Texture Analysis of Breast Thermogram for Differentiation of Malignant and Benign Breast

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***Abstract*—In this paper, we developed a new local texture feature extraction technique, called block variance (BV), for texture analysis in the thermal breast image. Then, present a method based on the different features extracted from the texture image obtained using BV to differentiate the malignant breast thermograms from the benign breast thermograms. Variance is an established measure of contrast in the image. Block variance (BV) uses the local variation of intensities to identify the contrast-texture in the gray-scale thermal breast image. Asymmetric temperature distribution between right and left breast in thermal breast image is an indicator of the presence of abnormality. Thus, we investigate the potential of our proposed features in asymmetry measure. For our experiment purpose, we used a set of forty malignant and sixty benign thermal breast images of DMR database. A feed-forward neural network (FANN) with gradient decent training rule has been employed to evaluate the classification performance. The effectiveness of our proposed features is compared against a feature set derived by Acharya et al. [16] in terms of classification accuracy, sensitivity, and specificity. From the experimental results, it is shown that the proposed features perform better compared to Acharya et al. features in differentiating malignant breast thermograms from benign breast thermograms.**

***Index Terms*—texture features; block variance; block classification; benign breast thermogram; malignant breast thermogram**

I. Introduction

Breast cancer is the most frequently occurring form of cancer in women in worldwide, which accounts for nearly 25% of all cancer cases in women [1]. Over the last few years, the incidence rate of breast cancer has rapidly increased; accounting $25\% - 30\%$, in India and the mortality rate is also considerably higher compared to the developed countries [1]. These facts have stimulated the research on developing new technologies for early breast cancer detection, as it is a highly curable disease with 95% possibility of cure rates if detected in the very early stage [2]. As a result, for the last three decades, various diagnostic imaging modalities have been developed for the detection of breast cancer. Amongst them, mammography is considered as the most cost-effective and reliable screening modality for the detection of breast cancer. However, despite the considerable advantages, mammography based screening also have some limitations [3]. The major problem that associated with mammography is electromagnetic radiation, which aids the growth of breast cancer, especially in pre-menopausal and young women. Also, it is quite difficult to acquire adequate breast mammogram for a fibrocystic, implant, and dense breasts. Lots of studies have reported that there exists a wide variation in its sensitivity and specificity [4]. Furthermore, it is an invasive technique, hence, lead to the rupture risk of cancerous tumor.

Due to the problems associated with mammogram and other imaging modalities, it is necessary to develop a new alternative imaging modality for the diagnosis of the breast cancer. In this respect, medical thermography has received lots of attention in recent years for the use in early breast cancer detection, because it is non-invasive, painless, simple, low-cost, radiation free, and highly accurate if used appropriate patient protocol and properly calibrated thermography. Breast thermography is the physiological exam, which records the variation of temperature on the breast surface using infrared radiation discharged from the surface of the breast. Typically, this temperature change is influenced by the level of blood perfusion in the breast skin. The changes in blood perfusion occur due to various causes such as inflammation, presence of tumor, or angiogenesis. The thermal infrared camera can record these changes very well and thus breast thermal image can be used to detect breast abnormality in its early stage. Importantly, compared to the mammogram, a thermogram is more advantageous when detecting breast tumor in very early stage or in younger women. Because the breast thermography is a physiological exam and very much sensitive to the physiological changes over the breast surface which might occur due to the development of pre-cancerous tissue in the breast. While mammography is an anatomical exam and can detect tumor only when they exceed a certain size. Keyserlingk et al. [5] reported that the average tumor size, undetected by standard method such as mammogram is 1.66cm, while 1.28cm by the thermography. Hence, breast thermography can be used as the most promising and suitable alternatives for early detection of breast abnormality.

The objective of this work is to develop an algorithm based on texture analysis in the thermal breast image for distinguishing malignancy and benignity of breast abnormalities. Usually, the temperature profile in both the right and left breasts in the normal breast thermal image is almost symmetrical. Since it is very much exceptional to have tumor in both the breasts, a minute variation in temperature profile of both the breasts in the breast thermal image may indicate the presence of breast abnormality. Due to the constraint of human vision system, this minute variation of temperature is sometimes missed by the trained medical practitioner. However, texture analysis of thermal breast image has the potential to identify the minute difference of the temperature profile of both the breasts which may not easily extract by the human eye. In practice, typically, texture features represent the dominant surface characteristics of the object and their relationship to the neighboring environment, which are very much useful for the analysis of the thermal breast image. In this paper, we, therefore, developed a local contrast texture extraction method, called block variance (BV), to capture the edge and valley features of the thermal breast image. Followed by that, blocks are classified into eight classes and then two higher order moments and the mean value of the texture positions coordinates are extracted from each class. The blocks are classified to reflect the homogeneity characteristics of the blocks. The feature vectors are than classified using a feed-forward artificial neural network (FANN) with gradient decent training rule. Our experimental evaluation, on a dataset of benign and malignant breast thermograms, shows excellent bilateral asymmetry between right and left breast, and also the classification accuracy, sensitivity, and specificity. The main contributions of our proposed method are as follows:

- Proposed a system to differentiate the malignant breast thermograms from the benign breast thermograms using texture features.
- Proposed a block based version of variance calculation to capture the edge and valley texture features from the gray-scale thermal breast image.
- A method to derive a set of features which indicates bilateral asymmetry between two breasts very well.

The rest of the paper is arranged as follows. A short literature review on texture features used in the analysis of thermal breast image is presented in section 2. Section 3 illustrates the proposed system in detail. Section 4 describes the details experiment conducted along with performance analysis, and section 5 concludes the paper.

II. Related Work

As mention in [6], the basic temperature pattern in the normal left and right breasts is almost symmetrical, while this symmetry lost for the diseased breasts. Most of the time experienced radiologists missed this minute variation of the temperature pattern in the breasts due to various psychological issues of the radiologists, like carelessness, absent-mindedness and lethargy. Therefore, there is a high call for automated methods for asymmetry analysis in thermal breast image to provide an objective decision about the goodness of the breast, which can also be used as a second, unbiased opinion. The texture analysis plays a pivotal role to identify the minute difference in temperature patterns in both the breasts. There are lots of methods have been reported to study texture in the images [7]. Among them, statistical methods are the most popular techniques and often used by the researchers in asymmetry analysis and to detect abnormal thermal breast image of diseased breast [8-10]. Lipari et al. [11] have used three basic statistical features, such as mean, median, and standard deviation along with maximum and minimum gray-level of each breast and each quadrant to measure asymmetry between left and right breasts. But they have not reported the classification accuracy of identifying normal and abnormal thermal breast images. Koay et al. [12] extracted three basic statistical features, maximum and minimum gray-level, two higher order moments (skewness and kurtosis), entropy, area and heat content from each breast quadrant. Then, examine the association between the extracted features which are effective for diagnosis of the breast. In [13], authors have computed some statistical features like mean, variance, skewness, kurtosis, correlation, entropy, and joint entropy for each breast in thermal breast image. Then, they measure the asymmetry between right and left breast using these features. However, they have reported that only variance, skewness and kurtosis are the most significant features in asymmetry measure. Recently, Zadeh et al. [14] also computed four common statistical features, such as mean, variance, skewness, and kurtosis from the histogram of each breast to measure the asymmetry between two breasts. Borchartt et al. [15] extracted mean, standard deviation, range temperature, and the quantization of the higher tone in eight levels posterization from each quadrant of the breast. Although, they concluded that it is more effective to extract features from each quadrant of the breast then the whole breast. In [16], Acharya et al. extracted four moments, mean, homogeneity, energy, angular second moment, entropy, a contrast from the co-occurrence matrix of each breast. Along with these features, they also computed the run length matrix for each breast and then extracted some features like run percentage, short and long runs emphasis, gray-level non-uniformity, and run-length non-uniformity. Among all the features, they used only four features to identify the abnormal breast thermograms of the diseased breast. Milosevic et al. [8] have also computed the co-occurrence matrix for each breast in thermal breast image and total twenty features are extracted to differentiate the healthy breast from the unhealthy breast. Authors in [9], used mean, median, standard deviation, eight histogram features, 90-percentile, geometrical centre, the centre of gravity, the distance between moment centre, eight cross co-occurrence features, two Fourier spectrum based features, and mutual information to measure the asymmetry between right and left breasts. Francis et al. [17] have extracted texture features for each breast in curvelet domain to identify an abnormality in thermal breast image. They first extracted some first order statistical features from each breast in thermal breast image. Along with these, Haralick features were also extracted from the gray-level co-occurrence matrix of each breast. In [10], authors have extracted six first order statistical features like mean, variance, standard deviation, skewness, kurtosis and entropy as texture features from the histogram of each breast to measure the asymmetry between the right and left breasts.

III. Proposed System

Fig. 1 shows the pictorial diagram of the proposed texture analysis in thermal breast image to differentiate malignancy

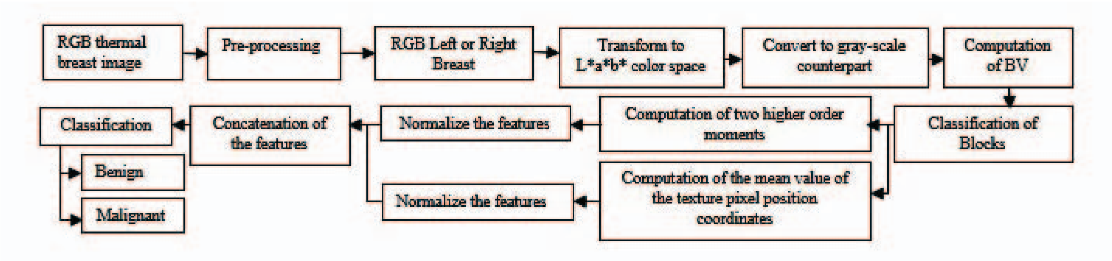


Fig. 1. Pictorial diagram of our proposed system.

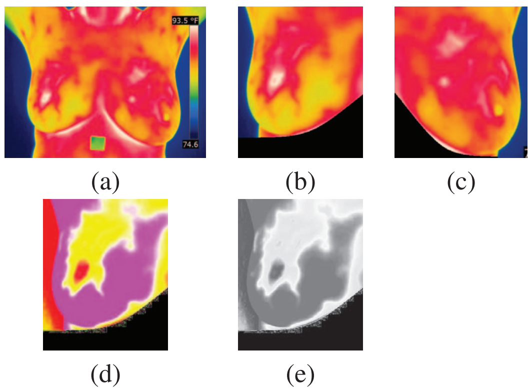


Fig. 2. shows (a) original thermal breast image, (b) manually segmented right breast, (c) left breast, (d) L* a* b* color space image corresponding to (b), (d) corresponding gray image.

and benignity of breast diseases. The proposed method consists of several steps: we begin with pre-processing of the thermal breast images, then transform the RGB color images into uniform color space, localized the texture pixels using proposed block variance (BV) method. After that blocks are classified into multiple classes, higher order statistical features are then extracted from each class, and finally features are normalized. Each of the steps will describe in the following subsections.

A. Pre-processing

The thermal breast images used in this work are acquired using FLIR SC-620 thermal infrared camera, which includes the breast region along with some extra body parts, as shown in Fig. 2(a). Extra body parts include upper body area (arms, neck) and lower body area (abdomen). Since the extra body parts do not provide any information regarding the diagnosis of breast cancer, it is necessary to segment the right and left breast regions only to process it further. However, there is considerable progress have been made to segment automatically the breast regions from thermal breast images [18-19]. But they are not applicable for color images and also not robust enough for the different types of thermal breast image databases. Thus, in this work, by taking the help of a medical expert we manually segmented the right and left breast regions from the color breast thermal images. Fig. 2(b) and (c) show the segmented right and left breast regions corresponding to the image Fig. 2(a).

B. Color Conversion

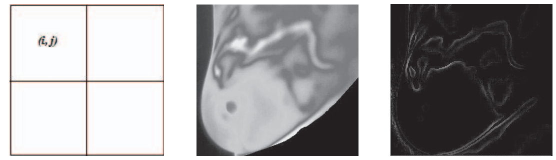
In the thermal breast images, RGB color model has been used to represent different rates of temperature regions. But the pseudo-color coding using the RGB color model has some obvious problems including perceptual non-uniformity, non-linearity, and high correlation of information among the channels. Hence, it is necessary to transform the original color breast thermal images into perceptually uniform color space to enhance the visual perception of the images. Two popular uniform color spaces CIELUV and CIELAB were suggested by the International Commission on Illumination (CIE) in 1976 [20]. In this work, we have used CIE (L*a*b*) model to transform all the breast thermal images into uniform color space. The detailed algorithm for RGB to CIELAB conversion could be found in [21]. Once the images are transformed into CIE (L*a*b*) color space, as shown in Fig. 2(d), the images are then converted into gray-scale counterparts, as shown in Fig. 2(e). Because the images in gray-level are usually preferred by radiologists, as they have a greater likeness to the images of the mammographic analysis. Also, there is no such convincing evidence available that can prove the false color representation provides more information to the viewers than gray-scale representation.

C. Proposed Block Variance (BV) as Texture Measure

The thermal image of a breast provides information about the surface isotherm pattern of the breast which is the valuable information for the diagnosis of the breast. The presence of tumor in the breast brings forth more heat than the normal breast tissue due to the different factors associated with the growth of the tumor. This local temperature increase leads to the change in breast skin surface temperature which would appear as a hot spot or a vascular pattern in the thermal breast image. The radiologist analyzes these visual characteristics in thermal breast image to identify the abnormal breast. Typically, the radiologist compared the thermal pattern of the right and left breast to identify a very small asymmetry between them. In general, the temperature profile in a normal breast thermal image is almost symmetrical in both the breasts. In case, benign breast, the growth of the tumor is very slow and round with a neighboring fibrous capsule [22], and this means that it generates a very less amount of heat, which leads to a slight change in breast skin surface temperature. Thus, the difference between isotherm patterns of benign right and left breast is considerably small. While the growth of the malignant tumor is usually very fast and no capsule that leads to generating more heat [22]. Therefore, the difference between isotherm patterns of right and left breast in a malignant thermal breast image is considerably high. However, it is very difficult for the radiologist to identify this minute difference due to the constraint in the human vision system. Since the thermal image of a breast exhibits only the vascular pattern, texture analysis in breast thermal image has the potential to identify the minute difference of the temperature profile of both the breasts which may not easily extract by the human eye. In practice, typically, texture features represent the dominant image surface characteristics that are very much useful for the analysis of thermal breast image. By observing the images used in this study, we note that in a benign breast thermal image the gray level changes smoothly from a high-to-low or low-to-high temperature and the shape of the isotherm pattern is very smooth, whereas for a malignant breast the gray level changes abruptly from a low-to-high or high-to-low temperature and the shape of the isotherm pattern is irregular. Thus, for the analysis of breast thermal image in search of breast abnormality detection both the edge and valley points are equally important. In this paper, we extracted these texture characteristics using the proposed Block Variance (BV) method. The texture in an image can be categorized into two classes based on two orthogonal properties: texture patterns (spatial structure), and the strength of the patterns (contrast). However, contrast is valuable information for the analysis of the images, as it is dependent on the gray scale and be unaffected by rotation. On the other hand, texture pattern is by default affected by rotation and independent of the gray scale. Variance is a very popular measure of contrast in an image. In the domain of gray image analysis, a variance of zero value indicates that all gray levels within an image are identical. A small variance indicates that the gray levels are very close to each other while a large variance shows that the gray levels are far from each other. In this work, we have proposed a block-based version of variance (BV) to compute the texture features such as edge and valley points from the thermal breast images. As variance is computed locally, the measure can resist the intra-image illumination variation up till the absolute gray value differences are getting affected. The block size for BV is chosen here as 2×2 because the smallest distance gave the local properties in more detail. If the intensity components in a block are varied in great, then the BV value will be large. The pixel configuration of the 2×2 block is shown in Fig. 3(a). Fig. 3(b) and (c) show the original image and corresponding BV image. The higher values of BV are shown brighter. The block variance (BV) is defined as

$$BV = \frac{1}{P^2} \sum_{(i,j)\epsilon B} (X(i,j) - \mu)^2 \tag{1}$$

where, $\mu = 1/P^2 \sum_{(i,j)\epsilon B} X(i,j)$ is the mean within the block B, $X(i,j)$ is the intensity of a pixel (i,j) in the block B of size $P \times P$.



(a) (b) (c)

Fig. 3. (a) Pixel representation of 2×2 block, (b) gray-scale right thermal breast image, (c) corresponding BV image.

D. Classification of Blocks

In the very first step, each thermal breast image is divided into non-overlapping blocks of size 2×2. The variance is then computed in each block. After that, blocks are classified into eight classes to reflect the homogeneity of the blocks. Usually, the thermal breast image contains various homogeneous regions, which leads to having similar variance in the multiple blocks. Thus, the classification of blocks based on the homogeneous characteristics is very much important to further process it. In the first step of the classification, all the blocks are grouped into two classes based on a threshold. The threshold is computed by taking the average of the variances over all the blocks in the image. In the next phase, each class is again grouped into two classes. But this time, the threshold is computed by taking the average of variances over all the blocks in each class. Repeats the same procedure until all the blocks are grouped into eight classes.

E. Feature Extraction

After classification of blocks into eight classes, two higher order moments, such as skewness and kurtosis along with the mean value of the texture pixel position coordinates are calculated as the features from each class. Lots of studies have suggested that the higher order moments are very much effective features to measure the contra-lateral breast asymmetry [13]. According to the Fourier law of heat conduction, the locations of the texture pixels in the thermal breast image are very much useful information for the automatic analysis of the thermal breast image [23]. The skewness, kurtosis, and mean values of the texture pixels position coordinates are calculated as follows:

$$\mu_3^n = \frac{1}{N} \sum_{(i,j)\epsilon C_n} (I(i,j) - \mu)^3 \tag{2}$$

$$\mu_4^n = \frac{1}{N} \sum_{(i,j)\epsilon C_n} (I(i,j) - \mu)^4 \tag{3}$$

$$m_x = \frac{1}{N} \sum_{i\epsilon R} x_i \tag{4}$$

$$m_y = \frac{1}{N} \sum_{i\epsilon R} y_i \tag{5}$$

where, $\mu_3^n(.)$ and $\mu_4^n(.)$ are the skewness and kurtosis for each class C_n, $\mu = 1/N \sum_{(i,j)\epsilon C_n} I(i,j)$ is the mean value of class C_n, $I(i,j)$ is the intensity of a pixel (i,j), N is the number of non-zero pixels in the corresponding class C_n, $m_x(.)$ and $m_y(.)$ are the mean values of x and y coordinates of the non-zero texture pixels in class C_n, R is the region within the class C_n having non-zero pixels.

After computation of skewness, kurtosis, and the mean value of texture pixel position coordinates for each class, they are combining separately to form two feature vectors. Let vector $[f_m]_{1\times 16}$ contains computed skewness and kurtosis of each class. At the same time, vector $[f_l]_{1\times 16}$ contains computed mean values of the texture pixel position coordinates of each class. The vector f_m and f_l can be defined as follows:

$$f_m = [\mu_3^{(1)}, \mu_3^{(2)}, \ldots, \mu_3^{(8)}, \mu_4^{(1)}, \mu_4^{(2)}, \ldots, \mu_4^{(8)}] \tag{6}$$

$$f_l = [\mu^1(x), \mu^2(x), \ldots, \mu^8(x), \mu^1(y), \mu^2(y), \ldots, \mu^8(y)] \tag{7}$$

F. Feature Normalization

The feature sets are then normalised individually before concatenating them to form a single combined feature vector. In this work, the Z-score rule [24] is used to normalize the feature sets. It gives a valuable measurement for comparing data elements from various data sets. The formula for computing the Z-score is given below:

$$z - score = \frac{a_i - m^{(f)}}{\sigma} \tag{8}$$

where, a_i is the element in the feature vector, $m^{(f)}$ is the mean of the feature vector and σ is the standard deviation of the feature vector.

After normalization of the feature sets, they are concatenated to form a 32 element feature vector for each breast. The feature vectors are concatenated as follows:

$$F^{(RorL)} = [f_m, f_l] \tag{9}$$

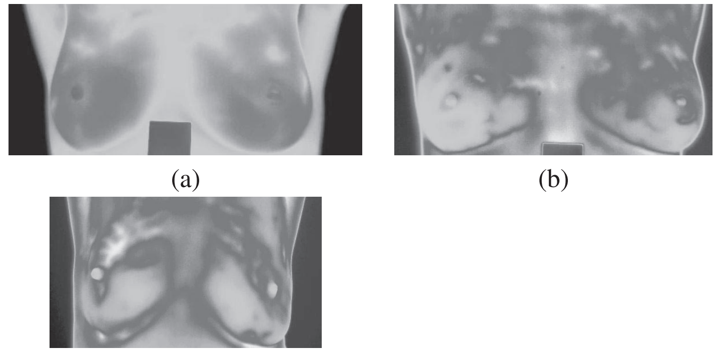
where, $F^{(RorL)}$ denotes the feature vector for right or left breast. Then, we calculated the absolute difference between the feature vectors of two breasts and considered as a feature vector for a thermal breast image. The final feature vector for each thermal breast image is defined as

$$F = F^R - F^L \tag{10}$$

where, F^R and F^L are the feature vectors of the right and left breasts respectively.

IV. Experimental Results

In this work, a dataset of 100 frontal view thermal breast images of DMR (Database for Mastology Research) database [25] are used to signify the efficacy of the proposed system. Among the 100 images, 40 images are of malignant tumor patients and remaining are of benign tumor patients. The DMR database includes breast thermograms of total 287 patients with three different stages, such as normal, benign, and malignant. In our work, we restrict our attention to differentiate the benign breast patients from the malignant individuals. For each patient, the database consists of different views breast thermograms, like the frontal view, and some lateral views. However, among them, the frontal view thermal breast image is regarded as the most informatics image by the medical experts in the breast cancer detection. Thus, in this work, we have only considered the frontal view thermal breast images for the diagnosis of the breast cancer. This section is further divided into two sub-sections: asymmetry analysis, and classification. In asymmetry analysis, we show the effectiveness of our proposed features in asymmetry analysis between right and left breasts. Detailed system accuracy to classify malignant and benign thermal breast images are presented in classification subsection.

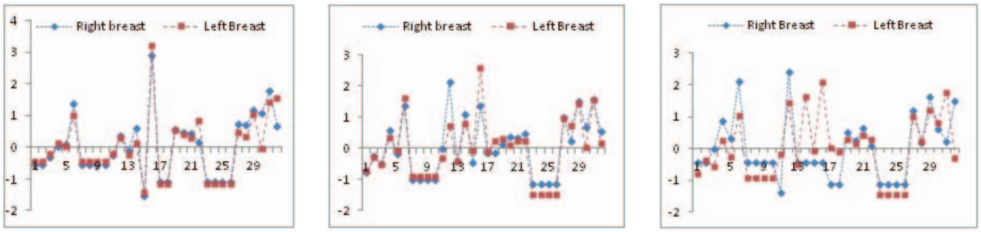


(a) (b) (c)

Fig. 4. (a) Normal, (b) benign, and (c) malignant breast thermograms.

A. Asymmetry Analysis

In this section, we analyse the effectiveness of our proposed features in asymmetry analysis between right and left breast of three different breast stages, such as normal, benign, and malignant. As discussed in the previous section, the temperature distributions in right and left breasts are almost symmetrical in the normal thermal breast image. A minute asymmetry in the temperature distribution of both the breasts may indicate breast abnormality. In [6], authors have shown that the study of bilateral asymmetry between right and left breast in the breast thermograms is an effective approach for the automatic detection of the breast cancer. Figure 4, shows the examples of the breast thermograms of three different conditions: normal, benign, and malignant. For each breast, we have computed a 32 element feature vector. It is observed that there is a notable difference between feature vectors of the right and left breast of the malignant thermal breast image. It is also observed that the absolute difference between the feature vectors of the right and left breasts of the normal and benign thermal breast images is considerably less compared to the malignant thermal breast images. The large absolute difference between the feature values of the right and left breast usually indicates the asymmetry and malignancy present in the thermal breast image. To understand the effectiveness of our proposed features in asymmetry analysis, we have graphically plotted the extracted feature values of the right and left breasts for the Fig. 4 (a), (b), and (c) which are shown in Fig. 5(a), (b), and (c). By observing the Figure 5, it can be noted that the feature values of the right and left breasts of the normal thermal breast image are almost similar. In the case of benign thermal breast



(a) (b) (c)

Fig. 5. Shows the graphical representation of the feature values extracted from the right and left breasts corresponding to the (a) Fig.4(a), (b) Fig.4(b), and (c) Fig.4(c).

image, there is a slight difference between the feature values of the right and left breasts. But in the case of malignant thermal breast image, the differences between the feature values of the right and left breasts are notable higher. Thus, we can conclude that our proposed features can differentiate the normal, benign, and malignant thermal breast images significantly well.

B. Classification

For the purpose of classification, we employed a three layer feed-forward artificial neural network (FANN). The input layer of the network consists of 32 neurons and used linear transformation function. The hidden layer and output layer consist of 64 and one neurons respectively. Sigmoid transfer function is used for both the hidden and output layer. The Levenberg-Marquardt learning rule is used for this network. For the purpose of training, gradient descent training algorithm is used and 60 breast thermograms (24 malignant and 36 benign) are randomly chosen from a set of 100 breast thermograms. Remaining samples are used to test the network.

The diagnostic performance of our proposed system is quantified based on the classification results. Since the classification between benign and malignant thermal breast image is a binary problem, we have calculated three very common performance measures, namely accuracy, sensitivity (probability that malignant breast thermograms are correctly classified as malignant), and specificity (probability that benign breast thermograms are correctly classified as benign) [26] using the obtained classification outcomes. In our work, we obtained the classification accuracy of 90%, the sensitivity of 95%, and specificity of 85% respectively, which are highly clinically significant. We also quantified our results using Receiver Operating Characteristic (ROC) curve, as shown in Fig.6. The area under the curve (AUC) is very much important information during the analysis of the system results and usually lies between 0.5 and 1 [16]. From the curve it is shown that our proposed system attained the AUC of 0.953 which is very near to 1. Also the system achieved 100% true positive recognition at less than 0.1 false positive rates. Typically, the AUC near of 1 signifies that the system discriminates the malignant breast thermograms from the benign breast thermograms considerably well.

Finally, we make a comparative study against a feature set used by Acharya et al. [16] for diagnosis of the breast cancer using thermal breast images. In their method, they have derived total 16 texture features from the gray level co-occurrence matrix and run length matrix of each patient's thermal breast image. But out of these, they have only considered four features, such as moment1, moment3, gay level non-uniformity, and run percentage and fed to the classifier to differentiate normal breast thermograms from abnormal breast thermograms. In this work, for the sake of a fair comparison, we also used all these sixteen features and fed to the FANN classifier for the classification of benign and malignant thermal breast images. The classification results regarding classification accuracy, sensitivity, and specificity of Acharya method (Acharya et al. features + FANN) and our proposed method are summarized in Table-I. From the Table-I, it can be seen that our proposed method performs better regarding classification accuracy, sensitivity, and area under the ROC curve. But specificity is less compared to the Acharya et al. method. Fig. 7 shows the ROC curve for the classification of the benign and malignant thermal breast images using Acharya et al. method. The area under the curve is 0.855, which is less compared to our method. At the same time their method achieved 100% true positive recognition at a very high false positive rate (i.e. 0.9 false positive rates).

TABLE I
PERFORMANCE OF THE ACHARYA METHOD AND PROPOSED SYSTEM

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	Area under the ROC curve
Acharya et al. features [16] +FANN	85	77.5	90	0.855
Our features + FANN	90	95	85	0.953

V. CONCLUSION

A measure of asymmetric temperature distribution between right and left breasts in thermal breast image is a very useful technique for breast abnormality detection. In the present work, we have proposed an effective method to differentiate malignant breast thermograms from benign breast thermograms based on texture features. In this respect, we have first presented a block based version of variance calculation technique to capture the texture features in thermal breast image. After that, we extract a set of statistical features indicating bilateral asymmetry from the texture image of each

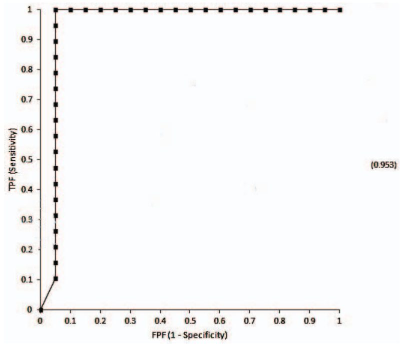


Fig. 6. ROC curve for the proposed method.

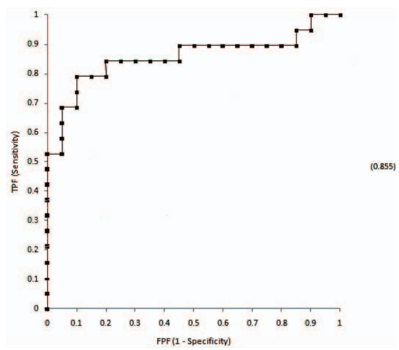


Fig. 7. ROC curve for the Acharya method.

thermal breast image. The feature sets are then classified using the feed-forward artificial neural network (FANN). Experimental results have shown that the proposed method provides considerably good classification accuracy, sensitivity, and area under the ROC curve compared to Acharya et al. features on a set of 100 frontal view thermal breast images. Also, our method provides 100% true positive recognition at less than 0.1 false positive rates.

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