Classification of Mass in Mammograms by Asymmetric Texture Features

Esma Uzunhisarcıklı[1], Volkan Göreke[2]

[1]Asc.Proffesor, Erciyes University, Kayseri, Turkey
[2]Lecturer, Cumhuriyet University, Sivas, Turkey

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Abstract - *Breast cancer is a malignant tumour that forms in the cells of breasts. Mammogram is the X-Ray image of the breast where low-dose radiation is used. Asymmetry analysis between the left and right mammographies of a patient can provide significant information about the existence of a tumour at early stages. Diagnosis of breast cancer with the investigation of bilateral asymmetry is difficult because the asymmetric symptoms are vague which can be seen in the mammography. In this study, a computer-aided model was applied to enhance the positive predictivity value for mammograms with asymmetry. The method consists of two stages: image processing and classification. In the image processing stage, the mammograms with noise were filtered and the low-contrast problem was resolved. ROIs were obtained from the mammogram image with mass and the symmetry image without mass. Primary and secondary texture features were obtained from ROIs. Mass classification in asymmetric mammograms was realized via neural networks using texture features. The performance of the method was measured in sensitivity and specificity values which were calculated as %93 and %93 respectively. The performance values show that the proposed method increase the positive predictivity value in the computer-aided interpretation of asymmetry regions. The specified feature set and the use of network structure as the classifier can be utilized to obtain better results in computer-aided systems.*

Key Words: CAD, Breast Mass, Artificial Neural Network, Mammogram, Asymmetry

1.INTRODUCTION

Breast cancer is a malignant tumour that forms in the cells of breasts [1]. It has been a significant cause of death among women worldwide for the past few decades according to the reports of World Health Organization. The symptoms of the cancer can be detected with the mammogram images which are obtained by using low-radiated X-Rays [2].

Bilateral asymmetry is defined as one of the four breast cancer symptoms by American College of Radiology [3,4]. The breasts should be compared as symmetric organs and internal structure should be very symmetric [5]. This strategy is used to detect anomalies while scanning the mammographies and it consists of comparing the right and left breast images side by side [6]. The analysis of the right and left mammographies provides the observation of tumorigenic variations at an early stage where more evident cancer symptoms do not exist yet [3,4].

In recent years, there have been many studies that rely on computational methodologies to help specialists in the interpretation of radiological images [7,8,9,10]. These computer-aided diagnosis (CAD) systems provide a second source of information and an enhanced success rate in the diagnosis of diseases such as breast cancer in modern medicine [7,8,11,12]. Supervised learning artificial neural network is a fundamental technique which is used in CAD systems for the classification of candidate regions as tumorous mass [8].

In this study, a total of 30 tumorous and normal (without tumour) mammograms from MIAS database were used. Preprocessing and image enhancement were applied on these images. ROI regions were obtained by manually cutting the mass areas that are defined in pixel coordinates in MIAS database and also the corresponding symmetry regions of these images in 16x16 pixels. 8 primary and secondary texture features were extracted from the ROIs. Artificial neural network (ANN) structure was designed using these features for classification of the mass as benign or malignant.

In Section 1, the investigation of the right and left breast images and diagnosis using asymmetry feature is explained. In Section 2, the image database and the software toolboxes used in the study were introduced. In Section 3, the scope of the study, image processing stages and the feature extraction process were explained. In Section 4, ANN was designed, classification and the performance tests were realized.

2. MATERIAL AND METHOD

By searching the bilateral asymmetry in the open access Mammographic Image Analysis Society (MIAS) database, 15 pairs of breast mammogram images (left-right) were detected and used. 9 of these images have malignant symptoms, while 6 of them have benign symptoms. Each image is 1024x1024 pixels and has a thickness of 200 microns. A software was developed using MATLAB Image Processing and Statistics Toolboxes. A feed-forward network-type ANN was designed for classification using MATLAB Neural Network Toolbox

3. SCOPE OF STUDY

The effective comparison of the related regions of a patient's right and left mammographies is a critical step in the bilateral asymmetry analysis [13,14]. Researchers in some of the studies in the literature handled the assymetry between the mammography pairs as a criteria for detecting the evident cancer symptoms such as masses and microcalcifications [15-19]. Computer schemes were

developed to detect the differences between the breast tissue density [13,14] based on various feature sets incuding shape, brightness, topological features [20] and the directional features that depend on Gabor wavelets [21, 22]

3.1 Image Preprocessing

The purpose of image preprocessing is to simplify the detection of anomalies and to limit the search process of anomalies by removing the extreme background effects [9, 23]. The images obtained from MIAS database contain noise, label data and digitization noise (some straight lines). These undesirable components were removed from the image using filtering and morphological operations.

Median filter is a commonly used statistical filter in which the neighboring pixels are sorted and the middle pixel value is used as the median [24]. Every output pixel includes a median value at a 5x5 neighborhood of the center input pixel [25].

Morphology is used for object extraction and noise removal purposes. The most fundamental morphological operations are opening which is defined as adding pixels to the edges of the object, and closing which is defined as removing pixels from the edges of the object [10]. The method introduced by Otsu in 1979 looks for an optimum threshold value to classify the pixel values of a gray-scale image as 0 or 1 [26]. The undesirable components such as labels were removed from the image by morphological opening and closing operations after the image was converted to binary format by applying Otsu global thresholding on the original image.

3.2 Contrast Enhancement

Contrast enhancement was realized by using contrast-limited adaptive histogram equalization (CLAHE) method.

In this method, the pixels are mapped using their four closest neighbors. The regions are divided to groups according to their neighborhoods while the bottom regions are combined together using bi-linear interpolation. This method is used in medical images for both noise reduction and removal of edge shadow effects in the homogenous areas [27].

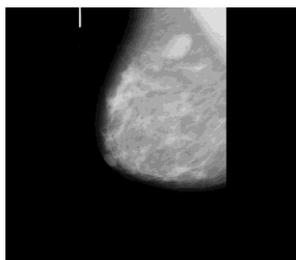The images for each step applied to a sample image are shown in Figures (1-6) respectively.

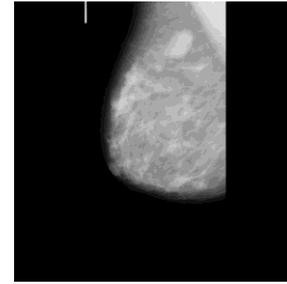**Figure -1:** Mammogram image mdb015 obtained from MIAS

Figure -2: The image after the application of median filter

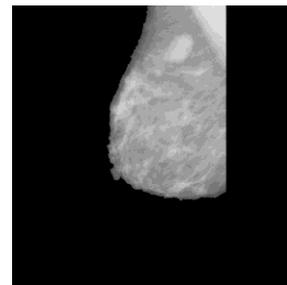**Figure -3:** Binary image after the application of global thresholding

Figure -4: The image after the application of morphological operations
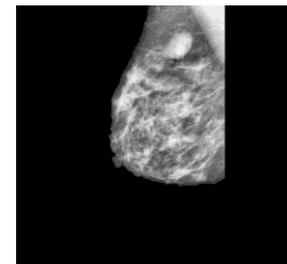

Figure -5: The image after the application of adaptive histogram equalization

Figure -6: 16x16 pixel area cut using the mass coordinates at the MIAS database

3.3 Feature Extraction

In this study, Haralick texture features were calculated using Gray Level Co-Occurence Matrices (GLCM). GLCM depends on the estimation of second order compound probability density function P(i, j | d, θ). This matrix denotes the possibility of passing from gray-level i to gray-level j when the distance between the pixels are d and the angle is θ [28]. In this study, a total of eight features were extracted for parameters d=1 and θ=0 that have a good performance in image processing [29]. The extracted features are energy, contrast, homogeneity, entropy and correlation (second order), mean and standard deviation (first order) and the texture correlation between the original image and the preprocessed image.

Texture analysis methods are used in the interpretation of medical images. Texture is a set of the statistical features of the pixel density. The gray-levels of two different pixels at different regions are compared [28]. The texture features can be calculated using the statistical features that depend on the co-occurence matrices [30].

GLCM is one of the best known texture analysis tools for the calculation of the second order statistical image features. These texture features are knows as Haralick texture features which are used for classification and segmentation purposes [31].

The mathematical expressions of features are given in Equations (1-8) .

$$Energy = \sum_{i,j} p^2_{ij} \tag{1}$$

$$Conrast = \sum_{i,j} |i-j|^2 p_{ij} \tag{2}$$

$$Homogeneity = \sum_{i,j} \frac{p_{ij}}{1+|i-j|} \tag{3}$$

$$Correlation = \frac{\sum_{i,j} (ij)p_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{4}$$

$$Entropy = \sum_{i,j} p_{ij} \log p_{ij} \tag{5}$$

where μ_x, μ_y, σ_x and σ_y are the mean and standard deviation of the rows and columns of the probability density function pij.

First order texture measures are calculated from the original image values. They do not consider the relationships with neighborhood pixel [32].

I is the image matrix, x and y are the coordinates. m, n represents the size of the matrix.

$$mean(\mu_i) = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} I_i(x,y)}{m \, x \, n} \tag{6}$$

$$Standart\ Derivation(\sigma_i) = \sqrt{\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}(I_i(x,y)-\mu)^2}{m \, x \, n}} \tag{7}$$

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}} \tag{8}$$

where x_i is the intensity of the ith pixel in image 1, y_i is the intensity of the ith pixel in image 2, x_m is the mean intensity of image 1 and y_m is the mean intensity of image 2 and r is the correlation coffecient.

4. Artifical Neural Network

Usually, an artificial neural network can be considered as an information system consisting of simple connected process elements such as neurons that form the network. The artificial neural network, which consists of the input layer, the hidden layer and the output layer, may expose complex behaviours to generate the expected outputs via supervised or unsupervised learning. The learning process adjusts the connection weights between neurons [8].

The basic structure of a neuron can be modelled as shown in Figure 7. Here, $X\{x_i, I= 1,2,...,n\}$ is the neuron input and Y is the output. Every input is multiplied by its weight, the bias value is added and transferred as the input of the transfer/activation function f. The relationship between the input and output is shown with Equation 9 below. Although there are various artificial neural networks in medical image processing, the most commonly used one is feed-forward network where the architectural information flow is in the forward direction [33].

A method that relies on the cross-validation techique can be used when there is not enough data to construct a reliable network structure [34].

In this study, multi-layer perceptron structure, which is a special feed-forward neural network structure, is used. The designed artificial neural network has a hidden layer. The hidden layer consists of three neurons while the output layer consists of a single neuron. The transfer function of the hidden layer is the tangent sigmoid and the transfer function of the output layer is linear. Levenberg-Marquardt back propagation algorithm was chosen as the learning algorithm. The eight inputs of the artificial neural network consists of texture features of the images. The output of the network is 1 for images that contain mass and 2 for images that do not contain mass.

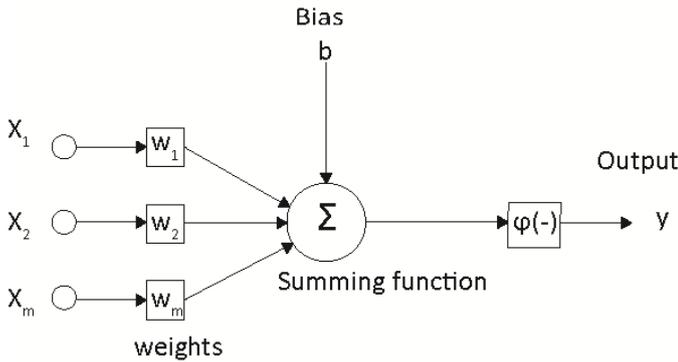$$Y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{9}$$

Figure -7: The basic structure of a neuron

The designed network structure is shown in Figure 8 and the neural network train regression graphs are shown in Figure 9.
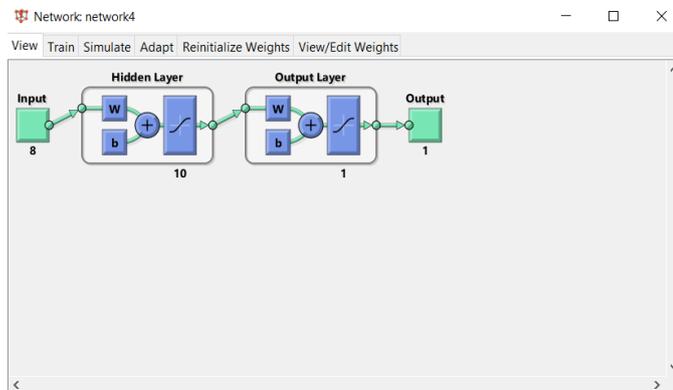
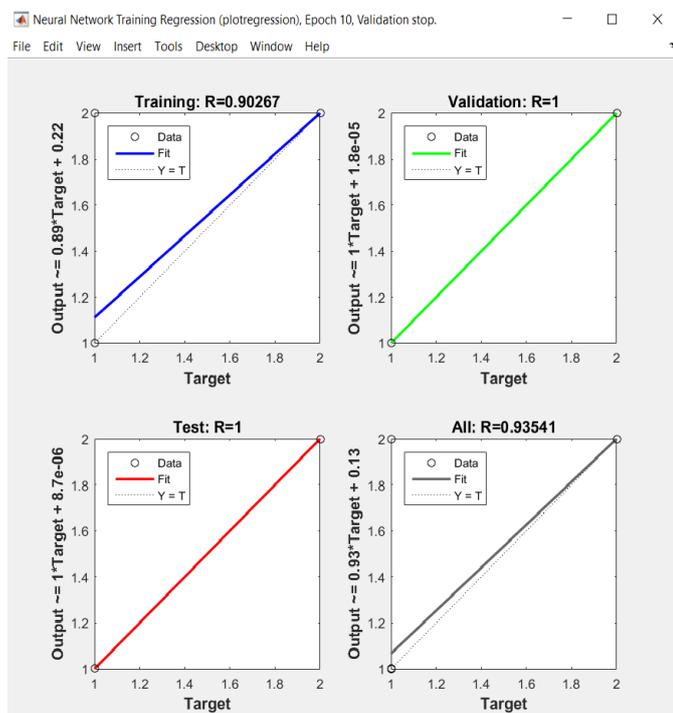

Figure -8: The designed ANN structure

Figure -9: ANN regresssion graphs

The performance measurement of the test can be realized by calculating the sensitivity of the system. The sensitivity and specificity is expressed in Equation 10 and Equation 11 respectively [22]. Here,

TP: classified as mass when it is a mass in real

FN: classified as not mass when it is a mass in real

FP: classified as mass when it is not a mass in real

TN: classified as not mass when it is not a mass in real

$$Sensitivity = \frac{TP}{TP+FN} \tag{10}$$

$$Specificity = \frac{TN}{TN+FP} \tag{11}$$

The sensitivity and specificity were calculated via the network output as %93 and %93 respectively.

5. CONCLUSIONS

As a result, the use of artificial neural networks can be a suitable method especially for CAD systems. Here, not only the existence of the mass but also the type of the mass (benign or malignant) can be determined by using more features as the input of the neural network or by having network structures with more layers.

In the literature, in a similar study which uses the same dataset, the sensitivity and specificity were calculated as %83 and %75 respectively[35].

In our study, higher success rates were acquired. Therefore, it can be expressed that the feature set and ANN type classifier that were used in our study, may lead to more succesful results for CAD systems.

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