Mammogram Classification using Back-Propagation Neural Networks and Texture Feature Descriptors

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***Abstract*—Breast cancer has an important incidence in women worldwide. Early diagnosis of this illness plays a key role in decreasing its mortality and improves its prognosis. Currently, mammography is considered as the standard examination for detection of breast cancer. However, the identification of breast abnormalities and the classification of masses on mammographic images are not trivial tasks for dense breasts, and is a challenge for artificial intelligence and pattern recognition. This work presents preliminary results of automatic classification of mammographies by texture characterization based mainly on the Haralick's descriptors. We implement an artificial neural network (ANN) for classification in three classes: normal, benign and cancer using leave one out technique. The set of images for training and testing the ANN, are taken from the Digital Database for Screening Mammography (DDSM). Results show that the percentage of correct classification occurs in average for 84.72% of the data set.**

***Keywords*—Breast cancer; mammography; texture analysis; artificial neural network (ANN); pattern recognition; classification; cross validation; gray level co-ocurrence matrix (GLCM).**

I. Introduction

Cancer is one of the leading causes of mortality in the world. In 2012, there were about 14.0 million new cases worldwide [1]. In 2015, cancer caused 8.8 million deaths. Approximately, one out of every six deaths in the world is due to this disease. The number of new cases is expected to increase by approximately 70% over the next 20 years. At the same time, new cases of breast cancer has increased significantly, especially in developed countries. According to the International Agency for Research on Cancer of the World Health Organization [2], breast cancer is the second leading cause of death, and certainly, the most frequent form of malignancy in women worldwide with 1.67 million new cases diagnosed in 2012 (25% of all cancers) [3]. Mammography is the best population-based breast cancer screening imaging modality in current clinical practice. It is the most efficient and effective technique used for detecting breast cancer at early stages. Recent study evaluates the performance of various breast imaging modalities for early detection of breast cancer [4].

There are several machine learning techniques for mammographic classification such as: ANNs, genetic algorithm (GA), k-nearest neighbors algorithm (K-NN), and support vector machine (SVM) [5] [6]. The ANNs are a type of artificial intelligence method that is inspired by the biological neural system in the human brain [7] [8]. The network is composed of an optional number of neurons, which connects the input set to output This work presents a scheme of mammogram classification on three classes: normal, benign and cancer using a multilayer perceptron trained net with back-propagation (BP) with forward connections. The design and implementation of the ANNs were developed with NeuralNetwork Toolbox of MATLAB 2014a. The algorithm assessment was carried out by applying the technique leave-one-out cross validation. The texture descriptors are extracted by using the features proposed by Haralick [9]. This technique is evaluated by using as input the DDSM of the University of South Florida [10]. The steps of the proposed method are shown in Figure 1.

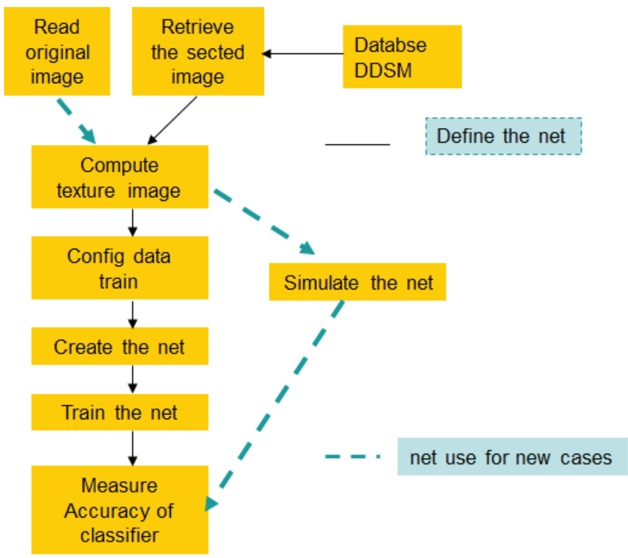

Figure 1. Steps of the proposed method

A. Related works

In this section, we summarize the most import works in the latter years that approach ANNs as classifier. Thus, in 2015, M. Pratiwi et al. [11], have used Radial Basis Function Neural

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Network (RBFNN) for mammograms classification based on Gray-level Co-occurrence Matrix (GLCM) texture based features for normal and abnormal classification. They used the Mammographic Image Analysis Society database (MIAS). The accuracy is measured based on the Region of Interest (ROI). A region of interest (ROI) is a portion of an image where some particular techniques are performed. In 2016, Levy and A. Jain [12] presented a scheme based on Convolutional Neural Networks (CNN) to directly classify pre-segmented breast masses in mammograms as benign or malignant. They used the DDSM and accuracy is based on the ROI. Valarmathi and Robinson [13] optimize the weight of a MLP based classifier with a Genetic Algorithm (GA), in order to select optimum input to the Neural Network and weight selection. The latter improves the reduction of the connections between the neurons without reducing the classification accuracy and hence, speeding up the computation. The proposed MLPNN GA weight selection with GA feature selection increases accuracy by 10.53% than MLP NN and by 8.69% when compared to MLPNN with GA feature selection. Sharma and Preet [14] proposed a CNN as a classifier on the mammogram images to enhance the accuracy rate of Computer-Aided Diagnosis (CAD) system. They use CNN classifier to boost the classification performance. This classifier performs better than previous classifiers in relation to misclassification rate of normal mammograms as abnormal. This approach performs on overlapping problem and the performance of the different classifiers is measured on the DDSM. Accuracy, sensitivity and specificity were measured. Sun et al. [15] presented a new method using Deep Neural Network (DNN) for near-term breast cancer risk analysis. They analyzed 420 cases with two sequential mammogram screenings, half of these cases were diagnosed as positive in the second screening and the other half remained negative. They designed a DNN with four pairs of CNN and one fully connected layer. They have their own database consisting of 420 images. They applied this method on the ROI. İşeri [16], developed a framework can detect microcalcification clusters, which are abnormalities in mammogram images. Apart from the two well-known methods, the author develops two different feature extraction techniques by using four types of descriptors: Gray Level Coocurrence Matrix-GLCM, Equal Width Discretization (EWD2), Wavelet Transform and Multiple Window Based Analysis (MWBA). The classification scheme was modeled by an ANN, whose highest AUC value was obtained by the MWBA method Area Under Curve (AUC=0.91) value. They used the MIAS and DDSM of the ROI. Ponraj et al. [17] present a Hough transform-based feature extraction method for the classification of mammograms. Hough transform is generally used to separate certain features according to a defined shape within an image. It is classified using BPNN. Their experiments were done by using the full image of MIAS database, instead of the ROI. Nithya and Santhi [18] used a correlation-based feature selection technique. The breast tissue classification based on texture features was evaluated by ANN, linear discriminant, and SVM and Naive Bayes classifier. They used MIAS database, and the metrics: accuracy, sensitivity and specificity of the ROI. In 2017, Sun et al. [19] used a semi supervised learning (SSL) DCNN for breast cancer diagnosis. Four modules form the diagnosis system: data weighting, feature selection, dividing co-training data labeling, and deep CNN. They used FFDM accuracy, sensitivity and specificity as measure of the ROI. Wang et al. [20] implemented a novel CAD system for detecting abnormal breasts in mammogram images. First, they segmented the ROI. Next, they used the Weighted-type fractional Fourier transform (WFRFT) to obtain the unified time-frequency spectrum. Third, PCA reduces the spectrum to only 18 principal components. Fourth, they used a FNN as classifier, which is trained by a novel algorithm-specific parameter free approach called Jaya. In order to evaluate the research [21] they used accuracy, sensitivity and specificity as measure. Alves-Ribeiro et al. [22] used machine-learning techniques in a ANN for masse detection using mammographic images. Results showed that the Random Forest algorithm performs the best classification rate. They used FFDM, the accuracy, sensitivity and specificity. Finally, Wang et al.[20] use an ANN modelling to estimate volumetric breast density (VBD) from FFDM on Japanese women with and without breast cancer. ANN calibration of VBD was performed using phantom data, they used FFDM on full image.

II. Materials and Methods

A. Data set used for experiments

The mammographic data used by us were taken from the DDSM [10] [23]. The database contains approximately 2.500 studies. DDSM is organized into ”cases” and ”volumes”. A case consists of between 6 and 10 files [10] [23]. The collection of cases are: normal, cancer, benign and benign without callback volumes. An example of cancer case is shown in Figure 2, where the abnormality is a malignant spiculated mass with calcifications. In this work, we use the following cases: normals, benigns and cancers. In total, we have used 600 images experiments, considering 200 images for each class.

B. Texture Analysis

Texture analysis of medical images has become increasingly popular in investigating diagnosis, assessment of cancerous disease. We use the Haralick texture features for clasification of mamograms in three clases, using a backpropagation neural network and cross-validation process [20]. We describe the spatial distribution of gray levels, which makes it useful in classification of similar regions in different images. Texture analysis was adopted for analysis in many medical imaging application, including oncology enabling description of tissue heterogeneity [24] [25][26] [27][28]. Haralick texture features [9] [29] [30] [31] calculate from a GLCM, a texture representation for image characterization. It is simple to implement and provides a set of interpretable texture descriptors [9] [32] [33] [34] [35] [36]. Texture analysis describes a region by quantifying spatial variation in pixel intensities. GLCM is a statistical method of texture examination by considering the spatial relationship of pixels. It is a matrix that counts the co-occurrence of neighboring gray levels in the image.

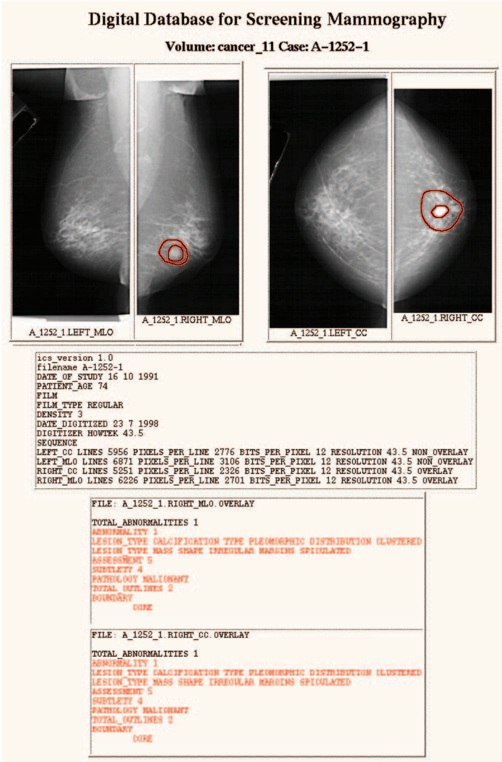

Figure 2. Example of case 1252 in the DDSM. The boundary of the toumor is marked by the larger marking and the core of the spiculated mass is marked by the smaller region.

Haralick texture features are computed from a GLCM. GLCM produces a square matrix, whose dimension is the number of gray levels in the region of interest (ROI) [9][37].

C. Artificial Neural Networks

The ANNs emulate the response of biological neural networks. In general, they consist of a series of units called neurons, connected to each other. ANNs are based on the functioning of the neuronal system of the human body. Learning is process that can be used to form ANNs. We can only transfer knowledge to the neural network through the learning procedure [38].

Each neuron receives an input value that is transformed according to a specific function called activation function. Transformed signal becomes the output of the neuron. The activation functions that are usually used are the identity function, the sigmoidal function and the hyperbolic tangent function. Neurons are connected according to a particular architecture. Neurons are grouped into different layers: an input layer, an output layer, and one or more hidden layers. The output of each neuron is propagated equally by these connections to the target neurons. Each connection has an associated weight that measures the numerical value of the signal traveling through it. Thus, ANNs can be seen as a graph whose nodes have similar functioning, which propagate the information through the different connections.
In our case, the number hidden layers is chosen experimentally. Number of neurons in output depends upon output vector. Features are used as inputs of the neurons of input layer. However, the best ANN structure is not known in advance [39]. The best ANN structure depends upon the number of hidden layers, number of neurons in each hidden layer, activation function, learning algorithm and training parameters. In [40] Several training algorithms are available for these tasks.

ANNs are data-based learning systems that the ability to solve a problem is closely linked to the patterns used during its learning phase. The learning of a ANN consists in finding the precise values of the weights of its connections so that it can solve the problem. The process consists of introducing a series of standard data and adjusting the weights according to a certain criterion.

The most common way to organize the neurons and layers of an ANNs is the MLP architecture. The training of a MLP [41] is based on repeat the presentation of pairs of vectors in the input and output layers (desired input and output vectors). The network creates a model based on adjusting its weights according to the training vectors, so that as these patterns are passed, for each input vector the network will produce an output value more similar to the expected output vector. These networks are also called backpropagation, name that is directly related to the type of learning used.

D. Neural classifier and cross validation

Usually, classifiers use features from the input data/image to learn how to classify the data/image that belongs to a particular class. ANNs form information processing system that are characterized by a large number of simple processing elements called the neurons. These neurons are interconnected to each other with each connection having an associated weight. These weights represent the information used by the ANNs to classify samples. A three-layered feed-forward ANN is shown in Figure 3.

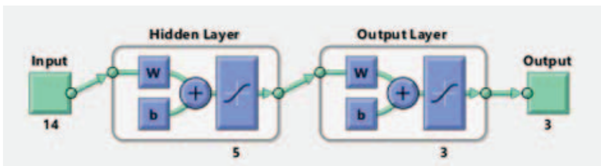

Figure 3. The Artificial Neural Network of our process

The input layer consists of neurons that receive the values of the features. The output layer presents the response of the ANNs. The hidden layer, which is the layer in between the input and output layers, is an optional layer included to handle more complex problems than that could be solved by using only the input and output layers. The neural networks in which the information signals flow from the input to the output units in a forward direction are called feed-forward networks [42].

The cross-validation process provides a much more accurate picture of a system true accuracy. In cross-validation, we divide our data into a large training set and a smaller validation set [43] [44]. To be a good measurement of accuracy, the validation data should represent the range of inputs the classifier is likely to encounter. In this work, we use the leave-one-out cross-validation, as a special case of k-fold cross-validation, where k equals the number of instances in the data. When the available samples for training are scarce, it is possible to obtain a more accurate measurement of this estimation by using cross validation [45]. Therefore, k-fold cross validation consists of partitioning the available data into k subsets with approximately the same number of samples. The cross-validation process involves k iterations, in which the training algorithm uses $k-1$ subsets to train, and leaves one of them out. The subset that is left out rotates in each iteration so that, at the end of the process, all the data have been part of the training and testing at some point (specifically $k-1$ times for training and one for testing).

E. Metrics

The assessment of our algorithm performance for classification among normal, benign or cancer cases, is described by the confusion matrix. A confusion matrix evaluates the classifier based on the real and predicted classifications. For a binary case, the four possible outcomes are: true positive, true negative, false positive and false negative. These possible outcomes of a classifier are shown in Table I. In this matrix four terms are handled which mean the following:

- **True Positive (TP)**: These are the cases in which the problem were correctly predicted.
- **True Negative (TN)**: These outcomes are the non detected cases when the condition is absent. For instance, the approach consider do not have the problem and it actually do not happens.
- **False positive (FP)**: For affirmative predictions, but, in fact, the image does not present the problem.
- **False negatives (FN)**: The image does not present the problem.

We introduce these concepts in terms of a binary classification (see Table I), but similar to two-class problem, this can be done using to represent more than two classes. In this case, we use the "plotconfusion.m" function. By default, this command will also plot the True Positive, False Negative, Positive Predictive, and False Discovery rates in they grey-colored cells. The green cells represent correct answers (3 first positions of the main diagonal of the matrix) and pink cells represent all types of incorrect response, as we see in Figure 4. In these cases, the 3 first positions of the main diagonal of the matrix represent the True Positive cases for each of the three conditions and, the last position of the diagonal of this matrix represents the True Negative cases for all conditions. There are False Negative for 3 conditions: benign, normal and cancer and False Positive for 3 conditions as well. For example, we may read the training set as: 175 samples from the class 1 was correctly classified as class 1, 196 samples from the class 2 was correctly classified as class 2 and 137 samples from the class 3 was correctly classified as class 3.

Table I: Confusion matrix for binary classifiers

	Cancer	**No Cancer**
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)
Total	TP+FN	FP+TN

III. Experimental Results

The first step of the proposed method consist of selecting the sample and reading the original image. After that, we convert to gray scale image and we obtain the texture image. The images for training and testing the ANNs were taken from the DDSM [23]. A set of 600 mammogram images, 200 for each cases of normal breast or with benign and cancer toumors are considered. Tests performed on this set of images, by applying the proposed techniques, can reveal classification of more than 80% of all data (see Figure 4). The implementation, training, simulation and learning of our ANNs for classification. In Figure 4, we present the data related to confusion matrix where show a summary of prediction results on a classification for muticlass case problem. In this figure, the first three diagonal cells show the number and percentage of correct classifications by the trained network. For example 175 image are correctly classifed as benign, which corresponds to 29.4% of all 600 images. Thus, the blue cell, overall, 85.0% of the predictions are correct and 15.2% are wrong classifications.

This strategy provided capacity to the network, generalized from examples, avoided the simple memorization of patterns during the learning stage, and generated a correct response to samples not used in the training stage. In the training process of the network, besides the learning error, the so-called generalization error was considered, facilitating a different test set than the training sample (Leave-one-out error estimation), allowing homogeneous results to be obtained in the 20 simulations that were performed, such as shown in Figure 4 and Table II, in which an average of more than 80% of good classification of the total data set can be observed.

IV. Conclusion

The BP neural network with 14 input, 5 hidden, and 3 out neurons was implemented for mammogram classifications based on the texture image. The 14 Haralick's texture descriptors were evaluated for the classification of mammograms in 3 cases. The classification accuracy rate of leave-one-out cross validation and test set were, in average, 84.72%. Overall, 84.72% of the predictions are correct and 15.28% are wrong classifications (see Table II). The results indicated that neural network with the classification accuracy (CA) rate for leave-one-out cross validation can provide a new method for the early diagnosis of breast cancer. Further work of this aspect is under investigation, specially to considering the use of proposals like SVM/Adaboost for more comparations of results with ANN. Also, we are testing other neural network architectures such as convolutional neural networks. Finally, for future works we are considering to do a comparative study with related works and to test this proposal for a dataset of mammograms.

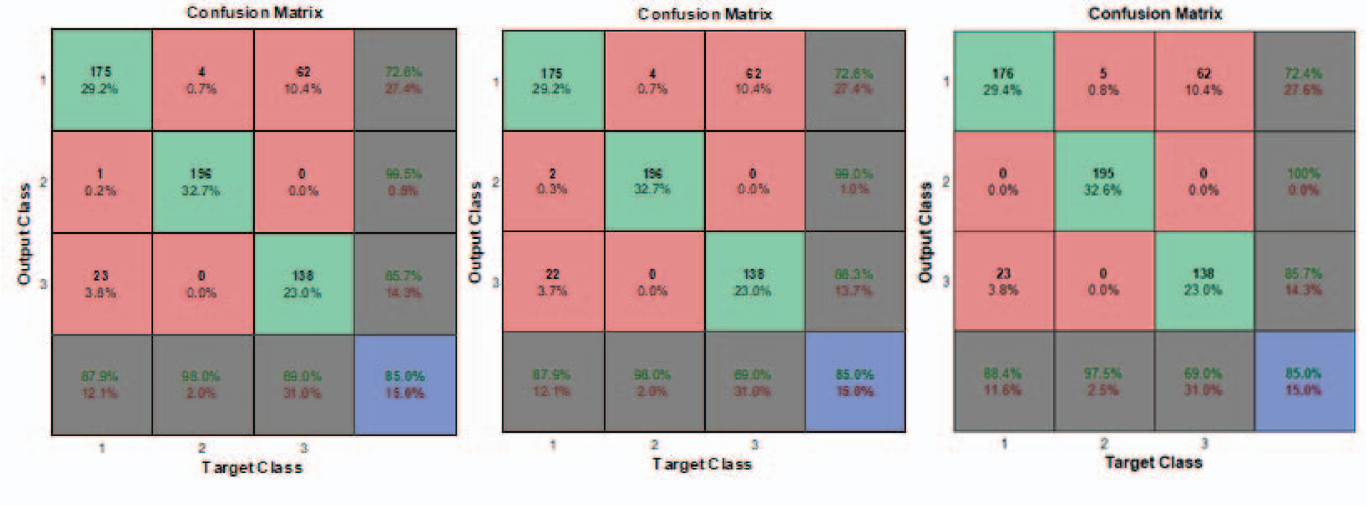

Figure 4. Confusion matrix considering 4, 5 and 6 hidden layers, respectively.

Table II: Results obtained in each simulation by correct (CP) and incorrect (IP) score prediction rates.

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Simul. Average
CP	85.1	84.6	84.8	85	84.8	84.6	84.8	84.3	85	84.5	84.5	84.6	84.8	85	84.8	84.6	84.8	84.3	85	84.5	**84.72**
IP	14.9	15.4	15.2	15.0	15.2	15.4	15.2	15.7	15.0	15.5	15.5	15.4	15.2	15.0	15.2	15.4	15.2	15.7	15.0	15.5	**15.28**

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