# Applying Artificial Neural Network for the Classification of Breast Cancer Using Infrared Thermographic Images

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**Abstract.** The second type of cancer that kills more women in the world is breast cancer. If the prognosis is done at an early stage of the disease, women can have a better chance of cure. However, the access to medical exams in poor countries is usually precarious. This work describes the study of a computer-assisted diagnostic system using thermal imaging. The images are generated by a thermographic camera that has a lower cost than the equipment used in conventional exams. We propose a system that classifies the thermographic breasts images in "normal" and "abnormal". We have analyzed 8 statistical characteristics: mean, variance, standard deviation (SD), skewness, kurtosis, entropy, range and median. The classification used an Artificial Neural Network (ANN) and got a result of 87 % in sensitivity, 83 % in specificity and 85 % in accuracy.

**Keywords:** Image processing · Thermography · Breast cancer · Artificial neural network

## 1 Introduction

Breast cancer is the second most common type of cancer in the world and the most common among women, corresponding to 25.2 % of new cases every year [1]. When breast cancer is detected at an early stage, the chance of cure is 85 %, but when it is detected at an advanced stage, the percentage drastically drops to 10 % [2].

A tumor may be identified through a series of tests such as mammography, ultrasound, tomosynthesis (3D mammography), magnetic resonance imaging and computed tomography. These tests can be painful, invasive, expose the patient to ionizing radiation or can require the use of contrast [3].

Cancerous cells were normal cells that suffered some kind of deformation. They have suffered an imbalance in the metabolic activity that makes the cell consumes a large amount of glucose and releases large amounts of lactate, causing regional vasodilation in the early stages of the disease and an increase in the formation of new blood vessels [4]. The increase of blood flow in the area causes a growth in the body temperature in the cancer area when compared to normal


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tissue temperature. The increase in temperature helps to detect cancerous tissue with infrared cameras, because they capture thermal information.

Recently, several studies have been using thermographic images to help on the diagnosis of breast cancer. Thermographic images is a non-invasive, painless method and does not need radiation or the use of contrast to generate images. Thus, it is completely safe for children and pregnant women. Our main contribution in this paper is to develop a system for the diagnosis of breast abnormalities using statistical characteristics and an artificial neural network.

## 2 Bibliography Review

Many authors are conducting experiments with breast thermographic images. The results shown the effectiveness of different statistical parameters and different classifiers in early detection and classification of breast cancer. The results are presented in Table 1, where the sample used in each experiment and in parenthesis the number of healthy patients and the number of patients with some abnormality. The authors presented some statistical measures to evaluate the performance of the experiment. Sensitivity is the ability of a diagnosis to identify the true positives in the individuals that are actually sick. Specificity is the ability of a diagnosis to identify the true negatives in individuals that are actually healthy. Accuracy is the ratio of successes, the total of true positive and true negative within the sample.

Koay et al. [11] used images of 19 patients, among which 14 patients were healthy and 5 of them had some breast abnormality. The extracted features were: average temperature, standard deviation, median, maximum, minimum, skewness, kurtosis, entropy, area and amount of heat. After the features extraction they have used the statistical software SPSS (Statistical Package for Social Sciences) to determine the correlation between the features. According to the authors, five characteristics are highly correlated: average temperature, standard deviation, skewness, kurtosis and amount of heat. They used an artificial neural network (ANN) with a single hidden layer, reporting only 10 % of false negatives. According to the authors, the failure of the experiment was due to the small number of images.

Tang et al. [12] analysed thermograms of a hundred and seventeen patients, among which forty-seven had malignant tumors and seventy patients had benign tumors. The authors suggested an analysis of a characteristic named by them "Local Temperature Increase" (LTI), which is an abnormality in the vascular patterns on the thermogram, with presence of very high temperatures. The proposed method of classification considers that the possible presence of a cancer is proportional to the maximum amplitude of the skin temperature in the suspicious region.

Arora et al. [13] analyzed ninety-two patients, among which fifty-eight cases had malignant tumors and thirty-four had benign tumors. They used a proprietary system (Sentinel Breast Scan) with unknown characteristics and classification with ANN model.

Wishart et al. [14] did not report extracted features. For the classification, they have used four tests: screening test, clinical examination, ANN and an artificial intelligence based method developed by the authors, called "No Touch Breast Scan" (NTBS). The results obtained using the NTBS had 48 % of sensitivity and 70 % of specificity.

Umadevi et al. [15] developed a software called "Infrared Thermography Based Image Construction" (ITBIC) for the interpretation of breast thermograms. The system captures three images of each patient (front, left and right side) and generates a simplified image. The simplified image is analyzed from logical decisions based on hot skin areas that have been extracted.

Acharya et al. [16] presented a study in which they used 50 breast thermograms, 50 % of them were normal and 50 % had breast cancer. The authors used sixteen characteristics based on texture: homogeneity, energy, entropy, the four first moments calculated by the matrix of co-occurrence, the second angular moment, contrast, median, emphasis in long primitives, uniformity in the level of grey scale and percentage of primitives. After comparison, only four characteristics were considered significant for classification: first moment, third moment, percentage of primitives and uniformity of the level of grey scale. The classifier used was a "Support Vector Machine" (SVM).

Bonini [3] used statistical measures as features: histogram, Higuchi fractal dimension and three methods of geostatistics: Geary coefficient, Moran index and Ripley's K function. The classification of these characteristics was performed by a "Support Vector Machine" (SVM).

**Table 1.** Comparison of results

| | Sample | Sensitivity | Specificity | Acuracy |
|---|---|---|---|---|
| Koay et al. [11] | 19 (14/5) | 60 % | 100 % | 89.5 % |
| Tang et al. [12] | 117 (70/47) | 93.6 % | 44.3 % | - |
| Arora et al. [13] | 94 (34/60) | 97 % | 44 % | - |
| Wishart et al. [14] | 106 (41/65) | 48 % | 70 % | - |
| Umadevi et al. [15] | 50 (44/6) | 66.7 % | 97.7 % | - |
| Acharya et al. [16] | 50 (25/25) | 85.7 % | 90.5 % | 88.1 % |
| Borchartt [3] | 51 (14/37) | 91.9 % | 78.6 % | 88.2 % |

## 3 Database

The thermographic images used for this paper came from DMR (Database for Mastology Research) [5]. To feed the database, a FLIR SC-620 camera, with a $640 \times 480$ pixels resolution was used. Currently, the DMR database has breast images in grey scale of normal patients and patients with some anomaly. We randomly selected 47 patients and 94 breasts images for our experiment: 48 of them had normal breasts and 46 had some anomaly.

# 4 Analysis of Breast Thermograms

As mentioned above, due to the temperature difference one can detect cancerous tissue. Patients with normal tissue have a symmetry in the breasts temperature. A small difference in the thermal pattern may denote an anomaly. However, tumors in both breasts at the same time are uncommon. Thus, a small difference in the breasts temperature may indicate an abnormal tissue.

In this paper, the method used for analysis of thermograms consists of an evaluation of quantitative temperature parameters for each patient. For the analysis of asymmetric thermograms the following steps were integrated:

1. Pre-processing
2. Segmentation
3. Feature extraction for asymmetry analysis
4. Classification

## 4.1 Pre-processing of Breast Thermograms

The extraction of the region of interest in thermal imaging is challenging because there is no clear limit among the regions. In the pre-processing method, we extracted all the unnecessary areas were extracted before processing the image [9]. The background has to be removed manually and the image must be at grey scale to be pre-processed.

## 4.2 Segmentation of Breast Thermograms

The segmentation of the region of interest (ROI) plays a very important role. We need to separate the areas of the right breast and the left breast properly, because the feature extraction and classification depend on this process. The Fig. 1 (Left) shows the original image acquired from DMR. To segment the region of interest, we need to create a mask Fig. 1 (Right), that is why we apply in the original image the Canny edge detector [6] using a threshold for the lower dish of each breast. With the help of the mask presented in Fig. 1 (Right) it is possible to

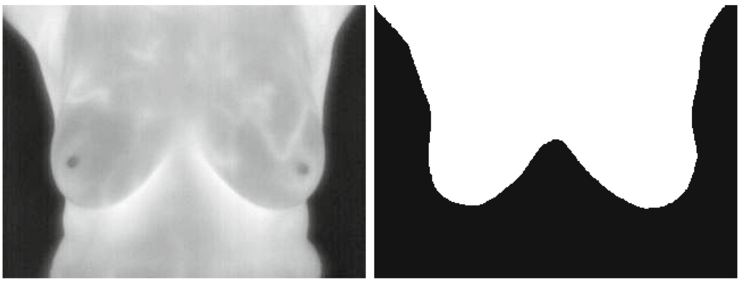

**Fig. 1.** Segmentation: (left) original image; (right) mask

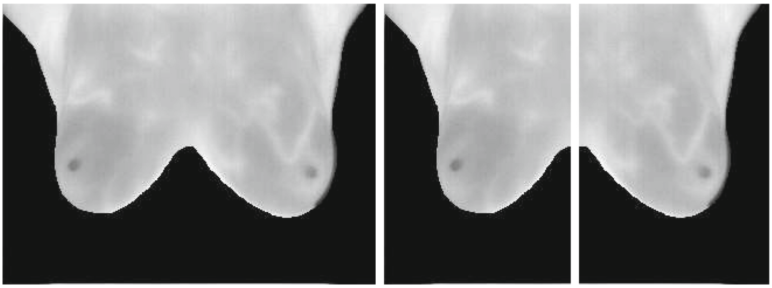

**Fig. 2.** Segmentation: (left) mamas segmented; regions of interest: (center) left breast (LB); (right) right breast (RB)

segment the original breast image as shown in Figure 2 (Left) and then separate the regions of interest, locating the center of the breasts, as shown in Fig. 2 (Center,Right) right breast and the left breast.

### 4.3 Feature Extraction for Asymmetry Analysis

Texture characteristics are most efficient for breast analysis thermograms [7]. Statistics measures allows extracting information from the breasts temperature to understand the relationship between the temperature values of healthy breasts and the ones with some pathology.

To analyze the pixels intensity distribution in each thermogram a histogram was used, where X indicates the temperature or the intensity (radiant heat), and Y represents the number of pixels for each intensity value. Figure 3 presents the histogram of the right and left breasts of two volunteers. We can observe that the breast with some anomaly have a higher pixel concentration where the temperature is higher (values near to 255). In other words, the lighter the

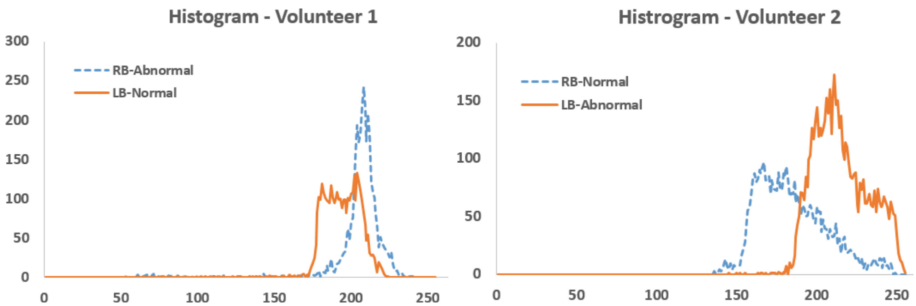


**Fig. 3.** Histogram of the left and right breast: (left) Volunteer 1 - Right breast abnormal and left breast normal; (right) Volunteer 2 - Right breast normal and left breast abnormal

image the higher the temperature. Thus, we conclude that the histogram is an important feature of asymmetry analysis in thermograms.

The first order statistical measures do not consider neighboring pixels and can be calculated directly from the image's histogram. The statistical measures of second order consider a pair of pixels at a random distance, orientation and position. Considering the difference presented in the histograms presented in Fig. 3, we have considered the first order statistical measurements: mean, variance, standard deviation (SD), skewness, kurtosis, entropy, range and median. If $P(i)$ is the probability of $i$ happening, where $i$ represents each grey level in the image $f(x, y)$ and G is the total number of grey levels:

**Mean:** Indicates the data concentration of a distribution. The mean can show the global temperature of the region of interest, as shown in Eq. 1.

$$\mu = \sum_{i=0}^{G-1} i * P(i) \tag{1}$$

**Variance:** Represents the deviation value of the image's grey levels related to the mean grey level. The Variance is computed using Eq. 2.

$$\sigma^2 = \sum_{i=0}^{G-1} (i - \mu)^2 * P(i) \tag{2}$$

**Standard Deviation:** Shows the dispersion of data around the mean. A low standard deviation indicates that the values are very close to the mean, while a high standard deviation indicates a wide dispersion of values towards the mean. The standard deviation presents a bigger or a smaller homogeneity or heterogeneity in the image, and it is computed using Eq. 3.

$$\sigma = \sqrt{\sum_{i=0}^{G-1} (i - \mu)^2 * P(i)} \tag{3}$$

**Skewness:** It refers to the degree of asymmetry of a distribution of specific feature around the mean. We can have positive or negative values, as given by Eq. 4.

$$\gamma_1 = \mu^{-3} [\sum_{i=0}^{G-1} (i - \mu)^3 * P(i)] \tag{4}$$

**Kurtosis:** It is also called "fourth normalized moment". It measures the levelling of a distribution with relation to a normal distribution, according to Eq. 5.

$$\gamma_2 = \mu^{-4} [\sum_{i=0}^{G-1} (i - \mu)^4 * P(i)] \tag{5}$$

**Entropy:** It measures the information contained in the segmented images and the amount of disorder in the system. The more symmetric the temperature distribution, the smaller the entropy. Individuals that have widely differing entropy in the images of the breasts (left and right) have a larger asymmetry and an increased probability of abnormality. The entropy is computed using Eq. 6.

$$H = \sum_{i=0}^{G-1} P(i) * log_2[P(i)] \tag{6}$$

**Range:** It indicates the temperature variation ($\Delta t$) inside the region of interest. The value is calculated from the difference between the highest and lowest temperature ($t$) in the region of interest. It is computed according to Eq. 7.

$$\Delta t = max_{0 \leq i \leq G-1} t_i - min_{0 \leq i \leq G-1} t_i \tag{7}$$

**Median:** It is the numerical value that divides the probability distribution in equal parts. The greater the difference between the median of the breasts of a patient, the greater the likelihood of a breast having an abnormality. Likewise, the smaller the difference, the greater the likelihood of no anomalies.

**Table 2.** Measure of asymmetry in left and right breast

| Statistical features | Volunteer 1 | | Volunteer 2 | |
|---|---|---|---|---|
| | Left breast normal | Right breast abnormal | Left breast abnormal | Right breast normal |
| Mean | 167.507 | 176.067 | 173.854 | 110.225 |
| Variance | 738.495 | 1050.057 | 1597.971 | 3563.663 |
| SD | 27.1752 | 32.4045 | 39.9746 | 59.6964 |
| Skewness | 1.2152 | 0.5795 | 1.3427 | 1.4518 |
| Kurtosis | 1.824 | 2.324 | 1.956 | 2.255 |
| Entropy | 4.8910 | 4.7182 | 5.0893 | 4.2360 |
| Range | 148 | 187 | 110 | 113 |
| Median | 194 | 205 | 215 | 184 |

Table 2 shows the statistical measures of right and left breasts of two volunteers. The features used can assist in the diagnosis of abnormalities in the breast, only with the analysis of differences. Because the probability distributions of the histograms are concentrated at higher temperatures, i.e., in the clearer pixels, the features "Mean and Median" showed higher values in the abnormal breast compared to the normal breast. The "Skewness" feature showed a lower degree of asymmetry for the abnormal breast. The other features were not conclusive for the selected volunteers.

## 5 Classification of Breast Thermograms

In order to classify the thermal breast images into "normal" or abnormal", we used an artificial neural network (ANN), which is widely used in pattern recognition problems. Artificial neural networks are computer models inspired by the central nervous system of an animal, particularly the brain. Neurons are arranged in layers and interconnected by connections known as synaptic weights, which represent the network knowledge. They are able to perform machine learning, as well as pattern recognition [10], with one layer of input neurons, one layer of output neurons and one or more intermediate layers [8].

We compare two ANN classification models. The first ANN used a single intermediate layer - this model is capable of solving a linearly separable problem, that is, a problem that can be separated by tracing a straight line on a hyperplane (Fig. 4 left), since the algorithm is able to adjust only one weight layer. The second ANN solves problems of non-linear classification using an algorithm to adjust more than one layer (Fig. 4 right) [17].

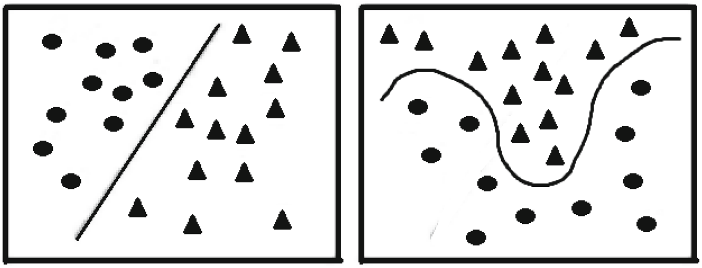

**Fig. 4.** Classification: (left) linear; (right) non-linear

After segmentation and feature extraction, we randomly selected 25 images with some anomaly and 25 normal images for ANN training. For the experiments, we used the 8 statistical features extracted from each image to the ANN training network and the backpropagation algorithm, which calculates the gradient of the sum according to a quadratic error function related to weights. It is an optimization method capable of finding the weight coefficients and thresholds for the neural network given a training set [10].

For linear classification, the training was considered satisfactory when it achieved the error rate equal to 0.205. The next step was to submit all the features of the 94 images for classification (47 of right breast and 47 of left breast). The displayed output is the data model in the interpretation network. For non-linear classification, the training was considered satisfactory when it achieved the error rate equal to 0.016. The ANN used has an input layer with 8 neurons, that are related to the features extracted from the image. The output layer has two neurons enabling the classification and 1 hidden layer with 5

**Table 3.** Matrix of confusion

| | | Linear | | Non-linear | |
|---|---|---|---|---|---|
| | | Normal | Abnormal | Normal | Abnormal |
| Real | Normal | 33 | 15 | 40 | 8 |
| | Abnormal | 20 | 26 | 6 | 40 |

neurons. The number of neurons was calculated based on the arithmetic mean of the input and output size of the network.

To analyze the ANNs performance, we calculated some statistical measures using the information present in the confusion matrix presented in Table 3. The non-linear model showed the best result reaching 87 % of sensitivity, 83 % of specificity and 85 % of accuracy. The linear classification had a lower result, showing 57 % of sensitivity, 69 % of specificity and 63 % of accuracy. The results presented by both ANNs concluded that a non-linear ANN best solves the problem.

## 6 Conclusion

The main objective of identifying breast cancer is to reduce the mortality rate caused by the disease. The earlier the prognosis the better the chances of cure. The thermographic image is a non-invasive, painless process, and does not need radiation or contrast to generate the image. It is therefore completely safe for children and pregnant women and the cost of equipment is low.

The experiments showed that we could have good results in cancer identification using thermographic images and classifying them with non-linear neural network.

This paper presents the first phase of analysis and experiments conducted for the development of a diagnostic computer-assisted system. The results indicate a possibility of further exploration for diagnosis using thermographic images. As future work, we will use other features and other classifiers in order to improve results.

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