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Breast cancer image classification using artificial neural networks

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Abstract

Breast cancer (BC) mostly develops on women breast region. Regular check ups are crucial for early detection and treatment of this cancer type. Pathologist performs the diagnosis of the breast cancer. Recent computer-aided methods for breast cancer diagnosis allow another and faster way of breast cancer diagnosis. Therefore, improvement of computer-aided methods has been developing for the breast cancer detection. In this paper, a method for automatic classification of images for breast cancer diagnosis is presented. Classification of the images is achieved using Back Propagation Neural Network (BPPN). The performance of the automatic classification of the breast cancer images is further improved by using radial basis neural networks (RBFN). The accuracies of the BPNN and RBFN are also reported 59.0% and 70.4% respectively.

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*Keywords:B*reast cancer; artificial neural network; classification.

1. Introduction

The diagnosis of the breast cancer is done by biopsy. Biopsy is a laboratory procedure and it is performed by a pathologist to detect the cancer. Pathologist collects samples of tissues from the breast region. There are several techniques for collecting samples of breast tissues. These techniques are fine needle aspiration, core needle aspiration, core needle biopsy, vacuum-assisted and surgical biopsy, Filipczuk et al. (2013). After, these cancer tissues are analyzed using microscope. Images obtained from microscope are also called histopathology images. Pathologist analyses the histopathology images and classifies them as cancerous or noncancerous images.

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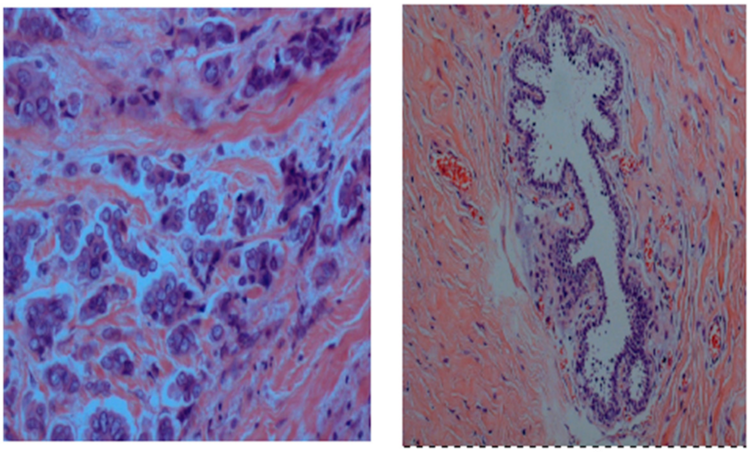
Computer aided diagnosis of breast cancer methods can be summarized as follows. Kowal et al. (2013) proposed an approach for automatic classification of images. Their approach is based on determination of nuclei regions on the images and then using these regions into the classifiers. Two-stage segmentation is applied to images. In the first stage, foreground and background segmentation is performed on the images using adaptive threshold. After, images contain nuclei, red blood cells, and other features. In the second stage, nuclei regions are segmented from blood cells, and other features. Finally, nuclei regions are represented with different features and these features are used as input to classifiers. Three classifiers, k-nearest neighbors, naive Bayes classifier and decision trees, are used. They report the classification accuracy of 96-100 % on the 500 images. Filipczuk et al. (2013) proposed a method for computer-aided breast cancer diagnosis. The proposed approach is determining the nuclei areas and segmenting these regions on the images. Nuclei areas are detected using circular Hough transform, Kerbyson and Atherton(1995). Then segmented regions are used as input to classifiers. These classifiers were k-nearest neighbor, Bayes classifier, decision tree and support vector machines. The performances of these classifiers were reported. The classification accuracy of 98.51 %is reported on the 737 microscopic images of the fine needle biopsies.George (2014) proposed a method for computer-aided breast cancer diagnosis. This method is similar to previously proposed method in Filipczuk et al. (2013) The proposed approach is determining the nuclei areas and segmenting these regions on the images. Nuclei areas are detected using circular Hough transform, Kerbyson and Atherton (1995). Then segmented regions are used as input to classifiers. These classifiers are multilayer perceptron based on back-propagation algorithm, probabilistic neural network, vector quantization and support vector machines. The performances of these classifiers are reported.A method for automatic classification of microscopic biopsy images is also proposed in Zhang (2011). Images are represented using Local Binary Pattern and Curvelet transformed images. Represented images are classified using two random subspace classifier ensembles. First, an ensemble of support vector machines is used. The output of this ensemble is classified using another ensemble of multiple layer perceptions classifiers. The classification accuracy of 97 %is reported on the database of the Israel Institute of the Technology.



a b

Fig. 1. (a) Cancerous image; (b) Non-cancerous image.

In this paper, automatic classification of cancerous and non-cancerous breast images is presented. Fig. 1(a) shows an example of cancerous image and Fig. 1 (b) shows an example of non-cancerous breast image. The proposed approach is based on the representation of images using discrete Haar wavelets and then inputting these transformed images into the neural networks. Back propagation, Jain (1996), and radial basis,(Jain (1996), Leonard and Kramer (1991), Chang(2010)), neural networks are used to learn content of the images for the classification.

2. Methodology

The Image representation of breast tissues is explained first and then the neural networks are described.

2.1 Image Representation

New images are created using discrete Haar wavelets for training of neural networks. First, all images in the database is converted to gray scale format. Second, Gaussian filter is apply to all images in order to mitigate the effects of the noise. Moreover, Haar discrete wavelets are calculated on an image. This resulted in four images which are approximate, horizontally detailed, vertically detailed, diagonally detailed images. These four images are summed to original image. Finally, inverse wavelets are calculated to reconstruct new image. Obtained images contained more clear edges and less background content. Fig. 2 shows four images, which are obtained from the Discrete Haar wavelet analysis. Fig. 3 shows inverse wavelet image and new image.

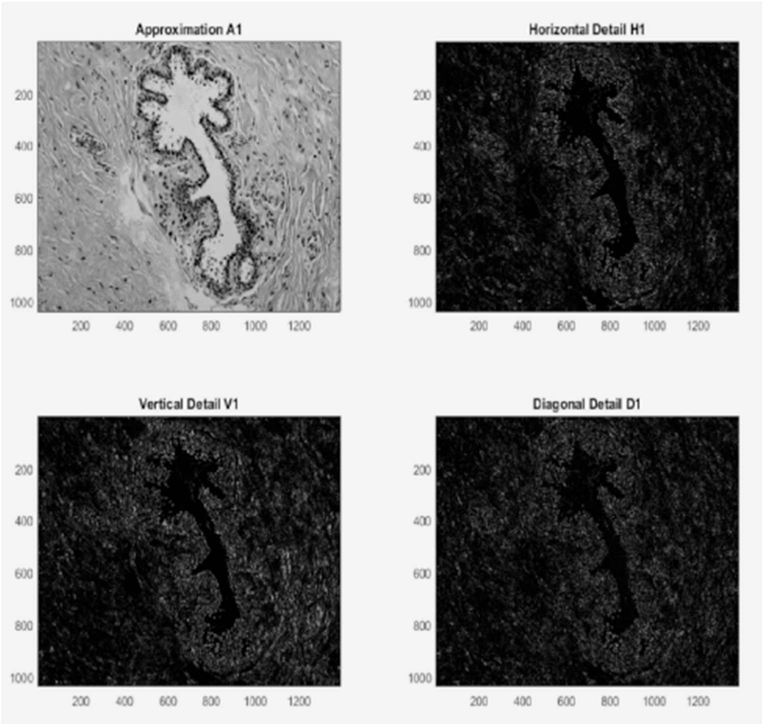


Fig. 2. Wavelet Transformed images.

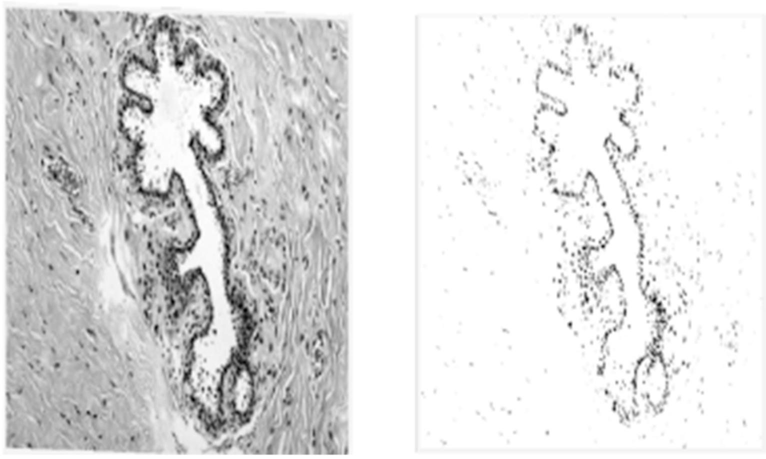


Fig. 3. (a) Inverse Wavelet Transformed image; (b) Summed image.

2.2 Neural Networks

The modeling of digital images for breast cancer classification is achieved using ArtificialNeural networks. Artificial Neural Network is trained on the images. The architecture of the ANN is based on a feed-forward network. This architecture is trained according to Back-propagation algorithm. The obtained results are further improved by using Radial Basis function network The performance of the radial basis function network outperformed the ANN. The ANN architecture can be seen in Fig. 4.

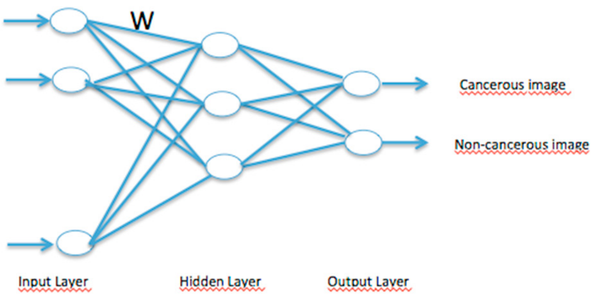


Fig. 4. Back Propagation Neural Network.

3.Evaluation

In this section, the database used for performance evaluation of the neural networks, is described. Then the performances of BPN and radial basis function networks are evaluated.

3.1 Dataset Description

Digital images of the breast tissues are obtained from Near East University Hospital. The total number of images is 176. The number of images, which show cancer on them, is 112. The number of images contained noncancerous content is 64.This database is divided into two sets of images. The first set of 115 images is used for training the BPNN and RBNN networks. The second set of 61 images is used for testing the performance of the BPNN and RBNN models.The number of images Table 1.

Table 1. Dataset Description

Images	Training	Testing
Cancerous	70	42
Normal	45	19
Total	115	61

3.2 Neural Network Description

Back propagation neural network is trained using 115 images. The number of hidden neurons is 100. The learning and momentum rates are also set to 0.3 and 0.75 respectively. 3000 epochs are also used to train the model. Training the BPNN network took 55 seconds and the mean square error of 0.01352 is reported.Radial Basis Neural network is trained using 115 images. The number of hidden neurons is 80. 100 epochs are also used to train the model. Training the RBFN network took 30 seconds and the mean square error of 0.0220 is reported. Table 2 and Table 3 show the network parameters of both neural networks.

Table 2. Back Propagation Neural Network

Network Parameter	Value
Number of Training Samples	115
Number of Hidden Neurons	100
Learning Rage	0.3
Momentum Rate	0.75
Maximum Epochs	3000
Training Time (sec)	55
Mean Square Error	0.01352

Table 3Radial Basis Neural Network

Network Parameter	Value
Number of Training Samples	115
Number of Hidden Neurons	80
Maximum Epochs	100
Training Time (sec)	30
Mean Square Error	0.0220

3.3 Results

The above neural networks are trained and test on the database. The same number and images are used for training and testing the both Back propagation and neural networks. The classification results of the both neural networks can be seen in Table 4.

Table 4. Results of Neural Networks

Neural Network	Back Propagation	Radial Basis
Training Images	115	115
Test Images	61	61
Classification result	59.02 %	70.49 %

4. Conclusion

Automatic classification of breast cancer using neural networks is presented. The proposed methodology is based on the representation of images using discrete Haar Wavelets and then inputting them into neural networks.Haar wavelets provide better image content representations and this contributes to better modeling of breast cancer regions using neural networks.Classification of the images is achieved using Back Propagation Neural Network (BPPN) and radial basis neural networks (RBFN). The accuracies of the BPNN and RBFN are also reported 59.0 % and 70.4 % respectively. Both networks are performed on the same training images and the same test images. Results show that RBFN outperforms the BPNN.

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