biomedical informatics 49:45–52, 2014.
18. Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L., and Lopez, M. A. G., Representation learning for mammography mass lesion classification with convolutional neural networks. Computer methods and programs in biomedicine 127:248–257, 2016.
19. Gubern-Merida, A., Kallenberg, M., Mann, R. M., Marti, R., and Karssemeijer, N., Breast segmentation and density estimation in breast MRI: a fully automatic framework. IEEE journal of biomedical and health informatics 19(1):349–357, 2015.
20. Virmani, J., Dey, N., Kumar, V., PCA-PNN and PCA-SVM based CAD systems for breast density classification. In Applications of intelligent optimization in biology and medicine, Springer, Cham, 159-180, (2016).
21. Fondón, I., Sarmiento, A., García, A. I., Silvestre, M., Eloy, C., Polónia, A., and Aguiar, P., Automatic classification of tissue malignancy for breast carcinoma diagnosis. Computers in biology and medicine 96:41–51, 2018.
22. Patel, B. K., Ranjbar, S., Wu, T., Pockaj, B. A., Li, J., Zhang, N., Lobbes, M., Zhang, B., and Mitchell, J. R., Computer-aided diagnosis of contrast-enhanced spectral mammography: A feasibility study. European journal of radiology 98:207–213, 2018.
23. Singh, K. A., and Gupta, B., A novel approach for breast cancer detection and segmentation in a mammogram. Procedia Computer Science 54:676–682, 2015.
24. Raghavendra, U., Acharya, U. R., Fujita, H., Gudigar, A., Tan, J. H., and Chokkadi, S., Application of Gabor wavelet and Locality Sensitive Discriminant Analysis for automated identification of breast cancer using digitized mammogram images. Applied Soft Computing 46:151–161, 2016.
25. Soulami, B. K., Saidi, M. N., Tamtaoui, A., A CAD System for the Detection of Abnormalities in the Mammograms Using the Metaheuristic Algorithm Particle Swarm Optimization (PSO). In Advances in Ubiquitous Networking,Springer, Singapore 2:505-517, (2017).
26. Chakraborty, J., Midya, A., and Rabidas, R., Computer-aided detection and diagnosis of mammographic masses using multi-resolution analysis of oriented tissue patterns. Expert Systems with Applications 99:168–179, 2018.
27. Schranzer, R., Rauscher, A., Haimburger, E., Bredies, K., Reishofer, G., and Grabner, G., Noise reduction in FLAIR2 images using total generalized variation, Gaussian and Wiener filtering. Zeitschrift für Medizinische Physik 28(4):286–292, 2018.
28. Makandar, A., and Halalli, B., Breast cancer image enhancement using median filter and CLAHE. International Journal of Scientific & Engineering Research 6(4):462–465, 2015.
29. Li, A., Jiang, W., Yuan, W., Dai, D., Zhang, S., and Wei, Z., Improved FAST+ SURF Fast Matching Algorithm. Procedia Computer Science 107:306–312, 2017.
30. Farokhian, F., Yang, C., Demirel, H., Wu, S., and Beheshti, I., Automatic parameters selection of Gabor filters with the imperialism competitive algorithm with application to retinal vessel segmentation. Biocybernetics and Biomedical Engineering 37(1): 246–254, 2017.
31. Yadav, P., Singh, N. P., "Classification of Normal and Abnormal Retinal Images by Using Feature-Based Machine Learning Approach." In Recent Trends in Communication, Computing, and Electronics, pp. 387-396. Springer, Singapore, 2019.
32. Ding, S., An, Y., Zhang, X., Wu, F., and Xue, Y., Wavelet twin support vector machines based on glowworm swarm optimization. Neurocomputing 225:157–163, 2017.
33. Dheeba, J., Singh, N. A., and Selvi, S. T., Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. Journal of biomedical informatics 49:45–52, 2014.