# Breast thermal images classification using optimal feature selectors and classifiers

*AmirEhsan Lashkari, Fatemeh Pak, Mohammad Firouzmand*

*Department of Bio-Medical Engineering, Institute of Electrical Engineering & Information Technology, Iranian Research Organization for Science and Technology (IROST), Tehran, Iran*
*E-mail: lashkari.eng@gmail.com*

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**Abstract:** In this study, a full automatic technique has been presented to assist physicians in early detection of breast cancer based on different degrees. First the region of interest is determined using full automatic operation and the quality of image is improved. Then, some features including statistical, morphological, frequency domain, histogram and grey-level co-occurrence matrix features are extracted from segmented right and left breasts. Subsequently, to achieve the best features and increase the accuracy of the proposed method, feature selectors such as minimum redundancy and maximum relevance, sequential forward selection, sequential backward selection, sequential floating forward selection, sequential floating backward selection and genetic algorithm have been used. Finally, to classify and TH labeling procedures, supervised learning techniques such as AdaBoost, support vector machine, nearest neighbor, Naïve Bayes and probability neural network are applied and compared with each other. The results obtained on native database showed the significant performance of the proposed algorithm in comprising to the similar studies. The experimental results gave the best mean accuracy of 88.03% for only using 0° image with combination of mRMR and AdaBoost and for combination of 3 degrees with combination of GA and AdaBoost.

## 1 Introduction

Breast cancer is the most common type of cancer among the women. The important key to treat is early detection of it, because according to many pathological studies more abnormalities are still benign at primary stages; so in recent years, many studies and extensive research have been done to early detection of breast cancer with higher precision and accuracy [1, 2]. There are a number of techniques such as mammography, ultrasound and magnetic resonance imaging (MRI) for diagnosing the breast cancer. Each of these has well-known advantages and disadvantages. Mammography has been treated as the gold standards for detection of breast cancer, but still suffers from limited sensitivity, specificity and several other limitations as a screening tool. Ultrasound is used as adjunctive tools in screening women with dense breast in coordination with mammography. The limitations of MRI are that it is not good at detection of ductal carcinoma in situ, is slow, expensive and fails to show all calcifications. However all these modalities suffer from one or more common disadvantages of radiation exposure, breast compression, only structural imaging and breast density [3–5]. To remove the disadvantages of current methods, infrared thermography can be used as a complementary method for detecting breast abnormalities in thermal images. Infrared thermography uses a highly sensitive infrared camera to obtain the image of the temperature distribution in the human body. This imaging technique due to the use of non-ionising radiation (passive), non-contrast enhanced injection, non-contact and non-invasive is very valuable in many biological and medical applications in compared or in combination with other imaging modalities. Moreover, recording temperature distribution patterns in thermography leads to the physiological interpretation of tissues (temperature change based on interaction patterns) which could reveal suspected areas of cancer tissue even when there is no anatomical abnormalities on the tissue surface and it seems quite healthy [6–9]. Also, some research on the temperature dynamic variation of the body surface after a cold stimulation to patients has been done that may be having an advantage in helping physicians especially in early disease diagnosis. Stimulation of the sympathetic nervous system causes a constriction of the normal blood vessels in the breast. The blood vessels supplying a cancerous tumour will resist constriction or fail to constrict. Consequently, dynamic digital thermal subtraction gives us the possibility of isolating the vessels that supply nutrients to the tumour. This test ultimately raises the suspicion that a cancerous tumour might be present [10]. So this study is an effort to diagnose breast cancer by processing the information obtained from medical infrared imaging. Table 1 shows the related studies done in breast cancer detection using thermography techniques.

In the present paper, due to a lot of attractions of breast thermography, a method with a very notable accuracy, sensitivity and verity has been proposed. First the region of interest (ROI) is determined using full automatic operation and the quality of image is improved. Then, some features including statistical, morphological, frequency domain, histogram and grey-level co-occurrence matrix (GLCM) features are extracted from segmented right and left breasts. Subsequently, to achieve the best features and increase the accuracy of the proposed method, feature selectors such as minimum redundancy and maximum relevance (mRMR), sequential forward selection (SFS), sequential backward selection (SBS), sequential floating forward selection (SFFS), sequential floating backward selection (SFBS) and genetic algorithm (GA) have been used. Finally, to classify and TH labelling procedures, supervised learning techniques such as AdaBoost, support vector machine (SVM), k-nearest neighbours (k-NN), Naïve Bayes (NB) and probability neural network (PNN) are applied and compared with each other to find the best suitable one. The results obtained on native database showed the significant performance of the proposed algorithm in comprising to the similar studies.

## 2 Patients and methods

In this research, to evaluate the performance of the proposed method, the native database has been used. The thermography images obtained by Fanavaran Madoon Ghermez (FMG) Co., Ltd. [23] infrared camera (Thermoteknix VisIR 640, resolution: 480 × 640) from the patients who were suspicious to have breast cancer, referred to Imam Khomeini hospital [24] by their physician and labelled as $TH_1$–$TH_5$ depend on the stage of cancer by an oncologist observing all ethical issues. This database contains images with different angles 0°, ±45° and ±90° before and after ice test (Ice Test: Putting their hands on a mixture of ice & water for about 20 min) from 67 patients that participating in the examination. So we will have 10 images from 67 patients (total 670 images). In this paper, 3 views 0°, +45° and +90° and their combinations of images before the ice test for all 67 participate have been used and compared with images after the ice test that obtained in [25].

Table 1 Previous proposed methods of detecting breast cancer using thermogram images

| Study | Proposed approach |
|---|---|
| Williams *et al.* [11] | showed the possibility of detecting breast cancer from increased temperature at breast tissue acquired by infrared thermography (temperature sensitivity was about 2°C in the image acquired during a few minutes) |
| Parisky *et al.* [12] | about 4 years of a clinical trial on 769 patients, reported that infrared thermal imaging is a non-invasive and safe technique, can be very valuable in determination of the benign or malignant breast abnormalities combined with mammography |
| Arora *et al.* [13] and Kennedy [14] | showed that the combination of thermotherapy and other diagnostic techniques can improve the accuracy of breast abnormality detection |
| Tang *et al.* [15] | new criterion of breast cancer detection and method of its realisation is proposed as follows: (i) surface temperature distribution of healthy breast usually exhibits a gentle variation which is background. (ii) localised surface temperature of a carcinomatous breast will increase on the basis of the above background which is LTI. (iii) The carcinomatous possibility is proportional to the LTI maximum (amplitude) of the suspicious focus region. (iv) The LTI amplitude can be measured through morphological signal processing |
| Schaefer *et al.* [16] | breast cancer analysis based on thermography is performed, using a series of statistical features extracted from the thermograms quantifying the bilateral differences between left and right breast areas, coupled with a fuzzy rule-based classification system for diagnosis |
| Acharya *et al.* [17] | texture features are extracted from co-occurrence matrix and run length matrix. Subsequently, these features are fed to the SVM classifier for automatic classification of normal and malignant breast conditions |
| Satoto *et al.* [18] | Wiener filter used to eliminate the noise. Using histogram equalisation, image contrast improved. The last step of the pre-processing procedure uses region growing method. Then statistical features such as mean, standard deviation, entropy, skewness and kurtosis of the images extracted and finally the fuzzy algorithm is used for classification |
| Kapoor *et al.* [19, 20] | background and additional areas of the image removed at first. Breast boundaries extracted using 'canny' edge detection and gradient operator used to determine the boundary curves of the left and right breasts. Lower bounds of breast determined using two elliptical curves, and the area under the curve has been eliminated. Then, a separator for separating the right and left breasts has been used. In the feature extraction stage, the features of skewness, kurtosis, entropy and features based on co-occurrence matrix such as energy, homogeneity and correlation extracted. Finally the Multi Layer Perceptron (MLP) network is used for classification of features. |
| Nicandro *et al.* [21] | information such as the temperature difference between the left and right breasts, hot spots in the breast, the temperature difference between the hot spots, the centre of the hot zone, features based on the histogram, patient age, … used to determine the suspected areas. To evaluate the performance. NB classifier, hill climbing, iterative hill climbing, artificial neural networks, decision trees $ID_3$ and $C_{4.5}$ decision tree have been used. The iterative hill climbing algorithm had the best performance with the accuracy of 76.12% among all classifiers |
| Dinsha and Manikandaprabu [22] | first, using CLAHF, the quality of thermal images improved and noise are eliminated using a non-linear filter. To achieve strong edges, Gaussian filter with weighting coefficients corresponding pixel intensities has developed. The segmentation was performed using both *k*-means and FCM algorithms and features based on co-occurrence matrix separately. Finally, SVM and Bayesian classifiers used on feature space |

LTI: localised temperature increases, CLAHF: contrast limited adaptive histogram equalisation, FCM: fuzzy C means and, SVM: support vector machine.

The camera has been designed in a way that has always been to reduce/eliminate technical errors in the imaging process. For medical applications, a controlled environment helps to increase accuracy. Infrared camera should be placed at certain distance from the patient. Some of pixels considered as foreground. So, there are parameters that can be completely useful and effective in a matter of testing/diagnosis or treatment and instructions that should be observed during data collecting procedures [26]. Also, in the previous paper [25] mentioned to these parameters and instructions. During the experiments, asked the patient to put her hands on her head in rest state. Five different angles (0°, ±45° and ±90°) images obtained (before ice test). Then patient asked to put their hands into the mixture of water and ice for about 20 min and so five another different angle images (0°, ±45° and ±90°) obtained again (after the ice test).

Table 2 shows the distribution of patients whom their cancer stages (standard level: TH) labelled by oncologist according to a paper by Gautherine *et al.* [27] for both right and left breasts separately.

The proposed method includes four stages: (i) pre-processing and segmentation, (ii) feature extraction, (iii) feature selection and (iv) classification and TH labelling. Fig. 1 shows the structure of the presented method [25].

### 2.1 Pre-processing and segmentation

Pre-processing, especially in data driven studies, is a very important stage. To distinguish between normal and abnormal tissues, pre-processing and segmentation performed in three stages: (i) ROIs detection and thermal images enhancement, (ii) breast tissue segmentation and (iii) suspicious regions detection and image matrix normalisation. Fig. 2 shows the result of this section [25].

### 2.2 Feature extraction

In the feature extraction stage, some information from right and left breast images should be extracted for distinguishing between normal and abnormal tissues, correctly. The extracted features the same as the previous paper [25] are based on statistical features such as median, mod, skewness, kurtosis, central moment and entropy, based on histogram such as mean, standard deviation, max-value, min-value and norm, based on GLCM such as contrast, homogeneity, energy and correlation, based on morphology of suspicious regions such as Euler number, area, perimeter, shape factor and Hurst coefficient and also based on frequency domain such as maximum value of fast Fourier transform (FFT) and mean value of FFT.

Table 2 Distribution of standard level labelled by oncologist for both right and left breasts separately

| TH | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| right breast | 24 | 22 | 12 | 4 | 5 |
| left breast | 6 | 28 | 14 | 13 | 6 |

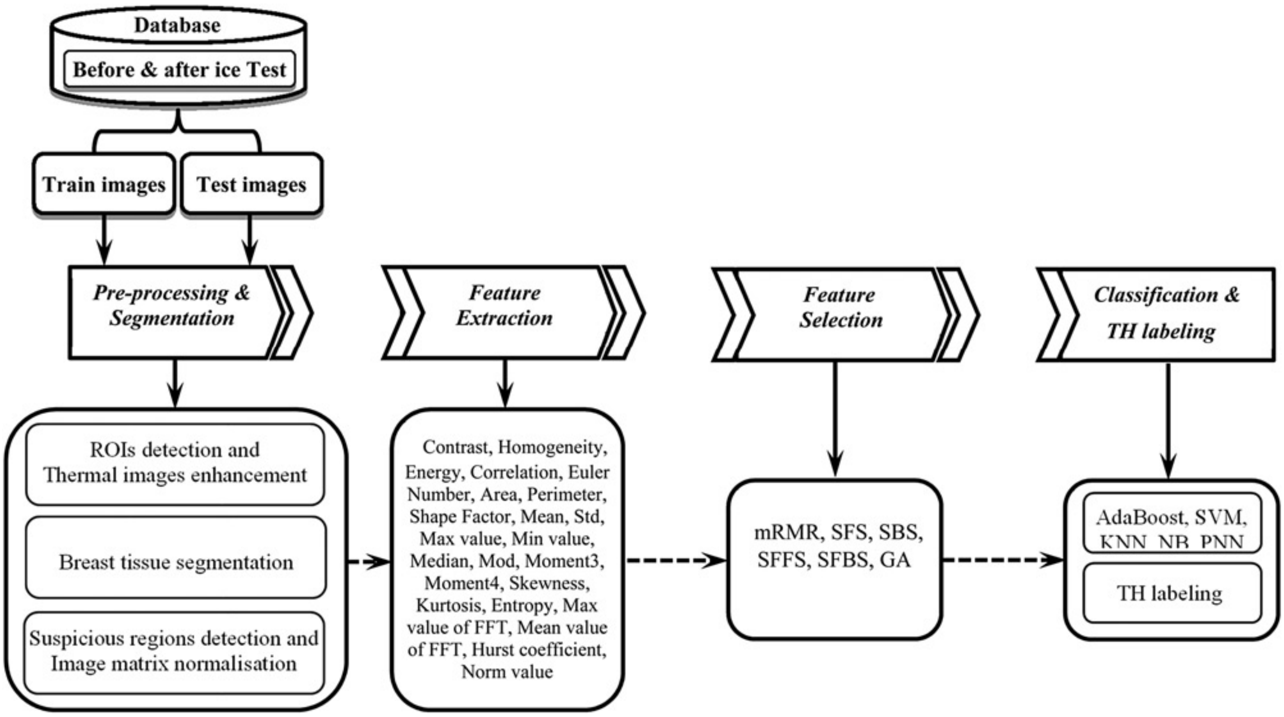


**Fig. 1** *Proposed system architecture*

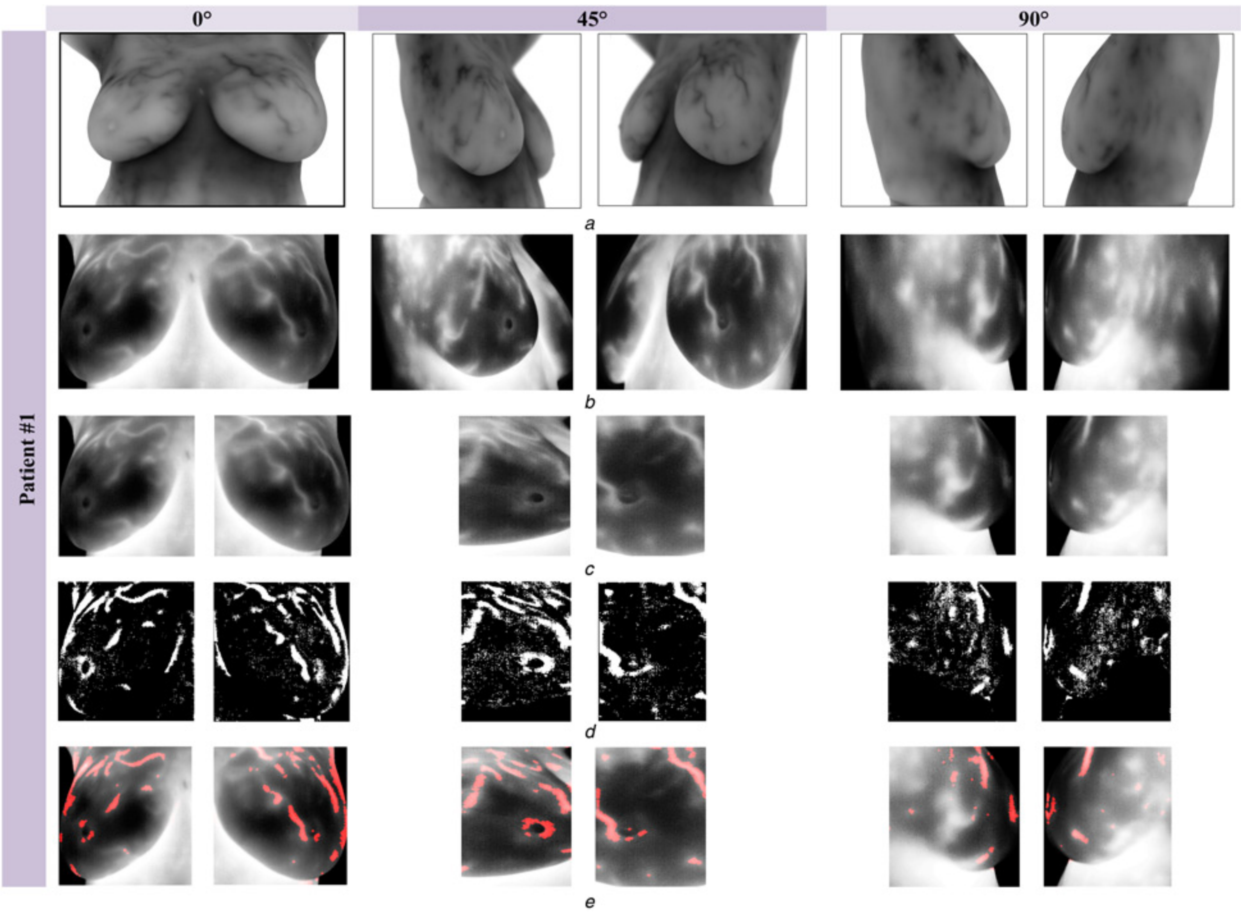


**Fig. 2** *Breast segmentation based on different degrees*
*a* Original image
*b* Removing additional margins and determining ROIs
*c* Separating right and left breasts
*d* Suspicious regions detection
*e* Applying suspicious regions to the breast images in step (c)

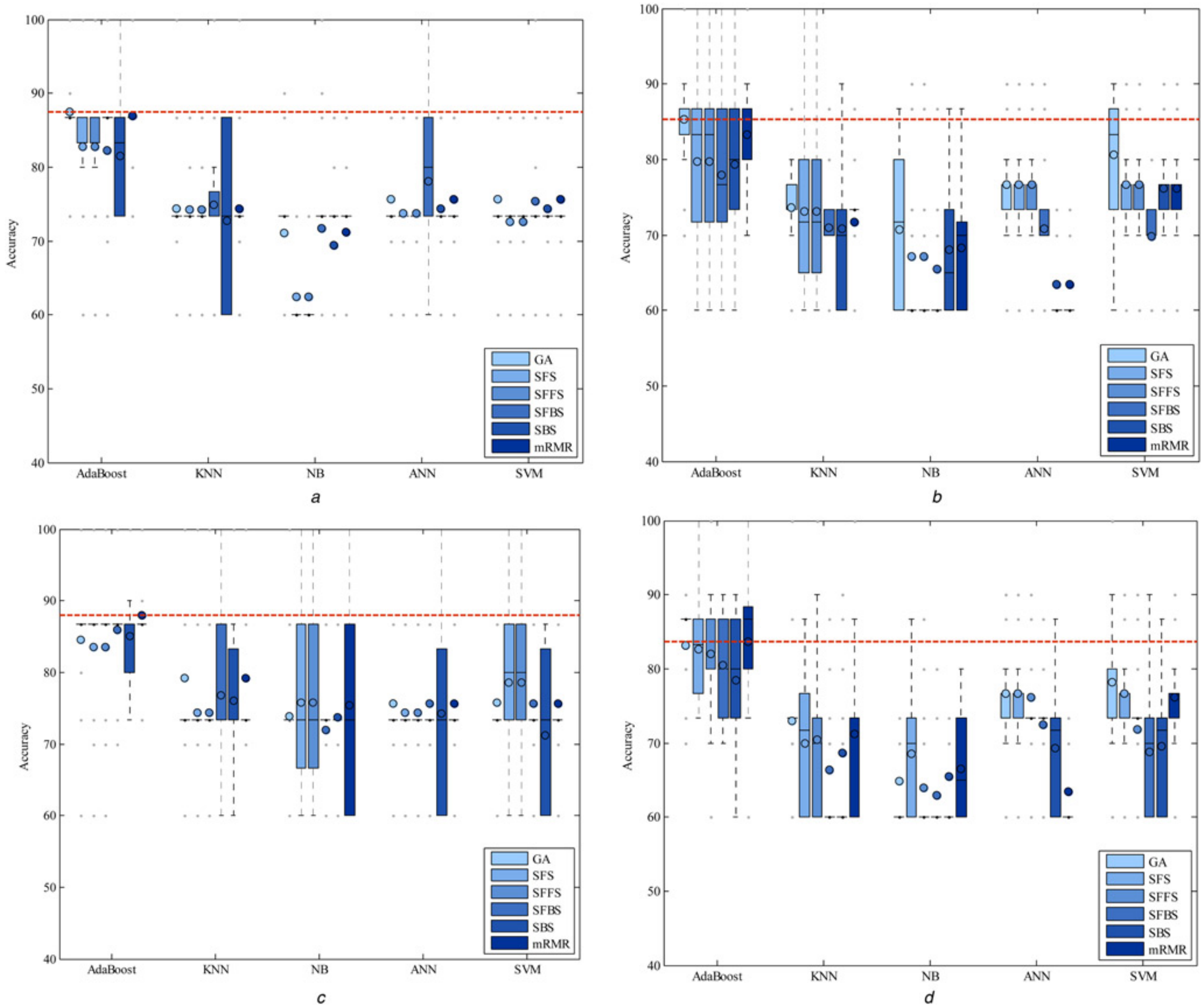


**Fig. 3** *Accuracy of the proposed system, corresponding to different feature selector and classifiers on 0° breast images*
*a* Right breast images in before ice test (best combination: GA and AdaBoost)
*b* Left breast images in before ice test (best combination: GA and AdaBoost)
*c* Right breast images in after ice test (best combination: mRMR and AdaBoost)
*d* Left breast images in after ice test (best combination: mRMR and AdaBoost)

### *2.3 Feature selection*

Various information causes a high dimensionality feature matrix obtained that reduces accuracy and increases computation burden. So to obtain a more accurate selection and further reduction of the number of extracted features, different feature selection methods are used. In this paper, the minimal-redundancy and maximal-relevance (mRMR) [28], SFS [29], SBS [29], SFFS [30], SFBS [30] and GA [31] are applied and then compared with each other.

### *2.4 Classification and TH labelling*

Classification is the final stage in the proposed approach. So classification is the final stage in the proposed approach. So selected feature matrix fed into the classification algorithm to detect TH. TH is a standard measure to analyse thermovascular's breast that was proposed in 1980s. So physicians classify thermal images into five categories based on the combined vascular and temperatures patterns across the two breasts as: $TH_1$: normal non-vascular, $TH_2$: normal vascular, $TH_3$: equivocal, $TH_4$: abnormal and $TH_5$: severely abnormal [32]. In this research, to show the performance of the proposed method, different classification algorithms have been applied and their results have been evaluated and compared with each other to obtain the best results. These algorithms are AdaBoost [33, 34], SVM [35], k-NN [36], NB [36] and PNN [37]. The description of each method has been accessed [25].

## 3 Results

In this research, to evaluate the performance of the proposed method, the native database with 67 thermography images from ten people (total 670 images) has been used. The thermography images obtained by FMG Co., Ltd. [23] with infrared camera (Thermoteknix VisIR 640, resolution: $480 \times 640$) in Imam Khomeini hospital [24] by their physician and labelled as $TH_1$–$TH_5$ depend on the stage of cancer by an oncologist observing all ethical issues. This database contains images with different angles 0°, ±45° and ±90° in before and after ice test. In this paper, 3 views of images 0°, +45°, +90° and their combinations in before the ice test for all 67 participate have been used and compared with images after the ice test.

In the proposed approach, after determining ROIs and enhancing thermal images, right and left breast tissues have been separated by edge detection operators. To detect suspicious regions in each breast, 'Erosion' morphological operator have been used. Also,

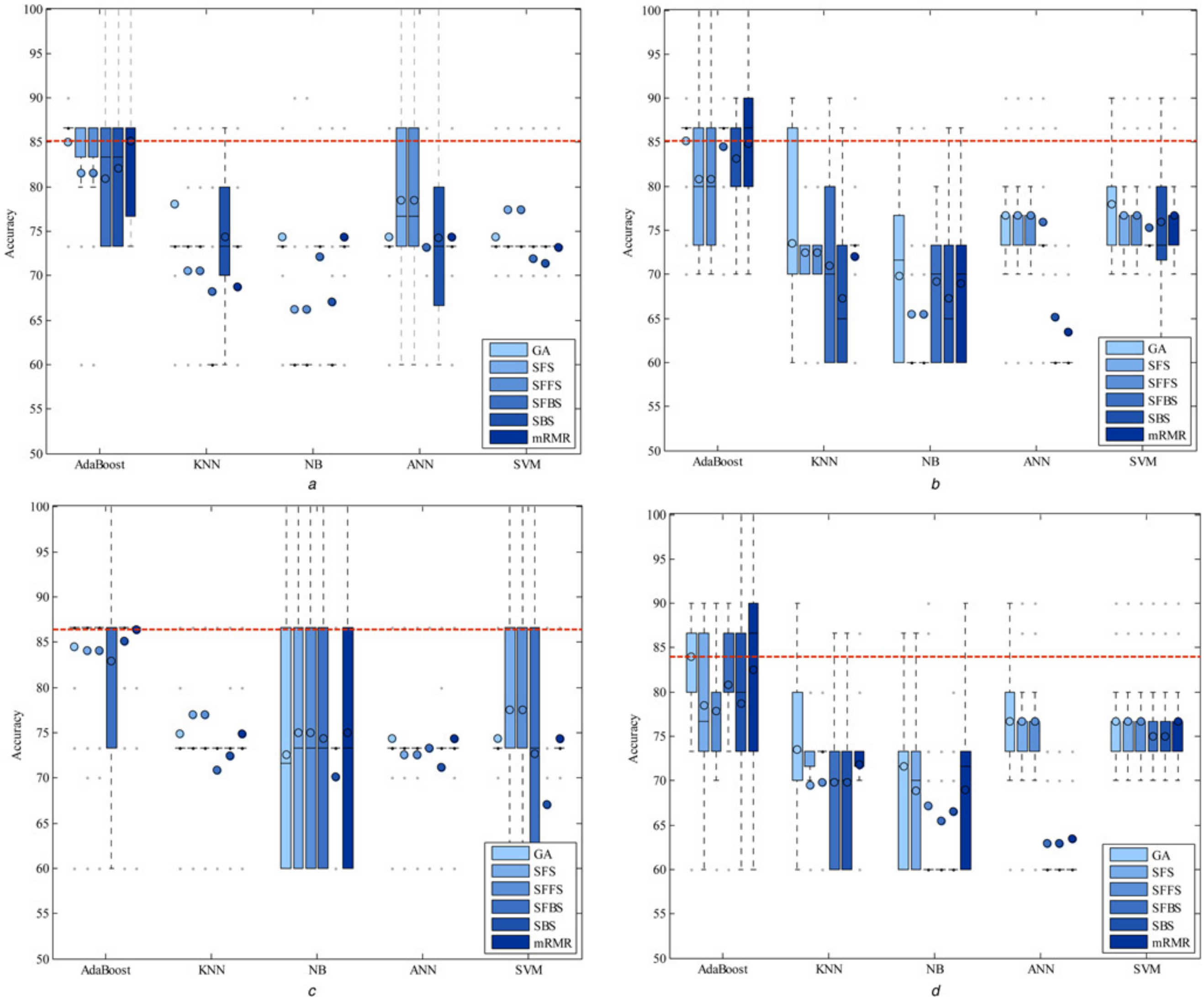


**Fig. 4** *Accuracy of the proposed system, corresponding to different feature selector and classifiers on 45° breast images*
*a* Right breast images in before ice test (best combination: mRMR and AdaBoost)
*b* Left breast images in before ice test (best combination: GA and AdaBoost)
*c* Right breast images in after ice test (best combination: mRMR and AdaBoost)
*d* Left breast images in after ice test (best combination: GA and AdaBoost)

different degrees of breast images are used to evaluate the suspicious regions of thermogram images and the performance of the proposed algorithm validated based on these degrees [25]. Then, the mentioned features in Section 2.2 have been extracted from right and left breast images. To obtain optimal features, different feature selection methods as mentioned in Section 2.3 have been applied. Finally, the selected feature matrix fed to different classifiers for determining TH that AdaBoost showed the best result among the other classifiers. Experimental results show the best result obtained when $k$, the number of neighbours in k-NN classifier is equal to three, the smoothing parameters in PNN classifier is equal to 0.35 and also Gaussian kernel with degree six is used for SVM classifier and value of parameter $C$ is considered equal to 1. To evaluate the proposed method, the same as [25] 20-fold cross-validation for left breast images and 22-fold cross-validation for right breast images have been used. In addition, to show the performance of the provided method, some measures such as sensitivity, specificity, area under curve (AUC), equal error rate (EER), precision, recall, F-measure and false positive rate (FPR) have also been calculated.

### *3.1 Evaluation of extracted features based on feature selectors*

To obtain optimal feature space, six feature selection methods such as mRMR, SFS, SBS, SFFS, SFBS and GA are used in two situations of before and after ice test. Feature space obtained in before ice test has been studied in the previous paper [26] and after ice test has been studied in this paper. In the proposed algorithm, each feature, selected by several feature selection methods several times on the right and left breasts, can be introduced as effective feature. It should be noted that the specified features as good features are only the effective features and they can be used together with other features to obtain good result. To better understand, it is necessary to note that:

- Each of the feature selection method evaluated with different classifiers.
- In SFS, SBS, SFFS and SFBS, the features selected for one time then are evaluated by different classifiers.
- In mRMR and GA, the optimal number of features should be obtained. So, the number and type of the selected features by these two methods will be different by applying different classifiers. Also, based on combination of mRMR and GA methods with five

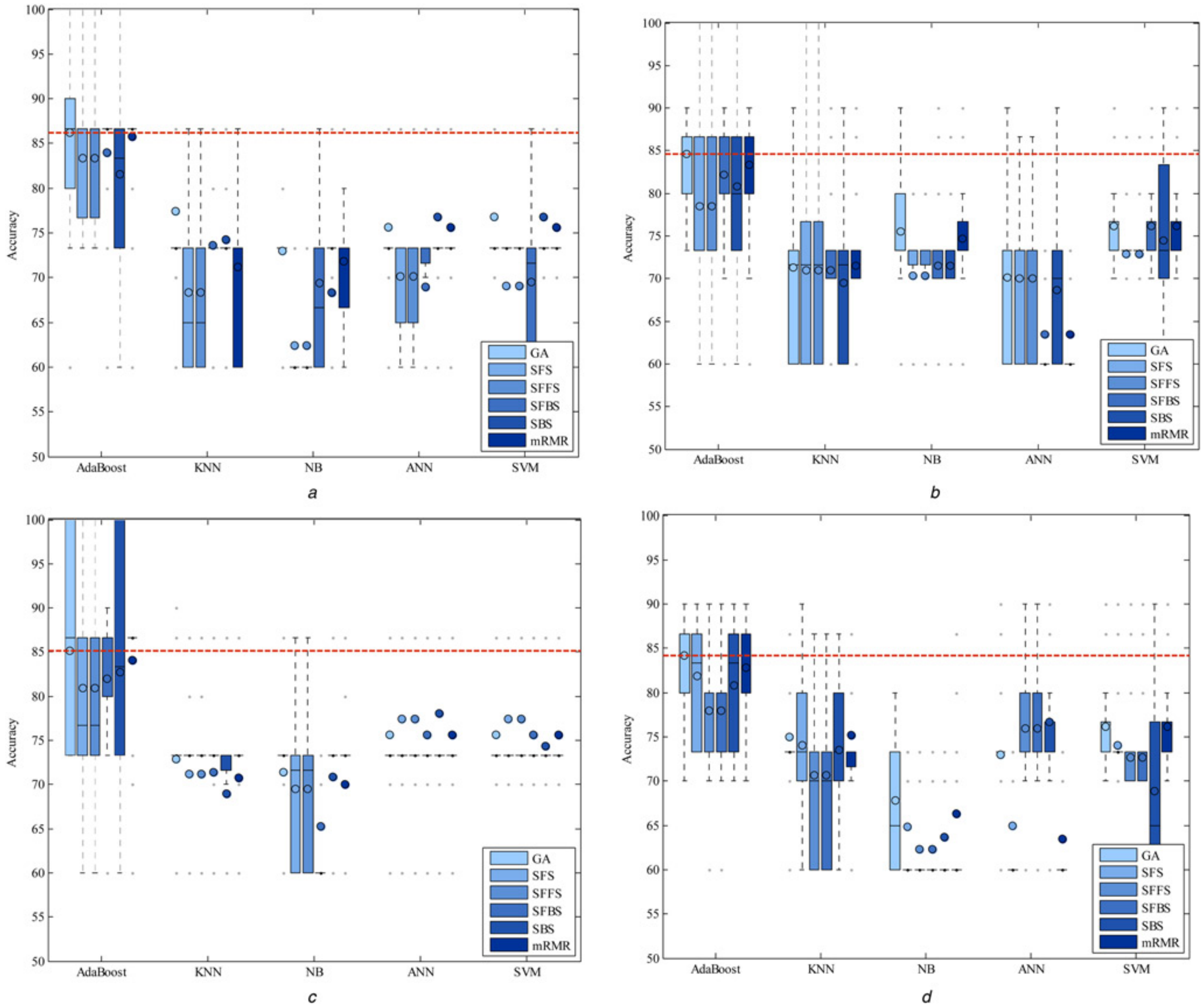


**Fig. 5** *Accuracy of the proposed system, corresponding to different feature selector and classifiers on 90° breast images*
*a* Right breast images in before ice test (best combination: GA and AdaBoost)
*b* Left breast images in before ice test (best combination: GA and AdaBoost)
*c* Right breast images in after ice test (best combination: GA and AdaBoost)
*d* Left breast images in after ice test (best combination: GA and AdaBoost)

classifiers, each feature may be selected one or more than one time. The obtained values can be shown that a feature may be evaluated by different classifiers as good feature and has been able to increase the accuracy of the algorithms.

- Features could be suitable if they are selected by at least three of the feature selection methods in left or right breast images.
- Features could be good if they are selected by at least two of the feature selection methods, but the mRMR and GA methods have selected them several times.
- Features are not very good or very bad if these features selected by at least two of the feature selection methods that mRMR and GA methods have selected them few times.
- Features are not very good (bad) if selected only by one of the feature selection method such as mRMR and GA.
- Features are not suitable if they are not selected or only selected by one method.

The effective features in before ice test [25] were contrast, Euler number, area, mean, central moment4 and skewness for 0° images, contrast, perimeter, Shape_Factor, Max_value, Min_value, mod, skewness, kurtosis, entropy, mean value of FFT and norm value for 45° images and also area, Shape_Factor, standard deviation, central moment3, central moment4, kurtosis, maximum value of FFT, mean value of FFT, Hurst coefficient and norm value for 90° images. Moreover the effective features in before ice test for combination of 3° are Euler number, area, perimeter, central moment3, central moment4, skewness, kurtosis, entropy, maximum value of FFT, Hurst coefficient and norm value.

### *3.2 Evaluation of different feature selections on right and left breasts in different degrees*

In the proposed method, to obtain optimal features, different feature selection methods have been used. The probability of selected each feature is specified by one of the feature selection methods in after ice test situation. The before ice test results reported before [25]. As before, the number and type of the selected features in mRMR and GA methods will be different by applying different classifiers. So, in this experiment, because of the highest accuracy of the AdaBoost classifier, AdaBoost is used for its combination by mRMR and GA to select the features.

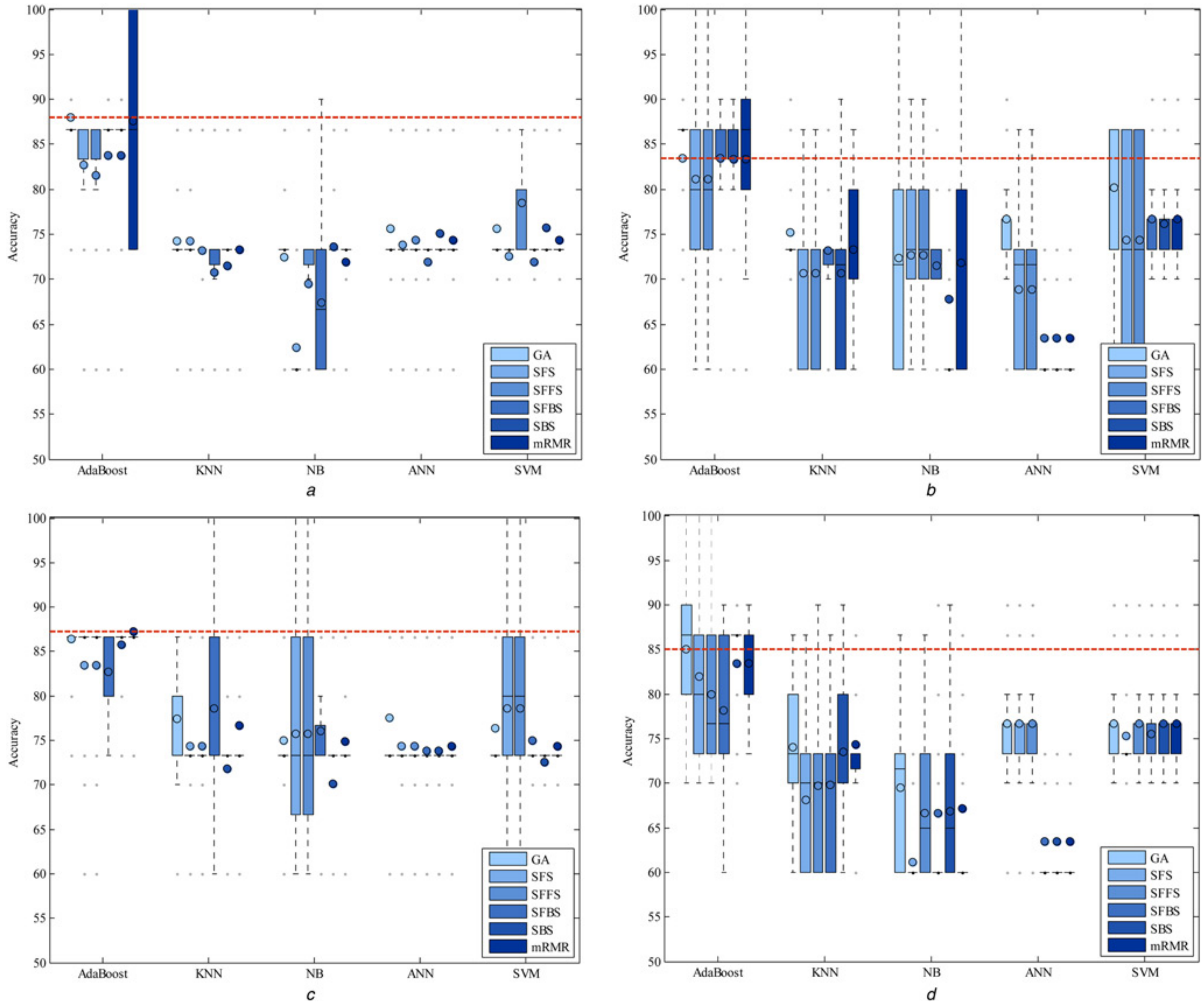


**Fig. 6** *Accuracy of the proposed system, corresponding to different feature selector and classifiers on the combination of 0°, 45° and 90° breast images*
*a* Right breast images in before ice test (best combination: GA and AdaBoost)
*b* Left breast images in before ice test (best combination: GA and AdaBoost)
*c* Right breast images in after ice test (best combination: mRMR and AdaBoost)
*d* Left breast images in after ice test (best combination: GA and AdaBoost)

### *3.3 Performance assessment of the proposed method*

In this section, the performance of the proposed method has been evaluated with combinations of different feature selection methods and classifiers. In this experiment, five classification methods such as, AdaBoost, SVM, k-NN, NB and PNN combined with six feature selection methods such as mRMR, SFS, SBS, SFFS, SFBS and GA have been used. The results are expressed by using box–whisker plots in Figs. 3–5 for 0°, 45° and 90°, respectively and Fig. 6 for combination of 0°, 45° and 90° in before and after ice test. Horizontal axis shows different classifiers and vertical axis shows measures for evaluating the performance of the method. Box-plot also can show average and median. On each box, the horizontal line denotes median, the circle denotes mean and the horizontal lines outside each box identify the upper and lower whiskers and dot points denote the outliers. The dotted line in each figure shows the highest mean accuracy for combination of one feature selection method with one classification method among the other combinations in left and right breast images. The best combination obtained are noted in these figures. As can be seen in Figs. 3–6, AdaBoost has better performance compared with the other classifiers. So, the combination of AdaBoost with six feature selection methods have been studied in recursive operating characteristic (ROC) curves in Figs. 7–10 to evaluate different feature selectors. Moreover, AdaBoost without feature selector has been also shown in these ROC curves. The best combination obtained are shown in the box–whisker plots, these are also evident in ROC curves and the proximity of the feature selectors performance can also be seen in ROC curves. It should be noted that the placement of some curves might be different from their situations in box–whisker plots, because of using two-class classification to plot ROC curves.

### *3.4 Evaluation of the proposed method in different degrees of breast images in before and after ice test*

As mentioned in previous sections, to evaluate the proposed algorithm, different degrees of breast images are considered in both situations before and after ice test. Now, the best accuracies obtained by the best combinations in different conditions have been studied in this section and the results obtained were also compared with each other in Table 3. The following results can be obtained from Table 3.

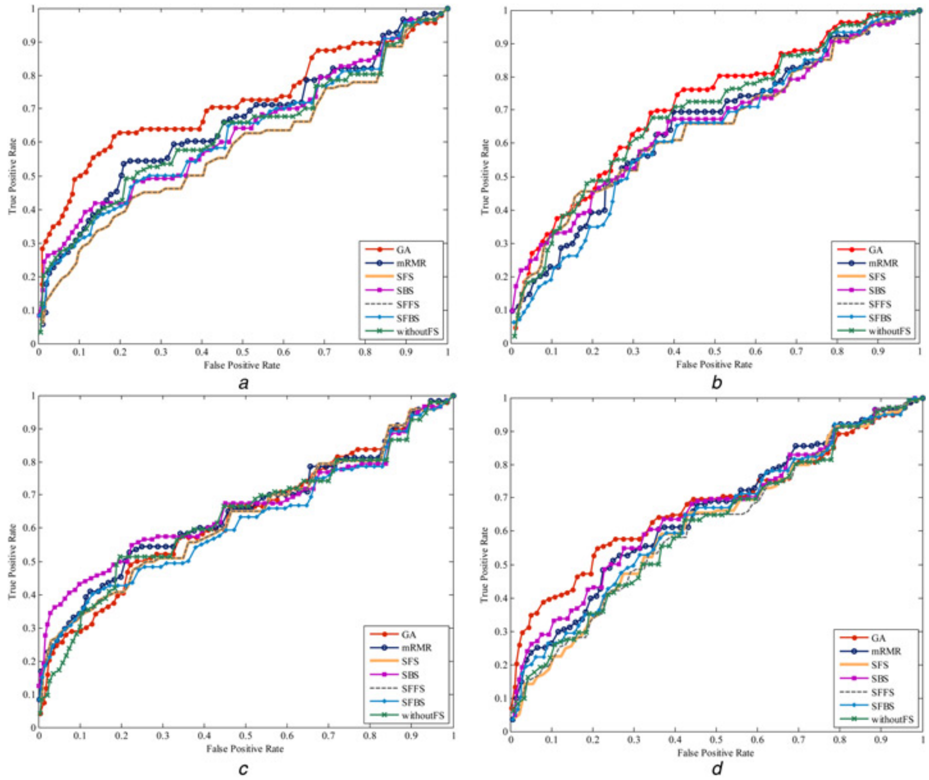


**Fig. 7** *ROC curves for comparison of different feature selection methods in 0° breast images*
*a* Comparing results on right breast images in before ice test
*b* Comparing results on left breast images in before ice test
*c* Comparing results on right breast images in after ice test
*d* Comparing results on left breast images in after ice test

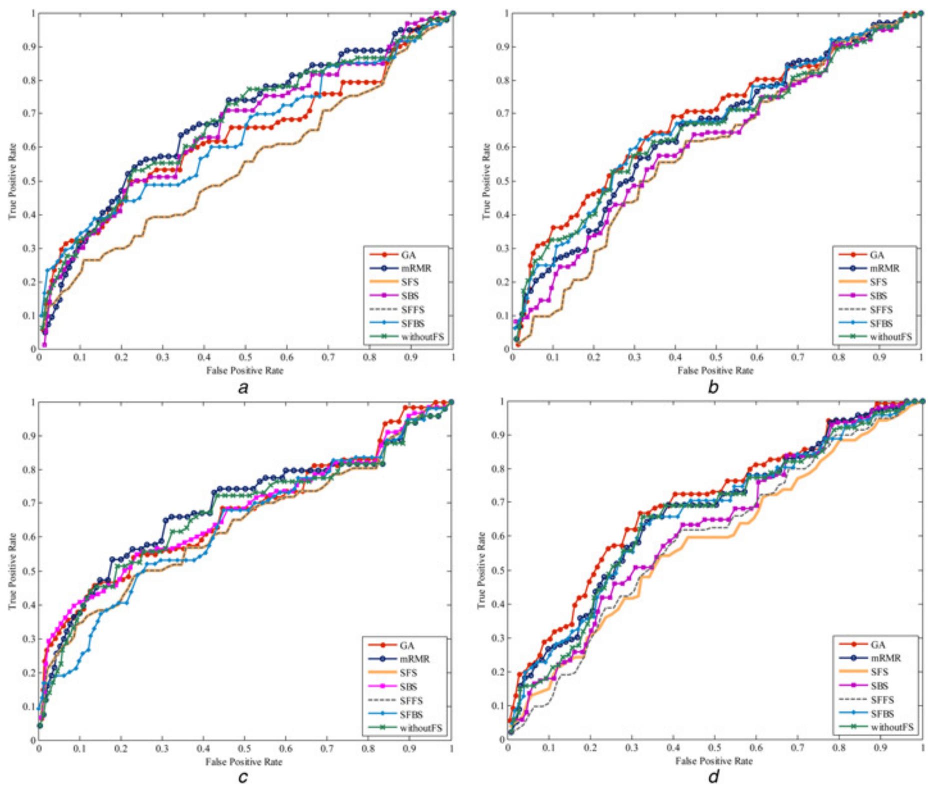


**Fig. 8** *ROC curves for comparison of different feature selection methods in 45° breast images*
*a* Comparing results on right breast images in before ice test
*b* Comparing results on left breast images in before ice test
*c* Comparing results on right breast images in after ice test
*d* Comparing results on left breast images in after ice test

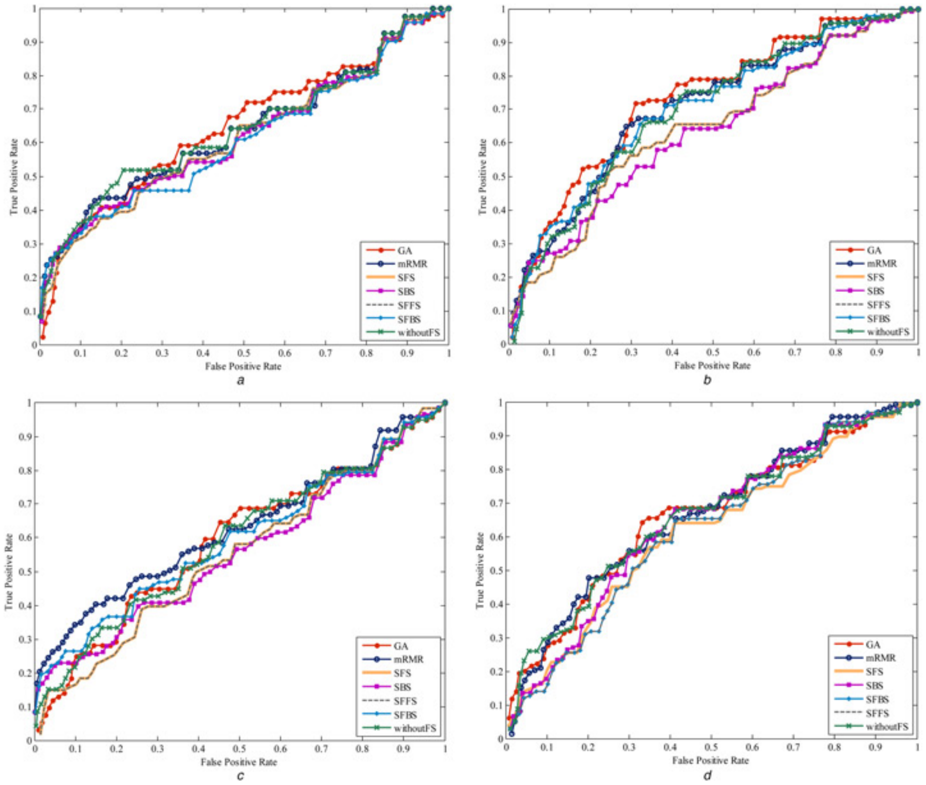


**Fig. 9** *ROC curves for comparison of different feature selection methods in 90° breast images*
*a* Comparing results on right breast images in before ice test
*b* Comparing results on left breast images in before ice test
*c* Comparing results on right breast images in after ice test
*d* Comparing results on left breast images in after ice test

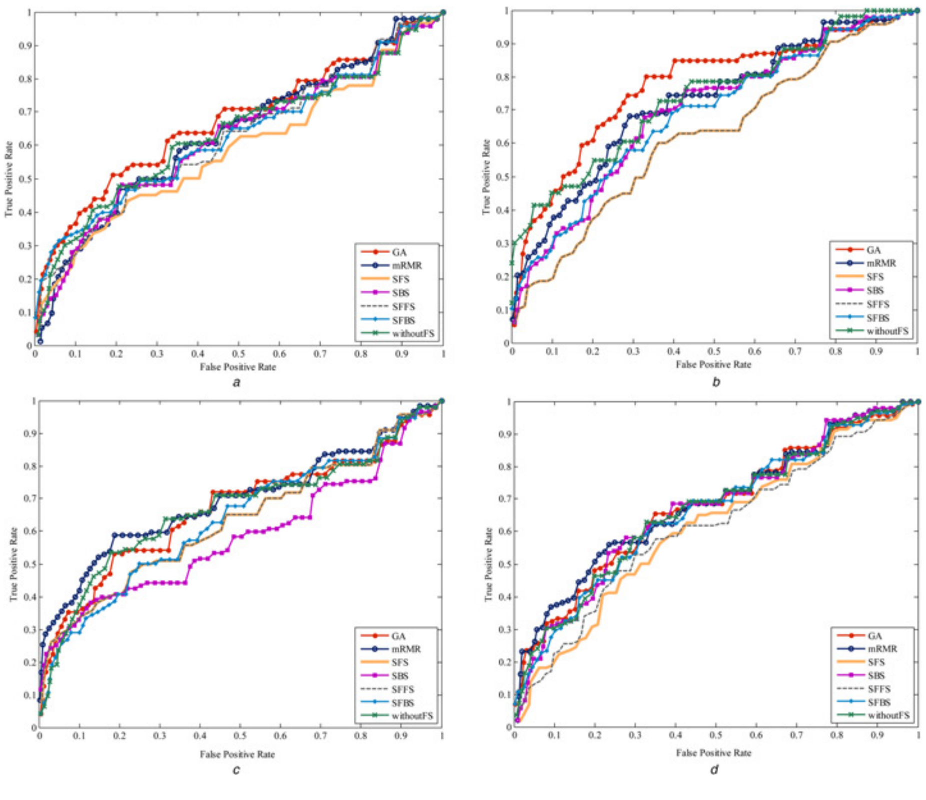


**Fig. 10** *ROC curves for comparison of different feature selection methods in combination of 0°, 45° and 90° breast images*
*a* Comparing results on right breast images in before ice test
*b* Comparing results on left breast images in before ice test
*c* Comparing results on right breast images in after ice test
*d* Comparing results on left breast images in after ice test

**Table 3** Evaluation of the best combinations obtained on the right and left breast images in different breast images degrees in before and after ice test

| | degree | The best combinations | Mean accuracy, % | Mean sensitivity | Mean specificity | Men AUC, % | Mean EER | Mean F-measure, % | Maximum accuracy, % | Mean FPR |
|---|---|---|---|---|---|---|---|---|---|---|
| before ice test | 0 | AdaBoost + GA on the left breast | **85.33** | 0.6333 | 0.9083 | 77.08 | 0.2292 | 63.33 | 100 | **0.0917** |
| | | AdaBoost + GA on the right breast | **87.42** | 0.6856 | 0.9214 | 80.35 | 0.1965 | 68.56 | 100 | **0.0786** |
| | 45 | AdaBoost + GA on the left breast | **85.17** | 0.6292 | 0.9073 | 76.82 | 0.2317 | 62.91 | 100 | **0.0927** |
| | | AdaBoost + mRMR on right breast | **85.15** | 0.6288 | 0.9072 | 76.79 | 0.2320 | 62.78 | 100 | **0.0928** |
| | 90 | AdaBoost + GA on the left breast | **84.67** | 0.6167 | 0.9042 | 76.04 | 0.2395 | 61.66 | 100 | **0.0958** |
| | | AdaBoost + GA on the right breast | **86.21** | 0.6553 | 0.9138 | 78.45 | 0.2154 | 65.53 | 100 | **0.0862** |
| | 0 and 45 and 90 | AdaBoost + GA on the left breast | **83.50** | 0.5875 | 0.8969 | 74.21 | 0.2578 | 58.75 | 100 | **0.1031** |
| | | AdaBoost + GA on the right breast | **88.03** | 0.7008 | 0.9252 | 81.29 | 0.1870 | 70.07 | 100 | **0.0748** |
| after ice test | 0 | AdaBoost + mRMR on the left breast | **83.67** | 0.5916 | 0.8979 | 74.47 | 0.2552 | 59.16 | 100 | **0.1021** |
| | | AdaBoost + mRMR on the right breast | **88.03** | 0.7007 | 0.9251 | 81.29 | 0.1870 | 70.07 | 100 | **0.0748** |
| | 45 | AdaBoost + GA on the left breast | **84** | 0.60 | 0.90 | 75 | 0.2500 | 60 | 100 | **0.10** |
| | | AdaBoost + mRMR on the right breast | **86.36** | 0.6591 | 0.9148 | 78.69 | 0.2131 | 65.90 | 100 | **0.0852** |
| | 90 | AdaBoost + GA on the left breast | **84.17** | 0.6042 | 0.9010 | 75.26 | 0.2473 | 60.41 | 100 | **0.0990** |
| | | AdaBoost + GA on the right breast | **85.15** | 0.6288 | 0.9072 | 76.79 | 0.2320 | 62.87 | 100 | **0.0928** |
| | 0 and 45 and 90 | AdaBoost + GA on the left breast | **85** | 0.6250 | 0.9063 | 76.56 | 0.2343 | 62.50 | 100 | **0.0938** |
| | | AdaBoost + mRMR on the right breast | **87.27** | 0.6818 | 0.9205 | 80.11 | 0.1988 | 68.18 | 100 | **0.0795** |

The bold values are to attract attention, emphasis on the obtained accuracy and showing the superiority of the proposed method

*3.4.1 Comparing results based on different degrees:*

- The arrangement of accuracy obtained for the right breast images in before ice test

$$\text{combination of}\quad 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ > 0^\circ > 90^\circ > 45^\circ$$

- The arrangement of accuracy obtained for the left breast images in before ice test

$$0^\circ > 45^\circ > 90^\circ > \text{combination of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ$$

- The arrangement of accuracy obtained for the right breast images in after ice test

$$0^\circ > \text{combination of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ > 45^\circ > 90^\circ$$

- The arrangement of accuracy obtained for the left breast images in after ice test

$$\text{combination of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ > 90^\circ > 45^\circ > 0^\circ$$

*3.4.2 Comparing results in before and after ice test situation:*

- The arrangement of accuracy obtained for the right breast images in different degrees

$$\text{before ice test}_{\text{right}}\ (0^\circ,\ 45^\circ) < \text{after ice test}_{\text{right}}\ (0^\circ,\ 45^\circ)$$
$$\text{before ice test}_{\text{right}}\ (90^\circ) > \text{after ice test}_{\text{right}}\ (90^\circ)$$

$$\text{before ice test}_{\text{right}}\ (\text{combination of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ) >$$

$$\text{after ice test}_{\text{right}}\ (\text{combination of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ)$$

- The arrangement of accuracy obtained for the left breast images in different degrees

$$\text{before ice test}_{\text{left}}(0^\circ,\ 45^\circ,\ 90^\circ) > \text{after ice test}_{\text{left}}(0^\circ,\ 45^\circ,\ 90^\circ)$$
$$\text{before ice test}_{\text{left}}(\text{combintation of } 0^\circ \text{ and } 45^\circ \text{ and } 90^\circ) <$$

$$\text{after ice test}_{\text{left}}(\text{combination of } 0^\circ \text{and } 45^\circ \text{and } 90^\circ)$$

In these experiments, we expected that the accuracy of the proposed method increases in combination of 3° 0°, 45° and 90° and also in after ice test, but we witnessed the differences in obtained results. So, according to the results mentioned above, the following reasons can be discussed to justify the difference of accuracy in different degrees and also in before and after ice test in the proposed method:

- *How to stand the mass or lesion in breast*: For example, it is possible that the placement of the mass in image with 0° is better than the other degrees, and consequently the extracted features

**Table 4** Comparing the proposed method with previous methods

| Methods | | | | Mean accuracy, % | Maximum accuracy, % | Maximum sensitivity, % | Maximum specificity, % | Maximum FPR, % |
|---|---|---|---|---|---|---|---|---|
| Lee and Yang [38] | | | | – | – | – | – | 8.6 |
| Yaneli *et al.* [39] | | | | – | 78.56 | – | – | – |
| Dinsha and Manikandaprabu [22] | | | | – | 92.86 | 92.93 | – | – |
| Araujo *et al.* [40] | | | | – | 84 | 85.7 | 86.5 | 16 |
| Lashkari *et al.* [25] | BIC | right | 0° | 87.42 | 100 | 100 | 100 | 0 |
| | | left | 0° | 85.33 | 100 | 100 | 100 | 0 |
| proposed method | BIC | right | 0° and 45° and 90° | 88.03 | 100 | 100 | 100 | 0 |
| proposed method | | left | 0° | 85.33 | 100 | 100 | 100 | 0 |
| proposed method | AIC | right | 0° | 88.03 | 100 | 100 | 100 | 0 |
| proposed method | | left | 0° and 45° and 90° | 85 | 100 | 100 | 100 | 0 |

BIC: before ice test and AIC: after ice test

will be more suitable. These suitable features may not be suitable and effective in combination of degrees stage with alongside other extracted features from images with 45° and 90° and reduced the accuracy of the proposed method.

- *The segmentation fault*: For example, it is possible that the segmentation of the images with 0° is done correctly, but according to the problem of the segmentation in images with 45° and 90°, their segmentation are done slightly incorrectly and the accuracy of the proposed method is decreased. So, the incorrect segmentation effect on the results of the combination of 3° and the accuracy of the proposed algorithm will be reduced.
- *Unstable of environment*: These experiments are very sensitive to environment so all conditions such as the room temperature, the necessary time for doing experiments to patient, waiting for a cold stimulation to patients and the time for putting the patients hands in ice should be stable.
- *Non-uniform temperature distribution*: After cold stimulation, because of the cold has entered to the breast by patients hands, the temperature distribution is not uniform in all areas in breast and the tissue of the breast would not be cold equally. Also, according to temperature distribution from hand to breast, the temperature distribution in different degrees of breast images will be different and the various accuracies will be obtained.
- *Unique temperature of everybody*: Owing to unique temperature of everybody, it may not be possible to consider the uniform condition for every person even if the waiting for a cold stimulation to patients are controlled.
- *Change contrast of breast images*: The contrast of images will be changed by applying the cold stimulation, and as a result the accuracy of the system may be reduced.

So, according to existing problem in ice test and little difference accuracy between the obtained accuracy in different situations, the cold stimulation can be omitted. However, this experiment can be used for observing the temperature diagram and thermal changes of everybody in before and after ice test and partly realised to the presence or absence of masses the same as the recent study [10].

## 4 Conclusion

In the proposed method, an imaging technique based on thermography was used to detect early changes occurring in the breast tissue and cancer cells. In this paper, an automatic method developed for breast cancer detection based on thermography to detect suspicious areas and labelled the related TH. To obtain the five categories TH$_1$–TH$_5$, four main stages in 3° 0°, 45°, and 90° implemented with or without considering ice test: pre-processing and segmentation, feature extraction, feature selection and classification. Pre-processing and segmentation stage, include ROI detection and thermal images enhancement, breast tissue segmentation, suspicious areas detection and image matrix normalisation. Some features with different types were extracted from right and left breast images and the effectively features were selected by different feature selectors. Area, MOMent4, skewness, kurtosis and norm value can be marked as the best features in 3° 0°, 45° and 90° of breast images in before ice test and energy, perimeter, kurtosis and Hurst coefficient can be marked as the best features in 3° 0°, 45° and 90° of breast images in after ice test. The selected features were evaluated by different classifiers. Finally, to evaluate the proposed algorithm, 20-fold cross-validation for left breast images and 22-fold cross-validation for right breast images are used. The best combination obtained in before ice test on right breast images is related to combination of AdaBoost with GA in combination of 3° 0°, 45° and 90° with mean accuracy of 88.03% and for left breast images is related to combination of GA and AdaBoost, again in 0° with mean accuracy of 85.33%. The best combination obtained in after ice test on right breast images is related to combination of AdaBoost with mRMR in 0° with mean accuracy of 88.03% and for left breast images is related to combination of GA and AdaBoost, in combination of 3° 0°, 45° and 90° with mean accuracy of 85%. These combinations, gained the maximum accuracy near to 100%. Also, FPRs for the mentioned combinations were equal to 0.0748, 0.0917, 0.0748 and 0.0938, respectively. The minimum FPR in these combinations has been reduced to near zero. It should be noted that the important reasons for the difference results between different breast image degrees are how to stand the mass or lesion in breast and unstable the environment that according to the existing problem in ice test and little difference accuracy between the obtained accuracy in different situations, the cold stimulation can be omitted. However, the temperature diagram and thermal changes of everybody can be used for detecting the presence or absence of masses. So, plotting the temperature diagram can be a symptom to help early detection and not increase the accuracy, necessarily. Moreover one of the reasons to justify the difference between left and right breasts results can be inequality in TH$_1$–TH$_5$.

Table 4 shows the comparison results of the proposed method with other methods. The obtained results indicate high efficiency of the presented algorithm. It should be noted that the best accuracy of mentioned methods in this table compared with the best accuracy of the proposed method.

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## 6 References

[1] Liberman L., Abramson A.F., Squires F.B., ET AL.: 'The breast imaging reporting and data system: positive predictive value of mammographic features and final assessment categories', *AJR*, 1998, **171**, pp. 35–40
[2] Liberman L.: 'Clinical management issues in percutaneous core breast biopsy', *Radiol. Clin. North Am.*, 2000, **38**, (4), pp. 791–807
[3] Rane K.P., Joshi R.R., Chaudhari L.A.: 'IR imaging: a new approach for breast cancer detection', *Int. J. Adv. Electron. Commun. Syst.*, 2014
[4] Medical Imaging Magazine, Cover Story, Women's Health, May 2001
[5] Arena F., Barone C., DiCicco T.: 'Use of digital infrared imaging in enhanced breast cancer detection and monitoring of the clinical response to treatment'. Proc. of the 25th Annual Int. Conf. of the IEEE on Engineering in Medicine and Biology Society, 2003, vol. **2**, pp. 1129–1132, doi: 10.1109/IEMBS.2003.1279447
[6] Gautherie M.: 'Atlas of breast thermography with specific guidelines for examination and interpretation' (Milan, PAPUSA, Italy, 1989)
[7] Ng E.Y., Ung L.N., Ng F.C., ET AL.: 'Statistical analysis of healthy and malignant breast thermography', *J. Med. Eng. Technol.*, 2001, **25**, (6), pp. 253–263
[8] Janda M., Youl P.H., Lowe J.B., ET AL.: 'Attitudes and intentions in relation to skin checks for early signs of skin cancer', *Prev. Med.*, 2004, **39**, (1), pp. 11–18
[9] Ghayoumi Zadeh H., Haddadnia J., Hashemian M., ET AL.: 'Diagnosis of breast cancer using a combination of genetic algorithm and artificial neural network in medical infrared thermal imaging', *Iran. J. Med. Phys.*, 2012, **9**, (4), pp. 265–274
[10] Zhang H., Li K.Y., Sun S.R., ET AL.: 'The value-exploration of the clinical breast diagnosis by using thermal tomography'. Fourth Int. Conf. on Natural Computation, 2008
[11] Williams K.L., Williams F.J., Handley R.S.: 'Infra-red thermometry in the diagnosis of breast disease', *Lancet*, 1961, **2**, (7217), pp. 1378–1381
[12] Parisky Y.R., Sardi A., Hamm R., ET AL.: 'Efficacy of computerized infrared imaging analysis to evaluate mammographically suspicious lesions', *Am. J. Roentgenol.*, 2003, **180**, (1), pp. 263–269
[13] Arora N., Martins D., Ruggerio D., ET AL.: 'Effectiveness of a non-invasive digital infrared thermal imaging system in the detection of breast cancer', *Am. J. Surg.*, 2008, **196**, (4), pp. 523–526
[14] Kennedy D.A., Lee T., Seely D.: 'A comparative review of thermography as a breast cancer screening technique', *Integr. Cancer Ther.*, 2009, **8**, (1), pp. 9–16, doi: 10.1177/1534735408326171
[15] Tang X., Ding H., Yuan Y., ET AL.: 'Morphological measurement of localized temperature increase amplitudes in breast infrared thermograms and its clinical application', *Biomed. Signal Process. Control*, 2008, **3**, (4), pp. 312–318
[16] Schaefer G., Zavisek M., Nakashima T.: 'Thermography based breast cancer analysis using statistical features and fuzzy classification', *Pattern Recognit.*, 2009, **42**, (6), pp. 1133–1137
[17] Acharya U.R., Ng E.Y., Tan J.H., ET AL.: 'Thermography based breast cancer detection using texture features and support vector machine', *J. Med. Syst.*, 2010, **36**, (3), pp. 1503–1510
[18] Satoto K.I., Nurhayati O.D., Isnanto R.R.: 'Pattern recognition to detect breast cancer thermogram images based on fuzzy inference system method', *Int. J. Comput. Sci. Technol. (IJCST)*, 2011, **2**, (3), pp. 484–487
[19] Kapoor P., Prasad S.V.A.V., Patni S.: 'Automatic analysis of breast tomograms for tumor detection based on biostatistical feature extraction and ANN', *Int. J. Emerg. Trends Eng. Dev. (IJETED)*, 2012, **7**, (2), pp. 245–255
[20] Kapoor P., Prasad S.V.A.V., Patni S.: 'Image segmentation and asymmetry analysis of breast thermograms for tumor detection', *Int. J. Comput. Appl.*, 2012, **50**, (9), pp. 40–45
[21] Nicandro C.R., Efren M.M., Yaneli A.A.M., ET AL.: 'Evaluation of the diagnostic power of thermography in breast cancer using Bayesian network classifiers', *Comput. Math. Methods Med.*, 2013, **2013**, Article ID 264246, pp. 1–10
[22] Dinsha D., Manikandaprabu N.: 'Breast tumor segmentation and classification using SVM and Bayesian from thermogram images', *Unique J. Eng. Adv. Sci.*, 2014, **2**, (2), pp. 147–151
[23] Fanavaran Madoon Ghermez (FMG) Co., Ltd. Available at http://www.fmg-med.ir
[24] http://www.ikhc.tums.ac.ir/en/
[25] Lashkari A., Pak F., Firouzmand M.: 'Full intelligent cancer classification of thermal breast images to assist physician in clinical diagnostic applications', *JMSS*, 2016, **6**, pp. 12–24
[26] Expanding the use of thermal imaging in the diagnosis of breast cancer. Documents 002–005, Ver 01
[27] Gautherine M., Haehnel P., Walter J.P., ET AL.: 'Thermovascular changes associated within situ and minimal breast cancers. Results of an ongoing prospective study after four years', *J. Reprod. Med.*, 1987, **32**, (11), pp. 833–842
[28] Peng H.C., Long F.H., Ding C.: 'Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2005, **27**, (8), pp. 1226–1238
[29] Whitney A.W.: 'A direct method of nonparametric measurement selection', *IEEE Trans. Comput.*, 1971, **20**, (9), pp. 1100–1103
[30] Pudil P., Novovicova J., Kittler J.: 'Floating search methods in feature-selection', *Pattern Recognit. Lett.*, 1994, **15**, (11), pp. 1119–1125
[31] Martin-Bautista M.J., Vila M.A.: 'A survey of genetic feature selection in mining issues'. Proc. Congress on Evolutionary Computation, 1999, vol. **2**, pp. 1314–1321
[32] Amalu W.C., Hobbins W.B., Head J.F., ET AL.: 'Infrared imaging of the breast – an overview', in Bronzino J.D. (ED.): 'The Biomedical Engineering Handbook–Medical Systems and Devices' (CRC Press, 2006, 3rd edn.)
[33] Freund Y., Schapire R.E.: 'A decision-theoretic generalization of on-line learning and an application to boosting', *J. Comput. Syst. Sci.*, 1997, **55**, (1), pp. 119–139
[34] Schapire R.E., Singer Y.: 'Improved boosting algorithms using confidence-rated predictions', *Mach. Learn.*, 1999, **37**, (3), pp. 297–336
[35] Burges C.J.C.: 'A tutorial on support vector machines for pattern recognition', *Data Min. Knowl. Discov.*, 1998, **2**, pp. 121–167
[36] Mitchell T.M.: Machine Learning (McGraw-Hill Education, New York, NY, USA, 1997, 1st edn)
[37] Specht D.F.: 'Probabilistic neural network for classification, map, or associative memory'. Proc. IEEE Int. Conf. on Neural Network, 1988, vol. **1**, pp. 525–532
[38] Lee M.Y., Yang C.S.: 'Entropy-based feature extraction and decision tree induction for breast cancer diagnosis with standardized thermograph images', *Comput. Methods Programs Biomed.*, 2010, **100**, (3), pp. 169–282
[39] Yaneli A.A.M., Nicandro C.R., Efren M.M., ET AL.: 'Assessment of Bayesian network classifiers as tools for discriminating breast cancer pre-diagnosis based on three diagnostic methods'. Proc. 11th Mexican Int. Conf. on Advances in Artificial Intelligence., 2012, vol. **7629**, pp. 419–431
[40] Araujo M.C., Lima R.C.F., de Souza R.M.C.R.: 'Interval symbolic feature extraction for thermography breast cancer detection', *Expert Syst. Appl.*, 2014, **14**, (15), pp. 6728–6737