A Comparison between Support Vector Machine and Artificial Neural Network for Breast Cancer Detection

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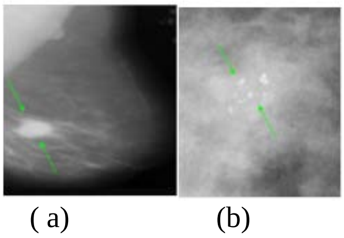
Abstract: - Breast cancer is one of the most common kinds of cancer, as well as the leading cause of disease among women. Early detection and diagnosis of breast cancer increases the chances for successful treatment and complete recovery for the patient. Mammography is currently the most sensitive method to detect early breast cancer; however, the magnetic resonance imaging (MRI) is the most attractive alternative to mammogram. Manual readings of mammograms may result in misdiagnosis due to human errors caused by visual fatigue. Computer aided detection systems (CAD) serve as a second opinion for radiologists. A new CAD system for the detection of breast cancer in mammograms is proposed. The discrete wavelet transform (DWT), the contourlet transform (CT), and the principal component analysis (PCA) are all used for feature extraction. As for classification the support vector machine (SVM) and the artificial neural network (ANN) are both used and their results are compared. The system classifies normal and abnormal tissues in addition to benign and malignant tumours.

Key-Words: - The artificial neural network; the discrete wavelet transform; the contourlet transform; the principal component analysis; the support vector machine.

1 Introduction

For years, cancer has been one of the biggest threats to human life; it is expected to become the leading cause of death over the next few decades. Breast cancer is one of the most common kinds of cancer, as well as the leading cause of decease among women. In Egypt, breast cancer is the most common cancer among women, representing 18.9% of total cancer cases [1].

Microcalcifications (MCs) and masses are two important early signs of the disease as shown in Fig.1. Although there are other signs but is still less important such as architectural distortion [2]. Manual readings of mammograms may result in misdiagnosis due to human errors caused by visual fatigue. Computer aided detection systems (CAD) serve as a second opinion for radiologists.



(a) (b)

Fig.1. Examples of mammograms (a) Mass area and (b) MCs area.

The main goal of the CAD system is to indicate the abnormalities with great accuracy and reliability.

A number of techniques for detection of the abnormalities have been developed in the past decades. Bhangale et al. [3] used the Gabor filters. Strickland et al. [4] introduced the undecimated wavelet transform by combining sub-bands from multiple transforms.

Wang and Karayiannis [5] used the wavelet based sub-band image decomposition. Bruce and Adhami [6] used the DWT modulus maxima method to extract multi-resolutional features that quantify the mass shapes. Yoshida et al. [7] combined a decimated WT and supervised learning. El-Toukhy et al. [8] introduced the curvelet transform. Gunawan [9] presented a new method for the detection of abnormalities using WT based on statistical methods; the detection rate was 96%. Juarez et al. [10] applied the functions db2, db4, db8, and db16 of the Daubechies wavelets family, the abnormalities were detected up to 80% accuracy. Balakumaran et al. [11] used the dyadic WT and introduced the fuzzy shell clustering algorithm in order to mark the MCs region. Lizcano et al. [12] used the CT for feature extraction and the SVM for classification. Adison et al. [13] used the PCA as a feature extraction technique to determine the breast cancer. Rejani and Selvi [14] used the SVM for classification; the sensitivity achieved was 88.75%. Sharkas et al. [15] used the proposed CAD system to detect the MCs and to classify between normal, abnormal tissues in addition to benign and malignant MC tumors using the SVM technique. The achieved rate was almost 98 %.

The aim of this paper is to detect the abnormalities in the breast especially the MCs using CAD systems. A new CAD system is proposed in which the DWT, the CT, and the PCA are used for feature extraction. Moreover, classifying normal from abnormal tissues, in addition to benign from malignant lesions is presented using the SVM technique compared to ANN technique

The paper is organized as follows: section II describes the CAD system and discusses the used system, section III shows the computed results of the proposed technique, section IV discusses the results, and finally, section V concludes the presented work.

2 The Cad System

The steps of the proposed CAD system are illustrated in Fig.2, which is described in details in the following sub sections.

2.1 Image Enhancement

In this step, the adaptive histogram equalization (AHE) is used, which is an image processing technique used to improve the contrast in images [16]. A generalization of AHE called contrast limited adaptive histogram equalization (CLAHE) was developed, where the histogram is calculated for the contextual region of the pixel [17].

2.2 Image Segmentation

The region of interest (ROI) is extracted from the original mammogram image as shown in Fig. 3.

2.3 Feature Extraction

There are many techniques for the feature extraction step; in this paper the DWT, the CT, and the PCA are introduced to detect the abnormalities in the breast.

2.3.1 Discrete Wavelet Transform (DWT)

DWT technique is discussed by many researchers in [2,10,19,20].

2.3.2 The Contourlet Transform (CT)

The CT or pyramidal directional filter bank (PDFB) is a combination of a Laplacian pyramidal and a directional filter bank (DFB) [21]. Band pass images from the Laplacian pyramid [22] are fed into a DFB so that directional information can be captured. The low frequency component is separated from the directional components. After decimation, the decomposition can be iterated with the same DFB in the low pass band to form a pyramid structure. The CT provides a multi-scale directional decomposition [23].

Do and Vetterli [24] proposed a PDFB in order to implement the CT, which is a discrete version of the curvelet transform. The proposed structure is a combination of the Laplacian pyramid and the DFB. Their pyramidal DFB has united two advantages of the two structures, which are multi-resolution and multi-direction. It attempts to separate the low frequency component from the rest directional components and reiterates with the same DFB in the low pass band, forming a pyramid structure.

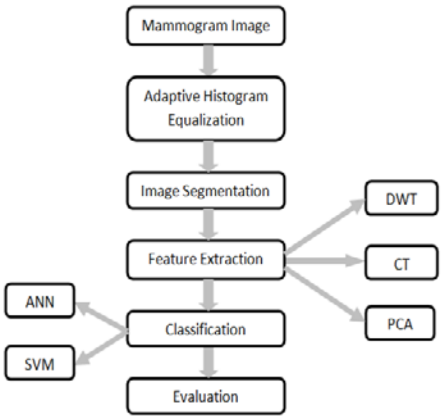
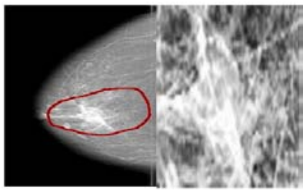


Fig. 2. Block diagram of the proposed CAD system.



(a) (b)

Fig. 3.Original mammogram image [18]
(a) The red region is the MC area and (b) the extracted enhanced ROI

2.3.3 Principal Component Analysis

PCA is a method that reduces data dimensionality by performing a covariance analysis between factors; it reduces the number of observed variables to a smaller number of principal components, which account for most of the variance of the observed variables. It is used when variables are highly correlated, and it is suitable for data sets in multiple dimensions [25].

PCA belongs to linear transforms based on the statistical techniques.

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2.4 Classifications

In this step, the ROI is classified as either malignant or benign. There are lots of classifiers techniques; among them the linear discriminant analysis (LDA), ANN, binary decision tree, and SVM [2].

In this paper a comparison is made between the ANN technique and the SVM technique. In the following subsections a brief introduction to ANN and SVM techniques is given.

2.4.1 Artificial Neural Network (ANN)

ANNs are the collection of mathematical models that imitate the properties of biological nervous system and the functions of adaptive biological learning. It is a self-learning system that changes its parameters based on external or internal information that flows through the network during the learning phase. ANNs are composed of an input, an output, and one or more hidden layers, the layer is composed of neurons. The advantage of ANNs is that they are often suitable to solve problems that are too complex to be solved by the conventional techniques, or hard to find algorithmic solutions. The disadvantages of ANNs are that they do not have common rules to determine their size, and they consume long time for training. There are three types of ANNs that are frequently used in the field of breast cancer detection and classification: the back propagation neural network (BPN), the self-organizing map (SOM) and the hierarchical ANN [26 – 28].

Many researchers used the ANNs in the classification of breast cancer lesions [29-33].

2.4.2 Support Vector Machine (SVM)

SVM is a learning tool originated in modern statistical learning theory [34].

The aim of SVM is to devise a computationally efficient way of learning and separating hyper planes in a high dimensional feature space [34]. SVM performs classification by constructing an N-dimensional hyper-plane that optimally separates the data into two categories. SVM models are closely related to neural networks.

The advantage of using SVM is that it achieves higher classification rates compared to other classification techniques.

There are two cases for SVM; linear SVM and non-linear SVM [35]. The linear SVM is only used here.

3 Results

To verify the proposed method, experiments were performed on the digital database for screening mammography (DDSM) mammogram database [18] using MATLAB. The DDSM database consists of 2620 cases available in 43 volumes. The volumes are normal, benign, or malignant samples. The resolution of a mammogram is 50 μm/pixel and the gray level depths are 12 and 16 bits.

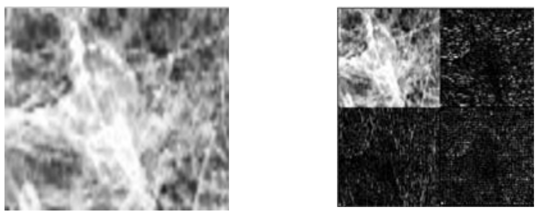
Hundred cases of MCs (50 malignant and 50 benign cases) and 60 normal cases were extracted from the database.

First, the samples are enhanced and segmented, and then features are extracted using three ways: DWT shown in Fig. 4, CT shown in Fig. 5, and PCA data. The samples go through the ANN technique and SVM technique for classification.

The ANN technique uses the backpropagation algorithm with 65536 input neurons, one hidden layer with 10 neurons, and one neuron in the output layer. The SVM technique uses the linear kernel function.

When classifying normal and abnormal MC tissues, sixty samples are trained and tested. The highest classification rate was for the approximate component of the first level DWT compared to the vertical, horizontal, and diagonal components. The rate was 99% achieved by the ANN technique and this is clear in the receiver operating characteristic (ROC) analysis curve shown in Fig 6. One should notice from this curve that the area under the curve is almost 1. Therefore, the computed classification rate is 99%. While for the SVM technique the highest classification rate was for the vertical component, which was also 99%. This is shown in Fig.7.

When distinguishing between benign and malignant MC tumors, a hundred samples are trained and tested. The highest classification rate was for the horizontal component of the first level DWT. This was 96% achieved by the ANN technique. The ROC curve is shown in Fig. 8 which shows that the area under the curve is 0.96. As for the SVM technique still the vertical component ranked the highest classification rate with 99% compared to the other components. This is shown in Fig.9.



(a) (b)

Fig.4 Extracted features using DWT, (a) original image for a malignant MC case and (b) 1st level DWT.

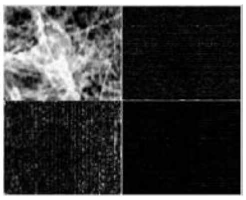


Fig. 5. The CT coefficients.

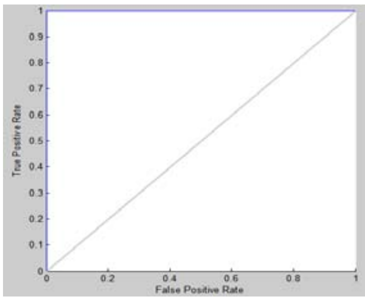


Fig. 6. ROC curve of the ANN classifier for the approximate component of the 1st level DWT.

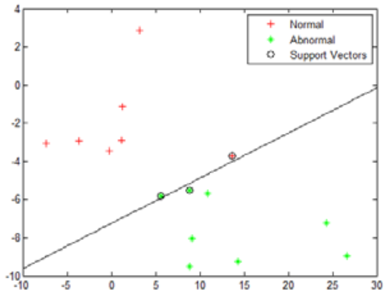


Fig. 7. SVM classification between normal and abnormal MC tissues for the vertical.

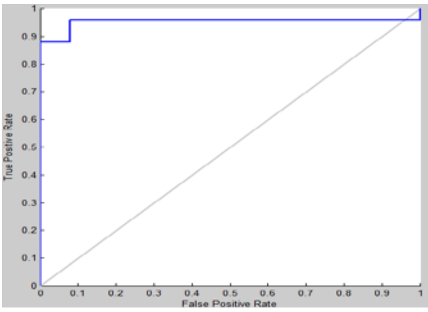


Fig. 8. ROC curve of the ANN classifier for the horizontal component of the 1st level DWT.

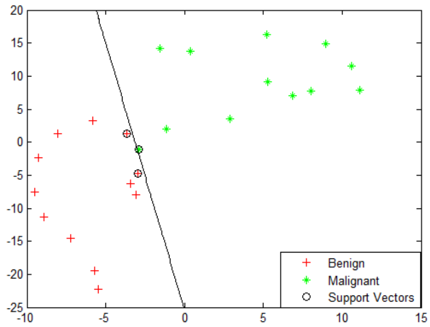


Fig 9. SVM classification between benign and malignant MC tumors for the vertical component of the DWT features.

Tables I and II show a comparison between the ANN and the SVM classifiers for the first level DWT different components in order to distinguish between normal and abnormal tissues and also between benign and malignant tumors, respectively. Furthermore, Tables III and IV illustrate a comparison between ANN and SVM techniques for the three types of feature extraction techniques' used to distinguish between normal and abnormal tissues and between benign and malignant tumors, respectively.

Table I. Classification rates for DWT features to classify between normal and abnormal MC tissues.

	ANN	**SVM**
Approximate	**99%**	66.7%
Vertical	90%	**99%**
Horizontal	95%	50%
Diagonal	75%	53.33%

Table II Classification rates for DWT features to classify between benign and malignant MC tumors.

	ANN	**SVM**
Approximate	94%	96%
Vertical	80%	**99%**
Horizontal	**96%**	52%
Diagonal	85%	56%

Table III. Classification rates for different feature extraction techniques to distinguish between normal and abnormal MC tissues.

	ANN	**SVM**
DWT	**99%**	**99%**
CT	90%	56.67%
PCA	98%	73.33%

Table IV. Classification rates for different feature extraction techniques to distinguish between benign and malignant MC tumors.

	ANN	**SVM**
DWT	**96%**	**99%**
CT	82%	80%
PCA	95%	66%

4 Conclusions

The goal of this work is to detect the MCs in the breast and to classify the tissues using both ANN and SVM techniques.

In this paper a new CAD system is introduced. The DWT, the CT, and the PCA are used for feature extraction; while the ANN and the SVM are used for classification.

The proposed methods achieved a high classification rate; the tissues are almost completely

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classified either for normal and tumor tissues, or benign and malignant tumors using the DWT features for both the ANN and the SVM classifiers.
It can be noticed that using ANN as a classifier instead of SVM greatly improved the classification results for CT and PCA features when classifying normal from abnormal MC tissues as shown in table III . Also when distinguishing benign from malignant MC tumors, the ANN classifier performed much better then the SVM for PCA features as depicted in table IV while there was a slight improvement in the case of CT features.

This CAD system can be applied for the detection of other abnormalities in the breast such as masses and architectural distortion.

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