Infrared Physics and Technology 102 (2019) 103041

Contents lists available at ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Computer-aided diagnosis for the identification of breast cancer using thermogram images: A comprehensive review

U. Raghavendra[a], Anjan Gudigar[a,*], Tejaswi N. Rao[a], Edward J. Ciaccio[b], E.Y.K. Ng[c], U. Rajendra Acharya[d,e,f]

[a] Department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, India
[b] Department of Medicine, Columbia University Medical Center, USA
[c] School of Mechanical and Aerospace Engineering, College of Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore
[d] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Clementi 599489, Singapore
[e] Department of Biomedical Engineering, School of Science and Technology, SUSS University, Clementi 599491, Singapore
[f] International Research Organization for Advanced Science and Technology (IROAST), Kumamoto University, Kumamoto, Japan

ARTICLE INFO

Keywords:
Breast cancer
Computer-aided diagnosis tools
Thermograms

ABSTRACT

Breast cancer is a cancer that can form in the cells of breasts. It is much more common in females than in males. The typical periods of cancer development are during puberty, pregnancy, and breastfeeding. Thermography can be utilized for breast analysis, and provides useful data on the location of hyperthermia and the vascular state of the tissue. Computer-aided diagnosis is an algorithmic approach which can be assistive during routine screening, so that human error in breast analysis for cancer detection is reduced. In early-stage cancer, the accuracy of the assessment then increases, enabling clinicians to make an improved diagnosis of benign versus malignant classification. Herein, we have reviewed thermogram-based computer-aided diagnostic systems developed during the last two decades for breast cancer screening and analysis. We explore the quantitative and qualitative performances of machine learning based approaches, which include segmentation based and feature extraction based methods, dimensionality reduction, and various classification schemes, as proposed in the literature. We also describe the limitations, as well as future requirements to improve current techniques, which can help researchers and clinicians to be apprised of quantitative developments and to plan for the future.

1. Introduction

Breast cancer is an uncontrolled growth of breast cells. These cells usually form a tumor that grows into (invades) surrounding tissues, or spreads (metastasizes) systemically. Breast cancer occurs primarily in women, but occasionally men contract it [28,29,130]. It is a common cancer in Indian women, with many new cases and 87,090 deaths reported in 2018 [117]. However, breast cancer is treatable if discovered early [36], and early detection of it can save lives. Breast imaging has enabled major advances to be made in the last decade to diagnose this cancer. Many novel methods are being utilized, and appear promising for detection of metastasis, recurrent disease, and to assess response to treatment. Mammograms, Clinical Breast Exams (CBE), and magnetic resonance imaging (MRI) are employed by healthcare providers to screen for breast cancer. Whereas, Thermography and Tissue Sampling are other screening tests being studied in clinical trials [53,68]. Breast Self-Examination (BSE) and the Clinical Breast Exam (CBE) are two common techniques used by women for personal screening [80,82,128,129]. Mammography (also called mastography) is a process using low-energy X-rays that is employed as a diagnostic and screening tool. However, analyzing mammogram images is a challenging task for radiologists. The accuracy of the technique depends in part upon experience level. As a result, radiologists can miss certain key evidences, which demands biopsy for correct diagnosis. Thermography is a physiologic test to establish heat pattern, and it is also intensely revealing of breast abnormality [35,128,129].

Study results in [1] indicate that far-infrared thermography is better than ultrasonography and mammography for screening purposes, based on sensitivity and specificity [96]. The procedure is non-invasive, rapid, and economical, making it suitable for assessment of large populations. Therefore, thermography can make a significant contribution in the preliminary screening of patients suspected of having breast cancer [2]. Observations from [3] suggested that in diseased breast, symmetry is generally lost and changes in thermovascular pattern will occur

* Corresponding author.
E-mail address: anjan.gudigar@manipal.edu (A. Gudigar).

https://doi.org/10.1016/j.infrared.2019.103041
Received 21 June 2019; Received in revised form 10 September 2019; Accepted 11 September 2019
Available online 12 September 2019
1350-4495/

between the left and right breasts. A new approach was then suggested by [4], which involves a preliminary screening process using thermography following mammography, by estimating tumor location, shape, and size.

Jakubowska et al. [5] used first and second order statistical parameters to calculate signatures of healthy and affected breasts, and the results for first order parameters are considered promising. However, the second order parameters are more sensitive to overall image structure. Salhab et al. [6] focused on dynamic thermal analysis, with 173 women being examined during clinical assessment of their breast symptoms, out of which 118 (68%) were found to have breast cancer. A new approach was proposed by Tang et al. [7] for asymmetric analysis of thermograms. The asymmetric analysis was performed both quantitatively and qualitatively according to the extracted features. The result of the analysis was an extraordinarily high bilateral ratio of variation. A more comparative method of breast cancer detection was proposed by EtehadTavakol et al. [8], which involved comparison between *sixty* contralateral breast images. It is reported that the more similar the thermal image of the right breast to the thermal image of the left breast, the closer the normalized mutual information value approached unity.

Computer-aided diagnosis is a cost-effective non-invasive technique to reduce clinical errors in the diagnostic process [50,125–127]. With the help of computer algorithms, it acts as an assisting tool for practitioners to use during their routine activities. We have systematically reviewed recent studies on thermogram based computer-aided diagnosis for breast cancer, and these are presented in the subsequent section.

2. Specifics of computer-aided diagnosis

Computer-aided diagnosis is one of the most common techniques used in regular clinical practice, and it has been found helpful for analysis of brain and skeletal abnormalities, vascular disorders, and breast cancer [84,85]. The structure of a computer-aided diagnostic system is shown in Fig. 1. The major processing stages are: preprocessing, segmentation or feature extraction, dimensionality reduction, feature selection, and classification. The following describes the steps.

2.1. Material description

Availability of a standard database plays a crucial role in research such as this, where there are varied results. Thermograms are stored mainly in private image databases, such that the images are accessible to the patient and physician for a limited time. Investigators have used the Compact Thermo TVS-2000 kit [42]. In [40,47] the Thermo TVS2000 MkIIST System with a 3.0–5.4 µm short wavelength was used. The images were converted to grayscale and then cropped [47]. Whereas, in [40] was used a constant resolution of 1280 × 1024 pixels. The URL http://visual.ic.uff.br/dmi enables user registration for access to all functionalities of the database [21]. Fig. 2 shows sample images of thermography from the private database.

2.2. Pre-processing

Geometric transformations such as rotation, scaling, and translation are the commonly used techniques for image enhancement [26].

Many researchers have relied upon advanced software and hardware to pre-process the thermogram so as to readily extract important data. The two most common approaches are: PCA (Principal Component Analysis) and LDA (Linear Discriminate Analysis). S. Mitra and C. Balaji also conducted some finite element simulations for the forward problem using the commercially available COMSOL multiphysics software [45]. Janghel et al. [46] have removed unwanted noise and data, as well as adding details during pre-processing. J. Koay et al. [39] have used several methods for image processing, including resizing the image and converting a true color image to grayscale. The images were cropped to a standard size prior to running them through the software [48]. From the obtained grayscale images of the right and left breasts are extracted textural parameters. In [77], the pre-processing of the thermogram images was done by enhancing the images using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method.

Thermograms collected by others have contained the breast region along with patient information, and a pseudocolor bar chart displaying temperature ranges [78]. Such regions are removed from the complete image in order to obtain the breast region alone, followed by RGB to grayscale conversion. In [39], a semi-automated region of interest (ROI) selection was performed using elliptical shape and boundaries. The Canny edge detector is useful to extract the margins, as it is one of the most precise edge detection operators [61]. Serrano et al. [76] extracted the ROI by selecting a square window of the same size for each thermogram. Then, preprocessing was utilized to generate right and left breast imagery. Various ways to segment images, some using threshold, edge, and region-based techniques are discussed in [67]. In this work, the Hough transform and Canny edge detection were applied. The images used were of dimension 320 × 240 pixels. The software of the thermal camera transforms the false-color images to grayscale images. After conversion to grayscale, the images can be passed through an automatic segmentation algorithm [62], resulting in ROIs of the left and right breast. This refinement aims to delete all of the contents of the segmented image that do not belong to the breast. Similar pre-processing is proposed in [58].

2.3. Feature extraction

Feature extraction is a process useful to extract meaningful information from images. The extracted features can play an efficient role during subject categorization. The various feature extraction methods are described as follows:

Texture: Textural changes are useful for feature representation. The Gray Level Co-occurrence Matrix (GLCM) [101], Fractal Dimensions [106], Run Length Matrix [105], Local Binary Pattern (LBP) [107], and Law's Texture Energy (LTE) [109] are employed to deduce normal versus abnormal thermal images.

Entropy: Entropy measures the degree of uncertainty of pixel values

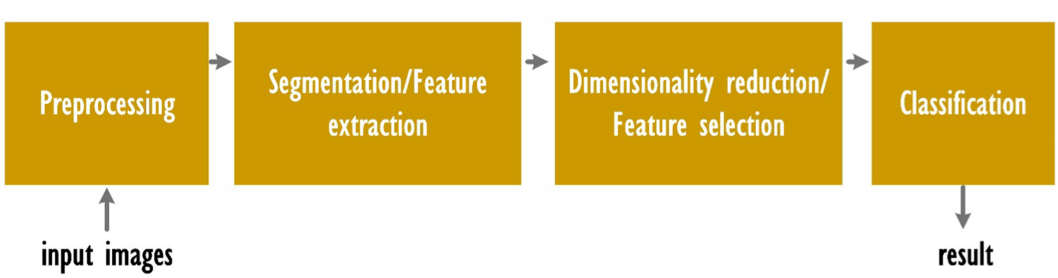

Fig. 1. Graphical illustration of computer-aided diagnosis system.

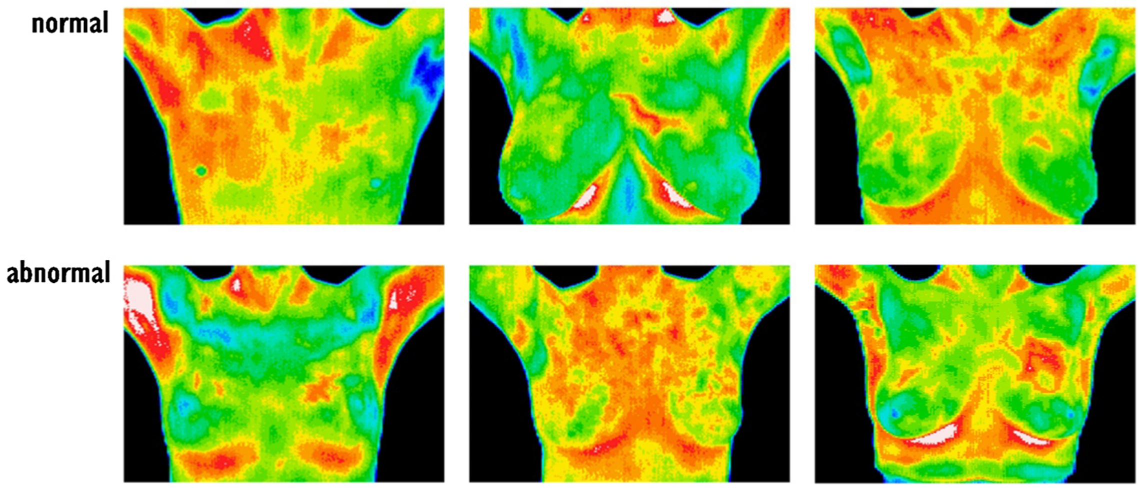

Fig. 2. Normal and abnormal sample thermal images [40].

or the amount of information content present in an image [100]. A higher entropy value indicates the richness of pixel intensity values of an image. Non-Shannon entropies can measure the dynamic range of scattering conditions in comparison with Shannon, and hence are widely used to evaluate scatter density and regularity.

Hu's Invariant Moments: Moments are mathematical functions used to describe the geometrical patterns present in an image. Moment Invariants, based on image moments, computes feature vectors which will remain intact under scaling, translation, and rotation of an image. Hu's invariants calculates seven moments based on normalized central moments up to the third order [99].

Discrete Wavelet Transform (DWT): DWT computes transient features of an image, which are localized with respect to time and frequency. DWT applies low-pass and high-pass filtering to the input signal in a successive fashion to generate approximation and detail coefficients. The approximation coefficients are further decomposed recursively based on the number of levels of decomposition required. DWT calculates coefficients with high spatial accuracy for features like sharp borders present in the thermographic pattern of a breast image [98].

Higher Order Spectra (HoS): HoS consists of moments whose order is greater than two. These higher order moments can be combined to obtain higher order cumulants. The spectrum consisting of third order cumulants, termed the bispectrum, is one of the most widely used HoS cumulants to extract features for automated diagnosis [97].

Fourier Spectrum (FS) Descriptors: Fourier Spectrum descriptors are capable of describing shapes with a closed contour. These descriptors are invariant to transformations like scaling and rotation and hence can be used to measure the changes in the edges of the image regions [103].

Statistical analysis: Statistical analysis is performed to obtain a summary of the data which has been collected, and also provides understanding of the various processes involved in generation of the stored data. Proper statistical analysis helps to draw significant, reliable, and valid conclusions from the data. A mathematical model is often used to perform the statistical analysis to derive in-depth details of the techniques involved in data generation [102].

Direct feature extraction using neural networks [39,33,84,85,42,95,79] and wavelet transformation are commonly used techniques [63,81,48,51]. HOG features with a Student's *t*-test based feature selection algorithm is employed in Raghavendra et al. [40]. It provides p-values and t-values for comparison of the features. Statistically, the feature with low p-value ($p < 0.05$), and higher t-value is preferred as a threshold level for determining significance in classification. O.D. Nurhayati et al. [37] extracted statistical features including the mean, variance, skewness, and kurtosis. M.R.K. Mookiah et al. [48] extracted statistically significant features based on GLCM and DWT from the thermograms. Similarly, Acharya et al. [47] extracted textural features of thermograms from the co-occurrence matrix and from the run-length matrix. Krawczyk et al. [49], aimed to analyze the asymmetry between thermograms. Hence, the temperature distribution captured in thermograms was calculated by computing the mean and standard deviation in temperature. In [64–66], statistical features were used for the detection of abnormality in thermal imagery.

M. EtehadTavakol et al. [9], developed an algorithm to detect benign and malignant tumors using fractal analysis. The method has shown significant differences among the benign versus malignant patterns. In [10], images were obtained from 50 females for a system that is represented as an ITBIC interpreter, to conclude whether a breast is normal or abnormal. The ITBIC interpreter identified 43 normal cases and 4 abnormal cases. Milosevic et al. [11] have developed a new segmentation and texture based algorithm and achieved 92.5% accuracy. Krawczyk et al. [12] presented a cost-sensitive classification approach in which a series of statistical image features were extracted, and an accuracy of 91.09% was achieved. In [13], various asymmetry features were used for improved classification. Acharya et al. [14] evaluated 5 HOS features from thermograms with a feedforward artificial neural network (ANN) classifier and achieved 92% sensitivity. Luna et al. [15] proposed a method based on the simulated annealing technique. M. EtehadTavakol et al. [16] have shown application of Lyapunov exponents for differentiating breast lesions. Sheeja V. Francis and M. Sasikala [17] concluded that texture-based asymmetry analysis of thermal imagery was useful to construct improved discriminative features, with an accuracy of 85.19%. M. EtehadTavakol et al. [18] showed that HOS features were helpful in differentiating classes of thermograms. With 11 normal, 12 benign, and 9 malignant cases, the malignant cases were detected with 95% accuracy. M. Etehadtavakol et al. [19] have developed a model using textural features and the Adaboost classifier, with a maximum performance having 86% accuracy. Nasser Samadzadeh Aghdam et al. [20] have tried a different model using the HSI and CIELAB color space. It is confirmed that the Gabor wavelet transform may be a best structural descriptor for the early diagnosis of breast lesions [22]. Sheeja V. Francis et al. [23], proposed a Curvelet transform based features representation for automated classification. The SVM classifier provided 86.36% and 90.91% accuracy for the statistical and Haralick features, respectively. Marcus C. Araujo et al. [24] have explored the application of interval data in symbolic data analysis (SDA) for breast abnormality detection, finding a sensitivity of 85.7% and specificity of 86.5% for the malignant class. In [25], different segmentation techniques were compared, and it was concluded that the level set is the better method to segment breast lesions.

In [34], localized temperature increases were studied. The

Table 1
Entropy based features [131,132].

Features	Normal		Abnormal			
	Mean	SD	Mean	SD	p-Value	t-Value
ENT1	0.005693	0.0037	0.004151	0.003668	0.145359	1.480181
ENT7	0.950635	0.002411	0.950127	0.003303	0.537592	0.620917
ENT4	4.031493	0.746851	4.173781	0.907806	0.547896	0.605202
ENT3	4.725452	0.158623	4.748076	0.161763	0.619854	0.499293
ENT5	6.371512	0.264839	6.407833	0.309125	0.657505	0.446137
ENT6	7.01906	0.128905	7.036765	0.159547	0.667983	0.431574
ENT2	7.396177	0.089203	7.405025	0.140746	0.791777	0.265479

Table 2
HOS based features [14,97].

Features	Normal		Abnormal			
	Mean	SD	Mean	SD	p-Value	t-Value
HOS69	1.996559	0.353697	1.796923	0.409678	0.071323	1.844253
HOS47	0.032103	0.011119	0.047372	0.040355	0.074408	1.823821
HOS29	0.129097	0.028813	0.152458	0.060406	0.087332	1.745302
HOS68	2.096655	0.344077	1.929365	0.414592	0.127108	1.552517
HOS65	1.922224	0.30816	2.048758	0.303069	0.149776	1.463766
HOS37	0.052513	0.044256	0.075832	0.067136	0.153567	1.449979
HOS17	0.682934	0.077897	0.651654	0.077287	0.160549	1.425273
HOS35	0.280964	0.115679	0.236315	0.11883	0.184567	1.346181
HOS4	0.648713	0.054103	0.628031	0.055729	0.189346	1.331399
HOS15	0.53986	0.063611	0.561553	0.054686	0.202183	1.293051

physiological changes with numerical simulation were determined in [43]. The various descriptors from the literature, such as entropies, HOS, HOG, and textures, were analyzed using 25 normal and 25 abnormal subjects. Tables 1–4 show the various significant features which are used to address the abnormalities. Although HOG produces the maximum feature vector, those features are significant and discriminable as compared to other conventional features [40]. A complete summary of the feature-based computer-aided diagnosis tool is described in Table 5.

2.4. Segmentation and feature extraction

Another approach in detecting abnormality in breast thermograms is segmentation of the ROI from the images, and then extracting the significant features from it [70,71,54,69,61,72,86,87,90,94,96]. P. Kapoor et al. [61] stated that the feature of the heat patterns will include salient statistical parameters such as skewness, temperature variation, and kurtosis. In [67], the authors have selected simple statistical features for analysis from ROI. They have used two different approaches for feature extraction. In the first, the entire image was used. In the second, the ROIs were divided into four components.

Table 3
HOG based features [40].

Features	Normal		Abnormal			
	Mean	SD	Mean	SD	p-Value	t-Value
HOG1598	0.002736	0.001773	0.004619	0.002328	0.002316	3.217902
HOG1625	0.00289	0.001966	0.004751	0.002318	0.003596	3.06211
HOG1411	0.0145	0.006548	0.022007	0.01067	0.004293	2.998199
HOG1150	0.015859	0.007767	0.025428	0.014201	0.004825	2.95563
HOG1098	0.043062	0.020115	0.029639	0.013081	0.007397	2.797122
HOG1125	0.041463	0.019484	0.029169	0.010936	0.00835	2.751254
HOG234	0.071202	0.012269	0.059717	0.0172	0.009111	2.717974
HOG1577	0.00116	0.000978	0.00249	0.002293	0.010392	2.667351
HOG1177	0.017817	0.010438	0.026731	0.013075	0.010483	2.663979
HOG864	0.047445	0.021007	0.03334	0.016614	0.011348	2.633182

Table 4
Texture based features [47].

Features	Normal		Abnormal			
	Mean	SD	Mean	SD	p-Value	t-Value
TEX23	299.3622	42.00853	314.7689	32.65284	0.154165	1.447831
TEX12	0.869213	0.012479	0.864863	0.013987	0.251628	1.160392
TEX27	0.039084	0.00615	0.040835	0.005949	0.311295	1.023302
TEX17	−0.23882	0.228029	−0.16367	0.362737	0.384854	0.877002
TEX8	63.37303	10.05265	65.84613	11.72238	0.427226	0.800744
TEX26	25.7899	14.61324	23.25354	6.730629	0.434432	0.788241
TEX21	25.87417	3.194179	26.53747	2.959981	0.45004	0.761574
TEX7	2.148516	0.12261	2.124952	0.116415	0.489255	0.696854
TEX1	24.29745	3.495498	24.92558	3.656249	0.537614	0.620882
TEX4	2.553508	0.185721	2.522821	0.183298	0.559288	0.588001

Luciano Boquete et al. [73] have proposed a method which involves separation of chrominances and luminance components, obtaining the independent components analysis (ICA) component extraction followed by segmentation of the tumor region. H. Qi et al. [58] have quantified the distribution of different intensities in the thermogram by calculating higher-order statistics as feature elements. From the above set of features the existence of asymmetry was decided. The first order statistical features along with fifteen textural features were extracted in another study [74]. In [79], ROI was segmented using the Canny edge detector, and asymmetric analysis based features were extracted. Serrano et al. [76] described a methodology of feature extraction based on fractal geometry. The complete details of the methods using segmentation based feature extraction are shown in Table 6.

2.5. Data dimensionality reduction/feature selection

Feature extraction generally extracts large amounts of data from an image, which makes evident the reason why selection and reduction is often needed. This suggests the necessity of data dimensionality reduction procedures. Indeed, more data is not always better - large amounts of redundant data may produce a worse performance in data analytics applications [83,108]. Jakubowska et al. [81] have applied two approaches based on the Fischer coefficient and minimization of classification error probability (POE). To enable data to be acquired which is less correlated and of lower order, PCA and LDA methods are utilized. PCA is often employed for improved dimensionality reduction [37]. This advantage, however, comes at the price of greater computational cost. Raghavendra et al. [40] have utilized different linear projection techniques including PCA, ICA, and Locality Preserving Projections, to reduce the dimensionality of the original data.

In order to reduce redundant data samples, most of the studies in the literature have employed various feature selection techniques. The most commonly used technique incorporates the t-value [40,118].

3. Classification

Automated classification algorithms are predictive models useful to determine the class/category of an unknown class/subject. The principle behind these classification algorithms is the discovery of features which separate individual classes from the training dataset.

The most commonly used classifiers are the support vector machine (SVM) [27] with various kernel functions including: Radial Basis Function (RBF), polynomial and linear. Decision Tree (DT) [30], Sugeno Fuzzy [31], k-Nearest Neighbor (k-NN) [30], Probabilistic Neural Network (PNN) [32], fuzzy rule based [60] and Self-Organizing Map (SOM) [104].

Tuan Zea Tan et al. [44], have proposed that complementary learning fuzzy neural networks (CLFNN) not only provide satisfactory performance in classification, but also are rapid in learning. In [33], RBFN was trained to produce the desired outcome, which was either

Table 5
Summary of feature based methods.

Authors	Method	Classifier	No. of Samples	Results
T.Z. Tan et al. [44]	Mean median, mode and standard deviation, skewness	FALCON-AART	78	Sensitivity/Specificity: Cancer Detection:100%/60% Breast Tumor Detection: 33.33%/ 90.91% Breast Tumor Classification: 33.33%/ 95.45%
E.Y.K. Ng and Eckee [33]	Mean median, mode and standard deviation	ANN & RBFN	90	Accuracy: 80.95% Sensitivity: 81.2% Specificity: 88.2%
Gerald Schaefer et al. [60]	Statistical features, histogram, cross co-occurrence, Mutual information, etc.	Fuzzy Classifier	150	Accuracy: ~80%
Mitra and Balaji [45]	Temperature measures	ANN	447	Accuracy: 98%
Janghel et al. [46]	–	ANN	699	Accuracy LVQ: 95.82% CL: 74.48% MLP: 51.88%
Nurhayati et al. [37]	Statistical features, Principal Component Analysis	–	150	–
Mookiaha et al. [48]	DWT, Texture Feature	DT, Fuzzy classifier	50	Accuracy: 93.30% Sensitivity: 86.70% Specificity: 100%
Acharya et al. [47]	Texture features	SVM	50	Accuracy: 88.10% Sensitivity: 85.71% Specificity: 90.48%
Krawczyk and Schaefer [49]	Statistical features, moment , Histogram, cross co-occurrence, mutual information, Fourier descriptors	multiple classifier system	150	Accuracy: 89.03% Sensitivity: 81.96% Specificity: 90.80%
Antony et al. [51]	DWT, GLCM, Texture and Gabor features	ANFIS	322	–
Raghavendra et al. [40]	HOG, KLPP	Decision tree	50	Accuracy: 98% Sensitivity: 96.66% Specificity: 100%
Nabil et al. [88]	Texture feature, Statistical features	SVM	80	Accuracy: 91.25% Sensitivity: 93.3% Specificity: 90%
Maira et al. [89]	Haralick and Zernike features	ELM	100	Accuracy: 73.38% Sensitivity: 78% Specificity: 88%
Vasconcelos et al. [91]	Temperature features	–SMO	380	Accuracy: 93.42% Sensitivity: 94.73% Specificity: 92.10%

positive for cancerous or negative for healthy cases. G. Schaefer et al [60] have proposed a fuzzy rule-based classification system consisting of N fuzzy if–then rules, each of which has a certain form. R. R. Janghel et al. [46] used a different neural network approach for the classification of the extracted features. Classification was done using the Multi-Layer Perceptron (MLP) Neural Networks, Radial Basis Function (RBF) Neural Networks, and Learning Vector Quantization (LVQ) Neural Networks in conjunction with a competitive learning algorithm. M.R.K. Mookiaha et al. [48] used different classifiers including DT, FS, Gaussian Mixture Model (GMM), KNN, Naïve Bayes (NB) and PNN for the extracted features. U. R. Acharya et al. [47] used the SVM for the automated diagnosis of breast cancer.

3.1. Performance evaluation and validation technique

The cross validation technique surveys a classifier with a training dataset. For this method, the entire dataset is randomly separated into k-equivalent (or practically equivalent) parts. Each part contains a similar proportion of tests from the two classes. In the main cycle (overlay), k-1 information parts are utilized to train the classifier and the rest of the part is utilized for testing. The emphasis is repeated k-1 times, incorporating an alternate test set (with the rest of the folds as preparing sets) each time. This method is employed to create classifiers for thermography based computer-aided diagnosis frameworks. In the offline framework, the order results are surveyed by execution measures, for example, False Positive (FP), True Positive (TP), False Negative (FN), True Negative (TN), Accuracy (A), Sensitivity (Se) and Specificity (Sp) [38]. This evaluation determines the most suitable grouping calculation for the online framework [40,47,48].

Receiver Operating Characteristic (ROC) plots provide a file of precision by exhibiting the limitations of a test's capacity to segregate between elective conditions of well-being over the total range of working conditions. Various investigations on IR thermography have utilized the ROC bend to gauge the cutoff point, symptomatic accuracy (shown by the territory under the bend), sensitivity, and specificity. From an algorithmic point of view, ROC is a strategy to assess the capacity of a test to separate infected cases from ordinary cases. ROC enables us to play out a target examination between at least two imaging modalities. ROC is a helpful methodology, as contrasted with different techniques that do not measure demonstrative exactness in an adequately complete or significant way. In a word, ROC investigation is valuable to choose the ideal slice point to dichotomize a constant scale [44].

4. Discussion

Although many researchers have demonstrated desirable results for breast tumor characterization, the number of sample images used thus far were low. Ng and Kee [33] used only 90 thermal images obtained from female patients at Singapore General Hospital, Singapore. R.R. Janghel et al. [46] used a database of 699 patients from The Wisconsin Breast Cancer Diagnosis (WBCD) database. Tang et al. [34] included 117 patients from the People’s Liberation Army General Hospital (PLAGH), China. Nurhayati et al. [37] examined thermal images of 150 female patients from Yogyakarta Hospital. Unlike the mammogram database — Digital Database for Screening Mammography (DDSM),

Table 6
Summary of segmentation based methods.

Authors	Method	Classifier	No. of Images	Results
Dinsha and Manikandaprabhu [77]	K mean and fuzzy c means, GLCM features	SVM & Bayesian	9	SVM/Bayesian Accuracy: 85.71%/92.86% Sensitivity: 92.31%/92.93% Precision: 92.31%/92.86%
Francis et al. [78]	Temperature based ROI selection, Bispectral Invariant Features	SVM	72	Accuracy: Normal-Benign: 91.6% Normal-Malignant: 90.3% Benign-Malignant: 80.6%
Chen et al. [41]	Manual ROI selection, Texture features	Neural Networks	140	Accuracy: 95.0% Sensitivity: 98.0% Specificity: 93%
Qi et al. [58]	Edge based segmentation, Hough transform, statistical features	k-NN	24	Cancerous Left/Right Mean: 0.0010/0.0008 Variance (10^{-6}): 2.0808/1.1487 Skewness: 2.6821/1.1507 Kurtosis: 1.0481/0.3459
Koay et al. [39]	Manual ROI selection, Statistical features	BPNN	19	–
Serrano et al. [76]	Window based ROI, Hurst Coefficient and Lacunarity features	Naïve Bayes	28	ROC Area: 0.958
Borchartt et al. [67]	Otsu thresholding, Statistical features	SVM	28	Accuracy: 85.71% Sensitivity: 95.83% Specificity: 25.0%
Boquete et al. [73]	Otsu thresholding, Independent Component Analysis		8	Sensitivity: 100.0% Specificity: 94.7%
Rodrigues et al. [52]	Automatic ROI selection, Texture feature	SMO	102	Accuracy: 61.7%
Ali et al. [74]	Data acquisition protocol, statistical and texture features	SVM	63	Accuracy: 100%
Lessa and Marengoni [79]	Canny edge detector, statistical features	ANN	94	Accuracy: 85.0% Sensitivity: 87.0% Specificity: 83.0%
Abdel-Nasser et al. [75]	Thresholding based ROI, HOG features	MLP	148	F-score: 0.95
Krawczyk and Schaefer [92]	Manual ROI selection, Statistical features, Fourier descriptor	Multiple Classifier System	146	Accuracy: 90.03% Sensitivity: 80.35% Specificity: 90.15%
Madhavi and Bobby [93]	Level-set segmentation, BEMD, RLBP, Texture analysis	LSSVM	67	Accuracy: 89%

there are no such thorough databases for thermography. Having a thorough database with a large number of thermal images helps in establishing a common source for thermal imaging, which can be used to test different approaches for breast cancer screening.

However, although many feature extraction techniques are experimented on thermogram images, the HOG based descriptor has been shown to have a maximum performance in terms of accuracy, sensitivity, and specificity [40]. It however requires testing on a large dataset to generalize its performance. The limitation of the HOG is that it requires dimensionality reduction as it produces large data. HOS and textural features are also experimented, but they are not discriminative as compared to HOG features (please refer to Tables 1–4). From Tables 1–4 it is observed that HOG based features have an improved p-value, less than 0.01, resulting in more significant features compared to other methods. This study has shown evidence for the benefits of using texture patterns in handling nonlinear data.

ROC [119], Bhattacharyya [120], Entropy based test [121,122] and Wilcoxon signed rank tests [123,124] can also be explored for further analysis. More experimentation can also be performed on segmentation-based approaches, as listed in [55,56,57,59]. A better feature section can be developed by using cutting edge optimization techniques, such as particle swarm optimization [134,135], genetic algorithm [133], and ant colony optimization [136].

Most non-invasive procedures are avoided because the rate of positive findings at biopsy for cancer is low, between 10% and 31%. To overcome the aforementioned shortcomings of mammography, only an efficient computerized model offers objective evidence; therefore, an optimal and stable high diagnostic rate is a future requirement.

Classification, as discussed earlier, is one of the most effective solutions in the machine learning methodology, to determine a category or class of a new observation. Since it is a recent advancement, only in recent published studies has this method been adopted. Although several papers have been published using ANN as a classifier thus far [33,45,46,79], SVM is considered as the most effective and efficient classifier due to its precision for minimum data samples [47,67,78,88]. Most nonlinearities are handled by its kernel functions. However, these classification algorithms outperform other techniques when the data samples are minimum and balanced.

As soon as deep learning was adopted in the field of medical image analysis, fuzzy classifiers (logic) and neural network techniques were also in use, with papers published based on the respective methods. The most recent of all of the classifiers are the ELM and MLP techniques, and to date only a few attempts have been made with these, although there is indication that these methods will be used more in the future. Nevertheless, in reality, normal data samples always acquire the maximum portion in any database, resulting in reduced classification accuracy. Hence, additional synthetic samples have to be generated to handle the situation. Adaptive synthetic sampling (ADASYN) is one such technique, which creates additional samples for the minority class [137]. Furthermore, these conventional techniques are computationally expensive, and work more efficiently for a smaller group of data.

To analyze the pixel organization of thermogram, it is better to create a subspace using geometric structure. Hence this increases the discrimination capability of the features. Further combination of graph embedding and feature selection framework can increase the efficiency of the system. On the other hand, it helps to categorize the thermogram images using a lesser number of features, which eventually reduces the memory requirement of the system. Thus it can be used as a standalone system in rural areas. There is a need to couple feature learning and deep neural networks to make a more robust system which is capable of handling small variations in pixel values. Consequently, the combination of various algorithms could reduce the diagnostic error. Thus diagnostic quality can be increased.

4.1. Future trends

Even with the latest methodologies, improvement is needed for breast tumor characterization.

4.1.1. Large dataset

One of the major drawbacks of the methods mentioned above are in the datasets. Those with only a small set of images brings up the question of whether the process is sustainable with larger data sets. The methodology should be modified to obtain precise results for larger datasets, which would be assistive to identify breast cancer at any time point during analysis.

4.1.2. Deep convolution neural network

As we have seen, deep learning techniques such as ANN and fuzzy logic were used in this particular study. A major breakthrough in medical image analysis was the emergence of the deep convolution neural network, which has the capacity to extract small bits of information from large datasets. Thus, testing this algorithm on thermograms is a goal of future work, which could be helpful to achieve higher accuracy.

It is possible to use the proposed calculation remotely with the help of online applications, by means of web servers which are being introduced in numerous emergency clinics. The acquired MR images are sent to the server for future investigation utilizing the proposed strategy. The symptomatic outcomes can be sent to the facility by data streaming.

Furthermore, the extraction and determination of highlights requires structural learning. To forestall the requirement for in-house expert assistance, many research groups have used neural system calculations for the advancement of computer-aided diagnosis frameworks [110–116,137–139]. With a reasonable change of layers and piecewise measure, they have demonstrated exceptional execution for big datasets. In future work, we intend to utilize DNNs for the examination of vast and multi-classification datasets, which would reduce hospital costs. With lesser expenses, the model can be introduced in clinical frameworks for analysis of breast abnormalities by utilizing thermograms.

5. Conclusion

The major advantage of thermography is that it will provide thermal information as well as vascular conditions of the breast. These functional representations are hypothesized to change prior to the onset of the structural changes that occur in a diseased or cancerous state. In this study, various machine learning based computer-aided diagnosis methods are discussed. The major limitation in our study is the procurement of larger datasets for analysis. It is evident that the adoption of a deep convolution neural network for breast thermograms may boost the overall performance and would be a long-term solution to provide effective early detection of breast cancer.

Compliance with Ethical standards

Conflict of interest: None of the authors have any conflict of interest.

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

References

[1] Xiaoli Yao, Wen Wei, Juanjuan Li, Lijun Wang, Xu. ZhiLiang, Yingwen Wan, Kaiyang Li, Shengrong Sun, A comparison of mammography, ultrasonography, and far-infrared thermography with pathological results in screening and early diagnosis of breast cancer, Asian Biomed. 8 (1) (2014) 11–19.

[2] Michel Gautherie, Charles M. Gros, Breast thermography and cancer risk prediction, Cancer 45 (1) (1980) 51–56.

[3] Michel Gautherie, Thermobiological assessment of benign and malignant breast diseases, Am. J. Obstet. Gynecol. 147 (8) (1983) 861–869.

[4] S.C. Fok, E.Y.K. Ng, G.L. Thimm, Developing case-based reasoning for discovery of breast cancer, J. Mech. Med. Biol. 03 (03n04) (2003) 231–245, https://doi.org/10.1142/S0219519403000764.

[5] T. Jakubowska, B. Wiecek, M. Wysocki, C. Drews-Peszynski, Thermal signatures for breast cancer screening comparative study, Proceedings of the 25th Annual International Conference of the IEEE In Engineering in Medicine and Biology Society, vol. 2, IEEE, 2003, pp. 1117–1120.

[6] Mohamed Salhab, W. Al Sarakbi, K. Mokbel, The evolving role of the dynamic thermal analysis in the early detection of breast cancer, International Seminars in Surgical Oncology, vol. 2, no. 1, 2006, pp. 3–8.

[7] Xianwu Tang, Haishu Ding, Asymmetry analysis of breast thermograms with morphological image segmentation, International Conference on Engineering in Medicine and Biology Society, China, (2005).

[8] M. EtehadTavakol, E.Y. Ng, C. Lucas, S. Sadri, N. Gheissari, Estimating the mutual information between bilateral breast in thermograms using nonparametric windows, J. Med. Syst. 35 (5) (2011) 959–967.

[9] Mahnaz EtehadTavakol, Caro Lucas, Saeed Sadri, E.Y.K. Ng, Analysis of breast thermography using fractal dimension to establish possible difference between malignant and benign patterns, J. Healthcare Eng. 1 (1) (2010) 27–43.

[10] V. Umadevi, S.V. Raghavan, Sandeep Jaipurkar, Interpreter for breast thermogram characterization, 2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), IEEE, 2010, pp. 150–154.

[11] Marina Milosevic, Dragan Jankovic, Aleksandar Peulic, Thermography based breast cancer detection using texture features and minimum variance quantization, EXCLI J. 13 (2014) 1204–1215.

[12] Bartosz Krawczyk, Gerald Schaefer, Michal Wozniak, Breast thermogram analysis using a cost-sensitive multiple classifier system, International Conference on Biomedical and Health Informatics (BHI), 2012, pp. 507–510.

[13] Bartosz Krawczyk, Gerald Schaefer, Effective multiple classifier systems for breast thermogram analysis, 21st International Conference on Pattern Recognition (ICPR), 2012, pp. 3345–3348.

[14] U Rajendra Acharya, Eddie Yin-Kwee Ng, S. Vinitha Sree, Chua Kuang Chua, Subhagata Chattopadhyay, Higher order spectra analysis of breast thermograms for the automated identification of breast cancer, Expert Syst. 31 (1) (2014) 37–47.

[15] Jose Manuel Luna, Ricardo Romero-Mendez, Abel Hernandez-Guerrero, Francisco Elizalde-Blancas, Procedure to estimate thermophysical and geometrical parameters of embedded cancerous lesions using thermography, J. Biomech. Eng. 134 (3) (2012) 031008.

[16] M. EtehadTavakol, Eddie Yin-Kwee Ng, C. Lucas, S. Sadri, M. Ataei, Nonlinear analysis using Lyapunov exponents in breast thermograms to identify abnormal lesions, Infrared Phys. Technol. 55 (4) (2012) 345–352.

[17] Sheeja V. Francis, M. Sasikala, Automatic detection of abnormal breast thermograms using asymmetry analysis of texture features, J. Med. Eng. Technol. 37 (1) (2013) 17–21.

[18] Mahnaz EtehadTavakol, E. Vinod Chandran, Yin Kwee Ng, Raheleh Kafieh, Breast cancer detection from thermal images using bispectral invariant features, Int. J. Therm. Sci. 69 (2013) 21–36.

[19] Mahnaz Etehadtavakol, E.Y.K. Ng, Vinod Chandran, Hossien Rabbani, Separable and non-separable discrete wavelet transform based texture features and image classification of breast thermograms, Infrared Phys. Technol. 61 (2013) 274–286.

[20] Nasser Samadzadeh Aghdam, Morteza Moradi Amin, Mahnaz Etehad Tavakol, E.Y.K. Ng, Designing and comparing different color map algorithms for pseudo-coloring breast thermograms, J. Med. Imag. Health Inform. 3 (4) (2013) 487–493.

[21] L.F. Silva, D.C.M. Saade, G.O. Sequeiros, A.C. Silva, A.C. Paiva, R.S. Bravo, A. Conci, A new database for breast research with infrared image, J. Med. Imag. Health Inform. 4 (1) (2014) 92–100.

[22] S.S. Suganthi, S. Ramakrishnan, Analysis of breast thermograms using gabor wavelet anisotropy index, J. Med. Syst. 38 (9) (2014) 101.

[23] Sheeja V. Francis, M. Sasikala, S. Saranya, Detection of breast abnormality from thermograms using curvelet transform based feature extraction, J. Med. Syst. 38 (4) (2014) 23.

[24] Marcus C. Araújo, Rita CF Lima, Renata MCR De Souza, Interval symbolic feature extraction for thermography breast cancer detection, Expert Syst. Appl. 41 (15) (2014) 6728–6737.

[25] N. Golestani, M. EtehadTavakol, E.Y.K. Ng, Level set method for segmentation of infrared breast thermograms, Excli J. 13 (2014) 241–251.

[26] Łukasz Neumann, Robert M. Nowak, Rafał Okuniewski, Witold Oleszkiewicz, Paweł Cichosz, Dariusz Jagodziński, Mateusz Matysiewicz, Preprocessing for classification of thermograms in breast cancer detection, Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2016, International Society for Optics and Photonics, 2016 pp. 100313A–100313A.

[27] V. Kecman, Learning and Soft Computing, MIT Press, Cambridge, 2001.

[28] https://www.cancer.org/cancer/breast-cancer/about/what-is-breast-cancer.html.

[29] Rebecca L. Siegel, Kimberly D. Miller, Ahmedin Jemal, Cancer statistics, 2017, CA Cancer J. Clin. 67 (1) (2017) 7–30, https://doi.org/10.3322/caac.21387.

[30] D.T. Larose, Discovering Knowledge in Data: An Introduction to Data Mining, Wiley-Interscience, USA, 2004.

[31] M. Sugeno, Industrial Applications of Fuzzy Control, Elsevier Science Inc, New York (NY), 1985.

[32] D.F. Specht, Probabilistic neural networks, Neural Netw. 3 (1990) 109–118.

[33] E.Y.K. Ng, E.C. Kee, Integrative computer-aided diagnostic with breast thermogram, J. Mech. Med. Biol. 7 (1) (2007) 1–10.

[34] X. Tang, H. Ding, Y. Yuan, Q. Wang, Morphological measurement of localized temperature increase amplitudes in breast infrared thermograms and its clinical application, Biomed. Signal Process. Control 3 (1) (2008) 312–318.
[35] V. Agostini, M. Knaflitz, F. Molinari, Motion artifact reduction in breast dynamic infrared imaging, IEEE Trans. Biomed. Eng. 56 (3) (2009) 903–906.
[36] G.C. Wishart, M. Campisid, M. Boswella, D. Chapmana, V. Shackletona, S. Iddlesa, A. Halletta, P.D. Britton, The accuracy of digital infrared imaging for breast cancer detection in women undergoing breast biopsy, Eur. J. Surg. Oncol. 36 (6) (2010) 535–540.
[37] O.D. Nurhayati, A. Susanto, T.S. Widodo, M. Tjokronagoro, PCA Combined with first order statistical method for breast thermal images classification, Int. J. Comput. Sci. Technol. 2 (2) (2011) 12–18.
[38] M. Kontos, R. Wilson, I. Fentiman, Digital infrared thermal imaging (DITI) of breast lesions: sensitivity and specificity of detection of primary breast cancers, Clin. Radiol. 66 (2011) 536–539.
[39] J. Koay, C. Herry, M. Frize, Analysis of breast thermography with an artificial neural network, IEMBS 1159–1162, 2004.
[40] U. Raghavendra, U. Rajendra Acharya, E.Y.K. Ng, Jen-Hong Tan, Anjan Gudigar, An integrated index for breast cancer identification using histogram of oriented gradient and kernel locality preserving projection features extracted from thermograms, Quant. InfraRed Thermography J. 13 (2) (2016) 195–209.
[41] Dar-Ren Chen, Ruey-Feng Chang, Yu-Len, Computer-aided Diagnosis Applied to US of solid breast nodules by using neural networks, Radiology 213 (1999) 407–412.
[42] E.Y.K. Ng, A framework for early discovery of breast tumor using thermography with ANN, Breast J. 9 (4) (2003) 341–343.
[43] Eddie Y.-K. Ng, N.M. Sudharsan, Computer simulation in conjunction with medical thermography as an adjunct tool for early detection of breast cancer, BMC Cancer 4 (2004) 17.
[44] Tuan Zea Tan, Chai Quek, Geok See Ng, Eddie Y.-K. Ng, A novel cognitive interpretation of breast cancer thermography with complementary learning fuzzy neural memory structure, Expert Syst. Appl. 33 (3) (2007) 652–666.
[45] S. Mitra, C. Balaji, A neural network based estimation of tumor parameters from a breast thermogram, Int. J. Heat Mass Transf. 53 (2010) 4714–4727.
[46] R.R. Janghel, et al., Breast cancer diagnosis using artificial neural network models, IEEE, 2010, pp. 89–94.
[47] U.R. Acharya, E.Y.K. Ng, J.H. Tan, S.V. Sree, Thermography based breast cancer detection using texture features and support vector machine, J. Med. Syst. 36 (2012) 1503–1510.
[48] M.R.K. Mookiaha, U.R. Acharyaa, E.Y.K. Ng, Data mining technique for breast cancer detection in thermograms using hybrid feature extraction strategy, Quant. InfraRed Thermography J. 9 (2) (2012) 151–165.
[49] Bartosz Krawczyk, Gerald Schaefer, A hybrid classifier committee for analysing asymmetry features in breast thermograms, Appl. Soft Comput. 20 (2014) 112–118.
[50] Oliver Faust, et al., Application of infrared thermography in computer aided diagnosis, Infrared Phys. Technol. 66 (2014) 160–175.
[51] Savari Antony, S. Julian, S. Ravi, Breast cancer detection on thermogram at preliminary stage using fuzzy inference system, J. Theor. Appl. Inform. Technol. 68 (3) (2014) 705–715.
[52] E.O. Rodrigues, A. Conci, T.B. Borchartt, A.C. Paiva, A. Correa Silva, T. Mac Henry, Comparing results of thermographic images based diagnosis for breast diseases, in: International Conference on Systems, Signals and Image Processing (IWSSIP), 2014, pp. 39–42.
[53] H.G. Zadeh, I.A. Kazerouni, J. Haddadnia, Distinguish breast cancer based on thermal features in infrared images, Can. J. Image Process. Comput. Vis. 2 (6) (2011) 54–58.
[54] C. Lipari, J. Head, Advanced infrared image processing for breast cancer risk assessment, in: Proceedings for 19th International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 2, 1997, pp. 673–676.
[55] C.L. Herry, M. Frize, Digital processing techniques for the assessment of pain with infrared thermal imaging, in: Proceedings of the Second Joint EMBS/BMES Conference, Houston, TX, USA, vol. 2, 2002, pp. 1157–1158.
[56] Q. Zhou, Z. Li, J.K. Aggarwal, Boundary extraction in thermal images by edge map, Proceedings of the 2004 ACM Symposium on Applied Computing, 2004, pp. 254–258.
[57] N. Scales, C. Herry, M. Frize, Automated image segmentation for breast analysis using infrared images, Proceedings of the 26th Annual International Conference of the IEEE/EMBS, San Francisco, 2004, pp. 1737–1740.
[58] H. Qi, P.T. Kuruganti, W.E. Snyder, Detecting breast cancer from thermal infrared images by asymmetry analysis, in: Medical Infrared Imaging, 2007, 2008.
[59] Z. Jin-Yu, C. Yan, H. Xian-Xiang, IR thermal image segmentation based on enhanced genetic algorithms and two- dimensional classes square error, Second International Conference on Information and Computation Science vol. 2, no. 1, (2009) 309–312.
[60] G. Schaefer, M. Zavisek, T. Nakashima, Thermography based breast cancer analysis using statistical features and fuzzy classification, Pattern Recogn. 47 (2009) 1133–1137.
[61] P. Kapoor, S.V.A.V. Prasad, Image processing for early diagnosis of breast cancer using infrared images, in: 2nd International Conference on Computer and Automation Engineering, vol. 3, no. 1, 2010, pp. 564–566.
[62] L.S. Motta, A. Conci, R.C.F. Lima and E.M. Diniz, Automatic segmentation on thermograms in order to aid diagnosis and 2D modeling, in: Proceedings of 10th Work shop em Informatica Médica, Belo Horizonte, MG, Brazil, vol. 1, 2010, pp. 1610–1619. Availablein: http://www.visual.ic.uff.br/proengS (accessed:27 January 2012).
[63] R. Kafieh, H. Rabbani, Wavelet-based medical infrared image noise reduction using local model for signal and noise, IEEE Stat. Signal Process. Workshop (2011) 549–552.
[64] G. Schaefer, S.Y. Zhu, B. Jones, An image retrieval approach for thermal medical images, Med. Image Understand. Anal. (2004) 181–183.
[65] G. Schaefer, T. Nakashima, M. Zavisek, Analysis of Breast Thermograms based on Statistical Image Features and Hybrid Fuzzy Classification, LNCS 5538, Springer, 2008, pp. 753–762.
[66] O.D. Nurhayati, T.S. Widodo, A. Susanto, M. Tjokronagoro, First order statistical feature for breast cancer detection using thermal images, World Acad. Sci. Eng. Technol. (70) (2010) 1040–1042.
[67] T.B. Borchartt, R. Resmini, A. Conci, A. Martins, A.C. Silva, E.M. Diniz, A. Paivaand, R.C.F. Lima, Thermal feature analysis to aid on breast disease diagnosis, Proc. COBEM (2011) 1–8.
[68] Tiago B. Borchartt, et al., Combining approaches for early diagnosis of breast diseases using thermal imaging, Int. J. Innovative Comput. Appl. 17 (4.3-4) (2012) 163–183.
[69] O.T. Silveira Filho, A. Conci, R. Carvalho, R. Mello, R.F.C. Lima, On using lacunarity for diagnosis of breast diseases considering thermal images, Proceedings of 16th International Conference on Systems, Signals and Image Processing, 2009, pp. 1–4.
[70] Hairong Qi, Nicholas A. Diakides, Infrared imaging in medicine, in: Engineering in Medicine and Biology Society, Proceedings of the 22nd Annual International Conference of the IEEE, vol. 2, 2000, pp. 1–10.
[71] E.Y.K. Ng, Y. Chen, L.N. Ung, Computerized breast thermography: study of image segmentation and temperature cyclic variations, J. Med. Eng. Technol. 25 (1) (2001) 12–16.
[72] Hossein Ghayoumi Zadeh, Iman Abaspur Kazerouni, Javad Haddadnia, Diagnosis of breast cancer and clustering technique using thermal indicators exposed by infrared images, J. Am. Sci. 7 (9) (2011) 281–288.
[73] Luciano Boquete, Sergio Ortega, Juan Manuel Miguel-Jiménez, José Manuel Rodríguez-Ascariz, Román Blanco, Automated detection of breast cancer in thermal infrared images, based on independent component analysis. J. Med. Syst. 36 (2012) 103–111.
[74] Mona A.S. Ali, Gehad Ismail Sayed, Tarek Gaber, Aboul Ella Hassanien, Vaclav Snasel, F. Lincoln, Silva, Detection of breast abnormalities of thermograms based on a new segmentation method, Federated Conference on Computer Science and Information Systems (FedCSIS), 2015, pp. 255–261.
[75] Mohamed Abdel-Nasser, Adel Saleh, Antonio Moreno, Domenec Puig, Automatic nipple detection in breast thermograms, Expert Syst. Appl. 64 (2016) 365–374.
[76] R.C. Serrano, J. Ulysses, S. Ribeiro, R.C.F. Lima, Using hurst coefficient and lacunarity to diagnosis early breast diseases, Proceedings of 17th International Conference on Systems, Signals and Image Processing, 2010, pp. 550–553.
[77] D. Dinsha, N. Manikandaprabu, Breast Tumour Segmentation and Classification using SVM and Bayesian from thermogram images, Unique J. Eng. Adv. Sci. 2 (2) (2014) 147–151.
[78] Sheeja V. Francis, N. Punitha, M. Sasikala, Cancer detection in rotational breast thermography images using bispectral invariant features, J. Chem. Pharmaceutical Sci. 9 (4) (2016) 2189–2194.
[79] Vanessa Lessa, Mauricio Marengoni, Applying artificial neural network for the classification of breast cancer using infrared thermographic images, International Conference on Computer Vision and Graphics, Springer International Publishing, 2016, pp. 429–438.
[80] B. Wiecek, S. Zwolenik, A. Jung, J. Zuber, Advanced thermal, visual and radiological image processing for clinical diagnostics, Proceedings of First Joint IEEE BMES/EMBS Conference, Atlanta, GA, USA, 1999, p. 1108.
[81] T. Jakubowska, B. Wiecek, M. Wysocki, C. Drews-Peszynski, M. Strzelecki, Classification of breast thermal images using artificial neural networks, in: Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE, vol. 1, 2004, pp.1155–1158.
[82] N. Arora, D. Martins, D. Ruggerio, E. Tousimis, A.J. Swistel, M.P. Osborne, R.M. Simmons, Effectiveness of a noninvasive digital infrared thermal imaging system in the detection of breast cancer, Am. J. Surg. 196 (4) (2008) 523–526.
[83] S. Ashok Rao, Noushath, survey: subspace methods for face recognition, J. Comput. Sci. Rev. 4 (1) (2010) 1–17.
[84] Mohamed Abdel-Nasser, Antonio Moreno, Domenec Puig, Breast cancer detection in thermal infrared images using representation learning and texture analysis methods, Electronics 8 (1) (2019) 100.
[85] Krithika Venkataramani, Lalit K. Mestha, L. Ramachandra, S.S. Prasad, Vijay Kumar, Priyanka J. Raja, Semi-automated Breast Cancer Tumor Detection with Thermographic Video Imaging, Society (EMBC), 2015.
[86] M.-A. Díaz Cortés, N. Ortega-Sánchez, S. Hinojosa, D. Oliva, E. Cuevas, R. Rojas, A. Demin, A multi-level thresholding method for breast thermograms analysis using dragonfly algorithm, Infrared Phys. Technol. 93 (2018) 346–361.
[87] Antony Morales-Cervantes, Eleazar Samuel Kolosovas-Machuca, Edgar Guevara, Mireya Maruris Reducindo, Alix Berenice Bello Hernández, Manuel Ramos García, Francisco Javier González, An automated method for the evaluation of breast cancer using infrared thermography, EXCLI Journal 17 (2018) 989–998 ISSN 1611-2156.
[88] Nabil Karim Chebbah, Mohamed Ouslim, Ryad Temmar, A new approach for breast abnormality detection based on thermography, Med. Technol. J. 2 (3) (2018) 257–265.
[89] Maíra Araújo de Santana, Jessiane Mônica Silva Pereira, Fabrício Lucimar da Silva, Nigel Mendes de Lima, Felipe Nunes de Sousa, Guilherme Max Silva de Arruda, Rita de Cássia Fernandes de Lima, Washington Wagner Azevedo da Silva, Wellington Pinheiro dos Santos, Breast cancer diagnosis based on mammary

thermography and extreme learning machines, RBE Journal 34 (1) (2018) 45–53.
[90] Mrinal Kanti Bhowmik, Usha Rani Gogoi, Gautam Majumdar, Debotosh Bhattacharjee, Dhritiman Datta, Anjan Kumar, Ghosh, Designing of ground truth annotated DBT-TU-ju breast thermogram database towards early abnormality prediction, IEEE J. Biomed. Health. Inf. 22 (4) (2018) 1238–1249.
[91] J.H. de Vasconcelos, W.P. dos Santos, R.C.F. de Lima, Analysis of methods of classification of breast thermographic images to determine their viability in the early breast cancer detection, IEEE Lat. Am. Trans. 16 (6) (2018) 1631–1637.
[92] Bartosz Krawczyk, Gerald Schaefer, Breast thermogram analysis using classifier ensembles and image symmetry features, IEEE Syst. J. 8 (3) (2014) 921–928.
[93] Vijaya Madhavi, T. Christy Bobby, Thermal imaging based breast cancer analysis using BEMD and uniform RLBP, in: 2017 3rd International Conference on Biosignals, images and instrumentation (ICBSII), 16–18 March 2017, Chennai.
[94] Elham Mahmoudzadeh, Maryam Zekri, Mohammad Ali Montazeri, Saeid Sadri, Sima Taghizadeh Dabbagh, Directional SUSAN image boundary detection of breast thermogram, IET Image Process. 10 (7) (2016) 552–560.
[95] Sebastien Jean Mambou, Petra Maresova, Ondrej Krejcar, Ali Selamat, Kamil kua, Breast cancer detection using infrared thermal imaging and a deep learning model, Sensors 18 (2018) 2799.
[96] Colleen H. Neal, Kelsey A. Flynt, Deborah O. Jeffries, Mark A. Helvie, Breast imaging outcomes following abnormal thermography, Acad. Radiol. 25 (3) (2018) 273–278.
[97] K.C. Chua, V. Chandran, U.R. Acharya, C.M. Lim, Application of higher order statistics/spectra in biomedical signals—a review, Med. Eng. Phys. 32 (2010) 679–689.
[98] Arne Jensen, Anders la Cour-Harbo, Ripples in Mathematics: The Discrete Wavelet Transform, Springer Science & Business Media, 2001.
[99] M.-K. Hu, Visual pattern recognition by moment invariants, information theory, IRE Trans. 8 (2) (1962) 179–187.
[100] A. Renyi, On measures of entropy and information, in: Proceedings of the Fourth Berkeley symposium on mathematical statistics and probability, vol. 1, 1961, pp. 547–561.
[101] Robert M. Haralick, Karthikeyan Shanmugam, Its' Hak Dinstein, Textural features for image classification, in: IEEE Transactions on Systems, Man and Cybernetics, vol. 6, 1973, pp. 610–621.
[102] M. Nixon, M.S. Nixon, A.S. Aguado, Feature Extraction & Image Processing for Computer Vision, Academic Press, 2012.
[103] R. Tomakova, V. Komkov, E. Emelianov, M. Tomakov, The use of fourier descriptors for the classification and analysis of peripheral blood smears image, Appl. Math. 8 (2017) 1563–1571.
[104] John A. Bullinaria, Self organizing maps: fundamentals, in: Introduction to Neural Networks: Lecture vol. 16, 2004.
[105] Xiaoou Tang, Texture information in run-length matrices, Article in IEEE Transactions on Image Processing, December 1998.
[106] Jian-hong Zhou, Olga Sourina, A new research on the application of fractal dimension, in: International Conference on Advanced Computer Theory and Engineering, 2008.
[107] Md. Abdur Rahim, Md. Najmul Hossain, Tanzillah Wahid, Md. Shafiul Azam, Face Recognition using Local Binary Patterns (LBP), in: Global Journal of Computer Science and Technology Graphics & Vision Volume 13 Issue 4 Version 1.0 Year 2013.
[108] L.K. Saul, S.T. Roweis, An introduction to locally linear embedding, J. Mach. Learn. Res. 7 (2001).
[109] Will D. Gillett, Image Classification Using Laws' Texture Energy Measures, Report Number: WUCS-87-25, 1987. All Computer Science and Engineering Research.
[110] U. Raghavendra, N. Shyamasunder Bhat, U. Anjan Gudigar, Rajendra Acharya, Automated system for the detection of thoracolumbar fracture using a CNN architecture, Future Gen. Comput. Syst. 85 (2018) 184–189.
[111] U. Raghavendra, Hamido Fujita, Sulatha V. Bhandary, Anjan Gudigar, Jen Hong Tan, U. Rajendra Acharya, Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images, Inf. Sci. 441 (2018) 41–49.
[112] Betul Ay, Ozal Yildirim, Muhammed Talo, Ulas Baran Baloglu, Galip Aydin, Subha D. Puthankattil, U. Rajendra Acharya, Automated depression detection using deep representation and sequence learning with EEG signals, J. Med. Syst. 43 (7) (2019) 205.
[113] Jen Hong Tan, Sulatha V. Bhandary, Sobha Sivaprasad, Yuki Hagiwara, U. Akanksha Bagchi, A Krishna Raghavendra, Biju Raju Rao, Nitin Shridhara Shetty, Arkadiusz Gertych, Kuang Chua Chua, U. Rajendra Acharya, Age-related macular degeneration detection using deep convolutional neural network, Future Gen. Comput. Syst. 8 (2018) 127–135.
[114] U. Rajendra Acharya, Oh. Shu Lih, Yuki Hagiwara, Jen Hong Tan, Muhammad Adam, Ru Arkadiusz Gertych, San Tan, A deep convolutional neural network model to classify heartbeats, Comput. Biol. Med. 89 (2017) 389–396.
[115] Jen Hong Tan, Yuki Hagiwara, Winnie Pang, Ivy Lim, Oh Shu Lih, Ru Muhammad Adam, San Tan, U. Ming Chen, Rajendra Acharya, Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals, Comput. Biol. Med. 94 (2018) 19–26.
[116] Shu Lih Oh, Eddie Y.K. Ng, Ru San Tan, U. Rajendra Acharya, Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats, Comput. Biol. Med. 102 (2018) 278–287.
[117] http://cancerindia.org.in/ (accessed: 02.12.2018).
[118] Student t-test, Last Accessed: 26.03.2016. [Online]. Available: http://www.physics.csbsju.edu/stats/t-test.html.
[119] N.A. Obuchowski, Receiver operating characteristic curves and their use in radiology, Radiology 229 (2003) 3–8.
[120] T. Kailath, The divergence and bhattacharyya distance measures in signal selection, IEEE Trans. Commun. Technol. 15 (1) (1967) 52–60.
[121] M. Dash, H. Liu, Handling large unsupervised data via dimensionality reduction, in: ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery, 1999.
[122] N. Abe, M. Kudo, Entropy criterion for classifier-independent feature selection, in: Knowledge-Based Intelligent Information and Engineering Systems, ser. Lecture Notes in Computer Science. Springer Berlin Heidelberg, (3684), 2005, pp. 689–695.
[123] F. Wilcoxon, Individual comparisons by ranking methods, Biometrics Bulletin 1 (6) (1945) 80–83.
[124] N. Sundar, S.R. Lipsitz, G.M. Fitzmaurice, D. Sinha, J.G. Ibrahim, J. Haas, W. Gellad, An extension of the Wilcoxon rank-sum test for complex sample survey data, J. Roy. Stat. Soc. Ser. C, Appl. Stat. 61 (4) (2012) 653–664.
[125] E.Y.K. Ng, N.M. Sudharsan, Effect of blood flow, tumour and cold stress in a female breast: a novel time-accurate computer simulation, in: Proceedings of the Institution of Mechanical Engineers Part H-Journal of Engineering in Medicine, vol. 215(H4), 2001, pp. 393–404.
[126] Mahnaz Etehad Tavakol, E.Y.K. Ng, Breast thermography as a potential non-contact method in the early detection of cancer: a review, J. Mech. Med. Biol. 13 (2) (2013) 1330001.
[127] E.Y.K. Ng, A review of thermography as promising non-invasive detection modality for breast tumor, Int. J. Therm. Sci. 48 (5) (2009) 849–859.
[128] American cancer society, Last Accessed: 15.10.2018. [Online]. Available: http://www.cancer.org/cancer/breastcancer/detailedguide/breastcancer-detection.
[129] E.Y.K. Ng, S. Fok, Y. Peh, F. Ng, L. Sim, Computerized detection of breast cancer with artificial intelligence and thermograms, J. Med. Eng. Technol. 26 (4) (2002) 152–157.
[130] Subhhuraam Vinitha Sree, Eddie Yin-Kwee Ng, Rajendra U. Acharya, Oliver Faust, Breast imaging: a survey, World J. Clin. Oncol. 2 (4) (2011) 171–178.
[131] Anjan Gudigar, U. Raghavendra, T.R. San, E.J. Ciaccio, U. Rajendra Acharya, Application of multiresolution analysis for automated detection of brain abnormality using MR images: a comparative study, Fut. Gen. Comput. Syst. 90 (2019) 359–367.
[132] A. Gudigar, U. Raghavendra, E.J. Ciaccio, N. Arunkumar, E. Abdulhay, U.R. Acharya, Automated categorization of multi-class brain abnormalities using decomposition techniques with MRI images: a comparative study, IEEE Access 7 (2019) 28498–28509.
[133] M. Mitchell, An Introduction to Genetic Algorithms, MIT Press, Cambridge, MA, USA, 1998.
[134] J. Kennedy, R. Eberhart, Particle swarm optimization, in: IEEE Int. Conf. Neural Netw., 1995.
[135] Y. Shi, R. Eberhart, A modified particle swarm optimizer, Proceedings of the IEEE World Congress on Computational Intelligence, (1998).
[136] M. Dorigo, M. Birattari, T. Stutzle, Ant colony optimization, IEEE Comput. Intell. Mag. 1 (4) (2006) 28–39.
[137] H. He, B. Yang, E.A. Garcia, S. Li, ADASYN: adaptive synthetic sampling approach for imbalanced learning, in: Proceedings of the International Joint Conference on Neural Networks,{IJCNN} 2008, part of the IEEE World Congress on Computational Intelligence, {WCCI} 2008, Hong Kong, China, pp. 1–6.
[138] U. Rajendra Acharya, Hamido Fujita, Oh. Shu Lih, U. Raghavendra, Jen Hong Tan, Muhammad Adam, Arkadiusz Gertych, Yuki Hagiwara, Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network, Fut. Gen. Comput. Syst. 79 (Part 3) (2018) 952–959.
[139] U. Rajendra Acharya, Hamido Fujita, Oh Shu Lih, Muhammad Adam, Jen Hong Tan, Chua Kuang Chua, Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network, Knowl.-Based Syst. 132 (2017) 62–71.