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Breast Cancer Detection Using UWB Imaging and Convolutional Neural Network

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Abstract: In this paper, a novel method is used for the automatic detection of breast cancer by using UWB. Breast cancer is the severe threat occurs especially in women. To slacken the death rate, diagnosis and detection is a significant concern needs to be done accurately. This proposed work works well in identifying the tumor by using new algorithm and approaches. To quantize the acquired image into samples, thresholdbased segmentation is applied. The obtained input image will be preprocessed by using median filter. Median filter clear out the noise present in the UWB image. So denoising of image is needed to uphold the quality of image by noise suppression. Quality of image and feature extraction algorithm becomes unreliable due to the presence of noise. After quantization, the feature extraction is performed by using GLCM and then it is optimized. Finally Convolutional Neural Network is performed for classifying the extracted feature and it analogizes the test data with trained data. To prove its effectiveness, it is compared with other existing works, it generates a high accuracy. The accuracy achieved in this proposed work is 94%.

Keyword: Ultra wide-band(UWB), Median filter, Threshold based segmentation, Gray-level co-occurrence matrix (GLCM), Convolutional Neural Network(CNN).

I. INTRODUCTION:

Cancer is a group of over one hundred diseases, all of which share the common feature of uncontrolled spreading of malignant cells in the body. Almost one-fourth of those who develop breast cancer will still be alive compared to in the year of 1970's because of the reason cancer has turned out to be tougher to crack [1]. Nowadays death rates are falling because of the earlier detection of tumor and the enhanced use of existing treatment. Breast cancer is the severe one occurs especially in women. While detecting, two things needed to be concerned, whether the tumor is malignant or benign. While analogizing with benign, malignant tumor is found to be a precarious one. Earlier detection is essential because if it starts maturing it spread to its surrounding tissue and creates problem to other parts of the body. When the radiologists have to confirm about the existence of the tumor, MRI (Magnetic Resonance Imaging) has been used. By using MRI, patient could develop an allergic reaction to the contrasting agent or that a skin infection could occur.In this work, to analogize between cancerous and noncancerous cell, UWB technique is used [2], [3], [4]. Our proposed work's main role is to detect the tumor by using UWB image and also to analyze in an accurate manner, new algorithm and approaches were used. UWB is utilized because it has a low sensitivity to interference due to the absence of reflection of the wave itself. It is characterized by a low radiation emission. Algorithms used in this proposed work are median filter to perform preprocessing. Preprocessing is performed to convert a color image to gray scale image and its main role is to clear out the salt and pepper noise. After performing preprocessing operation, it undergoes segmentation by using threshold based technique and then the feature is extracted by GLCM technique and final comparison isperformed by using CNN classifier [11], [12]. It analogizes the test data with trained set to produce an accurate result. This proposed work works well to achieve the expected result and it provides the correct information to oncologist for the better treatment plan.

Related works:

Qinwei Li et al [2015] proposed direct extraction of tumor response based on ensemble empirical mode decomposition for image reconstruction of early breast cancer detection by UWB. In this paper, the tumor signal can be received directly, without using any calibration waveforms or any other tumor-free model, which helps in the early detection of the breast cancer by using the ultra-wide band microwave imaging. The IMF helps in the extraction of the tumor response signal. The cost may increase widely based on the ensemble number, i.e., the computational cost increases with increase in ensemble number.

Nadia Brancati et al [2019] proposed a deep learning approach for breast invasive ductal carcinoma detection and lymphoma multi-classification in histological images. In this paper, the histological images are obtained in a high resolution to detect the breast invasive carcinoma by using a deep learning technique was proposed. The workload is drastically reduced due to the integration of detection and classification stage also the implementation of the deep learning helps in reducing the workload and augment the pathologist ability to diagnose the carcinoma. Over completion of the unsupervised representation is learned by the auto encoders (AE) due to the usage of the non-linear activation function.

MoiHoon Yap et al [2019] proposed automated breast ultrasound lesions detection using convolutional neural networks. In this paper, using the patch-based LeNet, a U-Net, and a transfer learning approach, the breast ultrasound lesions detection is proposed. Using the terms like TPF(True Positive Fraction), FPs/image(False Positives per image) and F-measure, the qualitative results are explained. The lesion detection is not covered completely in this proposed work. The need of set of normal images for the training process causes issues like time consumption and which is also impossible to implement in clinical practice.

Tengfei Yin et al [2015] proposed a robust and artifact resistant algorithm of ultra-wide band imaging system for breast cancer detection. In this paper, to solve the issues from both artifact and glandular tissues, RAR (Robust and Artifact Resistant) algorithm is proposed, in which a neighbourhood pair-wise correlation-based weighting is designed. The efficacy and the robustness of the proposed model can be understood under various challenging scenarios such as the non-perfect artifact removal, and various levels of glandular tissues in breasts. For the detection of the tumour in a severely dense area of breasts, the performance of RAR cannot be found with the proposed work.

Xiaofei Zhang et al [2018] proposed classification of whole mammogram and tomosynthesis images using deep convolutional neural networks. In this paper, for 2D mammograms and 3D tomosynthesis image classification, a neural network model is proposed. Some frames are discarded and some are selected, if the discarded frame contains the information required for cancer diagnosis which the selected frame lacks, then loss of information may occur. Much bigger feature space is required to obtain the 3D tomosynthesis, on which the performance depends on.

Maarten Strackx et al [2015] proposed direct RF subsampling receivers enabling impulse-based UWB signals for breast cancer detection. In this paper, using the UWB (ultra wide band), a breast cancer detection method and implementation of the CMOS with direct RF subsampling receiver is proposed. To minimize the amount of the drain junctions, even number of the fingers are chosen. Resistive sensing is used to understand the Common-mode feedback (CMFB), whose phase margin is not compromised by the low-valued(40Ω) sensing of the resistors.

II. PROPOSED METHODOLOGY:

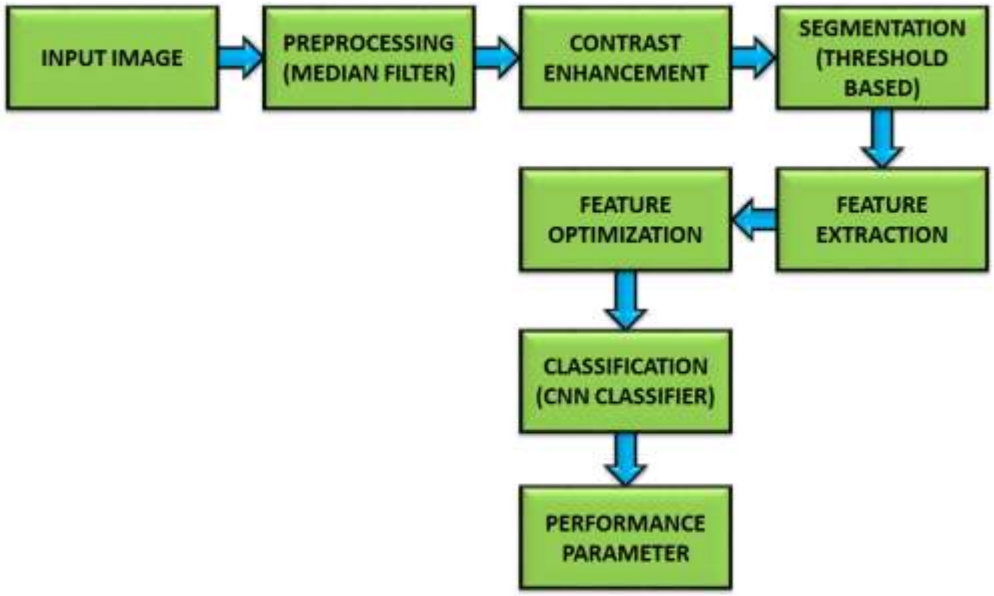


Fig 1: Block diagram of proposed work

Preprocessing:

Image preprocessing is performed to slacken the messiness because the acquired UWB image is from different resources. To feed them for further processing, they need to be standardized and cleaned up. To reduce the complexity and to increase the accuracy of the applied algorithmpreprocessing is performed. In this work, median filter is used.

Median filter:

It is an effective method to reduce the noise from image pixel. It is computed by sorting all the pixel value in numerical order and then it replaces the pixel being considered with the middle pixel value. It is not only performed to reduce the noise but also it preserves edges.

In median filter, the nonlinear function can be expressed as,

$$y(n) = med[\, x(n-k), x(n-k+1), \ldots, x(n), \ldots \ldots \ldots, x(n+k) \qquad (1)$$

Where y(n) is the output, x(n) is represented as input signal. The median filter gathers a window N-2K+1 containing input signal. After this it applies the median operation on the sample set. Instead of applying filtering operation on M valued signal. We can decompose it into M-1 channels each containing a binary median filter. Finally add up all the output of filters to get a good outcome.

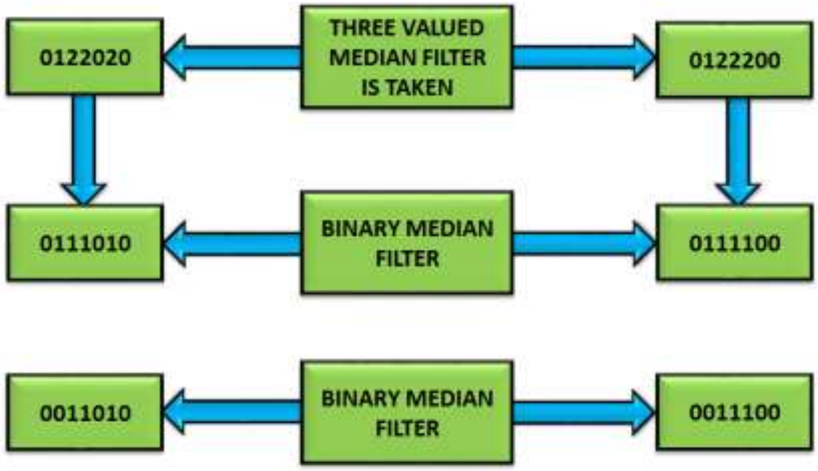


Fig: 2 working progress of median filter

Threshold based image Segmentation:

Segmentation operation involves recognition and measurement of features. The purpose of segmenting the image is to split up the image into meaningful set of pixels with respect to a particular application. Segmentation may be done in contextual or non contextual form. Threshold is a non contextual approach.

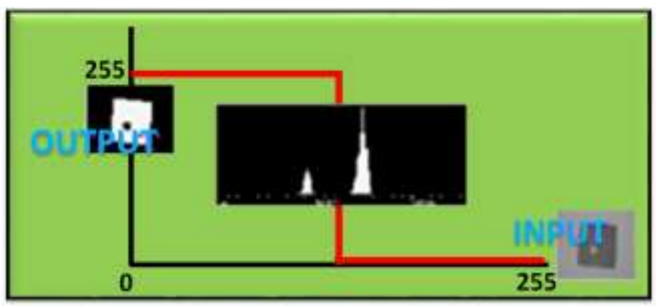


Fig:3 Threshold based segmentation

This technique is based on the threshold value and it turns a gray scale image to binary image. The advantage of acquiring a binary image is that it reduces the complexity and makes the recognition and classification easier byselecting a single threshold value to convert a gray scale image to binary image.

The Threshold operation takes the input in gray scale or color image and it segments the image into background and foreground region. Black pixels correspond to background and white pixels correspond to foreground.

g(x, y)=1 if f(x, y) is represented as foreground pixels and g(x, y)=0 if f(x,y) is represented as background pixels. In real time application, using histogram leads to complexity. So threshold selection based on histogram operation is applied. Histogram based threshold technique is applied to acquire all possible uniform regions in the image. The threshold T is computed by.

$$T = (p1+p2)/2$$
$$T = \min H(u)$$
$$U \in [p1, p2]$$

Where H (u) is denoted as histogram value between p1 and p2.

The three threshold algorithms used to generate a good result.

1. Global threshold
2. Local threshold

3. Adaptive threshold
For different local areas, different threshold values are used.

Global threshold:

It is utilized when the intensity distribution of objects and background pixels are sufficiently distinct. For the entire image, a single threshold value is used.

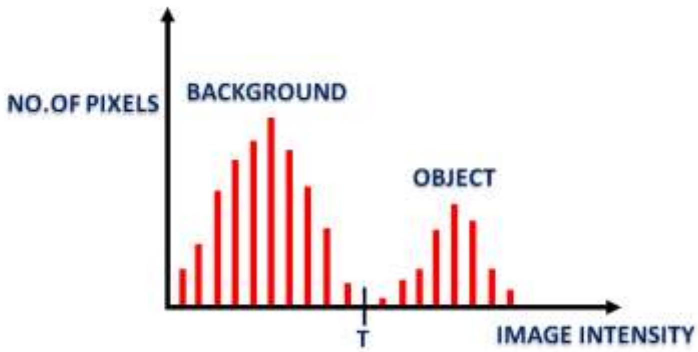


Fig: 4

If g(x, y) is a threshold version of f(x,y).

$$g(x,y) = \begin{cases} 1 & if\ f(x,y) \geq T \\ 0 & otherwise \end{cases} \qquad (2)$$

Local threshold:

In the obtained UWB image, sometimes there may occur uneven illumination due to shadow or direction of illumination. At that period of time, a single threshold did not work well. Local threshold is performed by partitioning the image into m×m sub image. After splitting it into sub image,select a threshold from the sub image. Local threshold works well in large input image. It is simple to perform and it is fast.

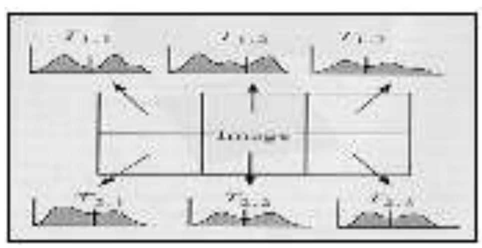


Fig 5: Sub image of an image

Threshold function T(x,y) is given by,

$$g(x,y) = \begin{cases} 0\ if\ f(x,y) < T(x,y) \\ 1\ if\ f(x,y) > T(x,y) \end{cases} \quad (3)$$

Where T(x, y) = f(x, y) + T

Adaptive threshold:

In adaptive method, a threshold is computed for each pixel in the image. If the pixel value is under the threshold it is set to the background value or otherwise it assumes the foreground value. Adaptive threshold is not chosen because of the following reason, it is computationally expensive and it did not work well in real time application. So in this proposed work, modified adaptive thresholding technique is used. It works as follows,

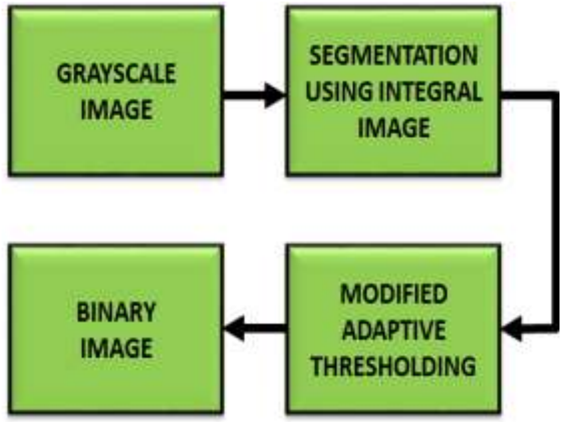


Fig 6: Block diagram of adaptive thresholding

Feature extraction using GLCM:

GLCM and associated texture feature computation are performed for the analysis of image. After quantizing the image into 256 samples by applying threshold based technique, Feature extraction is performed.It provides useful information about the texture of an image but it does not provide the spatial relationships of pixels in an image. It characterizes the texture of an image by computing how often pairs of pixel with specific values. It initially scales the input image which is composed of pixels. Each contains with intensity and it reduces the number of intensity values in gray scale image from 256 to 8. The number of gray level helps to determine the size of GLCM.

Algorithm:

(1) Quantize the data, the specimen that is taken is treated as a single image pixel and the value of the specimen is an intensity of that pixel.

(2) (i) Create the GLCM in a form of square matrix of $N\times N$.

(ii) Make the GLCM symmetric.

(a) Make a transposed copy of the GLCM.

(b) Add this copy to the GLCM itself.

(iii) Normalize the GLCM.

(a) Split each element by the sum of all elements.

(b) The elements of the GLCM are considered as probabilities of finding the relationship i, j in window size W.

(3) Compute the selected feature. It computes by using the values in the GLCM. These four features help for determination.

Energy:

It is also said to be uniformity or angular second moment. It creates the sum of squared elements in the GLCM. It computed as follows,

$$\text{Energy}= \sum_{i,j=0}^{N-1}(P_{ij})^2 \quad (4)$$

Contrast:

In the gray level co-occurrence matrix, it measures the local variations.

$$\text{Contrast} =\sum_{i,j=0}^{N-1} p_{ij}\,(i-j)^2 \quad (5)$$

Correlation:

It measures the joint probability occurrence of the specified pixel pairs.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} p_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (6)$$

Homogeneity:

It measures the closeness of the distribution of elements in the GLCM

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{p_{ij}}{1+(1-j)^2} \quad (7)$$

Where, p_{ij}denotes the element i, j,

N represents the number of levels. To estimate the intensity of all pixels in the relationship is computed by using the equation,

$$\mu = \sum_{i,j=0}^{N-1} i p_{ij} \qquad (8)$$

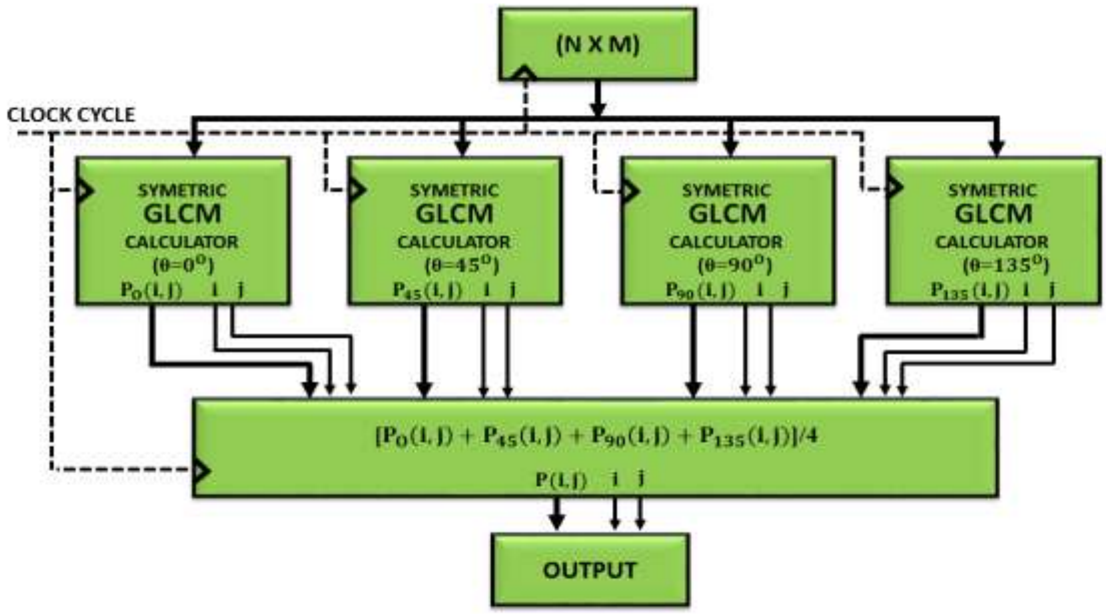


Fig 7: Working of GLCM

Feature optimization by ANN:

In a wide range of problem domain, ANN is an effective technique to solve the complicated problem. ANN has been used in optimizing the feature to predict a correlation between acquired input and output data. The feature is processed and made suitable for training. The acquired output data are normalized between the minimum and maximum value to obtain the value with the range of 0 to 1. The network is trained iteratively till the error between the actual and predicted value is minimized for all pattern pairs. While perform testing, a set of data is deployed and the output of the model is predicted. The output should generate an exact replica with minimum error.

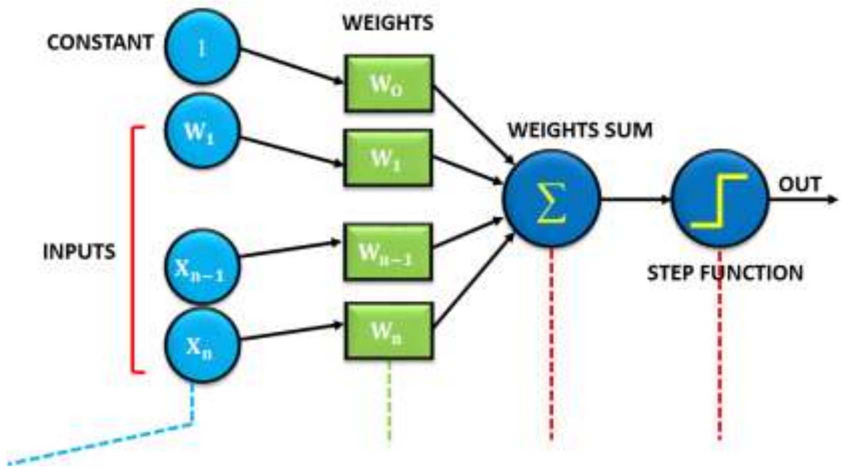


Fig 8: Structure of feature optimization

CNN Classifier:

For the purpose of image recognition and classification, this algorithm is used. It is also said to be convNet. It is a feed forward neural network generally used to analyze visual image by preprocessing data with grid like topology.

Layers in convolutional Neural Network is represented as follows,

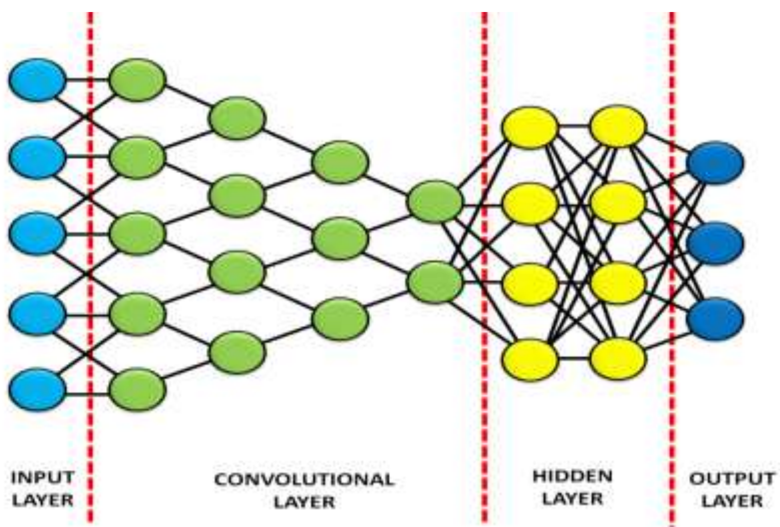


Fig 9:Layers in convolutional neural network

Input layer: Input layer accepts the pixels of the image as input in the form of arrays.

Convolution layer: Convolution layer is the building block of a CNN. It consists of a set of filters which has a small receptive field but it extends through the entire volume of the input. While performing forward pass, each filter gets convolved across the width and height of the input.To detect patterns in the image, this layer uses a matrix filter and performs convolution operation.

Convolution operation is computed as follows,

$$(f * g) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \qquad (9)$$

Hidden layer:Hidden layer carry out feature extraction by performing certain computations and manipulation. In hidden layer, multiple hidden layers like ReLu layer and pooling layer is performed.

ReLU layer: Its main function is to remove negative values from the activation map by setting them to 0. ReLU is chosen because it trains the neural network several times faster without a significant penalty.

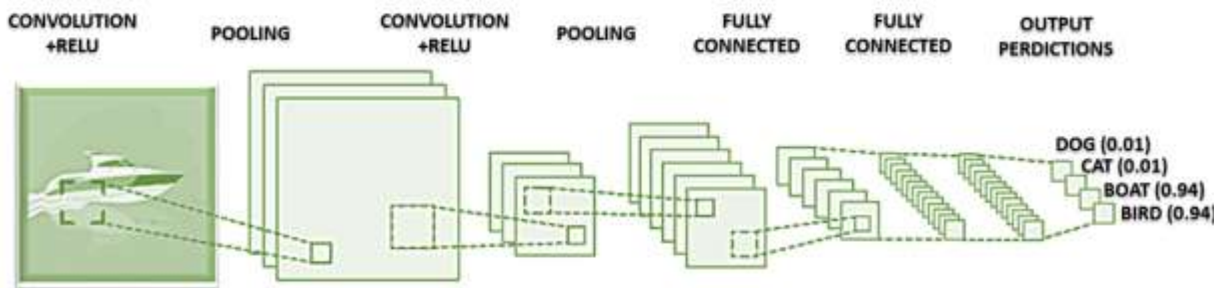


Fig 10: Working of convolutional Neural Network

Pooling layer:Pooling layer utilizes multiple filters to detect edges and corners. The rectified feature map goes through a pooling layer. Its main role is to reduce the dimensionality of the feature map.

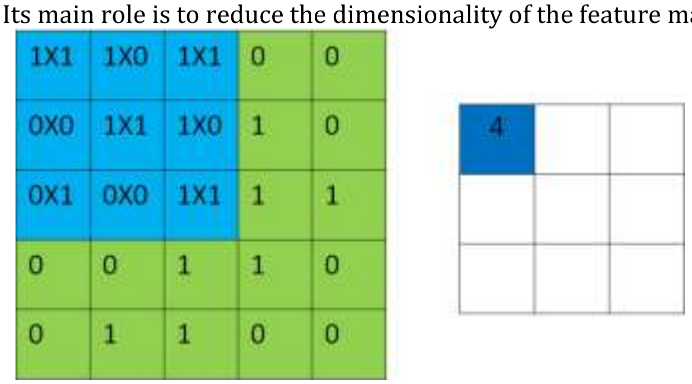


Fig 11: Input feature map Output feature map

Fully connected layer: The filtered matrix which is obtained from pooling layer is fed as input to the fully connected layer to classify the image. It analogizes the test data with trained set and it produces the high accurate result. The fully connected layer generates an output.

III. RESULTS & DISCUSSION:

The specimen of UWB planar images shown in figure 12 and 13 were taken for analysis. The image which was taken undergoes preprocessing and generates a good quality image for post processing technique.

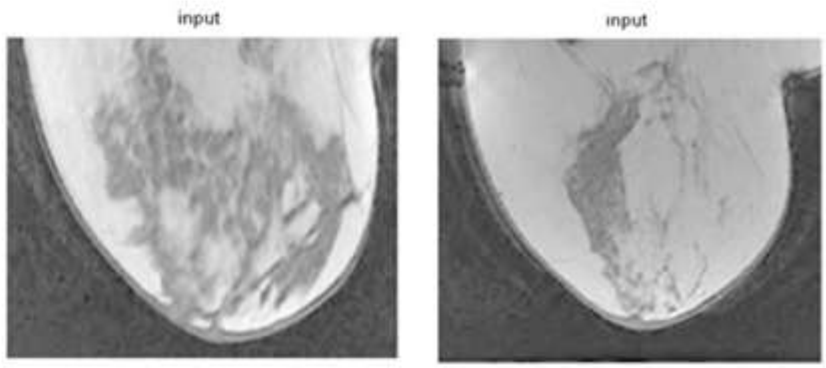


Fig 12. Input images taken for proposed analysis

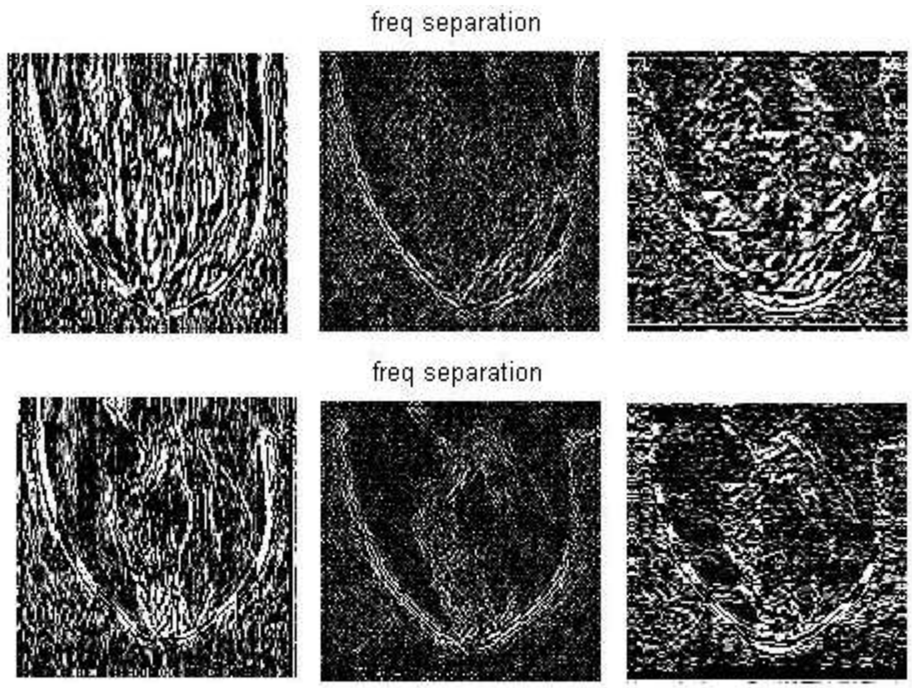


Fig 13. Noise separation from the input images

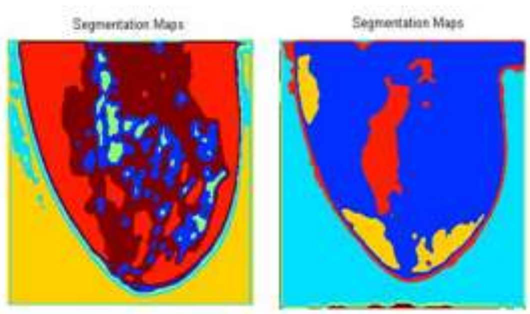


Fig 14. Segmentation mapping

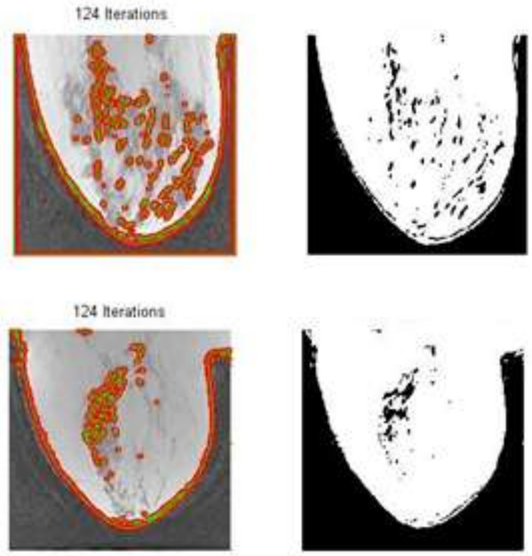
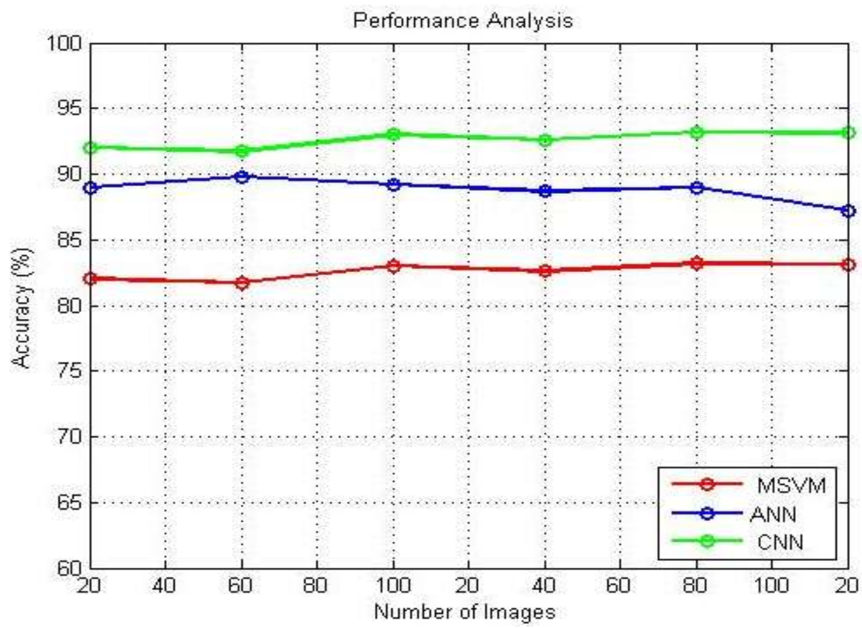
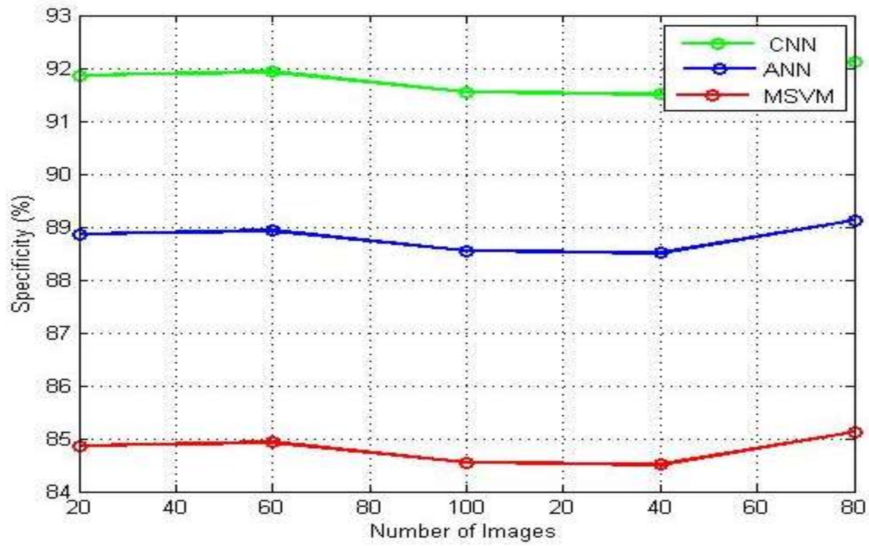


Fig 15. Classification result

The accuracy comparison of proposed CNN method is compared against ANN and SVM proves that the performance of our method better which is revealed from the above results.



The true negative rate is used to identify negative result of the patients (patient who does not have tumor) which eliminates unnecessary test and treatment of normal women. Higher rate of specificity is also essential to measure the performance of classifier. Comparatively our proposed method has higher value of specificity.



The ability of a system that can accurately detect patients who have tumor is defined as true positive rate or sensitivity.

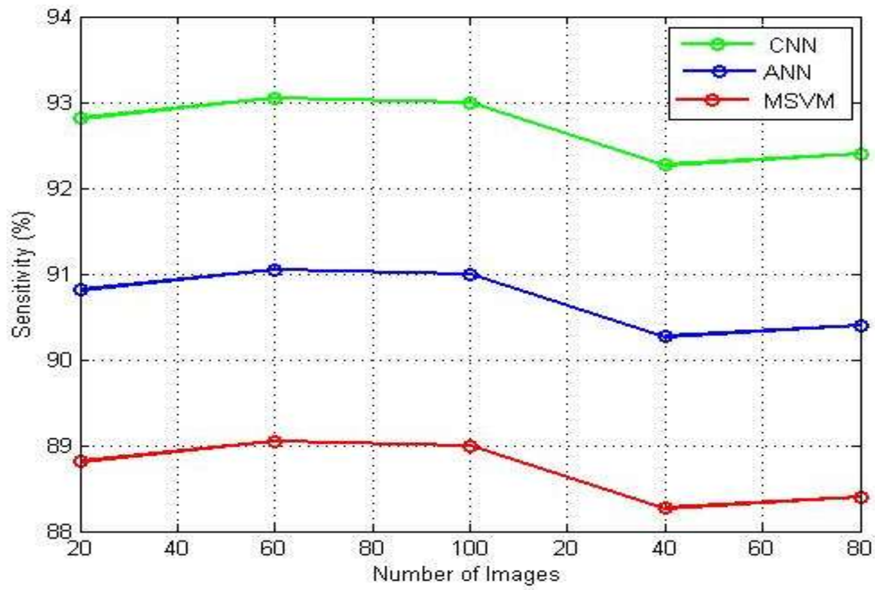


Fig 16. Accuracy, Specificity and Sensitivity comparison of Classifiers

The proposed segmentation algorithm outperforms the existing RAR algorithm in terms of energy, entropy, contrast, correlation and homogeneity.

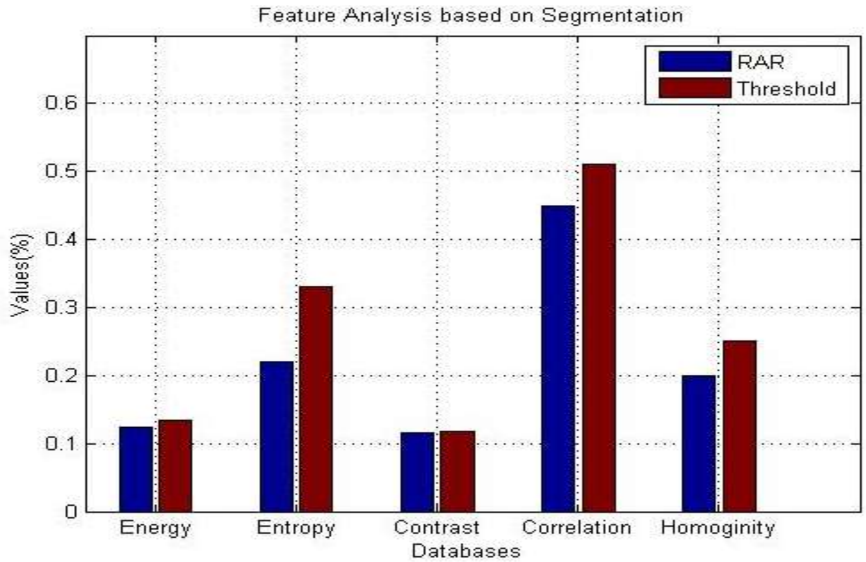


Fig 17. Comparison of proposed segmentation with RAR

IV. CONCLUSION:

To reduce the death rate of cancer affected person, two aspects needed to be concerned early and accurate detection of breast cancer and risk reduction. In this proposed work, detection of breast cancer based on UWB antenna image and to generate an expected resultby using deep neural network. A specimen of 100 images was taken. 80% of the data is taken for training and 20% of the data is used for testing. By using CNN classifier, analogization is performed between the trained and test set data and it achieved an accuracy of 94%. To prove its effectiveness, it is compared with other existing works, high accuracy is achieved and it is facile to perform.

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