Breast Cancer Detection and Classification Using Artificial Neural Networks

Conference Paper · November 2018

DOI: 10.1109/AiCIS.2018.00022

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Abstract* — *Image processing techniques play an important role in the diagnostics and detection of diseases and monitoring the patients having these diseases. Breast Cancer detection of medical images is one of the most important elements of this field. Because of low contrast and ambiguous the structure of the tumor cells in breast images, it is still a challenging task to automatically segment the breast tumors. Our method presents an innovative approach to the diagnosis of breast tumor incorporates with some noise removal functions, followed by improvement features and gain better characteristics of medical images for a right diagnosis using balance contrast enhancement techniques (BCET). The results of second stage is subjected to image segmentation using Fuzzy c-Means (FCM) clustering method and Thresholding method to segment the out boundaries of the breast and to locate the Breast Tumor boundaries (shape, area, spatial sizes, etc.) in the images. The third stage feature extraction using Discrete Wavelet Transform (DWT). Finally the artificial neural network will be used to classify the stage of Breast Tumor that is benign, malignant or normal. The early detection of Breast tumor will improves the chances of survival for the patient. Probabilistic Neural Network (PNN) with radial basis function will be employed to implement an automated breast tumor classification. The simulated results shown that classifier and segmentation algorithm provides better accuracy than previous method. Proper segmentation is mandatory for efficient feature extraction and classification.

Keywords* — *Image processing, Breast Tumors, Noise Reduction DWT, PNN-RBF, Contour initialization.

I. Introduction

Breast Cancer is a general term that refers to cells that grow larger than 1.5 mm in every 3 months and multiply out of control and spreads to other parts of the body. Breast Tumor (BT) is the first cancer and the second element of death among women. Since the reason of breast cancer is unknown, the methods for preventing of this disease are not specified. Recognizing of being tumor and the type of cancerous tumor would had a very important role on getting decision of doctors for applying the methods of true treatment and therefore reclaim the life of people (more than 40%) [1]. Cancer are groups of abnormal cells that form lumps or growths. They can start in any one of the trillions of cells in our bodies. Tumors grow and behave differently, depending on whether they are cancerous (malignant), non-cancerous (benign) or precancerous. In Cancerous tumors cancer can start in any part of the body. When cancer cells form a lump or growth, it is called a cancerous tumor. A tumor is cancerous when it [2]:

- grows into nearby tissues;
- has cells that can break away and travel through the blood or lymphatic system and spread to lymph nodes and distant parts of the body;

Cancer that spreads from the first place it started (called the primary tumor) to a new part of the body is called metastatic cancer. And when cancer cells spread and develop into new tumors, the new tumors are called metastases. In Non-cancerous tumors the tumors that aren't cancerous are called non-cancerous tumors:

- Stay in one place and don't spread to other parts of the body;
- Don't usually come back after they are removed;
- Tend to have a regular and smooth shape and have a covering called a capsule;
- May be moved easily in the tissue.

In [3] determining type of the Cancer is much more challenging. Some of the characteristics of malignant tumors are clustered, isolated ducts poorly defined mass and etc. A good classification process leads to the right decision and facilitates provision of good and appropriate treatment. Machine learning can help medical professionals to diagnose the disease with more accuracy. Where deep learning or neural networks is one of the techniques which can be used for the classification of normal and abnormal breast detection [4]. Artificial Neural Networks (ANNs) are one of the most widely used models for the classification of tumor cells. An ANN consists of a network of neurons that learn from experience [5]. Preparation process, light or electron microscopes are used to take digital histological images on the stained sections [6].

In [7] fuzzy logic and probabilistic neural network are used to classification and detection breast cancer diagnosis. Image feature extraction was utilized to retrospectively analyze screening mammograms taken prior to the detection of a malignant mass for early detection of breast cancer [8]. The optimum network for classification of breast cancer cells was found using Hybrid Multilayer Perceptron (HMLP) network. A combination of the proposed features gave the highest accuracy [9]. Feature extraction is only done by wavelet transform and classification is done by using PNN. In [10] used using artificial neural networks for the prediction and classification of breast cancer. The wavelet neural network is employed for breast cancer diagnosis [11]. In [12] used Support Vector Machine (SVM) for diagnosis of breast cancer. In [13] used RBF with Genetic Algorithm to detect tumors in mammogram images. It's being a novel approach, explored the capabilities of RBF. Authors claimed that the use of RBF increased the

978-1-5386-9188-5/18/$31.00 ©2018 IEEE
DOI 10.1109/AiCIS.2018.00022

search and classification accuracy. The latest version of histology image classification by using CNN, but histology image has its limitation which it is takes long time for the lab usage [14].

Some previously completed paper had used different types of neural network for classification mammogram image in breast cancer. Other methods like C-mean clustering has been used and suggested that along with genetic algorithm it gives better results for segmentation efficiency of affected region's extraction and detection [15]. Mammography is specialized medical imaging for scanning the breasts. A mammography exam (Mammogram) helps for the early detection and diagnosis of breast cancer and is useful in detecting the breast cancer regions [16]. The hierarchical RBF network model reduced number of input features with the high detection accuracy [17].

This article tries to solve the problem of how to make clearer the breast cancer contour with a minimal number of configurable parameters dependable on input image. Thus, we propose a set of computational procedures for image preparation for further analysis by medical specialists. Set of components can be distinguished: improvement of image quality and segmentation of objects of interest (breast tumors) with the formation of an edge map. The extracted features are used to classify the type of breast tumors as normal, malignant or benign. Wavelet Transform is a non-statistical method which gives local frequency information and detail coefficients of the image at various levels. We have used Discrete Wavelet Transform (DWT) in our work. DWT gives good contrast to an image. Due to good contrast, Discrete Wavelet extracted very low signals of images. For further classification, Probabilistic Neural Network (PNN) has been used. All the parameters are extracted and converted into computational representation from the image, the parameter values are uncorrelated using correlation-based feature subset selection algorithm. The Radial Basis Function Neural Network is simulated using the uncorrelated parameter values to classify the input features in three classes.

II. PROPOSED METHODOLOGY

To detect and classify the type of breast tumor of each patient, doctors usually refer to image and make the report about the image analysis of the patient. The method we have proposed will help the doctor in diagnosing breast tumor patients. And with the existence of proposed system, doctor can train the system with some known data and then use this system to generate the image report of the patient after testing the data.

The quality of images obtained from medical devices can influence the result of processing (analysis) when solving diagnostic medical problems. In most cases, obtained images (or an image sets) have noticeable noise caused by technological features of devices operation. Considering this, authors suggest the following procedure to process the medical images (Fig. 1).

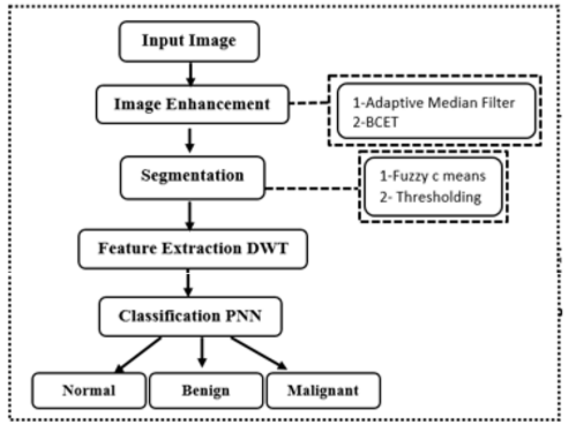

Fig. 1. The Block diagram of the proposed system

The obtained images are converted to grayscale format. Then the list of computational steps are performed:

- ❖ Image enhancement (applying Adaptive median filter to remove noise and Balance contrast enhancement using (BCET)).
- ❖ Applying Thresholding & Fuzzy C-Means (FCM) Segmentation methods.
- ❖ Applying Feature extraction by using Discrete Wavelet Transform (DWT).
- ❖ Tumor detection and classification using Probabilistic Neural Network (PNN).
- ❖ Data analysis.

The part of the image containing the tumor normally has more intensity then the other portion. The basic steps to detect tumor in our code are used.

At the same time, for an area with an estimated content of the object of interest, an additional processing can be carried out, considering the factors of required analysis. Depending on the medical problem, color coding can be applied both within the area of interest and its surroundings for analyzing the state of tissues, etc. Color coding allows visualizing the fine features of the tissue structure near the tumor, which is necessary for subsequent procedures of a diagnostic nature and comparison with existing reference data.

A. *Image enhancement*

The primary purpose of these filters is noise reduction, but a filter can also be used to emphasize certain features of an image or remove other features. We have used adaptive mean filter to remove noise from image. Since it is better among all the spatial filters and distinguish fine details from noise. The Adaptive Median Filter performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter (AMF) classifies pixels as noise by comparing each pixel in the image to its surrounding neighbor pixels. The size of the neighborhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test. We are initially converting the image into grayscale image using rgb2gray () function then applying adaptive mean filtering to the resulting image and then converted the image into unsigned integer 8 using unit8 () function.

To improve the contrast for highlighting the area of interest we proposed to use Balance Contrast Enhancement Technique (BCET). Typically, during medical image processing, the contrast enhancement is required for the area of interest. For example, Contrast Limited Adaptive Histogram Equalization (CLAHE) allows to improve features and gain better characteristics of medical images for a right diagnosis [18]. Another example is LIP, PLIP and GLIP algorithms used to enhance a medical image and to improve visual quality of digital medical images.

In proposed methodology we use Balance Contrast Enhancement Technique (BCET). The contrast of the image can be stretched or compressed without changing the histogram pattern of the input image (IOld). The solution is based on the parabolic function obtained from the input image. The general form of the parabolic function is defined as:

$$I_{New} = a \cdot (I_{old} - b)^2 + c \quad . \tag{1}$$

Coefficients a, b and c are derived from the input, minimum value of the output image (I_{New}), maximum value of the output image, and mean value of the output image:

$$b = \frac{h^2 \cdot (E - L) - s \cdot (H - L) + l^2 \cdot (H - E)}{2 \cdot \left[h \cdot (E - L) - e \cdot (H - L) + l \cdot (H - E) \right]}, \tag{2}$$

$$a = \frac{H - L}{(h - l)(h + l - 2b)}, \tag{3}$$

$$c = L - a(l - b)^2, \tag{4}$$

$$s = \frac{1}{N} \sum_{i=1}^{N} I_{Old}^2 (i), \tag{5}$$

where l and h are the minimum and the maximum values of the input image respectively, e is the mean value of the input image, L and H are the minimum and maximum value of the output image, S denotes the mean square sum of the input image. The results of AMF and BCET shown in following figure.

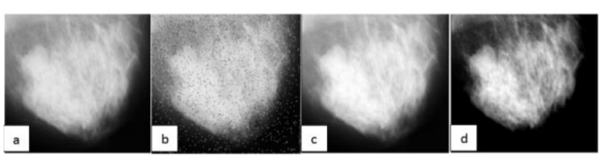

Fig. 2. Example of the enhancement method: a) original image, b) noise image, c) result after AMF, d) BCET Results

B. *Segmentationt*

In this method we have used two types of segmentation, the first is Fuzzy C-Means segmentation that to segment the out boundaries of the breast, and the second is Threshold segmentation that used to locate objects (breast tumors) and boundaries (shape, area, spatial sizes, etc.) in images.

Fuzzy C-Means segmentation: Fuzzy C-Means clustering performs clustering by iteratively searching for a set of fuzzy clusters and the associated cluster centers that represent the structure of the data as best as possible. It allows to split an existing set of points of power n by a given number of fuzzy sets. In [19-20] a special feature of the method is used of a fuzzy membership matrix W= {wik}, which elements determine the degree of membership of the k-th element of the initial set of vectors to the i-th cluster. Given a number of clusters c, FCM clustering divides the data X = {x1, x2… xn} into c fuzzy clusters with the centers of the clusters V = (v1, v2 ... vc) by minimizing objective function [19]:

$$F(W, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} (w_{ik})^m \cdot \left\| \mathbf{x}_k - \mathbf{v}_i \right\|^2, \quad w_{ik} \in [0,1], \quad i = \overline{1, c}, \quad k = \overline{1, n}, \quad 1 \le m < \infty, \tag{6}$$

where m is the fuzziness index, wik is the degree of membership of xk in the i-th cluster, vi is the center of the i-th cluster, and ||xk - vi||2 represents the distance between the data xk and the cluster center vi.

$$w_{ik} = \left(\sum_{j=1}^{c} \left(\frac{\left\| \mathbf{x}_k - \mathbf{v}_i \right\|}{\left\| \mathbf{x}_k - \mathbf{v}_j \right\|} \right)^{2/(m-1)} \right)^{-1}, \qquad \sum_{i=1}^{c} w_{ik} = 1, \tag{7}$$

$$\mathbf{v}_i = \frac{\sum_{k=1}^{n} (w_{ik})^m \cdot \mathbf{x}_k}{\sum_{k=1}^{n} (w_{ik})^m} . \tag{8}$$

In each iteration of the FCM clustering algorithm, matrix W is computed using Eq. 8 and the associated cluster centers are computed as Eq. 8. This is followed by computing the square error in Eq. 7. The algorithm stops when either the error is below a certain tolerance value or its improvement over the previous iteration is below a certain threshold. The number m governs the influence of membership grades in the performance index. The partition becomes fuzzier with increasing m, and if m → ∞ all objects will belong to all clusters with the same degree. The number m also allows, when calculating the coordinates of cluster centers, to strengthen the influence of objects with large values of degrees of membership and to reduce the influence of objects with small values of degrees of membership.

Threshold segmentation: Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Thresholding technique segments the MR images by a binary partitioning of the image intensities [21].

I (p) = 1; if it's gray level > T =0; if it's gray level < T. (9)

A grayscale image is turned into a binary (black and white) image by first choosing a grey level Tin the original image, and then turning every pixel black or white according to whether its grey value is greater than or less than T.

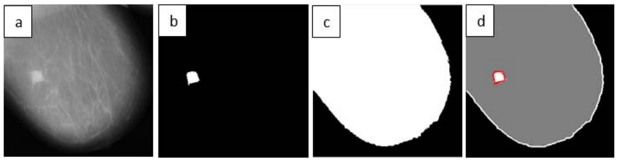

Fig. 3. Example of the segmentation methods: a) original image, b) Result after Thresholding, c) Result after Fuzzy C-Means, d) Final result of segmentation

C. Feature extraction scheme using DWT (Discrete Wavelet Transform)

The proposed system uses the Discrete Wavelet Transform (DWT) coefficients as feature vector. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from medical images. The main advantage of wavelets is that they provide localized frequency information about a function of a signal, which is particularly beneficial for classification. The continuous wavelet transform of a signal x (t), square integrable function, relative to a real-valued wavelet, (t) is defined as:

$$W_\Psi (a, b) = \int_{-\infty}^{\infty} f(x) * \Psi_{a,b}(t)\, dx \quad ,$$

where, $\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}$. (10)

The wavelet Ψ (a, b) is computed from the mother Ψ wavelet by translation and dilation, wavelet, the dilation factor and b the translation parameter (both being real positive numbers). Under some mild assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT can be expressed as:

$$DWT_{x(n)} = d_{j,k} = \sum (x(n)h * j(n-2jk)) - d_{j,k} - \sum (x(n)g * j(n-2jk)) \,. \quad (11)$$

The coefficients $d_{j,k}$, refer to the detail components in signal x (n) and correspond to the wavelet function, whereas a j, k, refer to the approximation components in the signal. The functions h(n) and g(n) in the equation represent the coefficients of the high-pass and low-pass filters, respectively, parameters j and k refer to wavelet scale and translation factors [22-23].

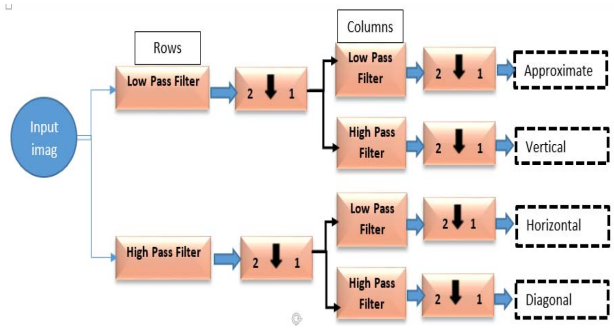

Fig. 4. Diagram of Discrete Wavelet Transform (DWT)

The main feature of DWT is multi scale representation of function. By using the wavelets, given function can be analyzed at various levels of resolution. Fig: 4 illustrate DWT schematically. The original image is process by h (n) and g (n) filters which, is the row representation of the original image. As a result of this transform there are 4 sub band (LL, LH, HH, and HL) images at each scale. In this, various statistical features are calculated such as: 1) Mean 2) Standard Deviation 3) Entropy. The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image information, compared with other multi scale representations [22-23].

D. Probabilistic neural network for classification

In 1990, Donald F. Specht proposed a method to formulate the weighted-neighbor method in the form of a neural network. He called this a "Probabilistic Neural Network". The probabilistic neural network (PNN) was introduced by Donald Specht. This network is based on the theory of Bayesian classification and the estimation of probability density function. It is necessary to classify the input vectors into one of the two classes in Bayesian optimal manner.

In this paper, the PNN has three layers: the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance. The network structure is illustrated in Fig. 5. The symbols and notations are adopted as used in the book Neural Network Design [23]. These symbols and notations are also used by MATLAB Neural Network Toolbox. Dimensions of arrays are marked under their names.

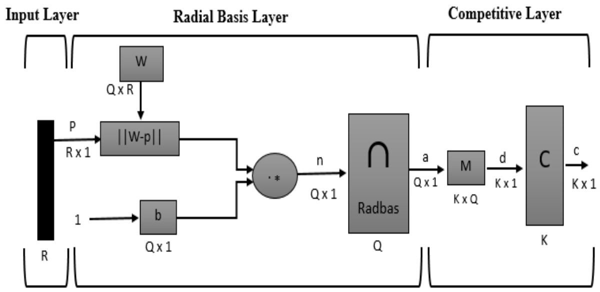

Fig 5: Architecture of Probabilistic Neural Network

Layers of PNN

1) Input Layer: The input vector, denoted as p, is presented as the black vertical bar in Fig.5. Its dimension is $R \times 1$. In this paper, $R = 3$.

2) Radial Basis Layer: In Radial Basis Layer, the vector distances between input vector p and the weight vector made of each row of weight matrix W are calculated. Here, the vector distance is defined as the dot product between two vectors [8]. Assume the dimension of W is $Q\times R$. The dot product between p and the i-th row of W produces the i-th element of the distance vector $\|W-p\|$, whose dimension is $Q\times 1$, as shown in Fig. 5. The minus symbol, "–", indicates that it is the distance between vectors. Then, the bias vector b is combined with $\|W- p\|$ by an element-by-element multiplication, represented as ".∗" in Fig.5. The result is denoted as $n = \|W- p\| .\ast p$. The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, it is defined as

$$radbas(n) = e^{-n^2} \quad . \tag{12}$$

Each element of n is substituted into Eq. 12 and produces corresponding element of a, the output vector of Radial Basis Layer. The i-th element of a can be represented as

$$a_i = radbas(\|\mathbf{W}_i - \mathbf{p}\| .\ast \mathbf{b}_i) \quad , \tag{13}$$

where W_i is the vector made of the i-th row of W and b_i is the i-th element of bias vector b.

3) Some characteristics of Radial Basis Layer: The i-th element of a equals to 1 if the input p is identical to the ith row of input weight matrix W. A radial basis neuron with a weight vector close to the input vector p produces a value near 1 and then its output weights in the competitive layer will pass their values to the competitive function. It is also possible that several elements of a are close to 1 since the input pattern is close to several training patterns.

4) Competitive Layer: There is no bias in Competitive Layer. In Competitive Layer, the vector a is firstly multiplied with layer weight matrix M, producing an output vector d. The competitive function, denoted as C in Fig. 5, produces a 1 corresponding to the largest element of d, and 0's elsewhere. The output vector of competitive function is denoted as c. The index of 1 in c is the number of tumor that the system can classify. The dimension of output vector, K, is 2 in this paper.

III RESULTS AND DISCUSSION

For the experimental research 75 images were selected. Examples are shown in Fig.6. Medical images contain difference breast tumors that are characterized by different locations and different types of pathologies, shape, size and density, as well as the size of the area of the affected tissue near the tumor space.

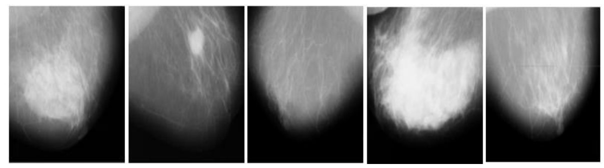

Fig. 6. Experimental data set images

Differentiating normal cells and tumor cells and these also help to calculate the area of tumor affecting portions. It shows the area of calculation in unit of pixel. Discrete Wavelet Transform help to determine the area of tumor. Intensity based techniques and gray level co-occurrence matrix (GLCM) techniques are used. Intensity based techniques helps to determine mean value, standard deviation. And GLCM techniques are helps to determine energy, entropy, contrast, correlation, homogeneity and sleekness.

A comparison is shown between our method and methods in [16-24]. Through visual analysis, it is clear that our method is able to segment tumor region better than another method. Where the methods in [16-24] includes some non-tumor region in the final segmented image, our method only detects tumor region locate tumor region on original input image successfully with color result. Final results of the proposed method are shown in Fig. 7; where, the top row represent the original images (Digital Database for Screening Mammography (DDSM)) ordered from 1 till 5 in the same order of the five images presented into Table 1. The second row is the result of applying the image enhancement that explained in Section2 in this paper. The third row is the result after masking and processing (final contoured images).

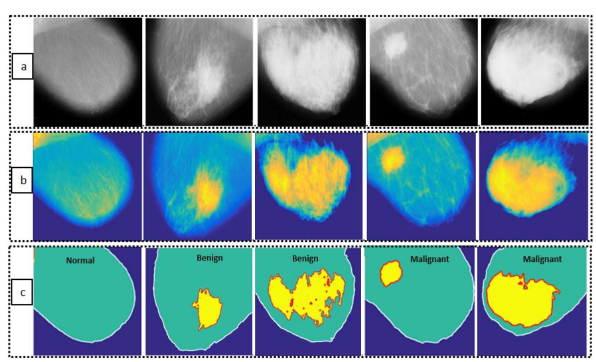

Fig.7. (a) Input images, (b) Pre-processed images, (c) Results of segmentation and classification of different types of Breast tumor

To evaluate the reliability and correctness of the Detecting Breast tumor obtained by proposed method the following parameters were used: Intensity Based Features, Mean value, Standard Deviation (SD), gray level co-occurrence matrix (GLCM), Energy and Entropy. The percentage of pixels that were correctly detected is and is defined as intensity based features.

Intensity Based Features: Intensity based features are first order statistics depends only on individual pixel values. The pixel intensities are Mammogram proposed method simplest available feature useful for pattern recognition. The intensity and its variation inside the mammograms can be measured by features like mean and standard deviation.

GLCM Features: The gray level co-occurrence matrix (GLCM) texture measurement is a method to analyze image texture. It is robust method that has been developed for calculating first and second order texture features for image. The GLCM matrix is a tabulation of how often different combinations of gray level occur in an image. Gray level co-occurrence matrix was formed and the statistical texture features such as mean value, Standard deviation (SD), contrast, correlation and homogeneity are obtained from the LH and HL sub bands of the first five levels of wavelet decomposition. For this purpose, the MATLAB command "graycomatrix" along with the command "pca" which returns the principal component coefficients for the matrix.

Energy: Energy represented the orderliness of a mammographic image. Energy is generally given by the mean squared of a mammographic image.

$$E= \sum_{j\ i=}^{n-1} P\ (i,j)2 \tag{14}$$

Entropy: The amount of disorder in a mammographic image is called as entropy. The entropy value is high in micro calcification. This is because the variation in intensity values in the image is high due to the presence of white calcification spots.

$$H=\sum_{i=0}^{n} p(i.j) \log P(i,j) \tag{15}$$

TABLE 1. TEXTUAL FEATURES OF BREAST TUMOR

Image Methods	***Image 1***	***Image 2***	***Image 3***	***Image 4***	***Image 5***
Mean	0.0046	0.0047	0.0030	0.0046	0.0040
Standard Deviation	0.1163	0.2457	0.4074	0.2136	0.4201
Entropy	0.9621	1.4279	2.4515	1.3145	2.1575
Smoothness	0.9634	0.9638	0.9444	0.9635	0.9576
Kurtosis	76.6846	45.2858	36.6682	69.9548	47.3600
Skewness	6.5483	3.6951	3.1644	5.5903	4.0113
Contrast	0.4449	0.3428	0.3159	0.4064	0.3435
Correlation	0.1491	0.1649	0.0900	0.0889	0.1252
Energy	0.9322	0.8851	0.8410	0.8999	0.8718
Homogeneity	0.9775	0.9660	0.9550	0.9706	0.9630
Type	Normal	Benign	Benign	Malignant	Malignant

The most used kernel function for PNN is Radial Basis Function (RBF) because of their localized and finite responses across the entire range of real x-axis. The classification accuracy of RBF kernel was high; also, the bias value and the error rate of RBF kernel were small when compared to other kernels.

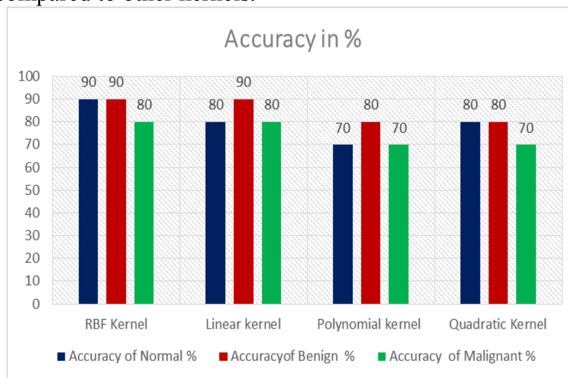

Fig.8: Performance & Parameters analysis when Normal, Benign, and Malignant Tumors are Detected

IV CONCLUSION

Accurate recognition of breast tumor is very important for sufficient treatment. This research has proposed the designing of an accurate system for detection of breast cancer tumor as standard procedure for breast cancer diagnosis. Digital mammography is currently as standard procedure for breast cancer diagnosis, various techniques are used for classification problem in the area of medical diagnosis. Feature extraction of image is important step in mammogram classification. These features are extracted using image processing techniques. Area of tumor is calculated by the DWT (Discrete Wavelet Transform) tumor affecting portions are denoted. The normal and cancerous cell is showing separately, and entropy, mean, standard deviation, energy, skewedness" etc. are calculating d from the database image. And breast cancer detection Probabilistic Neural Network has been proposed and developed. This system classifies mammogram images into 3 categories: normal, benign and malignant with high rate than 90%. The system which can assist and help the doctor or specialist nurse to speed diagnosed the mammograms.

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