BREAST CANCER IDENTIFICATION USING IMAGE PROCESSING AND NEURO FUZZY CLASSIFIER

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Abstract : Computer aided medical analysis is the upcoming trend in tumour diagnosis. One of the most powerful techniques for early detection of breast cancer is based on digital mammogram. In order to detect the breast cancer, the radiologist usually searches the mammograms visually for specific abnormalities. This project presents a suitable solution for identifying the presence of tumours using image processing methods and a fuzzy classifier. The proposed method uses MATLAB for applying GABOR filter space, which is the artificial visual cortex system and computation of GLCM. In verilog the presence of parallel multiplication and accumulation units make the physical size of filter bank heavy which can be optimized by constructing the same filter bank with MATLAB. This works aims at lossless compression of medical images using lifting scheme, feature extraction using GLCM and then finding optimal combination of features for the neuro fuzzy classifier.

IndexTerms – **Mammograms ,Gabor Filter, GLCM, Neuro fuzzy classifier.**
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I. INTRODUCTION

Breast cancer is among the most common and deadly of all cancers, occurring in nearly one in ten women. Breast cancer is a cancer that starts in the tissues of the breast. There are two main types of breast cancer:
Ductal carcinoma starts in the tubes (ducts) that move milk from the breast to the nipple. Most breast cancers are of this type.
Lobular carcinoma starts in the parts of the breast, called lobules, that produce milk.
In uncommon cases, breast tumor can begin in different territories of the breast cancer. Breast tumor may be obtrusive or noninvasive. Obtrusive means it has spread from the milk pipe or lobule to different tissues in the bosom. Noninvasive implies it has not yet attacked other bosom tissue. Noninvasive breast malignancy is called "in situ." ductal carcinoma in situ (DCIS), or intra ductal carcinoma, is bosom growth in the coating of the milk pipes that has not yet attacked adjacent tissues. It may advancement to intrusive malignancy if untreated Lobular carcinoma in situ (LCIS) is a marker for an expanded danger of intrusive growth in the same or both breast cancer.

- Age and sexual orientation - Your danger of creating bosom malignancy expands as you get more established. Most developed breast growth cases are found in ladies over Ladies are 100 times more prone to get bosom malignancy than .
- Family history of breast malignancy - You might additionally have a higher danger for bosom disease on the off chance that you have a nearby relative who has had breast, ovarian, or colon tumor. Around 20 - 30% of ladies with bosom malignancy have a family history.
- Qualities - Some individuals have qualities that make them more prone to create bosom malignancy. The most well-known quality imperfections are found in the Brca1 and qualities. These qualities typically deliver proteins that secure you from tumor. On the off chance that a guardian passes you a deficient quality, you have an expanded danger for bosom tumor. Ladies with one of these imperfections have up to a 80% shot of getting breast tumor at some point amid their
- Menstrual cycle - Women who got their periods right on time (before age 12) or experienced menopause late (after age 55) have an expanded malignancy .

II.LITERATURE REVIEW
The general architecture of a CAD system includes image pre-processing, definition of region(s) of interest, features extraction and selection, and classification. As a whole, the techniques of computer aided mammography cover image enhancement, segmentation, detection and classification. Image pre-processing is a necessary step to improve the image quality of mammograms. The general methods of image pre-processing can be divided into: de-noising, enhancement of structure, and enhancement of contrast. The methods of de-noising refer to mean filters, median filters, Laplacian filters and Gaussian filters, the methods of enhancing the edges of image structures include unsharping and wavelet transform, and the method of enhancing image contrast can be histogram equalization.
 The pre-processing of digital mammograms refers to the enhancement of mammograms intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, etc summarized the three kinds pre-processing techniques for digital mammograms: global histogram modification approach, Local-processing approaches, and multiscale processing approach. Texture

classification is an image processing technique by which different regions of an image are identified based on texture properties. This process plays an important role in many areas such as industrial automation, biomedical image processing, Content Based Image Retrieval and remote sensing application. In spite of the importance of textures in many areas of image processing, there is no universally accepted definition for the texture. We prefer to adopt the definition suggested in, because of its generality and it is given as follows:

A region in an image has a constant texture if a set of local statistics or other local properties of the picture are constant, slowly varying, or approximately periodic. This definition explains many of the textures found in natural images. The local statistics or property that is repeated over the textured region is called a texture element or Texel. The texture has both local and global meaning, in the sense that it is characterized by the invariance of certain local attributes that are distributed over a region of an image. The different approaches for the texture analysis and classification employed by various research workers are: Markov random fields Gibbs random fields entropy-based algorithms, and Wavelet representation the important steps in a classification problem are the choice of features, and the design of classifier. A comparison between few texture feature extraction schemes has been presented in which the Fourier spectrum, second order gray level statistics, co-occurrence statistics, and gray level run length statistics features are considered. It is observed that the co-occurrence features were the best of these features. Initially, texture analysis was based on the first order or second order statistics of textures.

III. SYSTEM FOR TUMOUR DETECTION USING NEURO FUZZY CLASSIFIER
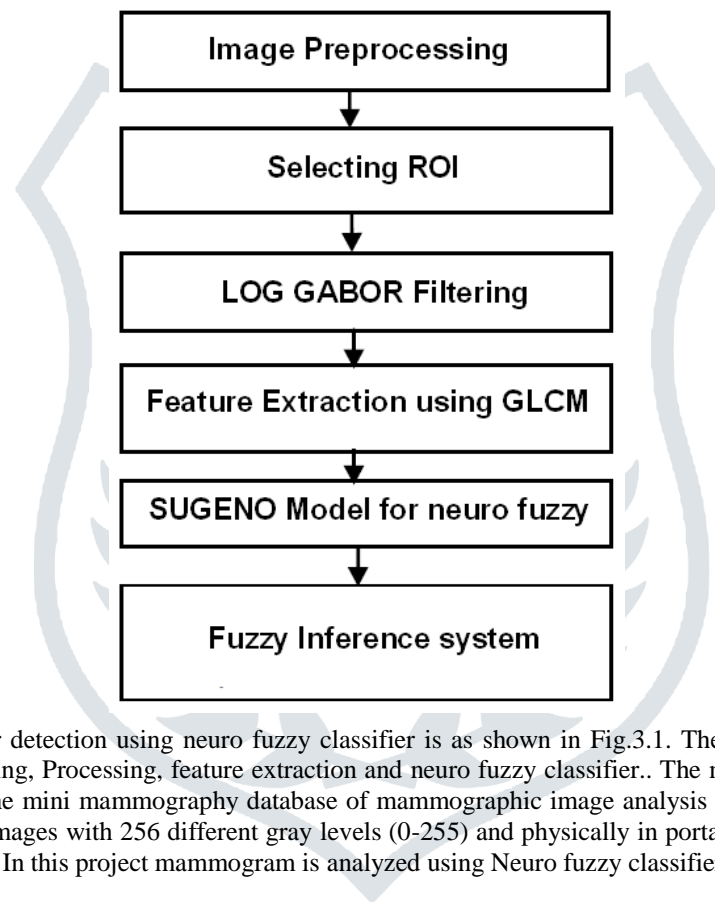
The block diagram for tumour detection using neuro fuzzy classifier is as shown in Fig.3.1. The proposed system involves four major steps called Pre-processing, Processing, feature extraction and neuro fuzzy classifier.. The mammogram images used in this experiment were taken from the mini mammography database of mammographic image analysis society (MIAS) . All images are held as 8-bit gray level scale images with 256 different gray levels (0-255) and physically in portable gray map (pgm) format with size 1024 pixels x 1024 pixels. In this project mammogram is analyzed using Neuro fuzzy classifier and coded in MATLAB.

3.2 **PRE-PROCESSING**

Image acquisition is a highly important step for the automatic quality control because it provides the input data for the whole process. The acquisition is performed by an optical sensor which is always a video camera (with one line or a matrix of CCD) that provide accurate and noiseless image. Local illumination is directly linked with the quality of image acquisition because it is straight forward to demonstrate that its variations can heavily affect the patterns visibility in the textile texture image. Consequently the natural sources of light which are non-constant must not be employed and their influence should be carefully eliminated. Thus the use of a strictly controlled illumination provides control, exclusively by one or more artificial light sources is the reasonable alternative.

3.3 PREPROCESSING METHOD FOR TEXTILE TEXTURE IMAGES

Preprocessing is the important method that influences automated detection of defects. The following are the preprocessing methods under study

(a) Contrast adjustment

(b) Intensity adjustment

(c) Histogram equalization

(d) Binarization

(e). Morphological operation

(a) Contrast adjustment

The complexity of a picture is the conveyance of its dim and light pixels. A low-differentiation picture shows little contrasts between its light and dull pixel values. The histogram of a low-complexity picture is restricted. Since the human eye is touchy to

difference as opposed to supreme pixel intensities, a perceptually better picture could be gotten by extending the histogram of a picture so the full dynamic scope of the picture is filled.

(b) Intensity adjustment

Picture upgrade methods are utilized to enhance a picture, where "enhance" is some of the time characterized impartially (e.g., build the sign to-clamor degree), and off and on again subjectively (e.g., make certain gimmicks less demanding to see by adjusting the colors or intensities).intensity alteration is a picture improvement method that maps the image intensity values to a new range. The low-contrast image with its histogram and all the values gather in the center of the intensity range. Figure-3(a) shows the original image and 3(b) image after intensity adjustment

(c) Histogram equalization

The Histogram Equalization evenly distributes the occurrence of pixel intensities so that the entire range of intensities is considered. This technique generally expands the worldwide differentiation of pictures, particularly when the usable information of the picture is spoken to by close complexity values. Through this change, the intensities might be better circulated on the histogram. This considers zones of lower nearby differentiation to increase a higher complexity. Histogram adjustment achieves this by successfully spreading out the most successive power values. Then probability density function (pdf) is calculated for the histogram.

To make it simple, histogram equalization technique changes the pdf of a given image into that of a uniform pdf that spreads out from the lowest pixel value (0 in this case) to the highest pixel value ($L-1$). This can be achieved quite easily if the pdf is a continuous function. However, with a digital image, the pdf will be a discrete function. Suppose that for an image x, and for the dynamic range for the intensity r_k varying from 0 (black) to $L-1$ (white), the pdf can be approximated using the probability expressed as follows ,

$$pdf = p(r_k) = \frac{r_k}{x}$$

where 'r_k' total pixels with intensity and ' x ' total pixels in image. From this pdf, one can then obtain the cumulative density function p(Sk) (cdf) as follows: The output pixels from the histogram equalization operation are equal to the cdf of the image. Mathematically it can be represented as,

$$pdf(x) = \sum_{k=0}^{L-1} p(r_k)$$

to get the pixel value p(Sk),

$$p(S_k) = \sum_{k=0}^{L-1} p(r_k)$$

the resultant value is rounded to the nearest integer.

3.4 LOG-GABOR FILTERS

In processing stage the suspicious region of interest (ROI) is cropped. For that first order statistical features such as mean and standard deviation are calculated by using the below two equations. Next the cropped ROI is convolved with Log-Gabor filter for four different orientations.

$$mean = \frac{1}{N^2} \sum_{i,j=1}^{N} R(i,j)$$

$$standard\ deviation = \sqrt{\frac{1}{N^2} \sum_{i,j=1}^{N} [R(i,j) - mean]^2}$$

Where $R(i,j)$ is ROI matrix.

Gabor channels are a conventional decision for acquiring restricted recurrence data. They offer the best concurrent restriction of spatial and recurrence data. On the other hand they have two fundamental impediments. The greatest transmission capacity of a Gabor channel is restricted to pretty nearly one octave and Gabor channels are not ideal if one is looking for wide ghastly data with maximal spatial limitation. An option to the Gabor capacity is the Log-Gabor capacity proposed by Field. Log-Gabor channels could be developed with subjective transfer speed and the data transmission might be improved to create a channel with insignificant spatial degree.

One can't build Gabor capacities of discretionarily wide transmission capacity and still keep up a sensibly little DC segment in the even-symmetric channel. This trouble could be checked whether we take a gander at the exchange capacity of an even-symmetric Gabor channel in the recurrence space. The exchange capacity is the whole of two Gaussians focused at in addition to and short the core recurrence.

An alternate point in backing of the log Gabor capacity is that it is reliable with estimations on mammalian visual frameworks which shows that cell reactions that are symmetric on the log recurrence scale. In this manner, one demand may be forced by the most extreme sharpness of the channel that we can successfully speak to. More noteworthy investment is to study the variety of the spatial width of channels with data transfer capacity. A helpful goal may be to minimize the spatial width of channels so as to get maximal spatial confinement of our recurrence data. Channels are developed regarding two parts.

    1) The spiral part, which controls the recurrence band that the channel reacts to

2) The rakish segment, which controls the introduction that the channel reacts to.

The two parts are reproduced together to develop the general channel.
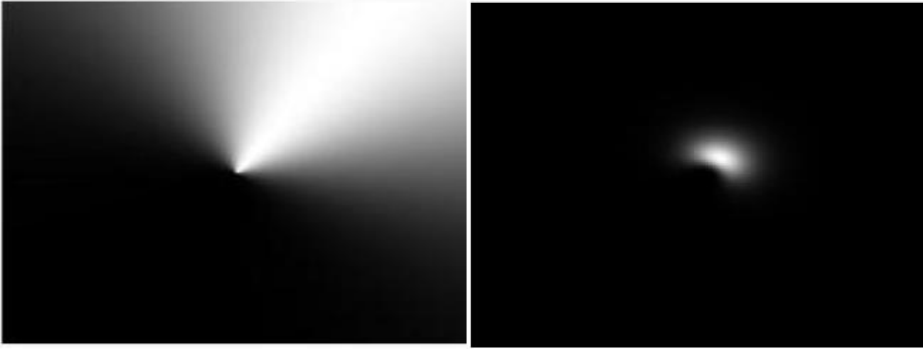

Fig. (a)Angular Component of the filter (b)Product of Angular and Radial Components to produce the frequencydomain representation of the log Gabor Filter.

Gabor multi resolutions have been successfully used for image analysis and applications where exact reconstruction is not required, such as texture analysis, texture synthesis, edge/contour extraction, object recognition and, even without exact reconstruction they have been shown useful for image restoration applications. In parallel, different methods for reconstruction improvement have been proposed to recover the highest frequencies to avoid excessive low-pass overlapping, to improve the reconstruction or to cover more uniformly the Fourier domain.

Then Log-Gabor filter is applied on the cropped ROI for single scale (n_s =1) and four different orientations (n_t =4) those are at (0^0, 45^0, 90^0 and 135^0) is given

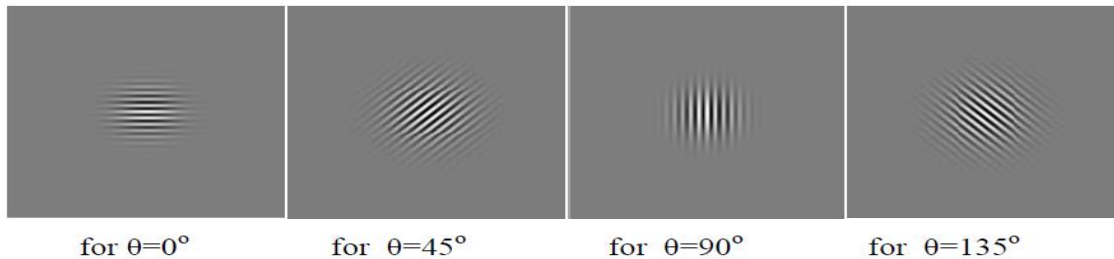for θ=0°   for θ=45°   for θ=90°   for θ=135°

Fig. Log Gabor Filter for four different orientations

3.5 GRAY LEVEL CO-OCCURRENCE MATRICES

One can try to represent the probability density functions involved as discrete functions defined on the discrete domain, rather than as parametric functions. For example, the probability of a pixel obtaining a certain value may be calculated directly from the data by computing the histogram of the image and normalizing it by dividing by the total number of pixels in the image.

Now, given that the gray levels are discrete, this function is defined over pairs of discrete grey values and so it becomes a 2D discrete function which may be represented by a matrix. Such matrices are called co-occurrence matrices as they convey information concerning the simultaneous occurrence of two values in a certain relative position. Co-occurrence matrices are very rich representations of an image.

At the same time they are very bulky. One may use directly some of the elements of co-occurrence matrices to characterize a texture, particularly for the cases where some reduction in the number of grey values has already been applied. In particular, ratios of the co-occurrence matrix have been shown to be good texture descriptors. This is because they capture the relative abundance of certain image characteristics. The following figure3.4 shows how to calculate a few values in the GLCM of the 4-by-5 picture.

Component (1, 1) in the GLCM contains the worth 1 in light of the fact that there is stand out occasion in the picture where two, on a level plane contiguous pixels have the qualities 1 and 1. Component (1, 2) in the GLCM contains the worth 2 in light of the fact that there are two occasions in the picture where two, on a level plane nearby pixels have the qualities 1 and 2.

Initially proposed by R.m. Haralick, the co-occurrence matrix representation of surface gimmicks investigates the ash level spatial reliance of composition. A scientific meaning of the co-occurrence matrix is as follows:

- Given a position administrator P(i,j),
- Let A be a n x n matrix
- Whose component A[i][j] is the quantity of times that focuses with ash level (force) g[i] happen, in the position tagged by P, in respect to focuses with light black level g[j].
- Let C be the n x n matrix that is delivered by isolating A with the aggregate number of point combines that fulfill P. C[i][j] is a measure of the joint likelihood that a couple of focuses fulfilling P will have values g[i], g[j].
- C is known as a co-occurrence lattice characterized by P.

Samples for the administrator P are: "i above j", or "i one position to the right and two beneath j", and so forth. This can likewise be outlined as takes after…

Consequently, for every Haralick surface gimmick, we acquire a co-event network. These co-occurrence lattices speak to the spatial distribution and the reliance of the grey levels inside a neighbourhood. Every (i,j) [th] entry in the matrixes, represents the

probability of going from one pixel with a grey level of 'i' to another with a grey level of 'j' under a predefined distance and angle. From these matrices, sets of statistical measures are computed, called feature vectors .
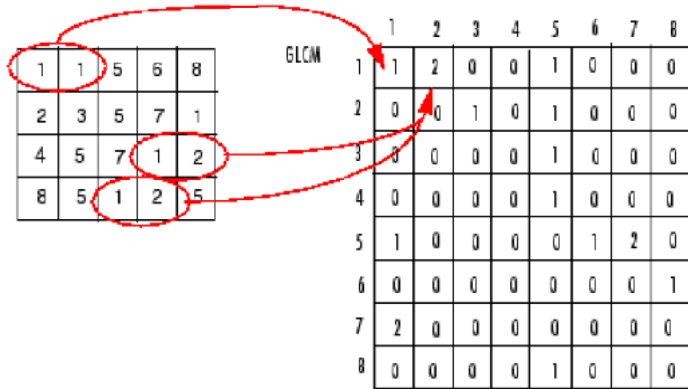

Fig: Pictorial Calculation Of Glcm Matrix

After applying Log-Gabor filter on the cropped ROI, GLCM matrix is formed. From that second order statistical features, i.e. Co-occurrence matrix features such as contrast, energy, homogeneity, correlation, entropy, Cluster shade , cluster prominence are calculated using the equations.

Contrast: The intensity contrast between a pixel and its neighbor over the whole image.

Correlation: Statistical measure of how correlated a pixel is to its neighbor over the whole   image; Range = [-1 1].Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

Energy: summation of squared elements in the GLCM; Range = [0 1]. Energy is 1 for a constant image.

Homogeneity: Closeness of the distribution of elements in the GLCM to the GLCM diagonal; Range = [0 1]. Homogeneity is 1 for a diagonal GLCM.

Entropy: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

Cluster shade and cluster prominence: are measures of the skewness of the matrix, in other words the lack of symmetry.

IV. RESULTS AND CONCLUSION

Mean of ROI for three cases

Standard deviation of ROI for three cases.
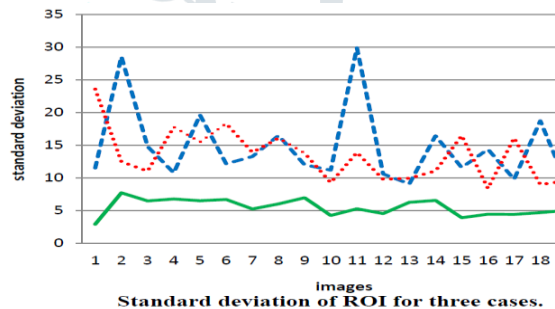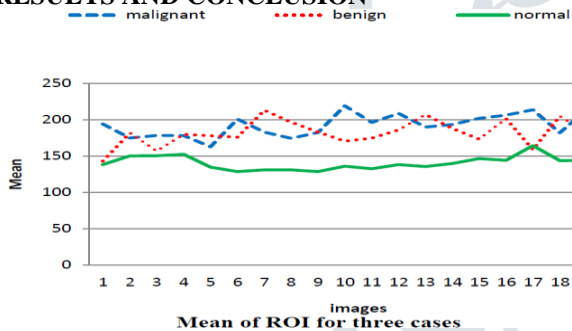
From the the above figures, one can observe that, feature vector F1 can able to distinguishing normal mammogram from malignant mammogram but failed in distinguishing benign from normal and malignant. However, when Fig is considered, it is cleared that, feature vector F2 effectively distinguishing normal, benign and malignant mammogram images.
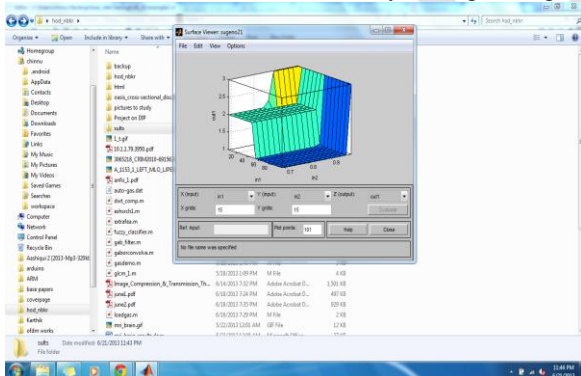
This is the output of neuro fuzzy controller using Gaussian bell membership functions and two selected glcm parameters.
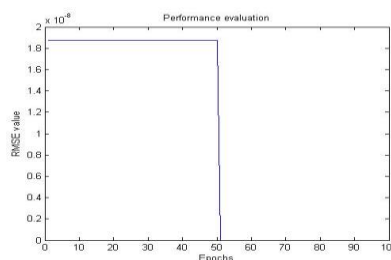
This curve shows the performance of proposed system. The error becomes zero just after training for 50 epochs. Convergence rate is more.
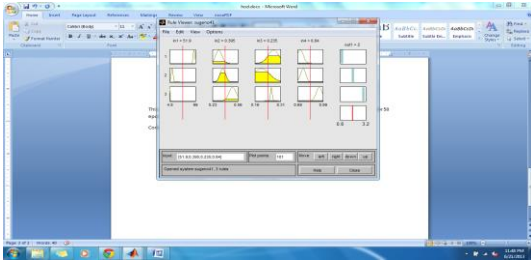

Fig This graph shows the results of neuro system with 4 input parameters. The output of new test image is predicted from the last column.

From the results we obtain the FIS structure, in which in1 , in2, in3, in4 corresponds to 4 optimal GLCM features

in1- contrast

in2=correlation

in3=energy

in4=homogeneity

the output corresponds to category i.e.1,2 ,3

1-normal

2-benign

3-malignant

The proposed system is having more convergence and precision than anfis. anfis will round off values but the proposed system won't. The membership functions and rules are written using "if-then" logic system. so all the required modules are developed and results are compared. Please note that as size of database increases accuracy also increases. neuro fuzzy classifiers are two types

1.sugeno

2.mamdani

Here we considered sugeno system as it is versatile for real time applications and it has good error tolerance.

The proposed neuro fuzzy classifier operates on our data base(a difficult job to create) and the resulting output is very user friendly. the GLCM parameters of image under study are set using the sliders provided on the GUI and the system shows in which state the tumour is .i.e if that is '1' the case is normal, if the result is '2 the case is benign, if the result is '3' the case is malignant. These results are posted.

 CONCLUSION: Based on the results of our experiment, one concludes that the system proposed for mammogram analysis is based on Log-Gabor wavelet statistical features is accurate for distinguishing normal, benign and malignant. Since the Log-Gabor function has the advantage of the symmetry on the log frequency axis and it spread information equally across the channels, this filter produces an uncorrelated and less redundant representation for mammogram texture compared with ordinary wavelet filters. After obtaining the results from first order and second order statistical features then we are feeding these values to Neuro fuzzy classifier system to get accurate results without any manual errors.

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