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PATIENT FACING SYSTEMS

Analysis of Breast Thermograms Using Asymmetry in Infra-Mammary Curves

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Abstract
The objective of this research is to propose a methodology to analyse breast thermograms in order to detect breast abnormalities, including cancer. This research work mainly target to segmented ROI that show significant increase in temperature as compared to the neighbouring areas and contralateral sides in breast thermograms. The captured frontal thermograms from each patient is initially smoothed using a Gaussian filter with a standard deviation $\sigma = 1.4$ to reduce noise. Region of interest is segmented using bifurcation points obtained by identifying curve that passes through infra-mammary fold. Infra-mammary curve is detected using Horizontal projection profile. Once the segmentation for analysis is determined, exact location of an abnormality or a lesion is determined. Heat patterns are analysed for symmetry. Asymmetry analysis usually helps to detect abnormalities. Significance and challenges of thermal images are discussed. Once the segmentation for analysis is determined, exact location of an abnormality or a lesion is determined. Heat patterns are analysed for symmetry. Asymmetry analysis usually helps to detect abnormalities. Further, classifiers based on support vector machine and principal component analysis were tested on the dataset used for evaluation. Experimental results and statistical analysis support the proposed methodology is able to detect breast anomalies with higher accuracy. An average accuracy of 95%, sensitivity of 97.05% and specificity of 92.3% was obtained for a set of sixty images with 35 normal and 25 abnormal thermograms using SVM-RBF classifier.

Keywords Breast Thermography · Bifurcation points · Statistical test · GLCM texture feature · Support vector machine · Absolute asymmetry difference

Introduction

Breast cancer is common form of cancer globally and typically occurs in women and rarely in men. Diagnosis and dealing in early stages decrease the hazards during treatment. The vascular action of cancerous tissue is usually higher than that of healthy nearby tissues. Breast thermograms spot amplified blood circulation in vessels and metabolic changes indicating with infection. An irregular thermal pattern indicates breast abnormalities such as fibrocystic breast disease, benign tumor, mastitis, inflammatory breast disease, cancer and other abnormalities.

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Digital infrared breast thermography

Thermography assesses blood flow patterns and irritation [1] [2]. Whereas, Mammography, Ultrasound, Breast MRI assesses muscle density, fluids and masses. In a temperature-organized environment, breast of the patients is allowed to cool superficially to lab temperature (18–22 °C) for 10–25 min. With arms raised, the woman anterior and lateral view images are taken. Cold challenge may also be done, in which the hands are placed into water of 10 °C for 10 min. With cold inducement, abnormal physiology vascular system around tumors doesn't react normally, while normal breast tissue ensure normal activity [3]. Breast thermography was accepted by FDA in 1982 as an adjunct with other gold standard diagnostic breast cancer screening procedure.

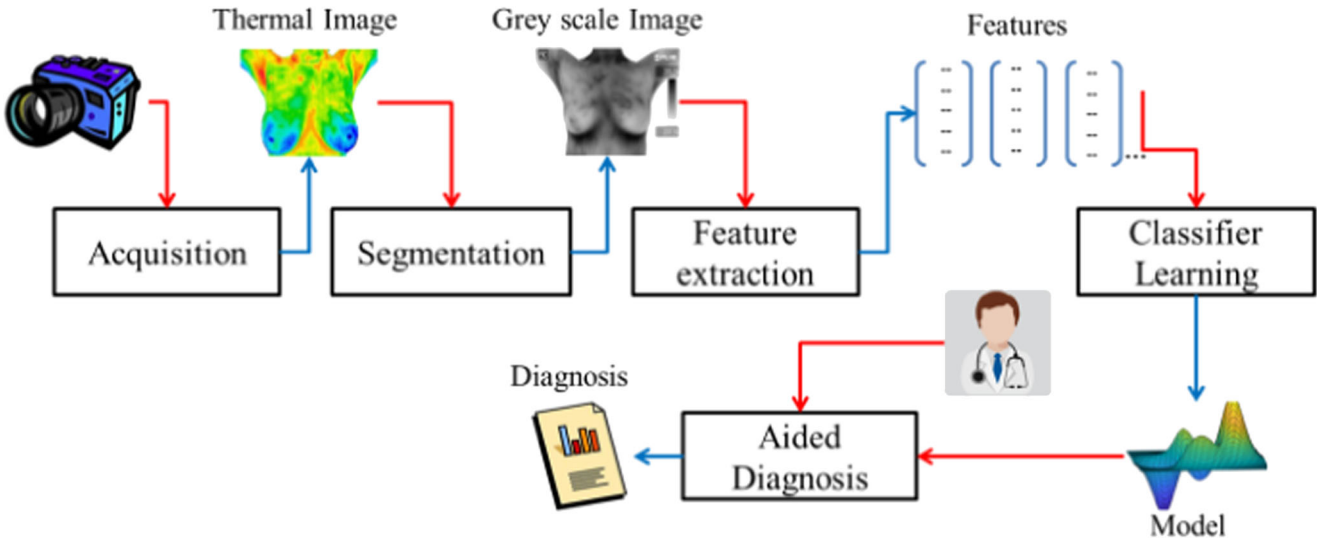


Fig. 1 Classical Approach to Biomedical Image Analysis

Steps involved during risk assessment

Breast thermography is an assessment tool that is used in addition with mammography like examinations along with other medical procedures [4, 5]. Early assessment of risk could be life-saving. A biopsy extracted from the diagnosed region confirms that those irregular patterns were cancer or not [6]. Digital infrared breast thermography uses special camera that detect radiation in infrared range of electromagnetic spectrum and create an image called thermograms.

The advantages of infrared thermography include a non-contact type technique. This technique has fast and reliable output. Whereas, cost of the instrument is high. Accurate temperature measurements are slowed down by differing emissivity and reflection from other surfaces. Multimodal approach may be performed in the configuration of thermography, clinical breast examination and mammography. Figure 1.

Significance of thermal images in medicine

- Thermography is ideal noninvasive screening modality for forecasting the hazard of breast cancer growth.
- Cancers can be detected in early stages for persistent abnormal thermogram carriers.
- No radiation is used to create images unlike other screening modalities. Unnecessary mutation can be avoided.

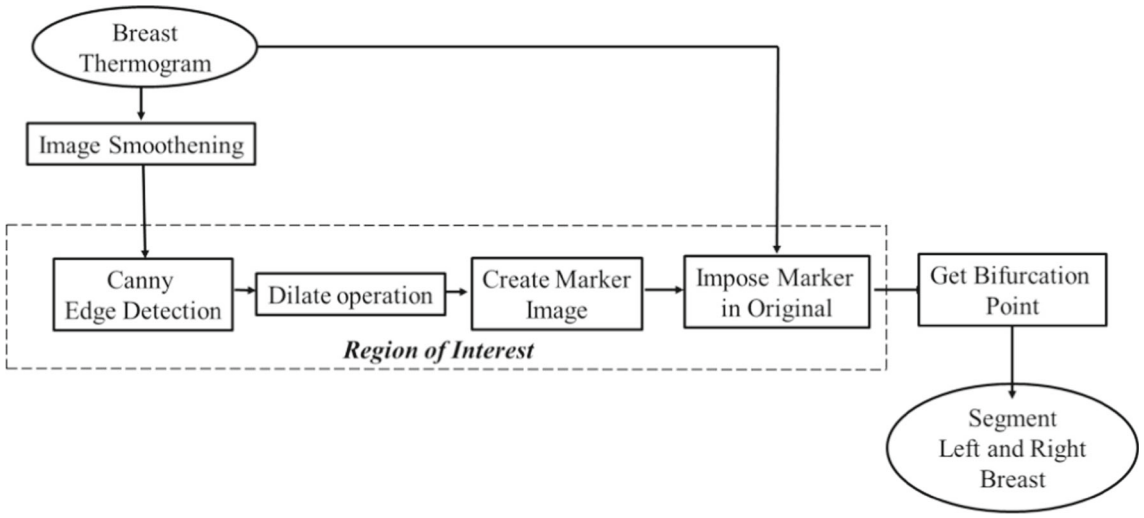


Fig. 2 Block diagram of breast thermogram segmentation

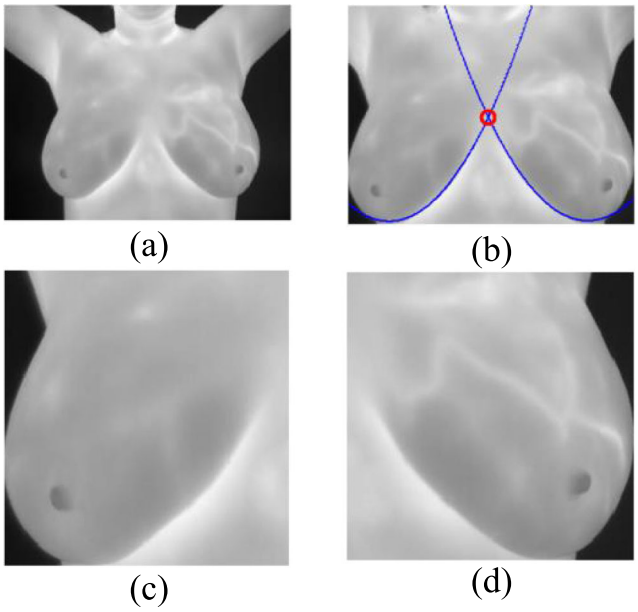


Fig. 3 a Input breast thermogram image b Bifurcation point fitting c Segmentation of right breast d Segmentation of right breast

- Advanced thermal cameras have high spatial and temperature resolutions. They are compact, cheaper, portable, and may be used at any angle.
- Painless and comfortable screening can be performed to detect inflammations.
- When used as part of a multimodal approach (thermography, clinical breast examination and mammography) higher risk of future breast cancer can be predicted.

Background

RN Lawson was first to do a significant research on breast thermogram. In 1956, [7] his findings made a clear approach of non-invasive breast cancer screening. This work suggests the hyper metabolic activity (inflammation) of malignancy and possibly hyper vascularization due to angiogenesis. In 1963, [8] RN Lawson and MS Chughtai suggested that breast malignancy alters surface skin temperature.

Harold Isard in 1972 examined on screening modalities using clinical examination, mammograms, and/or thermograms. [9] 10,055 women subjects were examined over a period of 4-year (1967–1970). 56% of symptomatic participants suffered palpable mass, nipple discharge, or pain. 46% of asymptomatic participants were having family history of breast cancer. In symptomatic participants, mammography showed 85% and thermography showed 72% true-positive results. Thermography along with mammography increased accuracy from 85% to 92%. In asymptomatic participants, 61% in thermography and 83% in mammograms were predicted precisely.

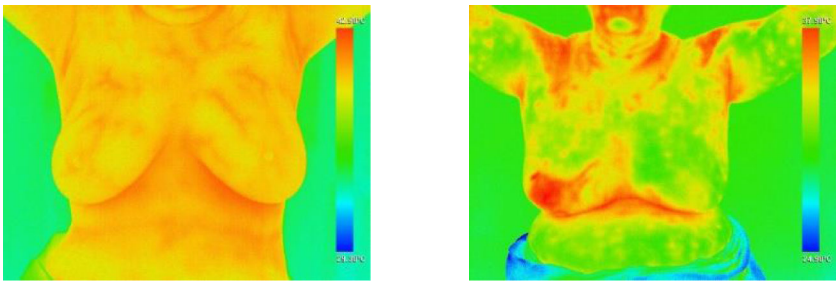
SA Feig et al., developed a Breast Cancer Detection and Demonstration Project (BCDDP) in late 1970s. 16,000 thermography images were compared along with their mammography results with sensitivity to be very low to 39% and specificity around 82% was found [10]. In 1980, M Gautherie and CM Gros studied 1275 women for the period of 5 yrs. Initially, these volunteers had moderate abnormal thermogram. After a period of 5 yrs one third of them had developed benign breast disease diagnosed and confirmed cancers [11]. This study showed that breast thermograms were effective tools for early diagnosis.

Advancement in digital image capturing technique relatively modernized thermography techniques. JR Keyserlingk et al. used high-resolution digital technology to detect ductal carcinoma. In [12] Digital Infrared Thermography Image [DITI] had 17% false negative rate. It concluded that thermography was unsuitable for standalone screening technique.

In 2003 Parisky studied thermograms of 769 subjects using dynamic computerized infrared imaging system in distinguishing between benign and malignant cancerous breast. These subjects were initially suspected for lesion by using mammography [13]. A study in 2008 performed DITI in 92 patients using sentinel BreastScan. Artificial Neural Network (ANN) evaluation criteria were used. Biopsy was used for Comparison with other Modalities. Good rate of early diagnosis resulted with

Table 1. Calculation of Sensitivity, Specificity and Predictive values

		Presence of Disease (Confirmed by Gold standards)		
		Disease Present	Disease Absent	
Test Outcome	Positive	True Positive (A)	False Positive (B)	→ Positive Predictive Value A/(A+B)
	Negative	False Negative (C)	True Negative (D)	→ Negative Predictive Value D/(C+D)
		↓ Sensitivity A/(A+D)	↓ Specificity D/(B+D)	



(a) (b)

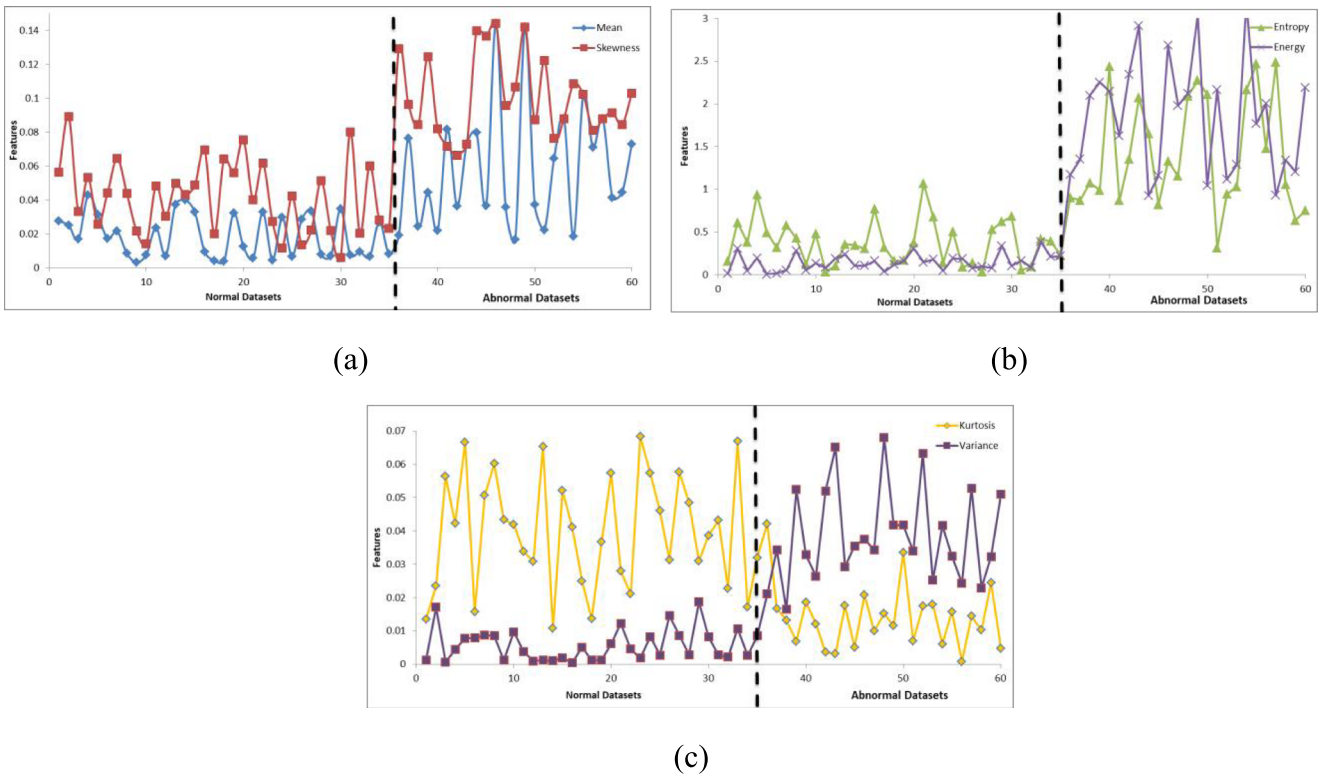
Fig. 4 Breast thermograms a Normal breast b abnormal breast

Table 2 Features on Fig. 4 Normal and Abnormal thermograms

Image Category	Features					
	Mean	Kurtosis	Entropy	Energy	Skew	Variance
Normal	0.0173	0.0657	0.3208	0.3208	0.0440	0.0079
Abnormal	0.1441	0.0207	1.3307	2.6851	0.1441	0.0375

97% sensitivity and 44% specificity. Author suggest for better standardized protocols which should be hold along with modern DITI techniques.

A study of 114 cases was evaluated by R. Berz 2012 [14] with suspicious breast lesions and MammoVision (Active Functional Infrared Breast Thermography) were compared statistically with X-Ray Mammography. The results clearly showed how thermography diagnosed the malignancy cases better where X-Ray Mammography failed to identify. An approach to examine left and right breast regions asymmetry using breast thermograms is presented in work based on image features and classifiers in 2014. 150 datasets of breast thermograms were classified



(a) (b) (c)

Fig. 5 Plot to compare normal and abnormal thermograms feature values: a Mean, Skewness b Energy, Entropy c Variance, Kurtosis

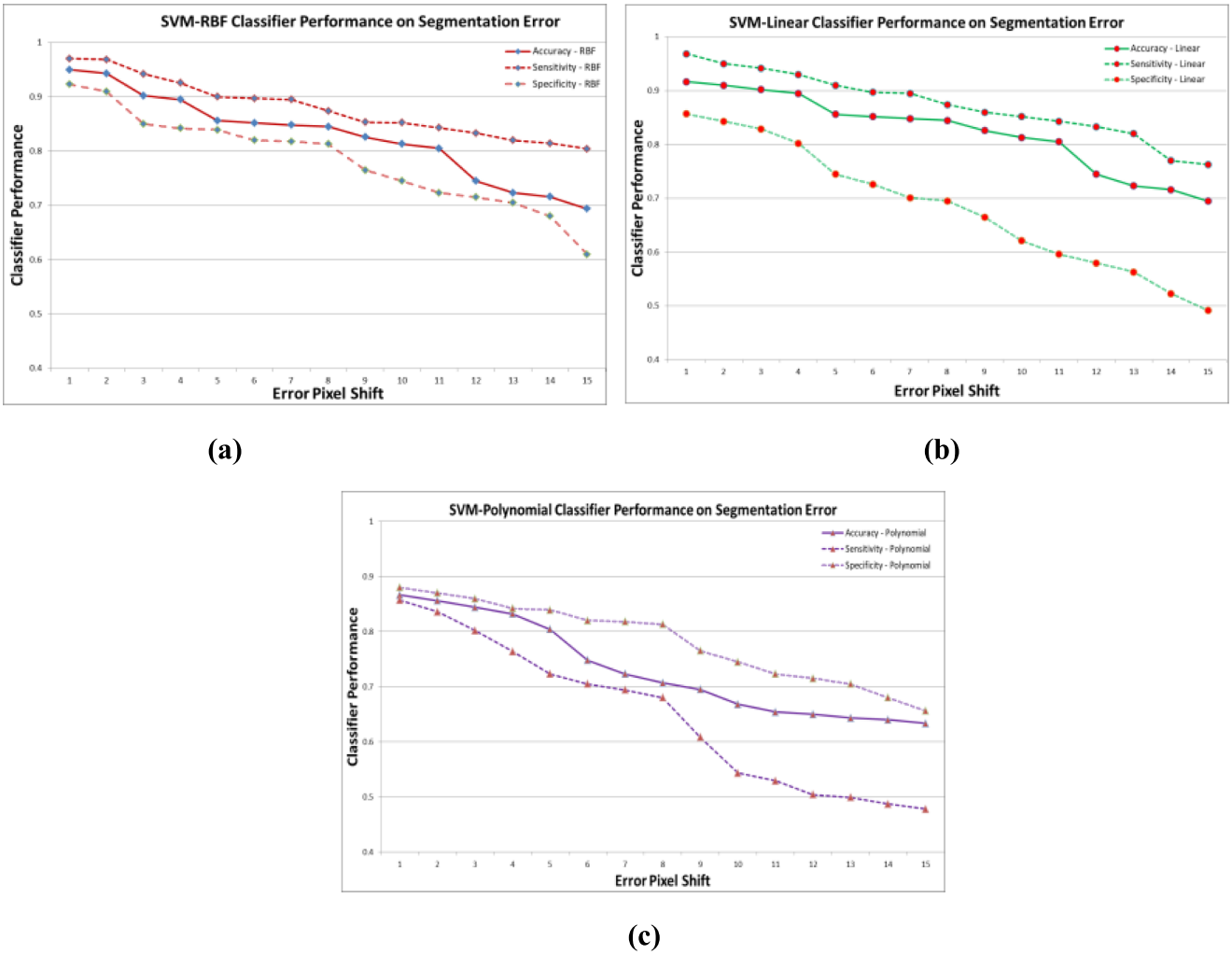


Fig. 6 SVM segmentation error performance on (**a**) SVM-RBF (**b**) SVM-Linear (**c**) SVM-Polynomial

using canonical classification approaches and classifier ensembles designed.

More recently, in 2016 Li-An Wu evaluated whether infrared imaging can be used for invasive breast carcinomas prognosis using cox proportional hazards model by evaluating IR signs [15]. The study concluded that patients with node-negative disease that is, asymmetrical thermography pattern were associated with mortality in patients.

Methods and analysis

Image database

Two sets of data are considered for analysis. In the set one benchmarked image datasets infrared images from Database for Research Mastology [16], were used for classification analysis. Only frontal images under static condition of the healthy and sick images were considered for examination during classification process. Estimation has achieved with thermal images of 60 patients which includes 25 clinically proven cancer data whereas 35 are healthy datasets. Second set of datasets under consideration were collected from DITI India – A digital infrared thermal imaging center. Real time images from the patients were captured by certified thermographer under controlled environment. Thermal scanning is carried out using thermal Imaging or radiometric camera with 640 × 480 resolution in the center. Both normal and abnormal thermograms in frontal as shown in Fig. 2 were collected in static condition for analysis purpose.

Right and left breast segmentation for analysis in asymmetry

Initially, thermogram is converted into their grey scale form. Then, they are smoothed using Gaussian filter. Edge is detected in original image using canny method. Edge detected image is dilated and used as marker to segment the image. Edge dilation operation with 3 × 3 structuring element provides better morphological segmentation [6]. Though adaptive thresholding of canny edge detection the edges of the ROI is formed. The noises in the form of unlinked

lines is eliminated using morphological closing edge marker and imposed on the original image to bound the region of interest. A standard deviation of $\sigma = 1.4$ is applied to filter noise.

By identifying infra-mammary line base region of the breast boundary is detected. Infra-mammary curve is detected using Horizontal projection profile (HPP). [17] Bottom and neck part of the image are segmented out and normalized projection profile is obtained. The peaks and their respective locations are noted. Similarly, left and right side of breasts are separated for asymmetry analysis [6]. Bifurcation point is found at intersection of two infra-mammary curves [4]. Boundary tracing and polynomial curve fitting is applied on these curves and bifurcation point is found. Figure 3b. marks the bifurcation point in breast thermogram. Figure 3c and d. shows right and left breast region respectively.

Feature extraction

Initially, high frequency component present in the ROI of right and left breast is enhanced using nonlinear spatial filter. Texture features is represented by temperature variations in thermograms. Asymmetry Features are extracted such as, absolute difference between left and right breast. Grey Level Co-occurrence Matrix (GLCM) is used for examining texture in spatial domain [18]. GLCM features and first order histogram features include mean, variance, entropy, contrast, correlation, energy, homogeneity, variance, skewness, kurtosis and entropy features are computed from thermograms to find for intensity distribution [19]. For grey images, the number of distinct shades is 256, for each grey scale intensity values.

Pseudo code for the proposed segmentation of ROI

Algorithm 1 Pseudo code for proposed method

Input : Breast Thermogram

Output : Right breast of interest ROI_r and Left breast of interest ROIl

1. Image smoothening and removal of noise by Gaussian filter;
   $\sigma = 1.4$
2. Apply Morphological edge dilation operation with 3×3 structuring element 's' = ROI;
   $ROI = ROI \oplus s$
3. Adaptive threshold by canny edge detection of image = ROI_{edge};
   $ROI_{edge} = CANNY\ (ROI)$
4. Get Horizontal and vertical Projection Profile for ROI_{edge} using Gaussian window : HPP, VPP;
5. Normalize Projection Profiles;
   $HPP = HPP / median\ (peaks)$
   $VPP = VPP / median\ (peaks)$
6. Apply Morphological closing on ROI_{edge};
   $ROI_{edge} = ROI_{edge} \bullet s$
7. Boundary trace ROI_{edge} ;
   $ROI_{trace} = Sort(traceboundary\ (ROI_{edge}))$
8. Infra-mammary curves ROI_1, ROI_2 are detected;
9. Apply Polynomial curve fitting on ROI_1, ROI_2 ;
10. Calculate Bifurcation point by intersecting two curves ROI_1, ROI_2
11. Return segmented Right breast image ROI_r and Left breast image ROI_l;

Algorithm 2 Extract Histogram features

Input : ROI of breast thermogram

Output : 'Mean', 'Variance', 'Skewness', 'Kurtosis', 'Entropy'

1. if image dataset is cell array, then extract all the features from all thermograms ;
2. else return the feature of individual image thermograms;
3. Get total number of pixels 'totPixCount' and grey levels in given image;
4. probability density of occurance of each grey level is given by,
   Prob = pixelCount / totPixCount;
5. normalize grey levels;
   graylevels = graylevels / (max(graylevels) - min(graylevels) + 1);
6. Calculate texture features of histogram by;
   Mean = sum(Probs .* graylevels);
   graylevels-mean diff = graylevels - Mean;
   Variance = sum (Probs * graylevels-mean diff.^ 2;);
   Skewness = sqrt(Variance) ^ (-3) * sum(Probs .* diff .^ 3);
   Kurtosis = sqrt(Variance) ^ (-4) * sum(Probs .* diff .^ 4);
   Entropy = sum(Probs .* Probs);
7. Return 'Mean', 'Variance', 'Skewness', 'Kurtosis', 'Entropy' values;

Table 3 SVM segmentation error performance

Number of Pixels	SVM Kernel - RBF			SVM Kernel - Linear			SVM Kernel - Polynomial		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
1	0.950	0.970	0.923	0.916	0.968	0.857	0.866	0.857	0.880
2	0.943	0.960	0.910	0.910	0.950	0.843	0.856	0.836	0.870
3	0.902	0.942	0.850	0.902	0.942	0.829	0.844	0.802	0.860
4	0.895	0.925	0.842	0.895	0.930	0.802	0.832	0.764	0.842
5	0.856	0.900	0.839	0.856	0.910	0.745	0.804	0.723	0.839
6	0.852	0.897	0.820	0.852	0.897	0.726	0.748	0.705	0.820
7	0.848	0.895	0.817	0.848	0.895	0.701	0.723	0.694	0.817
8	0.845	0.874	0.813	0.845	0.874	0.695	0.707	0.680	0.813
9	0.826	0.853	0.765	0.826	0.860	0.665	0.695	0.608	0.765
10	0.813	0.852	0.745	0.813	0.852	0.621	0.668	0.543	0.745
11	0.805	0.843	0.723	0.805	0.843	0.596	0.654	0.529	0.723
12	0.745	0.833	0.715	0.745	0.833	0.58	0.650	0.504	0.715
13	0.723	0.820	0.705	0.723	0.820	0.563	0.643	0.499	0.705
14	0.716	0.814	0.680	0.716	0.770	0.523	0.640	0.487	0.680
15	0.694	0.804	0.61	0.694	0.762	0.491	0.633	0.477	0.656

Feature classification and cross validation test

SVM classifier is used to classify significant features of thermograms into 'sick' and 'healthy' classes. SVM is a vector space with decision boundary called 'hyper plane' that is maximally far from any data points. A binary support vector machine classifier is trained with image features on kernel function like radial basis function (RBF). Classification accuracy of SVM is calculated by cross validation test of type Leave-One-Out [4]. Here, one feature is left out for testing and the remaining features are used for training the model.

A confusion matrix is generated along with all the test parameters, using true data, predicted data, and positive and negative class labels [19]. Quantitative measures used for evaluation of segmentation results by calculation of accuracy, sensitivity, specificity and predictive values as given in Table 1. Each validation test takes 59 samples as training input, and left one sample is used for testing.

Results and discussion

The proposed algorithm successfully segmented the ROI of breast thermogram and further into left and right breast. To concise upper portion of breast, shape concavity is considered. Similarly, to concise lower portion of the breast convexity is considered as shown in Fig. 3. In this article, with the help of statistical and histogram features of breast, ROI of breast is detected satisfactorily. Image database in the proposed work consists of 35 healthy and 25 sick fontal thermograms. Example normal and abnormal thermograms are given in Fig. 4.

As medical images are complex, thermograms were preprocessed using adaptive thresholding by canny edge detection. Then, the noises in the form of unlinked lines were eliminated using morphological closing edge marker. [20] The resultant image was fused on original image to bind the region of interest. By fitting polynomial line on infra-mammary curves using HPP value at fold of the breast, bifurcation points are accurately detected at curve intersection. When there are no infra-mammary curves, then a default values for x and y are chosen. Thereby, right and left breast are segmented.

Texture features and asymmetry features were extracted and statistically analysed. At default t-value 5, GLCM features mean, variance, entropy, contrast and others were computed. First order histogram features like mean, variance, skewness, kurtosis and entropy were computed from thermograms to find intensity distribution. [21] As an example, features of Fig. 4 normal and abnormal thermograms are summarized in Table 2. For the features like mean, skewness, entropy, energy, kurtosis and variance the variation between normal and abnormal thermograms are depicted in plots Fig. 5. For the features mean, skewness, energy, variance and entropy their respective values for abnormal thermograms are high when compared to normal ones. [21] This is due to asymmetry in abnormal images. However, kurtosis value decreases for abnormal thermograms.

SVM classifier was validated using Leave One out Cross Validation method. At each iteration, SVM classifier was trained using all extracted features. In our case 60 images were used altogether. For training the model 59 images were considered. And the left out image was used for testing the kernels. This process was repeated until all images are tested at least once. RBF, linear and polynomial kernel performances are presented in Fig. 6 at different segmentation errors. SVM kernel-RBF performed better in comparison with other kernels. An accuracy of 95%, specificity 92.3% and sensitivity of 97.05% was achieved with RBF kernal. Table 3.

Conclusion

The role of thermography in screening breast cancer is analyzed in proposed work using features based analysis. Algorithm is formulated such that proposed method help in early detection of breast cancer. Normal and abnormal thermograms are classified by analyzing thermal pattern and temperature across the surface of the breast. Statistically validation assessed the classifier performance for different SVM kernels of RBF, linear and polynomial kernels and error pixel shift is calculated. A better accuracy, sensitivity and specificity of 95%, 97.05%, and 92.3% respectively are achieved using SVM-RBF classifier. In future research, it would be beneficial to verify results against hospital records and compare the results in active thermography conditions. Such analyses form a supportive guideline for treatment planning.

Compliance with Ethical Standards

Conflict of Interest This paper has not communicated anywhere till this moment, now only it is communicated to your esteemed journal for the publication with the knowledge of all co-authors.

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

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