Detection of Breast Cancer Thermograms based on Asymmetry Analysis using Texture features

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***Abstract*—Breast Cancer is one of the most frequent diseases that occurs in every third woman in the world. Different measures of technology help in diagnosing the presence of the tumor in the breast. One of the most effective and early diagnosis methods is Thermography which records temperature values of the surface and creates an image called thermogram. In this paper, images are extracted from the temperature matrix, dataset available at DMR visual labs and the texture features based on different gray levels are extracted. The variation in temperature for the left and right breast is observed on the basis of asymmetry analysis. For classification, the performance of five models such as Support Vector Machine, Decision Tree, Random Forest, Bagging Classifier and Artificial Neural Network are critically assessed.**

***Index Terms*—Breast Cancer, Thermography, Feature Extraction, Asymmetry Analysis**

I. Introduction

Cancer is a disease where the cells of the infected area grow abnormally [1]. The cells spread in the body by further division of cells. These outgrown cells form a mass of cells called as tumor. A tumor can be malignant or benign. A malignant tumor spreads and grows in the neighbor organs. The benign tumor does grow but do not spread. Breast cancer is one among the most vulnerable diseases that occurs frequently in women. Initially, the size of tumor is small and slowly it grows in size but the early screening increases the higher chances of survival rate and Thermography is one of the modalities among detection of tumors that helps in diagnosing the presence of tumor at an early stage.

Thermography is a non-invasive, non-ionizing, radiation free, having no contact with the body and low cost technique in which the infrared camera captures the heat patterns of the skin surface [2]. Thermography helps in diagnosing women with all ages with all sizes of breast or fibrocystic breast or dense breast and paticularly for pregnant women. The temperature on the tumor is higher(by as much as 2 to 3 degrees) than the normal cells as because of higher metabolic activity or increased vascularity of the tumor compared to normal breast tissue [3] [4]. The device converts the thermal energy into electrical signals that show the temperature profile of the subject in the form of images called the thermograms. The breast thermograms help in analysing the symmetry in heat pattern of the subject. The variation in temperature is differentiated by different colors in infrared pseudo colour images. Because of some inherent advantages, thermography is preferred over mammography.

In this paper, we analyze the breast cancer detection on thermal images by extracting features from the GLCM and GLRLM texture features, based on asymmetry analysis of the left and right breast. The asymmetry depicts the abnormality in the breast which gives an indication towards the presence of tumor. An unhealthy breast with the tumor will have a temperature raise as compared to the healthy breast. Texture feature extraction of the images helps in giving the relationship of intensity between the neighboring pixels. Gray level Co-occurence Matrix(GLCM) and Gray level Run Length Matrix(GLRLM) features are extracted and the relevant features are selected and then fed to the classifiers for detection.

This paper is organized as follows: The second section gives the detail review of state of the arts, the third section gives the dataset details, the fourth section gives the methodology approached, the fifth section shows the results obtained and the sixth section concludes the entire work.

II. State of the Art

As compared to the other modalities, thermography is not an anatomical imaging modality, it is a technique which displays the variation of temperature values, which are observed and analyzed. Texture features describe the pixel intensity and the spatial relationship between them. So, the statistical features are estimated which help in analyzing the asymmetry between right and left breast thermograms.

As per a new feature extraction approach, Milosevic et al. for detecting and diagnosing abnormal patterns in breast thermograms had been proposed [5]. The effectiveness of the breast therograms had been analyzed by extracting the 20 features of GLCM with the haralick 13 features from individual breast. By this the texture features are observed for any abnormality by comparing the both sides of the breast. Krawczyk et al. proposed a medical decision support system based on the bilateral asymmetry analysis of the breast thermograms by extracting twenty eight different featutres [6]. Futher, a curvelet transform based feature extraction method for automatic detection of abnormality in breast thermograms had been proposed by Francis et al. [7]. In curvelet domain,

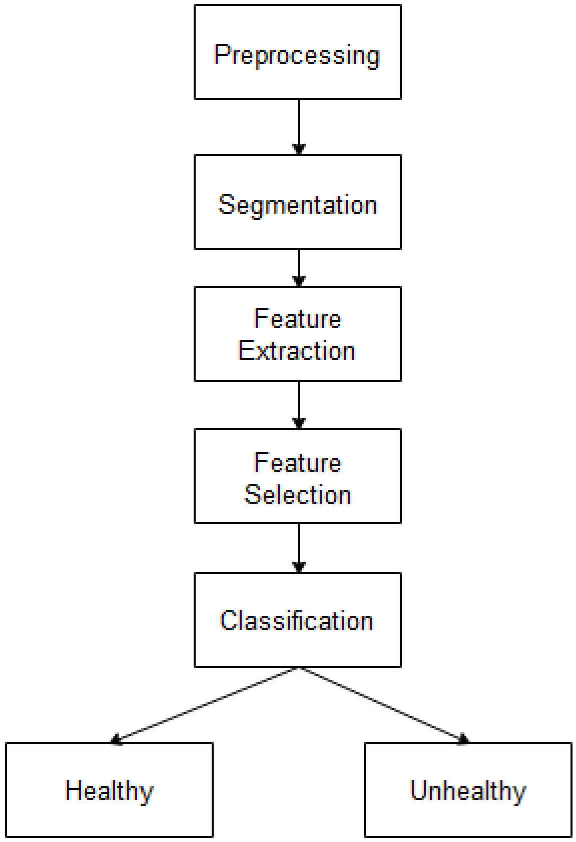


Fig. 1: Implementation for detection of breast tumor

both the statistical and texture features were extracted for each thermogram.

In the curvelet domain, extraction of the Haralick features [8] from the GLCM (gray-level co-occurrence matrix) is performed. Zadeh et al. proposed a method for early detection and diagnosis of breast cancer based on the histogram analysis. They had plotted histogram for each breast by taking the features like mean, kurtosis, variance and skewness which efficiently observed the difference in asymmetry analysis between both the sides of the breast. Another interesting approach was done by Koay et al. [10] where they had made four divisions in the breast. By using the SPSS software for statistical analyis, they had made the correlation in between the 10 statistical features including standard deviation, mean, median, skewness, kurtosis, area, energy, maximum, heat, entropy and minimum for each breast. Five features including skewness, standard deviation, mean, heat and kurtosis were observed to be highly relevant in detecing the abnormality in the breast. Further, Acharya et al. has evaluated the feasibility of infrared breast thermography in breast cancer detection by extracting four moment features from co-occurrence matrix and features like run-length percentage, and gray level non-uniformity were also extracted from the run-length matrix [11].

Breast thermal analysis for the temperature difference between the contralateral breasts had been performed by Borchartt et al [12]. Initially they segmented the breast region and then had extracted features including standard deviation, range temperature, quantization of the higher tone in eight level posterization and mean temperature.

III. Thermogram Dataset

For this study, the dataset is utilized from the existing DMR (Database for Mastology Research) database [13]. The dataset has breast thermograms of total of 56 subjects (640x480) of the individuals having 20 positional temperature matrix of each subject. Out of 56 subjects, 37 are unhealthy and 19 are healthy. This is an online available database for the breast thermograms. The thermograms are captured by the FLIR SC-620 THERMAL Camera with a 620x480 spatial resolution.

IV. Breast Thermograms Asymmetry Analysis

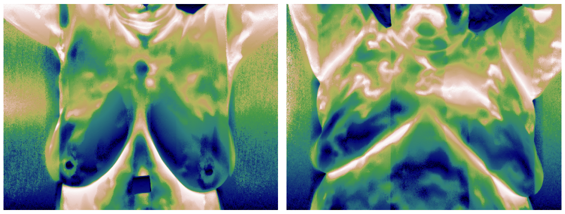
The texture features can be described in two forms as statistical and structural approach. The statistical approach is a primitive one which depicts the repeated relationship between the pixel intensity values. The structural approach is the quantitative measure of the pixel intensities in the spatial region. So the statistical approach is observed to be one of the efficient way to analyze the abnormality in the breast thermograms. The asymmetry analysis indicates a variation of temperature between the healthy thermograms and the unhealthy thermograms. The temperature of the healthy thermograms is less than the unhealthy thermograms. The breast thermograms having tumor consists of higher temperature values; hence the difference between the both, results in depicting the presence of tumor. This is carried out by first pre-processing the thermograms, then segmenting the breast area, extracting features, selecting the most relevant features and then classifying for the presence of tumor as shown in Figure 1.

A. *Pre-processing*

In pre-processing of the breast thermograms, the elements of the temperature matrix are converted into the images by applying normal distribution. It is a robust preprocessing technique as the effects of the outliers are reduced. The normalized values are ranged for the color mapping and pseudo images are obtained as shown in figure 2(a) and 2(b). These images are converted to the gray scale images. The gray scale makes the image more visualized as it requires less information provided for every pixel and it is relatively less complex as compared to the colored image.

B. *Segmentation*

In Segmentation, by selecting the coordinates of the left and right breast, area is segmented from the image manually. This process gives a better approach towards the asymmetry analysis of the breast thermograms.



(a) A healthy breast (b) An unhealthy breast

Fig. 2: Pseudo Images

C. Feature Extraction

Texture feature analysis holds the most informative characteristics of the image. Texture is a pattern of grey pixel intensity in a specific direction from the referencing pixels. These features reveal the information about the image by describing the mutual relationship among the different intensity values of the neighboring pixels. In this work, twenty GLCM(Gray level Co-occurence Matrix) features and seven GLRLM(Gray level Run Length Matrix) features are extracted from the gray scale segmented images of the left and right breast.

The GLCM features are the second order statistical features that mark the relationship between the different gray levels in various spatial orientations that are adjacent to each other [15]. Feature extraction based on grey-level co-occurrence matrix (GLCM) is the second-order statistics that can be use to analyse image as a texture. GLCM (also called gray tone spatial dependency matrix) is a tabulation of the frequencies or how often a combination of pixel brightness values in an image occurs. These twenty features are autocorrelation, contrast, correlation, cluster prominence, cluster shade, dissimilarity, energy, entropy, homogeniety, maximum probablity, sum of squares variance, sum average, sum variance, sum entropy, difference variance, difference entropy, information measure of correlation1, information relation of correlation2, inverse difference normalized and inverse difference moment.

The GLRLM features give the extent of homogeneous pixels running for each grey-levels [16]. That is, how many pixels of a given grey value occur in a sequence in a given direction of each pixel. Hence, a 2D matrix of the features is obtained as a result. Each element in this matrix gives the total number of occurrences of the gray level in the given direction. The GLRLM features obtained are short run emphasis, long run emphasis, gray level non-uniformity, run percentage, run length non-uniformity, low gray level emphasis and high gray level run emphasis.

D. Feature Selection

In feature Selection, out of 22 features, only eight features were selected based on the threshold value, which was kept 0.15 for each feature in GLCM. This was found to be a significant value as per the average values for each feature. The selected features are autocorrelation, cluster prominence, cluster shade, entropy, Sum of squares variance, Sum average, Sum entropy and Sum variance. Similary, out of seven features extracted, there were 3 features selected from the GLRLM based on the threshold value of 15 in GLRLM. The features selected are Run length Matrix, Gray-level Non-uniformity and High Gray Level Run Emphasis. The difference in features for left and right breast of both healthy and unhealthy class are shown in TABLE I.

TABLE I: Average Difference between the healthy and unhealthy class

Features	***Healthy***	***Unhealthy***
Autocorrealtion	0.381	2.18
Cluster Prominence	16.762	24.95
Cluster Shade	2.69	0.52
Entroy	0.20	0.10
Sum of Squares Variance	0.3	2.19
Sum Average	0.02	0.44
Sum Variance	0.21	7.44
Sum Entropy	0.15	0.05
Run length Matrix	17.37	224
Gray-level Non-uniformity	216.99	582.11
High Gray Level Run Emphasis	17.37	224

E. Classification Models Used

In this study, five important classification machine learning models such as Support Vector Machine(SVM), Random Forest (RF), Decision Tree(DT), Artificial Neural Network(ANN) and Bagging classifier for investigating the performance parameters for classifying the healthy and unhealthy breast. They are described as follows:

1) Support Vector Machine(SVM): Support vector machine is a classification algorithm and is mostly used for supervised learning [17]. It is widely used for two class classification problems. It creates a hyperplane for classification i.e, two sides of the hyperplane represents two classes. We can model the hyperplane by changing the parameters c and gamma

2) Decision Tree(DT): A decision tree is a simple classification technique. It is one of the most widely used technique for supervised learning [18]. The algorithm creates a decision tree(binary) for classification. In this tree each internal node is labeled with a feature and leaf nodes denotes the class. A data sample is classified if all the conditions from the root node to leaf node are satisfied. We need to create a decision tree which is small in size and gives gives high precision. Care has to be taken while training the model and ensure that it is not overfitted/underfitted is common in decision trees.

3) Random Forest(RF): RF is defined as randomized ensemble of decision trees [19]. In Random forest classifier we create a set of decision trees and assign a subset of training set to each of them. Then we take the votes of each decision tree to classify the data point as shown in fig. 3. Therefore random forest builds an ensemble of decision trees, trained by bagging method. By this we can ensure that the model is not overfitted,thus eliminating the disadvantage of decision trees.

4) Bagging Classifier: Bagging classification model is one of the good ensemble technique for classification and regression, that enhances both accuracy and stability for the machine learning algorithms [20]. It helps to combine the training sets that are randomly generated to form a final predictive

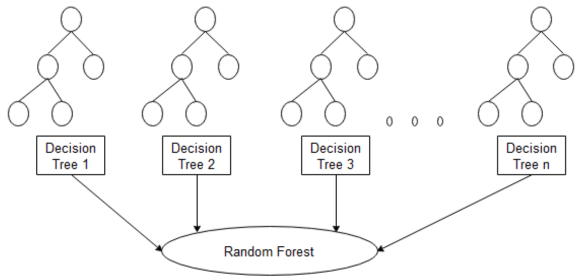


Fig. 3: schematical structure of Random Forest

class. Bagging supports variance reduction technique and then creates an ensemble for it. It is more popular because of its simple implementation and improved accuracy.

The main designed strategy is to combine a group of weak learners and ultimately to form a strong learner. In it, a decision tree is treated as a weak learner, and when taken together it creates a strong learner as shown in fig.4 . When a new instance is supposed to be classified, then it is recurred for each tree through the ensemble method and votes for a class. The final predictive class is obtained with maximum votes. Bagging is efficient one to handle large volume of datasets having numerous features.

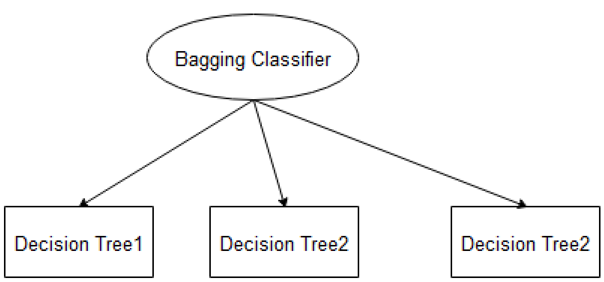


Fig. 4: Bagging: A Decision tree based model

5) Artificial Neural Network(ANN)): It approximates a non-linear function to a higher degree of accuracy [21]. It is constructed with three layers such as input layer, hidden layer and output layer as fig.5 . The input layer takes the input variable from each neuron. The hidden layer takes the non-linearity between the variables. The last layer is the output layer, which provides the predictive value. In a completely connected ANN, all layers in the lower layer are connected to upper layers. The weighted sum for the output of lower layers are calculated and passed through nonlinear function. During training, the pattern is applied and the output is compared to generate the error signal, and it helps to update the weights of ANN.

V. Result and Analysis

In this study, the most effective features which are relevant with the breast thermograms are selected from the extracted

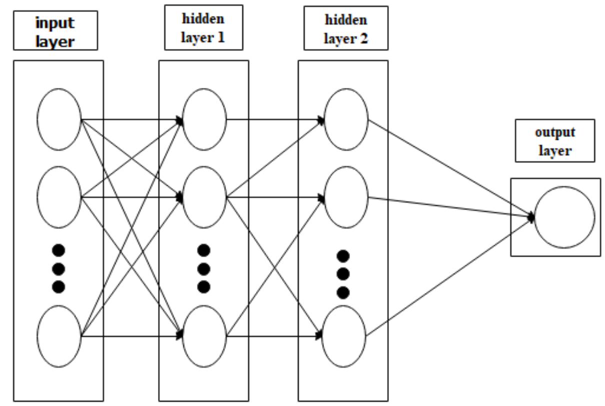


Fig. 5: schematical structure of ANN

TABLE II: Parameter Performance Assessment obtained from different Classifiers for reduced features set

Classifiers	SVM	Decision Tree	Random Forest	ANN	Bagging
Accuracy	80.00%	94.81%	97.03%	72.22%	69.86%
Precision	74.11%	92.86%	96.80%	60.71%	70.13%
Sensitivity	68.31%	92.47%	94.22%	57.87%	66.37%
Specificity	86.57%	96.10%	98.44%	80.00%	73.16%
F1-score	71.09%	92.66%	95.50%	59.26%	68.20%
MCC	55.95%	88.65%	93.33%	38.32%	39.64%

features on the basis of threshold value. The features extracted are from the GLCM and GLRLM for left and right breast are kept separated for each healthy and unhealthy breast. The average difference between the left and right breast for both the classes are calculated. It was found that the average difference of healthy class was low as compared to the unhealthy class. Further, the five classification models such as Support Vector Machine(SVM), Random Forest (RF), Decision Tree(DT), Artificial Neural Network(ANN) and Bagging classifier were fed with the healthy and unhealthy breast thermograms. Among the individual models, Random forest exhibits the optimized performance with a predictive accuracy of 97.03% for the reduced set of data with 11 features. As compared to full volume dataset having 27 features,the predictive accuracy is 94.78% as shown in Table II and Table III. Also specificity gives a significant performance of 98.44% for Random forest which shows that the rate of true negative is relatively higher as compared to other classification models. Other performance parameters such as Precision, F1-score and Matthews Correlation Coefficient(MCC) are also evaluated for both the datasets as shown in Table II and Table III.

VI. Conclusion

In this study, the asymmetry analysis based on texture features using GLCM and GLRLM is found to be one of the most efficient method to detect the presence of abnormality based on relevant features by examining both the breast for each subject. By assessing critically, we observed 11 features to be relevant out of 27 features calculated combined both from

TABLE III: Parameter Performance Assessment obtained from different Classifiers for all 27 features

Classifiers	SVM	Decision Tree	Random Forest	ANN	Bagging
Accuracy	79.55%	95.40%	94.78%	77.33%	68.78%
Precision	72.27%	92.02%	95.54%	79.91%	68.87%
Sensitivity	70.49%	94.81%	97.72%	62.37%	64.99%
Specificity	84.69%	95.72%	97.81%	88.40%	72.39%
F1-score	71.37%	93.39%	96.61%	70.06%	66.87%
MCC	55.48%	89.90%	94.97%	53.30%	37.45%

the GLCM and GLRLM feature Matrix, where the Random forest classifier performs the best with giving an classification accuracy and specificity of 97.03% and 98.44% as compared to the full set of features. Future work has been proposed to extend on finding thermal features for large number of datasets for verifying the classification accuracy with other highly distinctive classifiers.

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