Computer Methods and Programs in Biomedicine 183 (2020) 105074

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

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

Role of image thermography in early breast cancer detection- Past, present and future

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ARTICLE INFO

Article history:
Received 11 July 2019
Revised 30 August 2019
Accepted 6 September 2019

Keywords:
Infrared breast thermography
Region of interest
Segmentation
Feature extraction
Classification
Numerical simulation

ABSTRACT

One of the most prevalent cancers among women is the breast cancer. Accurate diagnosis of breast cancer at an early stage can reduce the mortality associated with this disease. Infrared Breast Thermography, which is a screening tool used to measure the temperature distribution of breast tissue, is a suitable adjunct tool to mammography. Breast thermography has many advantages as it is non-invasive, safe and painless. Thermographic image and usage of artificial neural networks have improved the accuracy of thermography in early diagnosis of breast abnormality. This paper presents survey based on the main steps of computer aided detection systems: image acquisition protocols, segmentation techniques, feature extraction and classification methods, used in the field of breast thermography over the past few decades. The detailed survey emphasizes on the improved reliability of breast thermography .This has become possible with the utilization of machine learning techniques for correct classification of breast thermograms. Numerical Simulation can be used as a supporting method to overcome high false positive rates in thermographic diagnosis. The paper also presents future recommendations to utilize recent machine learning advances in real time.

1. Introduction

Cancer is the condition in which cells grow irregularly and affect other parts of the body. Some of the cancers found commonly are breast, prostrate, lung, skin and pancreas. Cancer results in large number of mortalities worldwide [1,2]. The instances of growth of breast cancer amongst women in the age group of 30- 40 years, has increased significantly over the last few decades in India [3]. The most frequently diagnosed cancer in women is breast cancer. Rates of diagnosis of breast cancer have been increasing drastically every year in nearly every region of the world. Proper identification of breast abnormality prior to the beginning of a cancerous growth is the only effective way of reducing mortality due to breast cancer. This review paper presents a chronological review of some of the papers related to breast thermography, an adjunct imaging modality for early cancer diagnosis. The main objective of the review paper is to analyze the improvement in accuracy of thermogram classification based on the selection of segmentation techniques, feature selection, feature extraction and types of classifiers used. The work also highlights the limitations of breast thermography and suggests methods of improving the sensitivity.

The paper is organized in 7 sections. Section 2 briefly explains the methodology used in the review of literature. Section 3 introduces the concept of breast thermography and the need of such imaging technique. Subsection 3 presents some of the available database of breast thermograms. Section 4 outlines the parts of intelligent diagnosing systems used in early cancer detection. This section also highlights the importance of segmentation with the recent advances. Section 5 presents a detailed progress in feature extraction and classification techniques used. Section 6 briefly describes future needs in the field. Section 7 discusses the implications of the study. Section 8 presents the main conclusions and recommendations based on them.

2. Methodology

2.1. Sources

Research articles presented in the review paper are obtained from IEEEXplore, PubMed Central, Semantic Scholar, ResearchGate, ScienceDirect and other journal databases. Some of the articles were searched by going through the references of the searched papers.

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https://doi.org/10.1016/j.cmpb.2019.105074
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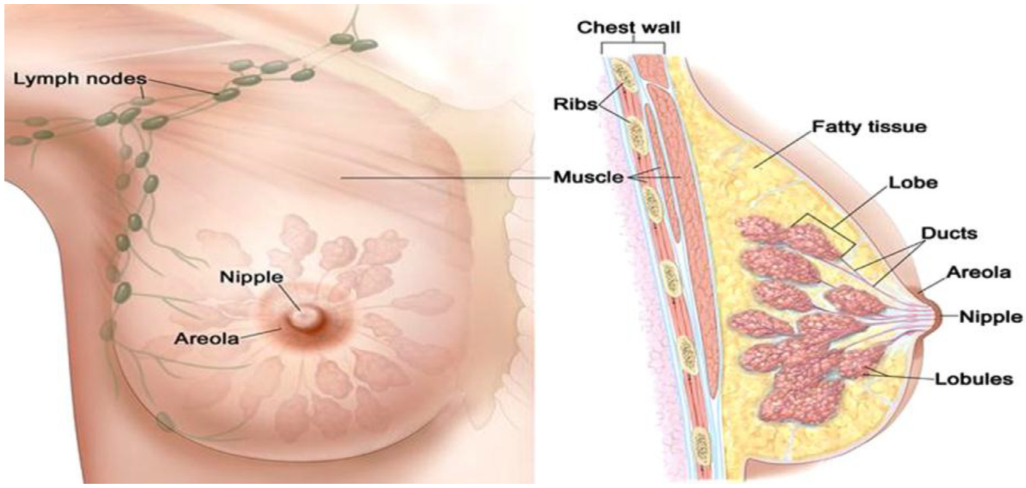

Fig. 1. Anatomy of female breast [4].

2.2. Keywords

Various possible combinations of keywords such as "Infrared Thermography", "Segmentation", "Intelligent Cancer Classification", "Machine Learning", "Feature Extraction" and "Numerical Simulation" have been used for the search of articles.

2.3. Inclusion and exclusion criteria

In order to shortlist relevant papers from the large collection of studies, emphasis has been given to the following factors:

(i) Improvement in performance of existing thermographic techniques in terms of accuracy.
(ii) Recent advances in machine learning techniques for supporting medical interpretation.
(iii) Number of thermograms/patients used in the study for practical relevance.

3. Breast thermography

There are many types of cancer that can originate in any part of the breast. Breast cancer begins either in milk carrying ducts or the milk producing lobules of the breast region. The detailed structure of female breast is shown in Fig. 1.

Proper identification of breast abnormality prior to the beginning of a cancerous growth is the only effective way of reducing mortality due to breast cancer. Various imaging modalities have been developed to detect prior symptoms of breast cancer. Apart from mammography, other imaging techniques used for breast abnormality detection are ultrasound, Magnetic Resonance Imaging (MRI) and breast Tomosynthesis. Perez-Raya et al. [5] provides a comparison of existing techniques with some recent techniques like Electronic Palpation Imaging (EPI) and Electrical Impedance Scanning (EIS). Tomosynthesis in combination with mammography can improve the efficiency of cancer detection, as compared to mammographic alone [6]. EPI method can be used for tumor detection by using an array of tactile sensors that record a mechanical measurement of pressure, which is caused by difference in breast tissue hardness. EIS [7] method quantifies the electrical impedance of the breast to provide an indication of presence of tumor.

Mammography [8] is the frequently recommended technique for breast cancer screening. It is used to diagnose cancerous tumor, presence of cysts and micro-calcification in the breast. Fig. 2 shows some specimen of the mammograms [9].

Some of the disadvantages of mammography [14,15] are listed as follows:

1. Repeated exposure to X-rays increases the chances of cancer.
2. It can generate false positives which, subsequently may not turn out to be cancerous.
3. Huge pressure is applied on the breast region for image, making the method very painful. Also, this may cause the rupturing of tumor encapsulation.
4. It is not suitable for women with dense breast tissues.

Infrared Imaging has been approved as an adjunct imaging modality to mammography by FDA (Food and Drug Administration) in 1982 .Thermography is a medical imaging technique that records the variation of surface temperature of human body based on the infrared radiation emitted by the surface of that body. The cancerous cells generate heat due to the following reasons: (1) release of nitric oxide into the blood causing alteration in microcirculation (2) Vasodilatation; dilation of blood vessels to increase blood circulation (3) Neo-angiogenesis; creation of new blood vessels to supply nutrients to tumor (4) increase in metabolic activity of cancerous cells [16].

Stefan–Boltzmann Law can be used to understand the correlation between the energy emitted by an object and its temperature. According to the modified Stefan–Boltzmann equation, the total emissive power from a radiating body is given as

$$E = \varepsilon \sigma T^4$$

Where, E denotes the total emissive power (W/m^2), σ represents the Stefan–Boltzmann Constant ($\sigma = 5.670373 \times 10^{-8}\, W/m^2\ K^4$), T denotes the absolute temperature (K), and ε is the emissivity of surfaces of non-full radiator. IR radiation emitted by human skin falls in the range of 2–20 µm.

The Pennes' bioheat equation [17] can effectively measure the heat produced by cancerous cells. Lawson [18] discovered the implications of rise in surface temperatures due to heat generation in cancerous tissue; he suggested that the temperature change is an important factor for indicating anomaly in breast. Breast thermography is a passive, fast, painless, moderate cost and risk free imaging technique. Moreover, it can be used for real time imaging and processing capability. It has been documented that thermography, when used with well-defined protocols, can detect early symptoms of cancer 8–10 years earlier than Mammography [19]. Advances in Infrared cameras that are used to capture thermal images of the breast and advancement in machine learning based detection systems have significantly improved the role of thermography as an effective tool for early breast abnormality detection.

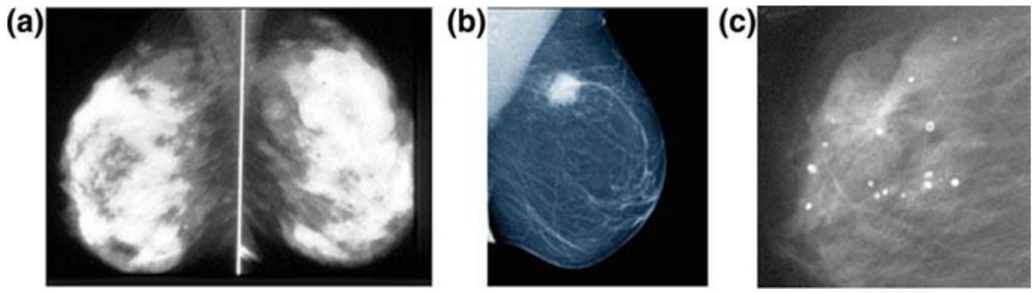

Fig. 2. (a) Dense breast mammogram: unable to distinguish between dense breast and tumor [10]. (b) Mammogram indicating a breast tumor [11,12]. (c) Micro calcifications in breast mammogram [13].

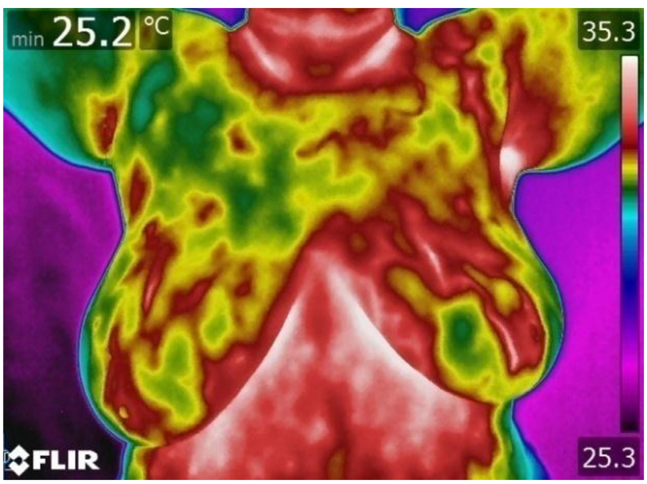

Fig. 3. Frontal view of a breast thermogram [22].

3.1. Thermal cameras and acquisition protocols for capturing thermal image

Efficiency of diagnosis using breast thermogram is affected by the sensitivity and resolution of the thermal sensors or thermal cameras used. Thermal cameras that have resolution of 640 × 480 pixels and better sensitivity can detect a minute difference in temperature [9]. Thermograms are affected by the condition of the room in which image is captured. Moreover, they are sensitive to many factors prior to the acquisition procedures and during acquisition of image. There is a need of defining standard procedures, to be followed during acquisition of Thermograms. A systematic description of the standards and protocols that needs to be taken care of during infrared image acquisition has been provided by Ng [20]. Fig. 3 shows a frontal view of a breast thermogram.

3.2. Public/Private available IR database

In addition to the need of standard protocols for breast thermogram acquisition, availability and quality of infrared breast thermogram marked with ground truth is of great importance for advancement of related research. Such database could support not only medical specialists, but also could be used for analysis by Artificial Intelligence algorithms during machine learning. The publically available database of the PROENG [21] project consists of images obtained from the patients/volunteers of the University Hospital at the UFPE (Brazil). The Department of Biotechnology-Tripura University-Jadavpur University (DBT-TU-JU) [22] breast thermogram database has been created by using well-defined acquisition procedure. Presently, the DBT-TU-JU database is composed of 1100 thermal breast images of 100 patients (45 healthy, 36 benign, 13 malignant and 6 with mild breast problems). The publically available DMR (Database for Mastology Research) [23] contains 287 Thermograms (47 sick and remaining healthy).

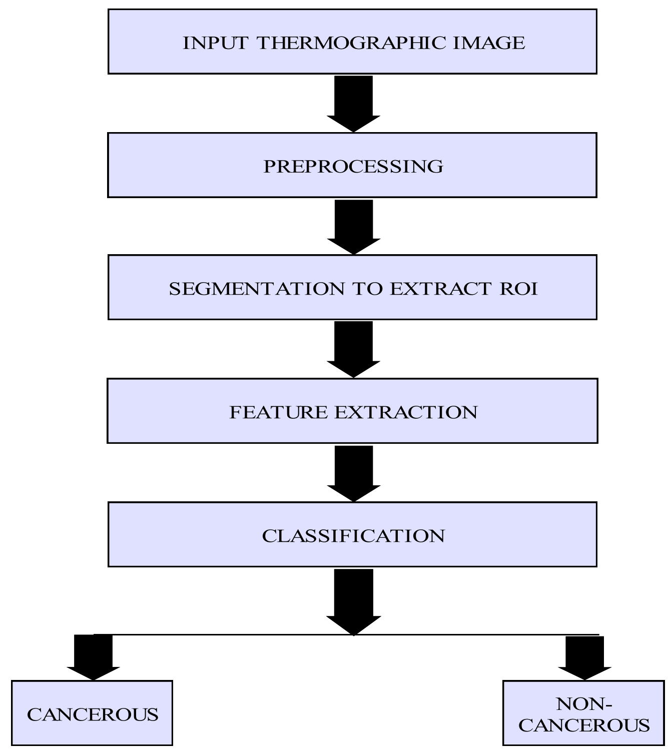

Fig. 4. Steps in Intelligent diagnosing systems for breast thermogram.

4. Machine learning based system for analysis of breast thermogram

Usage of intelligent Computer based system for analyzing the breast thermograms has emerged as an effective tool for providing the support to the radiologists. The process involves preprocessing of thermogram, extraction of region of interest or segmentation, extraction of features and classification. Fig. 4 illustrates the overall methodology involved in Cancer Diagnosis system used for thermographic images.

Breast thermograms obtained from a thermal camera may consist of some labels which are incorporated as a part of software in thermal cameras. Preprocessing involves removing all the labels and tags of an acquired thermogram in order to separate the background from the patient. The main purpose of segmentation of ROI (Region of Interest) is to identify the breast region to be processed. The extracted ROI must include all breast tissues, ducts, lobules and lymph nodes as much as possible.

Qi et al. [24] applied Hough transform (HT) to segment left and right breast and to obtain feature curve extraction. Automatic segmentation resulted in extracting breast boundaries, which was then processed using feature extraction and classification techniques.

EtehadTavakol et al. [25] applied K-means and fuzzy c-means algorithms for color segmentation of IR breast Images. Six thermal cases were used for segmentation and some useful features were extracted from the regions with the highest and the second highest temperature.

Jin-Yu et al. [26] proposed a genetic algorithm to improve SNR of IR thermal images and to reduce time of computation involved in image segmentation. This method combines the benefits associated with the improved genetic algorithm and chaotic two-dimensional Otsu algorithm. According to authors, the reduced average time of the segmentation of thermal images with a resolution of 198×173 pixels is computed as 4.83 s.

Motta et al. [27] presented an automatic segmentation method consisting of 7 main steps: (i) thresholding to detect lower limit of ROI which is the inframammary fold; (ii) background elimination by Otsu's method; (iii) ROI upper limit detection by finding axilla; (iv) Elimination of arms and other regions; (v) Central axis determination and breast separation; (vi) inframammary fold detection; and (vii) vertical displacement. The resultant segmented thermograms along with the ground truth are available in the publically available database [20].

Golestani et al. [28] discussed and compared three techniques of breast thermogram segmentation: k-means, fuzzy c-means and level set. In this paper, 30 thermal images were used. Experimental results have proved that the improved level set algorithm used here resulted in better efficiency, accuracy and robustness.

Mahmoudzadeh et al. [29] presented a unique extended Hidden Markov Model (HMM) for improved segmentation of breast thermographic images. The proposed algorithm is used to perform segmentation of images in ITU_OPTIC database. The results show that the there is reduction in execution time, as compared to other segmentation techniques like fuzzy c-means, Self Organizing Map (SOM) and standard HMM.

de Oliveira et al. [30] proposed an automatic ROI extraction method using threshold of histogram for balancing, clustering and detection of corners by Shi-Tomasi method. In this paper, PROENG [20] thermal images were used.

Pramanik et al. [31] applied segmentation by using Otsu's threshold to remove background, thereafter applying a reconstruction technique. Authors tested the method on Thermograms made available by Visual Lab, Fluminense Federal University, Brazil [20].

Rajagopal et al. [32] presented an automatic method of segmentation using Projection Profile Approach. This method can be generalized for various types of thermographic images with minor modifications like standardization of the image background, height and removal of the noise present in the image.

The main summary of above papers is presented in Table 1.

5. Emerging trends in extraction of significant features and classification

The main process in Medical image processing is Feature Extraction. This involves choosing certain parameters, known as features that will be extracted from a breast thermogram, analyzing and comparing the features to obtain significant results. This will reduce complexity in classification and recognition of images. Feature extraction techniques help in overcoming some of the disadvantages of breast thermography such as (i) its inability in diagnosing small tumors, (ii) identify increase in temperature due to reasons, other than tumor, and (iii) difference in interpretation by various physicians [4]. Another important aspect in computer-

Table 1
Segmentation for ROI extraction.

Paper	Segmentation Criteria/ Technique	Degree of Automation	Characteristics/ Advantages
Qi et al. [24]	Edge based segmentation using Hough Transform	Fully-Automatic	Loss of some breast area may discard regions with possible lesions and ROI's lack of symmetry
EtehadTavakol et al. [25]	k-means and fuzzy c-means for color segmentation	Automatic	Useful in identifying stage of cancer by computing regions with highest and second highest temperature and thereby detecting abnormal cases
Jin Yu et al. [26]	Two –dimensional Otsu's algorithm based on Chaos and Genetic Algorithm	Fully automatic	Improvement in speed of execution and better segmentation as compared 2-D Otsu's algorithm
Motta et al. [27]	Otsu's thresholding for background segmentation	Fully-Automatic	Suitable for tri-dimensional temperature profile and virtual surgery simulation
Golestani et al. [28]	k-means, fuzzy c-means and level-set methods	Automatic	Improved level set algorithm (energy functional formulation) has preferable efficiency, accuracy and robustness, as compared to k-means and fuzzy c-means
Mahmoudzadeh et al. [29]	Extended Hidden Markov model for segmentation	Fully automatic	Handling of random sampling of the images, less execution time than Fuzzy c-means, SOM and standard HMM, identification of semi-hot regions
de Oliveira et al. [30]	Segmentation by detection of corners by Shi-Tomasi method	Automatic	Mean accuracy-96% Mean sensitivity-97%
Pramanik et al. [31]	Otsu's thresholding to remove Background followed by a reconstruction technique, detecting lower limit of breast by inframammary fold and detecting upper limit by discerning the axilla	Automatic	Accuracy of 90.48% and sensitivity 87.6% (with discrete wavelet transform method for feature extraction)
Rajagopal et al. [32]	Projection Profile Approach	Automatic	Segmentation with average mean square error 0.036 [33]

aided medical imaging techniques is the selection and classification of the extracted features. Feature selection methods help in reducing the computational complexity and increasing the accuracy of the proposed algorithm. Sensitivity represents the measure of the extent of correctly identifying diseased person whereas Specificity denotes the extent of correctly rejecting healthy person. In order to classify between healthy and unhealthy breast, four cases are possible: true positive (TP), where a unhealthy breast is correctly identified as unhealthy, false positive (FP), where a healthy breast is falsely diagnosed as unhealthy, true negative (TN), where a healthy breast is rightly diagnosed as healthy; and false negative (FN), where an unhealthy breast is falsely diagnosed as healthy. Based on the number of Thermograms obtained in these categories, the main performance parameters are: accuracy = (TP + TN) / (TP + FP + FN + TN), sensitivity (or recall) = TP / (TP + FN) and specificity = TN / (TN + FP). One of the frequently used graphic tools that allows the comparison of various classification algorithms, is Receiver Operating Characteristic (ROC).It is a pictorial representation of correlation between the true positive rate and the false positive rate to evaluate tradeoffs between the sensitivity and specificity of a diagnostic technique.

A chronological review on some of the papers related to the feature extraction and classification techniques used in breast thermography are given in this section. Ng and Kee [34] proposed a combined diagnostic analysis consisting of Linear Regression (LR), Radial Basis Function Network (RBFN) and Receiver Operating Characteristics (ROC) for analyzing temperature data extracted from breast cancer thermogram. The authors used thermograms of 82 patients for the analysis: 30 normal patients, 48 patients with benign breast abnormality and 4 patients with cancer. According to the authors, an improved accuracy rate of 80.95% is achieved by using ANN RBF classifier. Qi et al. [24] proposed asymmetry based classification algorithms for feature extraction: k-means unsupervised learning and KNN based supervised learning. 6 normal Thermograms and 18 cancerous Thermograms were analyzed by the authors. It was observed by the authors that the higher order statistics (variance, skewness and kurtosis) indicated asymmetry more efficiently, as compared to the low-order statistics (mean and entropy). Schaefer et al. [35] used 146 Thermograms (29 malignant and 117 benign cases) to perform breast cancer analysis. A total of 38 descriptors or features were extracted for every breast thermogram that describes the asymmetry between the two sides of a breast. Then a fuzzy classifier is trained to distinguish cancer patients from healthy individuals. A classification rate of 79.53% is obtained with 14 fuzzy partitions per attribute, on test data set, which is comparable to other breast cancer diagnostic techniques.

Serrano et al. [36] extracted 133 features: 36 features based on Hurst Coefficient and 97 features based on Lacunarity from a thermal image. Hurst coefficient is a fractal dimension that represents the space occupied by an object or an image. Lacunarity measures the amount of gaps in the image or object. Machine learning techniques such as Naïve Bayes Simple, Classification Via Clustering, Naïve Bayes, Naïve Bayes Updateable, Random Committee and Nnge were used, with Naïve Bayes Updateable giving the best results (ROC area = 0.958). Pragati and Prasad [37] extracted Statistical features (skewness, kurtosis, entropy, energy, homogeneity, correlation and joint entropy) from the segmented thermograms. In the paper, a Multilayer Perceptron Neural Network classified thermograms as normal, benign and malignant. The three layer perceptron network is trained using 50 breast thermograms and remaining 10 are used for testing and validation. The network was trained for 5000 epochs. This method provided classification accuracy of 80%. A standalone GUI is also created using MATLAB Handle Graphics for real time thermogram analysis. EtehadTavakol et al. [38] computed the fractal dimension of first hottest regions of each thermographic image of the dataset (8 benign and 7 malignant). Fractal analysis (FD) plays a crucial role in differentiating between benign and cancerous tumor as malignant structures have rough and complicated boundaries. Box counting method has been used to estimate FD. The authors found from the mean and standard deviation of computed FDs, that there is a significant difference between fractal dimensions of cancerous and benign cases. The FDs for benign cases were found to be closer to 1, whereas that of malignant were considerably higher.

Borchartt et al. [39] extracted statistical features (the range, the mean and the standard deviation), as well as fractal features: the fractal dimension (FD), the local Lacunarity (LL) and the succolarity (LS). The statistical features' were extracted from a small number of patients (4 healthy and 24 abnormal). These features combined in different sets, when fed to different machine learning techniques, gave ROC area of 96% with the group using naïve Bayes classifier. These features were classified using free software LibSVM. Acharya et al. [40] extracted texture features from cooccurrence matrix and run length matrix. These features were given to SVM Classifier where 36 images (18 normal and 18 malignant) formed the training set and 14 images (7 normal and 7 malignant) formed the test set. The proposed system produced an improved accuracy of 88.10%, sensitivity and specificity of 85.71% and 90.48% respectively. EtehadTavakol et al. [41] used the bispectral invariant features for classifying breast thermal images into malignant, benign and normal classes. Authors obtained the image of the hottest region and normalized the 2D gray scale image. Radon transform is used for mapping the image to one dimension. Bispectral invariant feature are computed and divided into training and test set in the ratio of 80:20. The classifier used in this work, is adaptive boosting (Adaboost) classifier showing the accuracy of 95% with bispectral invariant features and 83% with normalized spectrum features. Peulic [42] computed 20 Gray Level Co-occurrence Matrices (GLCM) features from 40 thermographic images (26 normal and 14 abnormal). The classifiers used by the authors were Support Vector Machine (SVM), K-Nearest Neighbor (k-NN) and Naïve Bayes Classifiers. Using five-fold cross validation method and K = 5, the accuracy rate of 92.5% is achieved by using k-NN classifier in this paper. Francis et al. [43] proposed a feature extraction based on curvelet transform for the detection of irregularity in breast thermogram. The curvelet transform helps in representing edges and distinctiveness in curves in an image, so the classification accuracy improved, as compared to statistical features. The classifier provided the accuracy rate of 90.91% and the hypothesis testing of extracted features of normal and abnormal groups, resulted in statistical significance of Mode and Standard deviation with $p < 0.05$. Pramanik et al. [31] determined the initial feature point image (IFI) of each breast thermogram by computing discrete wavelet transform. In this work, Principal Component Analysis (PCA) has been used for reduction of dimensionality of each feature matrix (comprising of 3780 features), thereafter reducing to only six features. A feed-forward Perceptron consisting of four layers has been used by the authors on 306 thermograms of 102 individuals (123 abnormal and 183 normal). The obtained accuracy is 90.48% with sensitivity and specificity as 87.6% and 89.73% respectively. Lashkari et al. [44] had implemented intelligent classification of extracted features like statistical, morphological, frequency domain, histogram and GLCM. The authors used various feature selection algorithm to obtain the best features. The classification was done using distinct classifiers such as Adaboost, SVM, k-NN, Naïve Bayes and Probability Neural Network (PNN). According to the results, the best mean accuracy of 85.33% was obtained by the amalgamation of Adaboost with GA on the left and right breast thermogram with 0° angle.

Madhu et al. [45] extracted medically interpretable thermal features to differentiate malignant case from non-malignant case in the breast thermogram. 90 subjects were randomly selected from

Table 2
Feature Extraction and Classification.

Paper	Feature Extraction Techniques	No. of patients/thermograms	Classification Techniques	Accuracy/Results
Ng and Kee [34]	Mean, mode, points of temperature, median and biological data of patients	82 patients(30 N,48 B,4C)	ANN Radial Basis Function Single Layer Perceptron and ANN Back Propagation	Accuracy of BP-61.5% Accuracy of ANN RBF-80.95% Sensitivity-81.2% Specificity-88.2%
Qi et al. [24]	Histogram, mean, variance, skewness, kurtosis, entropy, joint entropy	24 patients(6 N,18 C)	k-means and KNN	High-order statistics most effective in asymmetry analysis (based on closeness metric)
Schaefer et al. [35]	4 basic statistical features, 4 moment features, 8 histogram features,8 cross-occurrence features, mutual information and 2 Fourier descriptors.	146 thermograms (29 M and 117 B)	Fuzzy rule-based classification and Genetic algorithm for rule-reduction	Accuracy-79.53% Sensitivity-79.86% Specificity-79.49% with 14 fuzzy partitions per attribute
Serrano et al. [36]	Lacunarity measure and Hurst Coefficient-133 Features(36 using Hurst Coefficient and 97 using Lacunarity)	28 thermograms	Naïve Bayes Simple, Classification via clustering, Naïve Bayes, Naïve Bayes updateable, Random Committee, Nnge	ROC area = 0.958 with Naïve Bayes updateable
Kapoor and Prasad [37]	Skewness, Kurtosis, Entropy, Joint Entropy, Co-occurrence Matrix features like energy, homogeneity and correlation	60 thermograms	Multi-layer Perceptron Network	Accuracy-80%
Etehad Tavakol et al. [38]	Fractal dimension using Box counting	15 thermograms(8 B, 7 M)	Not specified	Not specified
Borchartt et al. [39]	14 feature groups based on Local Lacunarity (LL) and Hurst Coefficient (HC)	28 patients (4 N, 24Ab)	NBS, RF, LAD Tree, CVC, NB, NBU, LMT, SL, KS, MP, L, MCC, Dec, RC, Rfor, RBFN, SVM and validation by numerical modeling to estimate tumor's height	Feature group using Naïve Bayes with ROC area-96%
Acharya et al. [40]	16 texture features-homogeneity, energy, entropy, moment-1,2,3,4,angular second moment, contrast, mean, short run and long run emphasis, run percentage, gray level and run length non-uniformity	50 thermograms(25 N, 25C)	SVM Classifier	Accuracy-88.10%, Sensitivity-85.71%, Specificity-90.48%
EtehadTavakol et al. [41]	Bispectral invariant features from Radon projections	32 thermograms (9 M, 12B, 11 N)	Adaboost Classifier	Accuracy- 95% with bispectral invariant features, Accuracy-83% with normalized spectrum features
Peulic [42]	20 Gray Level Co-occurrence Matrices (GLCM) features	40 thermograms(26 normal and 14 abnormal)	SVM, Naïve Bayes and KNN classifier	92.5% accuracy with KNN
Francis et al. [43]	Curvelet based Co-occurrence texture features proposed by Haralick	Thermograms of 22 women(11 C, 11 normal)	SVM	Accuracy-90.91%, Sensitivity-81.82%, Specificity-100%
Pramanik et al. [31]	Statistical features from Initial Feature Point Image(IFI)-mean, variance, entropy, skewness and kurtosis	306 thermograms of 102 individuals(123 Ab and 183 N)	Feedforward Multilayer perceptron network	Accuracy-90.48%, Sensitivity-87.6%, Specificity-89.73%

(*continued on next page*)

Table 2 (*continued*)

Paper	Feature Extraction Techniques	No. of patients/thermograms	Classification Techniques	Accuracy/Results
Lashkari et al. [44]	23 features including statistical, morphological, frequency domain, histogram and Gray Level Co-occurrence Matrix (GLCM) and feature selection methods	670 thermograms of 67 patients	Adaboost, SVM, KNN, Naïve Bayes, PNN	Best combination of feature selection method and classifier: GA+Adaboost with average accuracy of 85.33% and 87.42% on the left and right breast image with 0°
Madhu et al. [45]	Medically interpretable features such as Boundary features, thermal comparison of Contra-lateral Breasts, Relative temperature and Presence of Abnormal regions	265 individuals(78 C, 187 N)	SVM and Random Forests	Around 99% specificity and 100% sensitivity
Gogoi et al. [46]	Three set of features from 24 features	DBT-TU-JU Breast thermogram database (46 Ab, 24 N DMR Breast thermogram database (35 Ab, 45 N)	SVM, KNN, Decision Tree, ANN	In DBT-TU-JU, SVM-RBF and ANN yield highest accuracy of 84.29% In DMR database, ANN and SVM-Linear provide highest accuracy of 87.50%
Jeyanathan et al. [47]	Gabor wavelet, Dual Tree Wavelet, Curvelet Wrapping, Curvelet Non-spaced, Contourlet	25 N, 25 Ab	Multilayer Perceptron Back Propagation Neural Network (Grouping based on Wilcoxon-Mann-Whitney test)	Low mean square error(0.3) for Gabor Wavelet features classified significantly
De Santana et al. [48]	Combination of Zernike moments based on geometry and Haralick moments based on texture	1052 thermograms of 100 patients (227 N, 219 Cy, 371 B, 235 M)	BayesNet, NB, MLP, SVM, Knowledge Tree J48, RFor, Random Tree, ELM	Accuracy of 76.01% and kappa index(indicating inter-rater reliability) of 0.6402 with MLP using 10-fold cross validation
De Vasconcelos and de Lima [49]	Twenty features based on statistical measures and temperature interval measurements. Initial temperature, atmospheric humidity and patient's age also used as additional characteristics	Binary class with balanced images(190 C, 190 N) Multiclass with balanced images(78 N, 78 B, 78 M, 78 Cy)	BayesNet, NB, MLP, SMO, Rfor, Random Tree, IBK(KNN), LIBSVM	Fully balanced expanded thermogram classification(SMO based) yields 94.73% sensitivity for binary class and 80.77% sensitivity for multi-class

N – Normal, Cy – Cyst, B – Benign, C – Cancerous, M – Malignant, Ab – Abnormal, NBS – Naïve Bayes Simple, RF – Rotation Forest, LADTree – Logitboost Alternating Decision Tree, CVC – Classification Via Clustering, NB –Naïve Bayes, NBU – Naïve Bayes Updateable, LMT - Logistic Model Tree, SL – Simple Logistic, KS- Instance based Classifier KStar, MP – Multilayer perceptron, L – Logistic, MCC – Multi class Classifier, Dec – Decorate, RC – Random Committee, RFor – Random Forest, RBFN – Radial Basis Function Network, ELM – Extreme Learning Machine, SMO – Sequential Minimal Optimization, IBK – Instance based Learner, LIBSVM – Library for SVM.

the entire data set of 265 individuals, for training. The remaining dataset was divided in the ratio of 1:2 for cross-validation and testing respectively. SVM and Random Forest (RF) classifiers resulted in around 99% specificity and 100% specificity. Gogoi et al. [46] selected the most distinguishing features from a collection of 24 features based on Mann- Whitney- Wilcoxon statistical test. Total six classifiers have been used to implement the thermography based breast irregularity for efficient diagnosis. Results showed that ANN and SVM_Linear classifier provided the highest accuracy of 87.50% for DMR database. Jeyanathan et al. [47] applied wavelet, curvelet and contourlet transform to extract features from thermograms. The features were measured statistically using one sample t-test and independent t-test. The classification using Multilayer Perceptron back-propagation Neural Network showed that Gabor kind of wavelet features classified the thermograms into normal and abnormal, with Mean Square Error (MSE) value 0.3.

De Santana et al. [48] extracted the Zernike and Haralick moments based on geometry and textures, respectively. Thermograms of 100 patients, taken from eight different positions (219 cyst, 371 benign and 235 malignant lesions), were used in total eight classifiers. Extreme Learning Machine (ELM) classifier used in the study comprises of single-layer feed forward network with random generation of 100, 200, 300, 400 and 500 neurons in the hidden layer. Results show that ELM with 65.95% accuracy and 0.4822% kappa index(using percent split) and ELM with 71.221% accuracy and 0.6676 kappa (using cross-validation), give better results as compared to other classifiers. These results were obtained using only Haralick attribute extractors. Multi-layer perceptron (MLP) increased accuracy to 76.01% with kappa 0.6402(using 10- fold cross validation) with the combination of Haralick and Zernike moments. ELM proved to be a promising classifier with rapid training and reduced computational cost.

De Vasconcelos and de Lima [49] computed twenty characteristics based on maximum and minimum temperatures of left and right breasts. In this study, 233 thermograms were used for binary class (Cancer and non-Cancer) and multi-class (malignant, benign, cyst and normal) classification. Moreover, existing database was balanced by construction of synthetic vectors to reduce classifier bias. Sequential Minimal Optimization (SMO) based classifier resulted in 94.73% sensitivity for binary class and 80.77% sensitivity for multi-class analysis.

Table 2 presents the brief summary of the above mentioned papers.

6. Future trends in breast thermography

Machine learning based system proves to be effective in classification and detection in the medical field, with necessary training skills, selection of more significant features and reduced false positives. Moreover, there is a future need to develop database with millions of thermographic images for improving the efficiency of classifiers. The future research work may also involve improving the efficiency of classifiers with the limited number of thermograms available. There is also the need to overcome the main drawback of thermogram based detection, variation in sensitivity with the tumor dimension and high false positive results. Moreover, the thermal profile of complex human breast is also dependent on breast density [50,51]. Ng and Sudharsan [52] performed finite element method (FEM) based simulation on multi-layer three-dimensional breast model. The simulation showed that size and depth of tumor affects the surface temperature distribution. Amri et al. [53] has presented simulation results for tumor-depth detection using steady-state and transient-state thermography. In addition to investigating the sensitivity to parameters such as cold -stress temperature and cooling time, the work highlights the effectiveness of transient thermography as a supporting tool, which can be further improved by thermal contrast-based signal processing techniques.

7. Discussion

This article attempts to present the key factors to improve the efficiency of existing thermography based diagnosis. Validation of segmentation techniques (some are enlisted in Table 1), by the physicians with ground–truth further improves the reliability of methods used. Performance of classifier is dependent on the choice of features to be extracted from a thermogram: statistical, textural, fractal or medically interpretable. Authors in the paper have used various feature selection methods to enhance classifier accuracy. In addition to accuracy and sensitivity, Cohen's Kappa index [48] can also be used to estimate the level of agreement between two data sets. The major limitation of the study is lack of emphasis on integrating the medical interpretation of thermograms with training of classifiers to validate the diagnosis. In order to provide real-time diagnosis, Etehadtavakol [54] has proposed Lazy snapping algorithm for segmentation. This method allows faster extraction of the hottest or coldest regions from thermograms. In the review paper, comparison of feature extraction and classification techniques has been done in terms of accuracy, sensitivity, and specificity and ROC area. Maximum accuracy of 99.8% and maximum sensitivity of 99.8% is achieved by the combination of Adaboost classifier and Genetic Algorithm (inspired by theory of natural evolution) in the work proposed by Lashkari et al. [44]. We may also infer that features of medical significance proposed by Madhu et al. [45] prove to be promising in terms of classifier input, with 100% sensitivity. Many of the authors in the review have used SVM and MLP as classifiers.

8. Conclusion

The advent of computer-aided diagnostics in healthcare field has proved to be very effective in improving the role of thermography in detection of breast cancer. The study presents various segmentation, feature extraction and classification techniques used in breast thermography. High false positive and false negative values in thermography can be effectively reduced by suitable combinations of segmentation, feature extraction and classification techniques mentioned in the paper. Specific outputs from numerical simulation can also act as input to artificial neural networks, thereby integrating thermography and numerical simulation. This may further support real-time decisions regarding the condition of the patient. Existing intelligent systems also need improvement in commercially feasible interface with physicians, to validate the diagnosis.

Declaration of Competing Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpb.2019.105074.

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