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# An Intelligent Classification of Breast Cancer Images

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## Abstract

**Background/Objectives**: Breast cancer, is a highly diverse disease and women commonly witnesses this. This paper inducts an intelligent classification method for identifying the breast cancer from the images attained as benign and malignant. This elementary test mode supports in recognizing breast cancer at initial period and this initial stage discovery would support in recovering more number of women from this serious disease. **Statistical Analysis:** An intelligent system is projected which practices Artificial Neural Networks (ANN) that contributes the user; choices to analyze, sense and quantity the cancer. To attain exact outcome, the images acquired by different medical imaging modalities must be assessed using machine learning algorithms. A variety of features are extracted from the image for detecting and diagnosing nonthreatening and malicious tumour forms in digital mammograms. **Findings: A** number of features are extracted and established a blend of three or four features, such as entropy, standard deviation, area etc to discriminate a benign tumour from the malignant one. The accuracy using Classification using FFNN algorithm is 99%.

**Keywords:** Artificial Neural Networks, Breast Cancer, Feature Extraction, Mammogram, Wavelet Transform

## 1. Introduction

Immeasurable development of an explicit cluster of cells in a human body's meticulous part human body is referred as CANCER. A bulge or accumulation of an extra tissue will be formed on a group of separated cells which splits quickly. These bulge or accumulation is recognized as Lumps. These tumor cells are known as malicious tumors. Breast cells were foundation for establishing malevolent tumour, recognized as Breast Cancer. Groups of micro calcifications, architectural falsifications and lesions are protruding and alert signs. The extension ratio of breast cancer conveyed extraordinary in recent times. Simultaneously, continual presence percentage is likewise enlarged hypothetically over previous; it's majorly due to improved efficacy in analysis and treatments. Screening of breast cancer mostly precedes an anatomic methodology over X-ray mammography which necessitates the breast tumour to be advanced to a point where it is significantly thicker than healthier tissue. Dense thickness doesn't always close to the presence of cancer, dense lesions of tissue are additionally inspected via biopsy are often found to be benign[1]. As a corollary, mammography does not perceive 5%–15% of non-palpable breast lesions that are not sufficiently thicker than healthy tissue[2]. As an substitute of trusting on sturdiness changes, tumor can also be perceived by early molecular initials.

In 2011 United States, the American Cancer Society had presented a method with their pre-analysis evidence that practically around twenty three thousands of new patients of aggressive breast cancer and nearly 57,650 new patients of non-invasive breast cancer would be in treatment. Around 40000 women would decease out of the totally affected cases. Mammography, a renowned and familiar procedure in identifying Breast Cancer which customs low-dose X-rays, high-contrast and high-resolution indicators and the X-ray system deliberately used to capture the image the breasts. In Breast Cancer Screening and analysis, it's unspoken that Mammography serves the purpose of claim. This method is of two types, 1. Screen Film Mammography (SFM) – the screen of the film screen plays as the end recording instruments and 2.

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Full-Field Digital Mammography (FFDM) – digital indicators are the substitute for the recording instruments. In Image Processing, the FFDM made digital images that have extra qualities than the usual film screen.

Digital Mammogram is a key method to determine the Breast Cancer at an preliminary time at some degree. The benefits of digital mammography encompass the lack of ionizing energy, its non-invasiveness, the reasonably small size, and it's cheaper price. As[3] mentioned, Mammography is very fruitful and the outcomes were extremely reliable in recognizing breast cancer and it's well-known that only a least number of radiologists were tasked in construing and finding of Mammograms which is more by and large from people screening. It was said in the statement by[4] that there is always a threat of missing breast cancer cases, intricate in mammographic image adherence because the abnormal identifications were engrained by difference in arrangements of breast tissue.

## 2. Related Work

In[5] help is taken from neural networks in recognizing bounded lesions in digitized mammograms. Back Propagation algorithm is applied in exercise neural networks. The method of neural is generally distinguishes the histogram of malignant tissue and the usual tissue. In[6] how digital mammograms used in single and multi-layer detection of masses are studies. In mammograms, scaling has an important part in computerized procedure of distinguishing masses, it's largely because of the possible variety of masses can have.

It was investigated that if finding of lesions can be ended in only one measure or might be proper to practice the outcome at numerous stages. A computerized approach of perceiving micro-calcification in digital mammograms is presented in[7]. This approach applies on distinction in image in which the difference between the repressed and improved image, which removes the background in the mammogram. For take out micro-calcification signals, global and local threshold values based methods are used. Mammographic images development and denoising for breast cancer finding using dyadic wavelet processing is done in[8]. A progress of data based calculation method for detecting of micro-calcifications in digital mammograms is studied in[9].

Sustenance of filter bank in recognizing linear and nodular arrangements is done in[10]. The substitute images were produced with the essentials of a Hessian matrix at all resolution level with the help from filter bank. The small and Eigen values were considered and a new filter bank caused with three

characteristics, follows, 1. Nodular patterns can be improved with numerous sizes, 2. Several extents can be enriched in nodular and linear patterns together and 3. By eliminating these arrangements, an unique image can be created. In mammograms, filter bank is supported in improving the micro-calcifications.

A suggestion of two steps of CAD system for the automatic grouped micro-calcifications recognition is given in[11]. In first step, wavelet and gray level statistical characteristics applied in potential micro-calcification pixels segment and found them into objects of possible different micro-calcification. In next step, 31 statistical properties were applied to verify these latent objects. The outputs were encouraging but not sure; it's because of the training set practice in testing. RBF neural networks are used in combustion quality monitoring in PS boilers is presented in[12].

Computational Intelligence (CI) is relatively a new concept in the computer-science field which intentions to replicate biological intelligence. Moreover, it is a procedure including computers that can learn and adapt to new circumstances. CI incorporates artificial neural networks[13], genetic algorithms, and Fuzzy Logic (FL). CI techniques have been useful to a extensive variety of grounds from therapeutic to engineering applications in[14]. CI techniques can be useful to a digital mammogram to support radiologists in the initial analysis of breast cancer in[15,16]. In particular, FL techniques have introduced human reasoning to the analysis of digital mammograms in[17,18]. Digital mammograms are frequently fuzzy and ambiguous and very seldom have evidently projected irregularities. Efforts have been made to create CAD systems to provide medics with another method of examination for cancer. The main aim of CAD is to diagnose and detect abnormalities and doubtful zones in digital mammograms by systematizing the segmentation, extraction, detection, and classification processes.

An improved KNN algorithm in which anonymous test pattern is allocated to a specific class to the least value of the KNNs is in that class is stated by[19]. Bayesian methods for differentiation have been applied effectively in the application to analysis of breast cancers in[20,21]. Its decision-making process is based on selecting the almost

**Table 1.** Efficiency of various algorithms

| Authors | Features | Classifier Algorithms | Accuracy (%) |
|---|---|---|---|
| Wei et.al [16] | Statistical features | SVM and Kernel Fisher Discriminant (Multi-class classification) | 85 |
| Acharya et.al [18] | Area, Homogeneity, Micro calcification | ANN (Artificial Neural Network) and GMM (Gaussian Mixture Model) (Multi-class classification) | ANN – 88.9, GMM – 94.4. |
| Priebe et.al [19] | Fractal texture measures | Finite mixture model probability density estimation (Multi-class classification) | 88 |
| Andre et.al [21] | Shape factor measures, GLCM features | Multi-class classification (Perceptrons with several topologies) | Shape factors – 99, Texture feature – 63. |
| Dehghan et.al [24] | Wavelet features, gray level statistical features | SVM classifier with RBF kernel (Multi-class classification) | 89.5 |
| Chitre et.al [25] | Texture measures | Neural Network Classifier (Multi-class classification) | 87 |
| Ganesan et.al [26] | Texture measures | Decision Tree and SVM | 96 |
| Kinoshita et.al [27] | Shape and texture features | Three layer feed-forward neural network (Multi-class classification) | 81 |
| Rangayyan et.al [28] | Region based edge-profile | Acutance measures (Multi-class classification) | 92 |
| Verma et.al [29] | Statistical features | Fuzzy Neural Network (Multi-class classification) | 83 |
| The current study proposed | Feature extraction using wavelet transform | Classification using FFNN | 99 |

certainly class specified a precise feature vector. A probability of class membership is considered and applied to differentiate an extent or object. Differentiation of cancers and masses in mammograms using ANNs with size and texture characteristics is presented in[22].

The following is a list of features identified from the literature: entropy, deviation, mean[23], area[24] and mean absolute deviation. The Table 1 denotes the various algorithms implemented for identification of the breast cancer. The percentage accuracy of the algorithms is also tabulated here.

## 3. Materials and Methods

### 3.1 K-Means Algorithm

A set D = {**xi** | *i*= 1. . . *N*}, where **xi** indicates the $i^{th}$ data point.

Set of d-dimensional vectors. The process initiated with k points chosen from the initial k cluster data or "centroids". The initial value taken by using sampling at random on dataset, fixing it as the clustering solution, a small data subset or unsettled global mean of k times data.

Repeat this algorithm process till convergence,

Step 1: Assigning Data from set D

Every data point from set D is assigned to its closest centroids, with ties arbitrarily broken. Data partitioning is resulted.

*Step 2: "means" Relocation*

Every cluster representative data is replaced to the centre (mean) of all the data points assigned to it. The replacement is to the expectations (weighted mean) of the data partitions taking place if the data points reached the probability measure (weights).

Euclidean distance is the default measure of closeness, during this scenario, non-negative cost function applies always in Equation (1),

$$\Sigma \left(\text{argmin} \left\| X_i - C_j \right\|^2\right) \quad (1)$$

### 3.2 Wavelet Transform

The edge is the vital high-frequency material of a digital image. The conventional filter excludes the noise effectually. But the resultant image is blurred. So edge should be taken care when the noise is reduced. The wavelet analysis technique is a time-frequency investigation method which chooses the suitable frequency band

grounded on the features of the signal. Then the improved time frequency resolution is matched with the frequency band spectrum. The wavelet analysis technique has an clear consequence on the amputation of noise from the signal. According to the features of the multi-scale edge of the wavelet, it is analyzed that the de-noising technique of the orthogonal wavelet transforms which based on soft and hard threshold should be done[30]. A de-noising method is proposed based on the wavelet transform to face this problem of the noise lessening and fortification of the image edge, and apprehends the de-noising of two-dimensional image signal based on MATLAB.

From an image processing approach, the cancerous cells in the breast region are relatively high-frequency components immersed in the area of low-frequency components and very high-frequency noise in the mammograms. Since wavelets are contained in both the space and frequency domains, they have a multi-resolution property. This makes it suitable for eliminating malignant area from low-frequency areas and high-frequency noise. In specific, the wavelet transforms boundaries of the signal into signal bands of different frequency ranges. It can support help to classify beneficial data relevant to malevolent area and eliminate the bands which make slight impact to acquaintance. The wavelet features are formed by a wavelet decomposition and reconstruction algorithm. The gray level statistical structures used in this study are median and normalized gray level value. A multilayer FFNN classifier is then applied implemented produce a likelihood mapping of latent cancerous pixels by spending the mixed features as involvements.

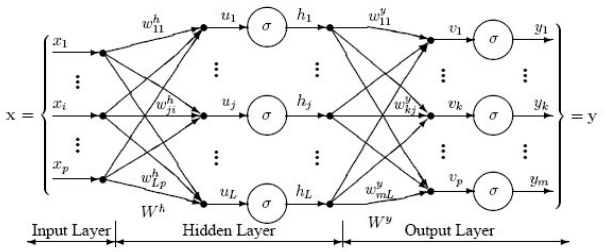



**Figure 1.** MLP architecture.

## 3.3 Mean

The *mean* of a data set is simply the arithmetic average of the values in the set, found by adding the values and dividing by the number of values. This is also called as the 1st order measurement which provides the mean color. It is denoted by $\mu_c$ and shown in Equation (2).

$$\mu_c = 1/MN\Sigma_i\Sigma_j P_{ij}^c \quad (2)$$

M and N are the dimensions of the image and $P_{ij}^c$ is the value of the $c^{th}$ colour component whose spatial co-ordinates are x and y. The mean is supportive for foreseeing future outcomes when there are no lengthy values in the data set. Though, the influence of extreme values on the mean may be imperative and should be kept in mind.

## 3.4 Standard Deviation

The Standard Deviation is a measure of how the numbers are distributed out. It is represented by σ and assumed by means of $P_{ij}^c$ and $\mu_c$. It is specified in Equation (3).

$$\sigma_c = [1/MN\Sigma_i\Sigma_j( P_{ij}^c - \mu_c)^2]^{1/2} \text{ for } i= 1 \ldots M \text{ and } j=1\ldots N \quad (3)$$

where M and N are the dimensions of the image and $P_{ij}^c$ is the value of the $c^{th}$ color component whose spatial co-ordinates are x and y.

## 3.5 Variance

It is defined as the average of the squared differences from the Mean. Variance is the square of the Standard Deviation (S.D). It is articulated in Equation (4).

$$\text{Variance} = (S.D)^2 \quad (4)$$

## 3.6 Mode

The **mode** of a set of data is the value in the set which happens most frequently. It is expected for the set of data values to require more than one mode. If there are two data values that occur most repeatedly, that the set of data values is bimodal. If there is no data value or data values that occur most repeatedly, that the set of data values has no mode. The mode is useful when the most common item, individual or value of a data set is needed.

## 3.7 Median

The median of a set of data values is the middle value of the data set when it has been arranged in rising order. That is, from the lowest value to the maximum value. The median may be valuable than mean when there are extreme values in the data set as it is not affected by the extreme values. It can also be found using the formula (n+1)/2.

## 3.8 Area

It is the pixel area to the interior of the object. It is defined as the total of total number of pixels inside boundary and pixels on boundary.

### 3.9 Intelligent Classifiers

This system has three layers. The first one is called as the input layer and the second one is the hidden layer and the final one is the output layer. All the three layers will have three neurons. To predict the variable there will be one neuron in each layer. The i/p involves of a vector of predictor variable values ($x_1 \ldots x_p$) is offered to i/p layer. The i/p layer (or processing before the input layer) regulates these values so that the range of each variable is -1 to 1. The i/p layer distributes the values to each of the neurons in the hidden layer. Furthermore to the predictor variables, a constant input of 1.0, called the *bias* that is given to every one of the hidden layers; the bias is multiplied by a weight and advanced to the amount in flowing into the neuron. The perceptron network with three layers is shown in Figure 1.

## 4. Performance Evaluation

The performance evaluation is done using various parameters like True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). True Positive (here) is defined as the images correctly identified as Benign or Malignant. True Negative (TN) is defined as Malignant images correctly identified. False Negative (FN) also called as type II error is defined as Benign or Malignant images incorrectly identified. Similarly the False Positive (FP) also called as type I error is defined as Benign incorrectly identified. The classification performance of the intelligent classifiers is evaluated using precision and recall. Precision is defined as the ratio of number of all the images retrieved to number of all the relevant images retrieved. Recall is defined as the ratio of number of all the relevant images retrieved to the number of all the images in each group.

## 5. Proposed System Architecture

The system architecture is depicted in the Figure 2. Mammogram result is taken as an input and given to pre-processing phase for filtering the data. In low-level image processing, pre-processing becomes an inevitable problem. By using various filtering techniques, noise presented in the image can be filtered out. The gray level of an image reduces while HPF passes the changes to a LPF. It means, the value smoothens and sharp edges were removed frequently, while applying LPF. The Median Filter is the best. The filter considers an image of area 3x3, 5x5, 7x7, etc., an element array is resulted by taking all the pixel values. The median value of an array is calculated and resulted by ordering element array. A famous sorting technique, Bubble sort is used in this element array sorting in an Ascending order, which returns a median value from the middle elements of the sorted array. The set, the median values of the array elements calculated for all the pixels, were resulted to an output image array[31]. The complete image array is arrived by repeating the Median Filter process.

End of pre-processing phase, all the processed data is fed into first classification algorithm (i.e., k-means algorithm). With the help of k-means algorithm, processed data can be converted into specified clustered data. Then clustered data is given as input in SVM algorithm and produces best classified data. The Figure 2 shows the system architecture.

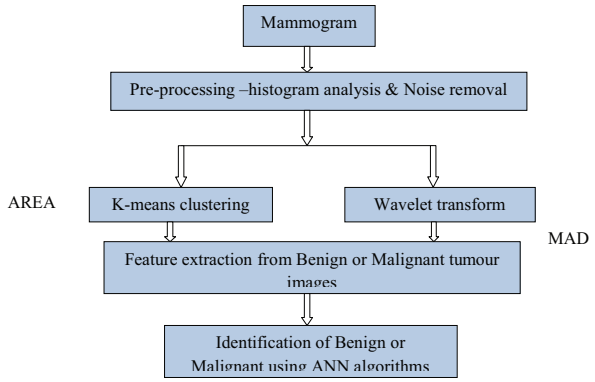



**Figure 2.** System architecture.

## 6. Results and Discussion

The identification of breast cancer from the MRI images is made automatic using K-means clustering and wavelet transform. The data base consisting of both normal and abnormal images of the breast are used for this analysis. The human perception at many times may lead to erroneous diagnosis. Variation in diagnosis may produce adverse effect on the patients. Hence to improve the accuracy this system is made automatic using machine vision algorithms.

## 7. MRI Data base Collection

The MRI images both consisting of normal and abnormal breast images are collected from a well known MRI scan centre. An opinion from the Radiologist is obtained

before implementing the Image processing algorithms for identification. The data base nearly consists of 51 images corresponding to three categories namely normal and abnormal (primary and secondary stages) respectively.

## 7.1 Pre-Processing

The histogram examination is through to finding out the distinction in the strength of the values for healthy and un healthy breast images as shown in Figure 3 and 4 respectively. The future work for this stage will include noise removal and edge detection. Presently, the images if corrupted with noise are removed using a suitable filtering method. The edges are identified so as to delineate the normal tissue of the breast from the abnormal region.

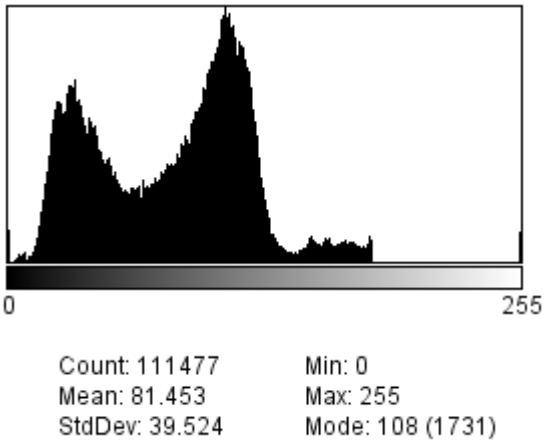



**Figure 3.** Histogram for normal breast image.

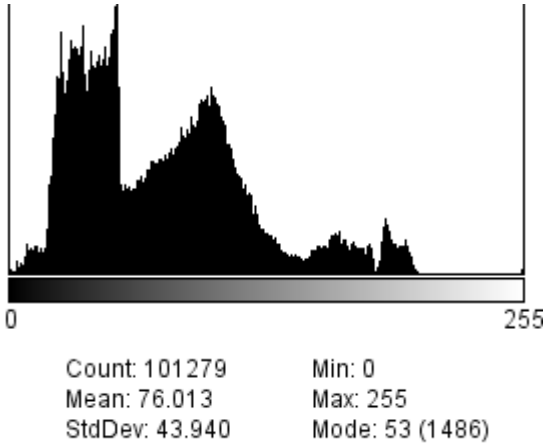
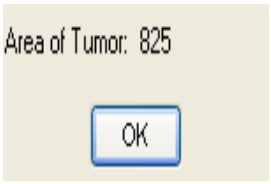



**Figure 4.** Histogram for abnormal breast image.

## 7.2 Feature Extraction

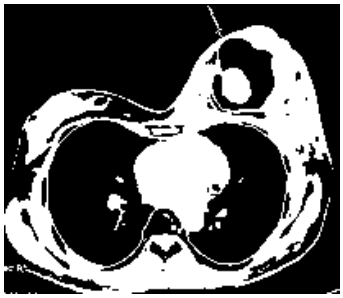
The feature represents the basic information in the image. These features when get repeated in different directions form an image. The various features include area, mean Standard Deviation (SD), mode and median. These features are further normalized which then used for classification of benign or malignant tumors. The area and Mean Absolute Deviation (MAD) is extracted using K-means and wavelet transform respectively. The results of K-Means algorithm is shown in Figure 5(a). The area computation is shown in Figure 5(b).

(a)



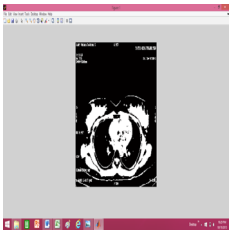

(b)

**Figure 5.** (a) Results for K-means clustering algorithm. (b) Area computation using K-means algorithm.

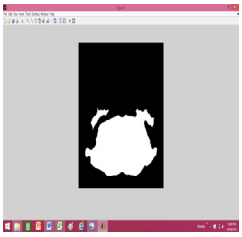


(a)

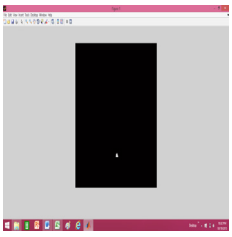
(b)



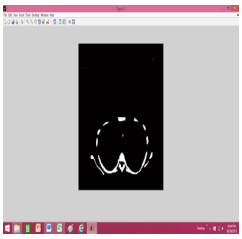
(c)



(d)



(e)



(f)

**Figure 6.** (a) EM segmentation of abnormal breast image. (b) Extraction of region of interest for abnormal image. (c) EM segmentation of normal breast image. (d) Extraction of region of interest for normal image. (e) Output for seed pixel. (f) Edge detection.

EM segmentation of abnormal breast image is shown in Figure 6(a) and 6(c). The extraction of region of interest for abnormal breast is shown in Figure 6(b) and 6(d). The output of seed pixel is shown in Figure 6(e) and the edge detection using K-Means algorithm is shown in Figure 6(e).

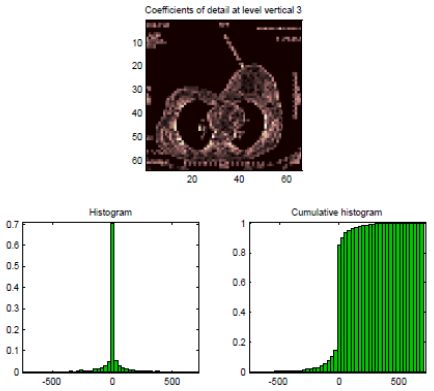
The Table 2(a) lists out the feature extracted from abnormal breast images and Table 2(b) lists the feature extracted from normal breast images.

**Table 2(a).** Feature Extraction from Abnormal breast Images

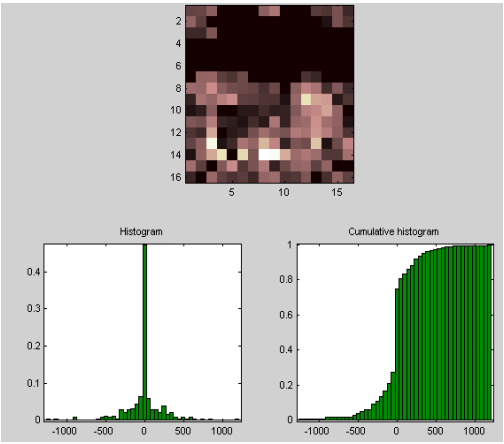
| Area | Mean | StdDev | Mode | Median | MAD |
|---|---|---|---|---|---|
| 53248 | 37.647 | 52.768 | 22.12 | 1 | 211.5 |
| 270336 | 31.648 | 61.032 | 24.38 | 0 | 221.3 |
| 270336 | 32.834 | 49.72 | 25.12 | 1 | 232.2 |
| 352256 | 38.881 | 62.625 | 26.22 | 0 | 236.4 |
| 352256 | 34.912 | 45.364 | 27.61 | 21 | 240.1 |
| 352256 | 61.475 | 71.262 | 32.7 | 31 | 242.8 |
| 352256 | 52.039 | 49.958 | 34.61 | 47 | 248.2 |

**Table 2(b).** Feature Extraction from Normal breast Images

| Area | Mean | StdDev | Mode | Median | MAD |
|---|---|---|---|---|---|
| 46336 | 33.908 | 51.102 | 0 | 1 | 101.5 |
| 262144 | 47.224 | 66.095 | 0 | 0 | 101.8 |
| 262144 | 38.951 | 49.631 | 1 | 8 | 104.4 |
| 262144 | 35.706 | 63.419 | 0 | 0 | 105.3 |
| 262144 | 25.102 | 40.944 | 1 | 2 | 106.7 |
| 262144 | 39.62 | 64.591 | 0 | 0 | 108.2 |
| 262144 | 30.295 | 43.843 | 1 | 8 | 109.2 |




(a)




(b)

**Figure 7.** (a) Output for wavelet transform - abnormal breast image. (b) Output for wavelet transform - normal breast image.

Figure 7(a) shows the output for wavelet transform of abnormal breast images and whereas Figure 7(b) shows the output for wavelet transform of normal breast image.

## 7.3 Back Propagation Algorithm for Classification of Breast Cancer Images

The network consists of three layers. They are feed-forward, perceptron neural network. The training results are shown in Figure 8.

**Algorithm – BPA**

- Initialize the weights.
- Normalize the input – output data.
- Present the input-output patterns.
- Compute the actual output and the error.
- Propagate the error.
- Update the weights using Generalized Delta Rule (GDR).
- Repeat till tolerance is reached.

Weight adjustments between output layer and hidden layer

- $W_{pqk}(n+1)=W_{pqk}(n) + \Delta W_{pqk}(n+1)$.
- $\Delta W_{pqk}(n+1) = \eta\, \delta_{qk}\, OUT_{pj} + a\, \Delta\, W_{pqk}(n)$.
- $\delta_{qk} = OUT_q(1\text{-}OUT_q)(TARGET_q\text{-}OUT_q)$.

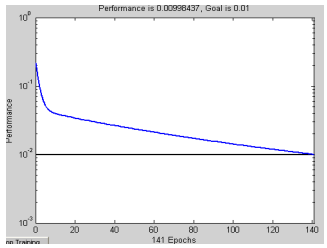
Weight adjustments between hidden layer and input layer

- $W_{mpj}(n+1)=W_{mpj}(n) + \Delta W_{mpj}(n+1)$.
- $\Delta W_{mpj}(n+1) = \eta\, \delta_{pj}\, OUT_{pj} + a\, \Delta\, W_{mpj}(n)$.
- $\delta_{pj} = OUT_{pj}(1\text{-}OUT_{pj})(sigma\delta_{qk})$.

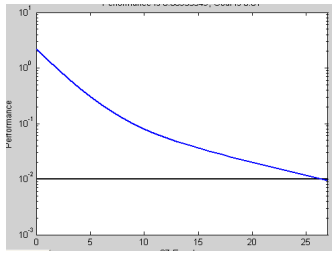
**Table 3.** ANN parameters

| Sl. No. | Network parameters | Value |
|---|---|---|
| 1. | No. of nodes in input layer | 6 |
| 2. | No. of nodes in hidden layer | 5 |
| 3. | No. of nodes in the output layer | 1 |
| 4. | Activation function – hidden layer | Sigmoid |
| 5. | Activation function – Output layer | Sigmoid |
| 6. | Mean Squared Error | 0.00961 |
| 7. | No. of iterations | 141 |
| 8. | Learning factor | 0.8 |

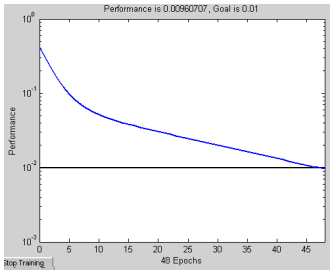
The ANN parameters like MSE, no. of repetitions, no.of nodes in many layers and the type of the stimulation function used are shown in the Table 3 below. Table 4 denotes the behaviour of the BPA classifier for finding the benign or malignant tumour images and their associated values. The performance measurement adhered for this are recall and precision. Both the values of recall and precision are closer to 1. Hence the BPA is able to provide an optimum quantity of values. The training the ANN with several input features is shown in Figure 8. The Figure 8(a) shows 3 features as input to ANN, Figure 8(b) shows 4 features as input to ANN, Figure 8(c) shows 5 features as input to ANN and Figure 8(a) shows 6 features as input to ANN.



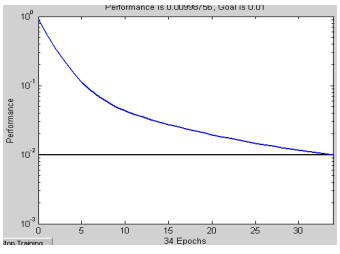

(a)




(b)




(c)




(d)

**Figure 8.** Training the ANN with various input features. (a) With 3 features as input to ANN. (b) With 4 features as input to ANN. (c) With 5 features as input to ANN. (d) With 6 features as input to ANN.

**Table 4.** Performance of the BPA classifier

| Comparison Testing / Validation | Recall | | Precision | |
|---|---|---|---|---|
| | Benign | Malignant | Benign | Malignant |
| Testing results | 1 | 1 | 1 | 0.894 |
| Validation results | 1 | 1 | 1 | 0.8358 |

## 7. Conclusion

A new framework for classification method in mammographic image investigation has been suggested. From a study of the existing literature, we find that the application of intelligent classifications to the problem of mammographic image analysis is infrequent. Hence it is supposed that the suggested system's performance can be ascended up and in addition enriched by enclosing new functional that is more pliable to mammograms. This article presents a very over-all view of two way classification architecture. It demonstrates how an abstract structure allows us to discover effective classification of breast cancer images. This algorithm will be implemented in future because it's simple and the results were encouraging, this will lead to a real-time breast cancer diagnosis system.

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