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DEVELOPMENT OF BREAST CANCER DIAGNOSIS SYSTEM BASED ON FUZZY LOGIC AND PROBABILISTIC NEURAL NETWORK

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Breast cancer is one of the most common kinds of cancers that infect females in the whole world. It has happened when the cells in breast tissues start to grow in an uncontrollable way. Because it leads to death, early detection and diagnosis is a very important task to save the patient's life. Due to the restriction of human observers, computer plays a significant role in detecting early cancer signs. The proposed system uses a multi-resolution analysis and a top-hat operation for detecting the suspicious regions in a mammogram image. The discrete wavelet transform feature analysis is utilized for extracting features from the region of interest. Fuzzy Logic (FL) and Probabilistic Neural Network (PNN) are utilized for classifying the tumor into normal or abnormal. The differences between the proposed system and other researches are the use of adaptive threshold value depending on each image, by using Discrete Wavelet Transform (DWT) in both segmentation and feature extraction phases, which decrease complexity and time. Additionally, the detection of more than one tumor in the breast mammogram image and the utilization of FL and PNN work on increasing the system efficiency that led to raising the accuracy rate of the system and reducing the time. The obtained results of accuracy, sensitivity, and specificity were equal to 99 %, 98 %, and 47 %, respectively, and these results showed that the proposed system is more accurate than the other previous related works

Keywords: breast cancer diagnosis, fuzzy logic (FL), probabilistic neural network (PNN)

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1. Introduction

In the last few decades, cancer is one of the most critical and deadly diseases all over the world. Cancer starts in the cell, which is the building block that forms tissues. Tissues can be found in any portions of the human body, involving the breast. Generally, cells are created and split each time the body needs them, for growing and surviving. When the normal cell becomes old, it shrivels until die, then new cells will be created. Occasionally, this process does not follow a normal way, some new cells are created when they are not needed anymore, and old cells don't die to let the new cells to replace them. This uncommon creation of cells forms a chunk of tissue, also called a tumor, lump, or growth. Cancer formed in breast tissues is called breast cancer [1]. Because cancer leads to death, most of the countries around the world, especially the industrialized countries, have directed the efforts to the early detection of breast cancer, which will improve the chances of successful treatment. According to the World Health Organization (WHO), in 2015, there were (8.8 million) deaths of cancer. Furthermore, 27 million cases of cancer are expected before 2030. The recent existing studies assured that breast cancer represents 18 % of all kinds of female cancers and the 5th cause of death worldwide [2].

The exclusive rescue for reducing the fatality of breast cancer is concentrated on early detection and proper diagnosing. Within the medical field, finding an accurate tumor classification is a very significant responsibility. The techniques of machine learning are widely employed to detect and classify various kinds of cancers since they provide accurate and high-performance results. These techniques can be vastly utilized for disease diagnosis in the medical field [3]. Therefore, the studies they are devoted to are of scientific relevance.

2. Literature review and problem statement

Breast cancer is a fatal disease that influences a considerable proportion of females around the world. Early detection of this disease helps in healing as well as decreasing the chance of death. X-ray mammogram is classified as the easiest and widespread technique for early detection of cancer. The radiologists might miss 10 % to 15 % of breast cancer tumors, so computer-aided diagnosis systems are used to take accurate decisions with reduced cost and time. The computer systems use various techniques and methods involving databases, machine learning, image processing and data analysis tools to detect and diagnose breast cancer with high accuracy.

There are many researches that have been introduced in the breast cancer diagnosis field, some of them are described briefly as follows. In [4], an optimized Neural Network (NN) approach was proposed for classifying breast cancer tumors as benign or malignant. New processes of crossover and mutation have been presented for reducing the devastating nature of these processes. This approach may represent a suitable approach only when the preferable structure of the NN is not known, or it is tough to reach the preferable structure utilizing the process of trial-and-error. The obtained accuracy was 98.52 % using the dataset of fine-needle aspiration. In [5], a technique of breast cancer detection using the models of image processing was proposed based on Artificial Neural Networks (ANN). Gray Level Co-Occurrence Matrix (GLCM) feature extraction is utilized for training ANN. The experiments were implemented on only forty-two mammogram images, and the obtained accuracy was 87.5 %. In [6], an auto-detection technique depending on ANN was proposed in which preprocessing is firstly done on the dataset of breast cancer, then, the obtained data are utilized as an input to the ANN for classifying the tumor as a cancerous or not. The results have achieved more than 90 % accuracy. In [7], a technique based on a Convolutional Neural Network (CNN) was presented to speed up the process of diagnosis for helping the specialists in abnormality detection. CNN is trained via enhanced mammogram images, then, the classifier presented a system for detecting the cancerous tumor, and this model required a few days to retrain. This technique was tested using 322 mammogram images and provided a fast diagnosis time with 82.73 % accuracy. In [8], a breast cancer detection system based on the Law's Texture Energy Measure (LTEM) method was presented. Backpropagation Artificial Neural Network (BPANN) algorithm is utilized for classifying the malignant, benign and normal tissue region. This technique provided accuracies of 94.4 %, 91.7 % and 66.66 % for normal-abnormal and benign-malignant classification, respectively. Further improvement should be satisfied in this technique by modifying the architecture and the number of nodes in the hidden layer. The study in [9] utilized the model of Bayesian Network (BN) and concentrated on utilizing the most significant features when collecting data, and this indirectly assists breast cancer oncologists to deal with a few features but may lead to losing some important features. The experiments were performed on datasets of clinical ultrasound and fine-needle aspiration cytology, and the highest achieved accuracies were 92.98 % and 98.87 %, respectively. In [10], a knowledge-driven feature learning and integration framework was proposed for distinguishing between malignant and benign lesions of the breast by utilizing multiple sequences of Magnetic Resonance Imaging. In this framework, several deep networks were constructed for extracting different subsequence features. Additionally, a module of weighting was used to provide the integration for these extracted features. The experiments were performed on one hundred images, and the achieved accuracy was 85 % and according to the obtained result, the construction of this framework needs to be improved.

3. The aim and objectives of the study

The aim of this study is to introduce a hybrid approach for breast cancer diagnosis based on FL and PNN to help the specialists to specify suspicious regions in the breast mammogram images.

To achieve this aim, the following objectives are set:

– enhance the mammogram image by removing the noise and increasing the brightness of suspicious regions;

– extract the important features to be beneficial in the stage of classifying the pattern;

– utilize the machine learning techniques to efficiently classify the masses in digital mammogram images;

– develop a model for diagnosing these masses as normal and abnormal for reducing the number of falsely classified cancers and increasing the accuracy of cancer detection and diagnosis.

4. Proposed system

This paper works on developing an efficient system that can accurately detect the tumors and classify them as normal (benign), or abnormal (malignant) from mammogram images. Fig. 1 shows the proposed system block diagram.

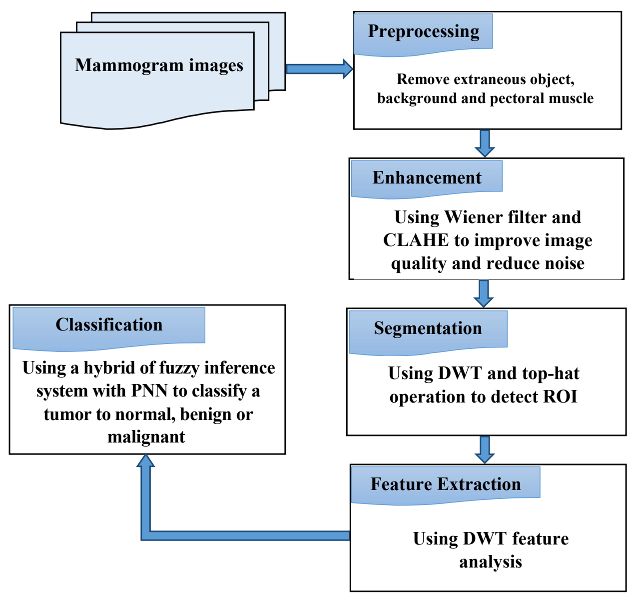


Fig. 1. Proposed system block diagram

As shown in Fig. 1, the first stage in this proposed system is preprocessing and enhancement, which involve removing the extraneous objects and noise, adjusting of contrast, and edge-enhancement. The second stage is segmentation, which is applied to detect suspicious regions. After that, the features are extracted and selected by using Wavelet Transform feature analysis. The last stage is the classification process, a hybrid fuzzy inference system and PNN algorithm are used to determine the normal, benign, or malignant regions in the breast.

4. 1. Preprocessing

This stage aims to decrease the number of objects in the mammogram image by extracting the relevant breast region and minimizing the area of the image to be examined. This stage starts with transforming the image into a binary image by using a global threshold to remove the extraneous objects (such as labels and wedges) from the digital mammogram image. In order to remove the labels and wedges, the physical area in a binary image of each object is calculated, and an object with the largest area is considered the breast profile. Then all the objects are removed except the largest one. After that, the area of the image is reduced by ignoring the surrounding dark area to reduce the time taken for operations. The pectoral muscle part can be removed by utilizing a technique of modified region growing. The technique of seeded region growing is worked depending on the value of the chosen pixel location and based on the selected seed point that can be chosen either adaptively or manually. In this system, the seed point is chosen automatically by taking into consideration the mammography orientation. This process defines the neighboring pixels of the seed point and examines if the next pixels should be combined with the region or not. This process is repeated until completely extracting the ROI. Fig. 2 shows the main steps of the preprocessing stage.

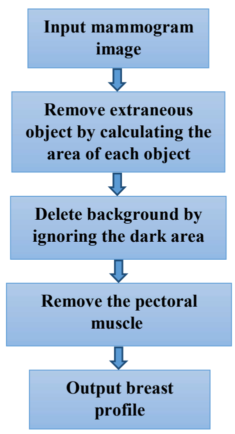


Fig. 2. Preprocessing stage block diagram

The steps of the preprocessing stage can be summarized as follows:

– *Step 1*: Input mammogram image of breast cancer and calculate the global threshold (level), which can be utilized for converting the mammogram image to the binary image;

– *Step 2*: Count on the threshold, the mammogram image is converted to a binary image;

– *Step 3*: Examine the set of areas associated with each connected object in the binary image;

– *Step 4*: Replace all pixels with zero except those in the range of the above index;

– *Step 5*: Multiply every pixel in the original image by the corresponding pixel in the resulted image;

– *Step 6*: After the removal of all extraneous objects, ignore all the dark areas by calculating the sum for every column; if this sum equals "0", do not transform the column to the new image; apply this process to all rows as well;

– *Step 7*: Remove pectoral muscle, and finally, the mammogram image (breast profile) is obtained.

4. 2. Enhancement

To enhance the mammogram image, the noise should be removed and the brightness of suspicious regions should be increased. Fig. 3 shows the main steps of the enhancement stage.

This stage includes two steps:

Step 1. Apply a Wiener filter of 3×3 mask and SNR equal to 0.2. The Wiener filtering is based on the consideration of images and noise as a random process and the function is to obtain an estimated $\hat{f}$ of the uncorrupted image f in such a manner that the mean square error among them is reduced. The error measure is provided as follows:

$$e^2=\left\{E\left[f(x,y)-f(x,y)\right]^2\right\}. \tag{1}$$

Here, $E\{...\}$ represents the predictable value of the argument. It is supposed that the image and noise are uncorrelated; that one or the other holds "0" mean; and that the gray levels in the estimation are levels linear function in the degraded image.

$$g(x,y)=h(x,y)*f(x,y)+n(x,y), \tag{2}$$

$$(x,y)=w(x,y)*g(x,y). \tag{3}$$

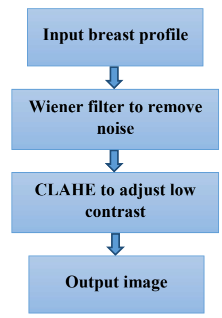


Fig. 3. Enhancement stage block diagram

Since we have assumed that H is linear shift invariant and f is stationary, applying Fourier transform leads to

$$\hat{F}(k,l)=\left[\frac{H(k,l)}{\left|H(k,l)\right|^2+S_{u(k,l)}/S_{x(k,l)}}\right]G(k,l), \tag{4}$$

where S_u is the noise power spectrum and S_x is the signal power spectrum.

Step 2. The process of Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the results of the first step. In this process, excessive amplification and noise amplification will overcome it by cutting the spikes and also improving the speed of calculation. The steps of CLAHE are:

1. Divide the image into blocks.
2. Calculate the intensity histogram of each contextual region.
3. The derived graph to every block is cut and re-normalized.
4. The function of desired mapping is computed only in a sample of pixels and the function of mapping to the other pixels is found via approximating the functions of mapping related to the four adjacent blocks.
5. The functionality of mapping is performed to obtain an improved image contrast.

4. 3. Segmentation

In this stage, the image is partitioned into a number of objects that have similar characteristics regarding a set of predefined criteria, or into constituent regions. Fig. 4 shows the main steps of the segmentation stage.

There are several steps in the segmentation stage:

– *Step 1*: Input the enhancement mammogram image and choose the global-local minima;

– *Step 2*: The size of the image is standardized into a multiple of 4;

– *Step 3*: Applying a 2D wavelet decomposition;

– *Step 4*: Using the wavelet decomposition-based histogram-thresholding, and the threshold value is selected via applying 1D wavelet-based analysis of the histogram of wavelet transformed image at various channels;

– *Step 5*: Obtain the results from the binary image according to the threshold segmentation image;

– *Step 6*: Obtain the results of the amplifier;

– *Step 7*: Utilize morphological filtering enhancement (top-hat operation) for reducing the occurrence of false objects;

– *Step 8*: Open operation is applied;

– *Step 9*: Return the fine segmentation results (suspicious lesions region).

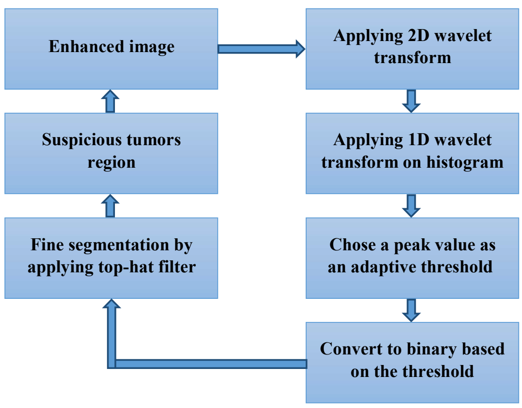


Fig. 4. Segmentation stage block diagram

4. 3. 1. Coarse segmentation

1) Wavelet Transforms: since tumor regions are mostly denser than normal surrounding tissue regions, in this work, the detection of suspicious regions is done by using adaptive thresholding based on the multi-resolution analysis in mammogram images. The low-frequency sub-images at different resolutions can be obtained by applying the Daubechies wavelet (DB6) transforms two times. The detection is obtained from the coarsest resolution to the finest resolution by utilizing the techniques of adaptive thresholding. A combination of two thresholding segmentation techniques (coarse and fine) is utilized for segmenting suspicious regions in multi-scale images. Firstly, the coarse segmentation is used to obtain a rough representation of the localization of suspicious regions and, secondly, the fine segmentation is utilized for improving the rough representation to generate more accurate segmentation results.

2) Wavelet-based thresholding: the transformation of Daubechies wavelet is performed on the preprocessed image. A scaling channel is selected appropriately by utilizing the prior information related to the probable size of the target. The histogram is obtained after performing the wavelet transform. After that, a scale 1D db10 wavelet transform is performed. The local minima of the 1D wavelet transformed histogram at the chosen scale are calculated. The threshold value is chosen via utilizing the obtained local minima value. The next segmentation is given via utilizing the threshold value for obtaining the coarse segment ranges.

4. 3. 2. Fine segmentation

A mass pattern-dependent enhancement approach is designed by using an algorithm based on the properties of morphological filters. The algorithm is performed by dual morphological top-hat operations after subtraction takes place. These processes can be described as follows:

– *Step 1*: A top-hat operation is used to extract the textures that do not contain the information pattern of interest.

$$r_1(i,j) = \text{maximum}\left(0, \left[f(i,j) - (foB_1)(i,j)\right]\right), \qquad (5)$$

where $f(i,j)$ indicates the original image, and $r(i,j)$ indicates the residue image between the opening of $f(i,j)$ via a certain structuring element "B_1" and $f(i,j)$. The size of this should be selected minimal than the suspicious regions size;

– *Step 2*: Make $r_2(i,j)$ become the mass model enhanced (via background correction) image:

$$r_2(i,j) = \text{maximum}\left(0, \left[f(i,j) - (foB_2)(i,j)\right]\right), \qquad (6)$$

where B_2 represents a chosen structuring element, which possesses a bigger size compared to the suspicious region;

– *Step 3*: Derive the enhanced image $f_1(i,j)$ as follows:

$$f_1(i,j) = \text{maximum}\left(0, \left[r_2(i,j) - r_1(i,j)\right]\right). \qquad (7)$$

The Dual-morphological operation can be utilized for removing the noises of background and structure within the suspected mass patterns, enhancing the mass pattern, and also removing some structural noise inside the mass region, which in turn can improve the results of mass segmentation.

4. 4. Feature extraction

In this stage, a Wavelet Feature Extraction method is used to find the suspicious region that might contain a tumor. Fig. 5 shows the feature extraction stage.

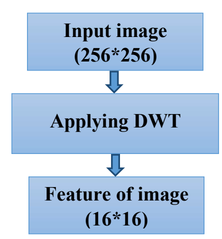


Fig. 5. Feature extraction stage block diagram

The DWT is performed for the segmented parts obtained from the previous stage for extracting the features, which would be beneficial in the next stage. There are two filters that are used on the image along the rows and columns, a high-pass filter for high frequency (H) and a low-pass filter for low frequency (L).

4. 5. Classification

PNN is presented in [9, 10] as an instance of the radial basis function-based model efficiently utilized for the problems of data classification. As a data classifier, it was drawn the researchers' concentration in the data mining domain. It is possible to be applied in image classification and recognition, digital image watermarking, medical prediction and diagnosis, etc. PNN is a complex structure of a feed-forward neural network. It includes an input layer, a pattern layer, a summation layer, and an output layer. In spite of the complexity of PNN, it has a single parameter of training. This is a smoothing parameter for the probability density functions (PDFs), which are used for the neuron's activation in the pattern layer. Fig. 6 shows a PNN structure [11].

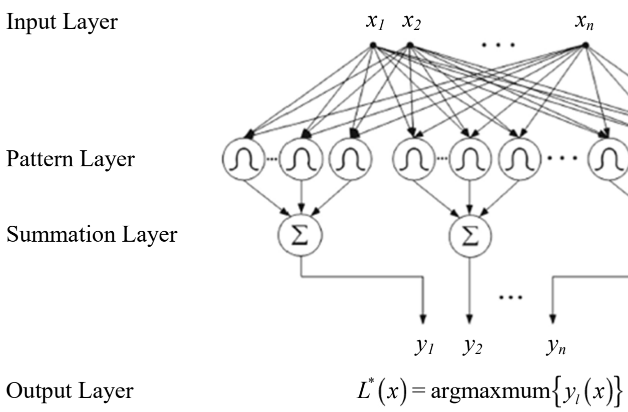


Fig. 6. PNN structure [11]

The input layer indicates the input vector and dimension for the number of features of the problem. The pattern layer (hidden layer) includes a neuron to every observation in the training dataset. The pattern neuron computes the Euclidean distance from the training sample (indicated via neuron) and the input feature vector, which is indicated as the feature vectors centroid of the class. The summation layer includes a neuron to every class the dataset indicates. The neurons in the summation layer compute the sum of the pattern layer neuron's output for the particular class they represent (encompasses an average depending on the number of observations for the class). The output layer (decision layer) performs a winner-takes-all approach: it identifies the class neuron in the summation layer with the largest value. Then, this class indicates the predicted class for the input vector. The main advantage of the PNN represents the robustness to noisy images. PNN works on removing or adding training samples to the algorithm, also it gives examples of training that can be included with no extensive retraining [12].

Classification is an important step in the proposed system, in which the tumor is classified into benign or malignant. A Fuzzy Logic is used to give a label to an input image. PNN is a model of data classification that performs the Bayesian decision rule. This rule can be given by; When suppose that:

1) there is a data pattern $\mathbf{x} \in R_n$ that is involved in one of the predefined classes $g=1,..., G$;

2) the $\mathbf{x}$ probability of belonging to the class g equals p_g;

3) the cost of classifying $\mathbf{x}$ into the class g is c_g;

4) PDFs $y_1(\mathbf{x})$, $y_2(\mathbf{x})$,..., $y_G(\mathbf{x})$ for all classes are known. Then, regarding the Bayes theorem, when $g \neq h$, the vector $\mathbf{x}$ is classified to the class g, if $P_g\ C_g\ Y_g(\mathbf{x}) > P_h C_h\ Y_h(\mathbf{x})$. Usually $p_g = p_h$ and $c_g = c_h$, thus if $y_g(\mathbf{x}) > y_g(\mathbf{x})$, the vector $\mathbf{x}$ is classified to the class g. The main steps of this stage are shown in Fig. 7.

The steps of the classification stage are as follows:

– *Step 1*: Input the image with the tumor and extract features by applying the DWT. The tumor image is decomposed into four sub bands (LL sub band, HH sub band, LH sub band, HL sub band). Where apply DWT four times on the image and in each time select the LL and ignore the rest, the result is a feature of the image;

– *Step 2*: Apply the fuzzy logic system to give the label of the input image; from the beginning until the count of the shape;

$$A(j) = \left[\sum (I \cup Bi) / \sum (I \cap Bi)\right], \qquad (8)$$

where I denotes the input shape and B is the shape saved in the knowledge base;

$$\mu_I = \text{maximum}(A), \qquad (9)$$

where the result enters in the probabilistic neural network;

– *Step 3*: Apply the results of the fuzzy system as an input to PNN to be used for classification (normal, benign, and malignant).

– *Step 4*: Build the PNN and load the feature extraction data for NN training.

– *Step 5*: Compute the estimated PDF for each hidden node in the pattern layer.

– *Step 6*: Compute the sum of each node in the summation layer (summation of estimated PDF to every class).

– *Step 7*: Compute the probability to every class by dividing the sum of estimated PDF to every class over the sum of all estimated PDFs.

– *Step 8*: Compute the reference in the feature extraction file.

– *Step 9*: Repeat from Step 5 until the end of the file, to obtain case is normal, benign, malignant.

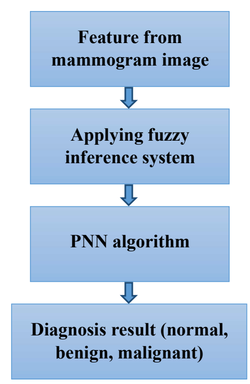


Fig. 7. Classification stage block diagram

5. Experimental results

The dataset used in this proposed system is the Mammographic Image Analysis Society (MIAS) Database (includes breast images for both sides (arranged in pairs films, where each pair represents the right mammograms (odd file name numbers) and left (even file name numbers) of a single patient) belonging to 81 patients, which means 163 images of size 1,024×1,024, each one belongs to one of normal, benign or malignant and distributed as: 80 normal images, 40 benign images, and 43 malignant images. Furthermore, this dataset has adequate information for all mammography images wherever a class of the abnormality, character and location of the background tissue.

The input mammogram image includes: a dark area (background), a label which is an extraneous object, a pectoral muscle, and a breast profile, as shown in Fig. 8.

At the first step, the extraneous objects (labels) in the image must be removed, this is done by converting the mammogram image to a binary image and calculating the area of each object. The breast profile will represent the largest object, so all the objects except the largest one are removed. Finally, the binary image resulting from the previous operation multiplies with the original image, as illustrated in Fig. 9.

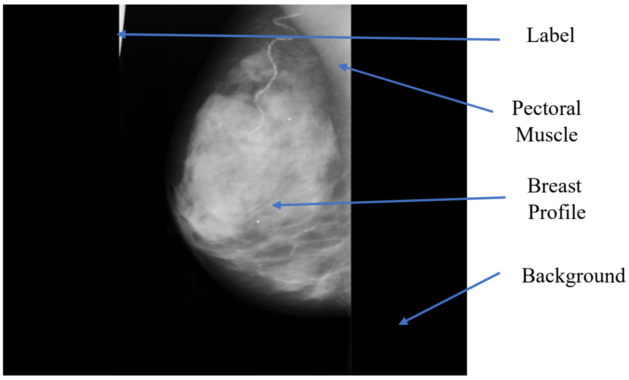


Fig. 8. Architecture of mammogram image

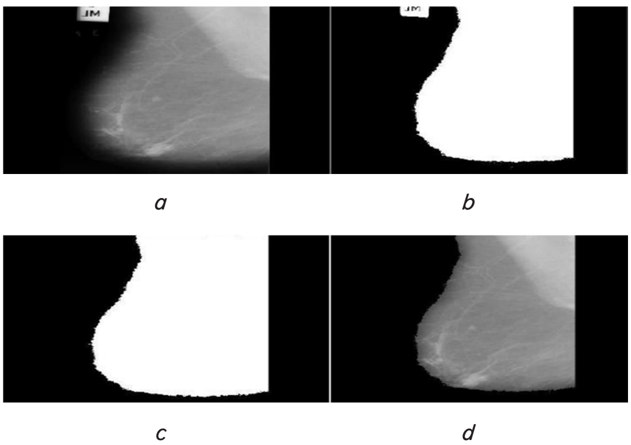


Fig. 9. Process of removing labels: *a* — original image, *b* — binary image, *c* — extract breast profile, *d* — multiplied images, *c* with *a*

To decrease the time of processing required for the stage of segmentation, the second step is to reduce the area of the mammogram image. This is done by extracting a region of interest from the image, this operation is performed by ignoring the dark areas (background).

Using the modified region growing technique assists in auto-selecting of the seed point for removing the pectoral muscle as shown in Fig. 10. The traditional selection of the seed point is adjusted depending on the image orientation. The dataset of mini-MIAS includes either right oriented images or left-oriented. Thus, the seed point is either right topmost or left topmost first non-zero pixel. The orientation of the image is obtained via dividing the image into half and calculating the non-zero pixels if left-oriented, the left part involves more pixels' else the right part involves more pixels.

The mammogram image must be enhanced to remove the noise and to increase the brightness of the suspicious region. To achieve that, a number of methods should be used. Firstly, smoothing the image by applying a Wiener filter to remove noise, and, secondly, applying CLAHE for adjusting the brightness, as shown in Fig. 11.

The segmentation process performed on a suspicious region is presented on a (2) size of image scale since this can be more effectively used in detecting tumors in the mammogram images, then for overcoming problems encountered when using wavelet transform mask the size is normalized to be a multiple of (4). Then a 2D wavelet transform is performed on the normalized mammogram image for obtaining a robust edge and identifying strong variations included in the mammogram images as shown in Fig. 12.

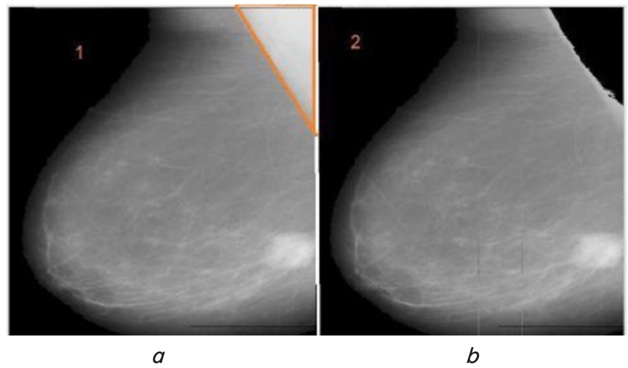


Fig. 10. Process of removing background and pectoral muscle: *a* — image after the background deletion, *b* — after pectoral muscle suppression

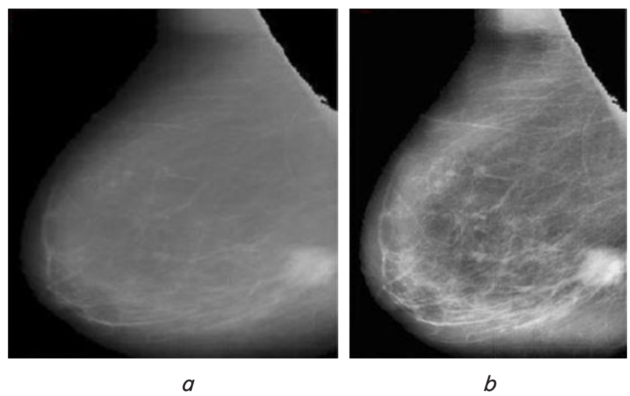


Fig. 11. Resultant image after applying: *a* — Wiener filter; *b* — CLAHE

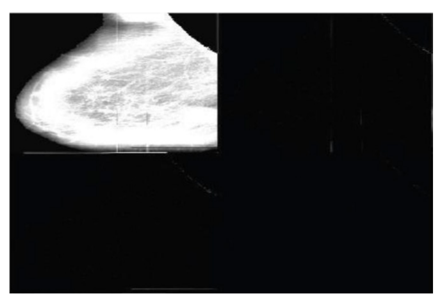


Fig. 12. Applying 2D Wavelet Transform

In this system, an automatic threshold value is chosen by using a 1D wavelet to select the global-local minima as shown in Fig. 13. Then the mammogram image is converted to a binary image according to this adaptive threshold.

Morphological filtering enhancement (top-hat operation) is used to achieve the fine segmentation, after that, an open operation is applied. Fig. 14 shows the obtained image after applying the coarse and fine segmentation.

In the feature extraction stage, the 2D DWT is implemented for two levels to extract the important feature. The size of the image is reduced to 16×16, which contains the details of the tumor. And at the classification stage, a PNN and fuzzy logic were devised, which, depending on the input variables, assists the prediction of the breast cancer type. To implement the network, 60 % of the data were exploited in the phase of network training, while the remaining 40 % were exploited in the phase of network testing.

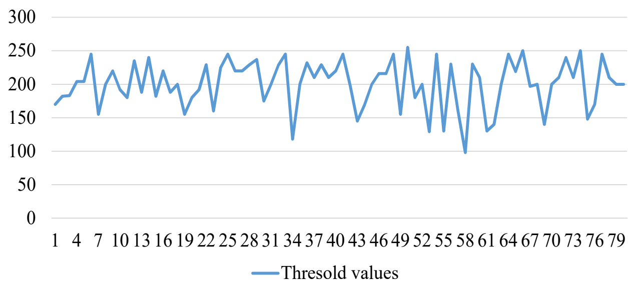
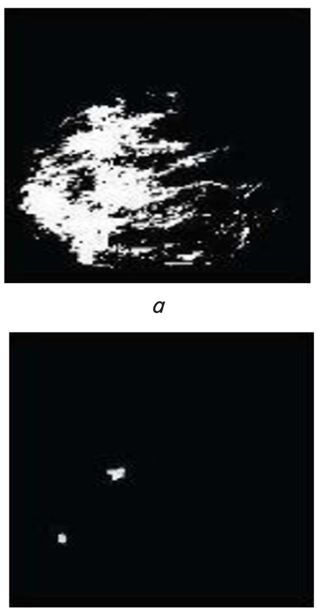


Fig. 13. Sample of the adaptive threshold



a

b

Fig. 14. Image after applying:
a – coarse; *b* – fine segmentation

Generally, the confusion matrix can be utilized for investigating the success and applicability degree of disease diagnosis and classification system. Four possible results can be obtained from the analysis of confusion matrices of disease diagnosis and classification: "TP" True Positive, "TN " True Negative, "FP" False Positive, and "FN" False Negative, as illustrated in Table 1.

Table 1

Confusion matrix

Terms	Result
TP	96
TN	85
FP	0
FN	2
Total	183

This confusion matrix supplies three indices that are utilized for assessing the classification performance, as shown in Table 2.

Table 2

Classification performance

Terms	Eq.	Result
Accuracy	(TP+TN)/Total	0.99
Sensitivity	TP/TP+FN	0.98
Specificity	TN/TN+FP	0.47

Here, sensitivity indicates the precision of the system in diagnosing the malignant type, specificity indicates the precision of the system in diagnosing the benign type, and accuracy is the proportion of all truly diagnosed cases.

6. Discussion of the proposed system

The proposed system was based on the available data of 183 cases of patients with breast cancer that were stored in UCI DBSM. 9 clinical variables were exploited as the network inputs, wavelet transform resulted in 16×16 size of the image, and the initial weight was determined by the fuzzy logic system.

The classification and pattern recognition represents the main stage in the proposed system, where 60 % of the data (110 cases) were utilized for neural network training. In order to perform PNN in Matlab, an input matrix was generated consisting of 16×16 rows and 110 columns, and another matrix was generated as the target matrix with two rows (two kinds) of benign and malignant tumors and 110 columns.

The data inputting to the network were normalized by the linear method for representing the binary values of zero and one. Two classes were included in the target matrix: benign and malignant. When the type of cancer matched the class of the column in the query, the value that corresponds to the row would be one, and the other would be zero. Within the proposed PNN, only one epoch was utilized to train the network, which represents the usefulness of neural networks compared to the other types of networks. Furthermore, 40 % of the data (73 cases), and these data had not been utilized in the phase of training, were implemented as a vector to the implemented NN in the software.

In the proposed system, one of the major causes for obtaining high sensitivity and specificity for the network could be related to the normalization of the input vector and the suitable chosen of the network for the functional purposes of the research. The proposed system results have been compared with several previous related works, as shown in Table 3.

From the above comparison, we found that the proposed system is more accurate than the other related works.

For future works, several improvements can be carried out in this work, such as the implementation of the proposed system on different datasets from different resources, and the utilization of a hybrid of multi-resolution analysis with unsupervised learning for improving the performance of the segmentation step.

Table 3

Comparison with some related works

Author/(s) name, Ref., Year	Classification Techniques	Datasets	Training – Testing Ratio	Accuracy
A. Bhardwaj et al., [4], 2014	Genetically Optimized Neural Network (GONN)	Wisconsin breast cancer dataset available (699 instances) from the UCI Machine Learning Repository	90–10 %	98.52 %
Saini and R. Vijay, [5], 2015	ANN	42 Mammogram samples obtained from a consultant radiologist	90–10 %	87.5 %
S. Naranje, [6], 2016	ANN	51 Digital Mammogram X-ray Images Dataset (MIAS)	50–50 %	90 %
Y. J. Tan et al., [7], 2017	CNN	Mini-Mammographic Image Analysis Society (mini-MIAS) database	–	82.73 %
I. Routray, and N. P. Rath, [8], 2018	ANN	MIAS database	70–30 %	84.25 %
Shuo Liu et al., [9], 2018	Bayesian Network (BN)	Clinical ultrasound and Fine-needle aspiration cytology datasets	60–40 %	92.98 % and 98.87 %
Hongwei Feng et al., [10], 2020	Deep Networks	100 MRI images for female patients at a high risk of breast cancer	60–40 %	85 %
Proposed system	FL and PNN	Mini-MIAS database	60–40 %	99 %

8. Conclusions

1. To enhance mammogram images, the winner filter is used, which represents so efficient filter to remove noise from the image, also, the CLAHE is used to deal with the low contrast images.

2. Extracting significant features by using the Discrete Wavelet Transform method represents an important stage, where the results of this stage assist in classifying the mass efficiently.

3. Choosing effective classifying techniques, supervising the experiments and observing the results of the techniques that are used in this paper played a very significant role in increasing the efficiency of the system that led to raising the system accuracy.

4. Owing to the good generalizability and high processing speed of PNN, it seems to be more effective than other NN systems, wherein this network, the process of training includes only one epoch and no other replication is required for modifying the weights.

References

1. Narain Ponraj, M. E. J. D., Poongodi, P., Samuel Manoharan, J. (2011). A Survey on the Preprocessing Techniques of Mammogram For the Detection of Breast Cancer. Journal of Emerging Trends in Computing and Information Sciences (ISSN), 2, 656–664.
2. Kahya, M. A. (2019). Classification enhancement of breast cancer histopathological image using penalized logistic regression. Indonesian Journal of Electrical Engineering and Computer Science, 13 (1), 405. doi: https://doi.org/10.11591/ijeecs.v13.i1.pp405-410
3. Abdullah, A. J., Hasan, T. M., Waleed, J. (2019). An Expanded Vision of Breast Cancer Diagnosis Approaches Based on Machine Learning Techniques. 2019 International Engineering Conference (IEC). doi: https://doi.org/10.1109/iec47844.2019.8950530
4. Bhardwaj, A., Tiwari, A., Chandarana, D., Babel, D. (2014). A genetically optimized neural network for classification of breast cancer disease. 2014 7th International Conference on Biomedical Engineering and Informatics. doi: https://doi.org/10.1109/bmei.2014.7002862
5. Saini, S., Vijay, R. (2015). Mammogram Analysis Using Feed-Forward Back Propagation and Cascade-Forward Back Propagation Artificial Neural Network. 2015 Fifth International Conference on Communication Systems and Network Technologies. doi: https://doi.org/10.1109/csnt.2015.78
6. Naranje, S. (2016). Early Detection of Breast Cancer using ANN. International Journal of Innovative Research in Computer and Communication Engineering, 4 (7), 14008–14013.
7. Tan, Y. J., Sim, K. S., Ting, F. F. (2017). Breast cancer detection using convolutional neural networks for mammogram imaging system. 2017 International Conference on Robotics, Automation and Sciences (ICORAS). doi: https://doi.org/10.1109/icoras.2017.8308076
8. Routray, I., Rath, N. P. (2018). Textural Feature Based Classification of Mammogram Images Using ANN. 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT). doi: https://doi.org/10.1109/icccnt.2018.8493957
9. Liu, S., Zeng, J., Gong, H., Yang, H., Zhai, J., Cao, Y. et. al. (2018). Quantitative analysis of breast cancer diagnosis using a probabilistic modelling approach. Computers in Biology and Medicine, 92, 168–175. doi: https://doi.org/10.1016/j.compbiomed.2017.11.014
10. Feng, H., Cao, J., Wang, H., Xie, Y., Yang, D., Feng, J., Chen, B. (2020). A knowledge-driven feature learning and integration method for breast cancer diagnosis on multi-sequence MRI. Magnetic Resonance Imaging, 69, 40–48. doi: https://doi.org/10.1016/j.mri.2020.03.001
11. Specht, D. F. (1990). Probabilistic neural networks and the polynomial Adaline as complementary techniques for classification. IEEE Transactions on Neural Networks, 1 (1), 111–121. doi: https://doi.org/10.1109/72.80210
12. Specht, D. F. (1992). Enhancements to probabilistic neural networks. [Proceedings 1992] IJCNN International Joint Conference on Neural Networks, 1, 761–768. doi: https://doi.org/10.1109/ijcnn.1992.287095
13. Kusy, M., Zajdel, R. (2014). Probabilistic neural network training procedure based on Q(0)-learning algorithm in medical data classification. Applied Intelligence, 41 (3), 837–854. doi: https://doi.org/10.1007/s10489-014-0562-9
14. Sawant, S. S., Topannavar, P. S. (2015). Introduction to Probabilistic Neural Network–Used for Image Classifications. International Journal of Advanced Research in Computer Science and Software Engineering, 5 (4), 279–283.