Advanced Segmentation Algorithm for Cancer Detection in MRI and Mammography Image

Parvathy.S.Kumar
M.TechStudent,Dept. of ECE
Mohandas College of Engineering, Kerala University
Trivandrum-695541, Kerala, India
Email: sasikumarparvathy@gmail.com

Nissa Surling
Asst.Professor,Dept. of ECE,
Mohandas College of Engineering,
KeralaUniversity, Trivandrum-695541,
Kerala, India , Email: nissa_surling@gmail.com

Abstract—**Breast cancer detection remains a subject of intense and ,at times, passionate debate. Mammography and MRI are being the mainstay of the cancer detection of breast and these are the two major screening test proven to reduce mortality.Computer-aided diagnosis(CAD) systems have the potential to assist radiologists in the early detection of cancer. Many techniques were introduced based on SVM classifier, spatial and frequency domain, active contour method, k-NN clustering method but these methods have so many disadvantages on the SNR ratio, efficiency etc. The quality of detection of cancer cells is dependent with the segmentation of the mammography image. Here a new method is proposed for segmentation. This algorithm focuses to segment the image depth wise. Here the identification of malignant and benign cells are done more easily and also to increase the efficiency of the mammogram images. In which the relative signal enhancement technique is also done for high dynamic range images. Markovian random process is been used in the depth segmentation. This algorithm is also based on coloured segmentation. Done with both the MRI and mammogram images..Done with both the MRI and mammogram images. An efficiency of 96.8 percentage is obtained based on size of the tumor the stage of the cancer growth can be calculated.**

Index Terms—***Mammogram; MRI; CAD; k-NN clustering; malignant; benign; Markovian Random Field;***
.

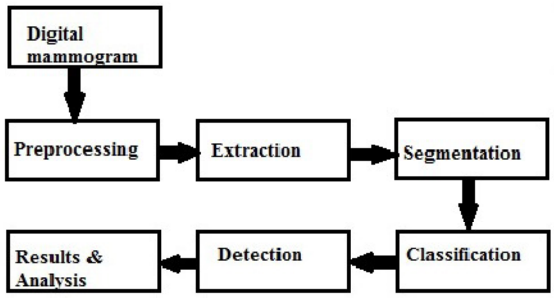
I. Introduction

Cancer is a continual multiplying of cells abnormally. The cells divide uncontrollably and will grow into adjacent tissue or unfold to distant parts of the body. Carcinoma is a number one reason for cancer deaths among women in many parts of the world. Breast cancer continues to be the foremost common diagnosed cancer among women in US. In the United States, every year, approximately, 182,000 new cases of breast cancer are diagnosed and more than 46,000 women die of it Since the causes of breast cancer still remain unknown, early detection is the key to control the breast cancer . Nowadays, mammography is considered to be the most reliable imaging modality for an early detection of breast carcinomas. If the tumor is detected at an early stage, the chances of successful treatment as well as patient survival rate will increases considerably. A mammogram is essentially distinct with four levels of the intensities such as background, breast parenchyma, fat tissue and calcifications with increasing intensity. Masses develop from the epithelial and connective tissues of breasts and their densities on mammograms blend with parenchyma patterns. Presently digital mammography is the most efficient and widely used technology for early carcinoma detection. The key diagnosing elements like masses, lesions in the digital mammograms are noisy and of very low contrast. An efficient segmentation approach to detect the early disease detection of breast cancer by enhancing the images of tumor. Most of the limitations of conventional mammography can be overcome by using digital image processing. Thus, in order to improve the correct diagnosis rate of cancer the image enhancement techniques are widely used to enhance the mammogram and assist radiologists in detecting it. Some of the efficient enhancement algorithm of digital mammograms based on wavelet analysis and modified mathematical morphology.

Adopt wavelet-based level dependent thresholding algorithm and modified mathematical morphology algorithm to increase the contrast in mammograms to ease extraction of suspicious regions known as regions of interest (ROIs) are used. Several segmentation techniques are used like the gradient vector flow snake (GVF Snake) with gradient map adjustment to obtain the accurate breast boundary from the rough breast boundary and an improved multi-scale morphological gradient watershed segmentation method for automatic detection of clusteredmicrocalcification in digitized mammograms. And in the case of breast the possibility to find these masses are not easy.Themostl commonly used methods of diagnosis are MRI and mammogram images.Here by changing the contrast a radiologist can easily identify the tumour in mammogram images while in the case of MRI this is done by giving gadolinium which is a reagent given as an injection to the patient.So that a contrast image can be taken.In this paper a approach is taken into consideration by a preprocessing follwed by a segmentation in which a color based segmentation is done by using the markovian random field and function as the major part of segmenting parameter.And finally the classification to find the detection part whether the mass or tumour is malignant or benign.And the analysis of the accuracy and performance based on the graph.

II. PROPOSED METHOD

With increasing use of Computed topography (CT) and Magnetic resonance (MRI) imaging for diagnosing, treatment and clinical uses, it has become nearly mandatory to use computers to help radiological experts in clinical diagnosis, treatment coming up with. Reliable algorithms are required for the delineation of anatomical structures and other regions of interest (ROI).The techniques obtainable for segmentation of medical images are specific to applications, imaging modality and kind of body part to be studied. For example necessities of brain segmentation are different from those of thorax. The proposed method is based on a segmentation technique in MRI images as well as high dynamic range MRI images mainly focused on the breast cancer detection. and also for the detection of benign and as well as malignant tumors. Usually the segmentation based on the lesions are done before the analysis and enhancement so here propose a technique based on the depth segmentation and then detect the carcinoma tumor in the mammography images.

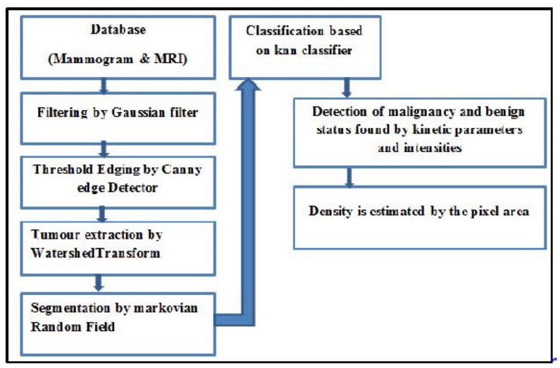


And this can be proposed based on the markovian depth segmentation and then finally enhanced, which is nothing but the denoising of unwanted speckles and noises. The artifacts,that have an effect on the brain image,can be affected in the case of breast images also.So an efficient denoising method can also be done.

A. Methodology

As the method deals with the basic process steps of the image processing the techniques used for this is different which deals with the detection of depth,densityetc of the tumor area in breast area.

MATLAB:Platform



1) Preprocessing: The input images are mammography images. These images were detaily investigated and labeled by an experts based on technical expertise and diagnostic test. The database is chosen as a result for different cases.The database consists of 30 images each of 40 patients of right and left breast wherever 20 were diagnosed as malignant, 8 as benign and 12 as normal. The abnormalities are classified as micro-calcification, mass, architectural distortion, circumscribed mass and asymmetry .In this study about322 mammogram images were chosen. The original mammograms are 409x700pixels, and almost 50% of the image comprised of the background with a lot of noise. Within the planned CAD system, micro-calcifications aren't thought-about; solely circumscribed mass, speculatedmass, architectural distortion, ill-defined

mass, and imbalances are thought of. The preprocessing part of digital mammograms refers to the sweetening of mammograms intensity and distinction manipulation, effect of noise reduction, unwanted background removal, edge sharpening and filtering. Filtering is often used to reduce noise within an image or to produce a less pixelated image. Image Filtering is a key technology of image enhancement, which can remove noise in images. Excellent Filtering algorithm can both remove various noises and preserve details. In the proposed system Discrete Wavelet Transform Technique is used for image Filtering. These algorithms have the ability of preserving details.And in this method the Sobel smoothing and Gaussian filtering is done. For mammogram images Sobel operator gives a best output and has the maximum noise reduction ratio.Along with this the Gaussian filter is again treated to obtain a higher efficiency.The mathematical equation for the smoothing and filtering functions are: Since the Sobel kernels can be decomposed as the products of an averaging and a differentiation kernel, they compute the gradient with smoothing. For example,$G_x$as the x-coordinate is defined here as increasing in the ”right”-direction, and the y-coordinate is defined as increasing in the ”down”-direction. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using

2) Feature Extraction: Here the main portion or region of interest is been detected for further process and are done based on the thresholding .This method is done to find the actual area of tumorspreadedthroughout the breast lesionsare done by selecting the region.For this the Thresholding parameter of operation is varied manually as a trial and error method.Normal and simple method that is canny edge detection is done to find the edge features so that the outline of the tumor is obtained and through which the area of spreading of fibro-glandular is detected.Noise Reduction:Since edge detection is susceptible to noise in the image, first step is to remove the noise in the image with a 5x5 Gaussian filter. Finding Intensity Gradient of the Image:Smoothened image is then filtered with a Sobel kernel in both horizontal and vertical direction to get first derivative in horizontal direction (G_x) and vertical direction (G_y). From these two images, we can find edge gradient and direction for each pixel as follows:

Edge gradient(G)=$\sqrt{G_x^2+G_y^2}$ (1)

Minu$\{G(u,f) = Tv(u) + \frac{\lambda}{2}||u - f||_2^2\}$ (2)

Gradient direction is always perpendicular to edges. It is rounded to one of four angles representing vertical, horizontal and two diagonal directions. Non-maximum Suppression:After getting gradient magnitude and direction, a full scan of image is done to remove any unwanted pixels which may not constitute the edge. For this, at every pixel, pixel is checked if it is a local maximum in its neighborhood in the direction of gradient. Hysteresis Thresholding: Any edges with intensity gradient more than maxVal are sure to be edges and those below minVal are sure to be non-edges, so discarded. Those who lie between these two thresholds are classified edges or non-edges based on their connectivity. If they are connected to ”sure-edge”’ pixels, they are considered to be part of edges. Otherwise, they are also discarded.

Edge Gradient (G) = $|G_x| + |G_y|$ (3)

That is based on the canny edge detection method to sharpen the edges. And Sobel operator is also applied as a part of preprocessing techniques

.

3) Watershed transform for segmentation: The most commonly used method of segmentation for the mammogram and MRI.So a brief idea of this method is been illustrated.Performing on an image , the system is usually applied on its gradient image. In this case, each object is distinguished from the background by its up-lifted edges.M1;M2; ;MRas the sets of the coordinates of the points in the regional minima of an (gradient) image g(x; y), and C(Mi) as the
coordinates of the points in the catchment basin associated with regional minimum Mi.The minimum and maximum graylevels of g(x; y) are denoted as min and max Denote T[n] as m the set of coordinates (s; t) for whichg(s; t) < n. Flood the topography in integer flood increments from n = min + 1 to n = max + 1 .At each flooding, the topography is viewed as a binary image.Denotes Cn(Mi) as the set of coordinates of points in the catchment basin associated with minimum $M_i$at flooding stage n.

$C_n(M_i) = C(M_i) \cap T[n]$

$C_n(M_i) = \subsetneq T[n]$

C[n]is defined as the union of flooded catchment basin portions at stagen.

C[n] =$\cup_{C=1}^{R} C_n(Mi)$
And

$C[\max + 1] = \cup_{i=1}^{R} C(M_i)$

Let C[min + 1] = T[min + 1].
At each step n, assume C[n -1] has been constructed. The goal is to obtain C[n]from C[n1].Denote Q[n] as the set of connected components in T[n]. For each q ∈Q[n], there are three possibilities:

(1) q∈C[n-1] is empty (q1) A new minimum is encountered as the q is incorporated into C[n-1]to form C[n].
(2) q∈C[n-1] contains one connected component of C[n-1](q2). q is incorporated into C[n-1] to form C[n].
(3) q∈C[n-1] contains more than one connected components of C[n -1](q3).

A ridge separating two or more catchment basins has been encountered. A dam has to be built within q to prevent overflow between the catchment basins Repeat the procedure until n=max+1.Final equation that is used as the watershed transform is

$$W_{shed}(f)=D\cap(\cup_{i=1} C_B(Mi))^2$$

The steps involved in watershed segmentation are :
_ Gradient magnitude of image is detected and watershed m transform is applied.
_ Opening-closing by reconstruction of the image is determined.
_ Regional maxima of opening and closing by reconstruction.
_ Thresholding is done.
_ Object boundaries are marked. Colored watershed label matrix is obtained through which the tumor is segmented from the input image. Wherever Times is specified, appearance to Times. Avoid using bit-mapped fonts if possible. True-Type 1 or Open Type fonts are preferred. Please embed symbol fonts, as well, for math, etc.

4) Kinetic Parameters and kinetic Intensity: For thediagnosis of cancer stage in mammography images could lead to effective treatment. Morphological features and kinetic parameters were evaluated to predict the case of malignancy and benign the foremost regular kinetic, morphological and kinetic patterns on the mammogram and MRI images of breast carcinoma are not easily predicted. Database appeared most frequently as non-mass- like lesions (12 lesions, 52.17%). The difference in the frequency of lesion types was technically done by significant of their kinetic morphology. The morphological patterns were detected and morphologic features,Fibro-glandular mass-like enhancement, segmental enhancement, segmental enhancement in different shapes based on the regular patterns of the mass or tumor. There was no significant difference in the frequency of morpho-kinetic patterns. The objective was to analyze the morphological parameters and kinetic features of images in the database to define the most frequent morphologic and kinetic pattern.We obtain a graph that shows the kinetic parameters based on position and intensity of the mass region. The diagnosis based on the intensity is also made so that the exact mass lesion is identified for further treatment. The risk of malignancy depends on the kinetic pattern, ranging from 6% in type I and 64% in type II to 87% in type III . Rapid uptake is most frequently related to DCIS within the initial section, whereas all 3 sorts of curves are seen within the delayed section, of that the image segmentation mentioned here will be graded on the idea of pertinence, suitableness, performance, and process computational cost. Segmentation techniques supported grey level techniques like thresholding, and region based mostly techniques are the only techniques and notice restricted applications.

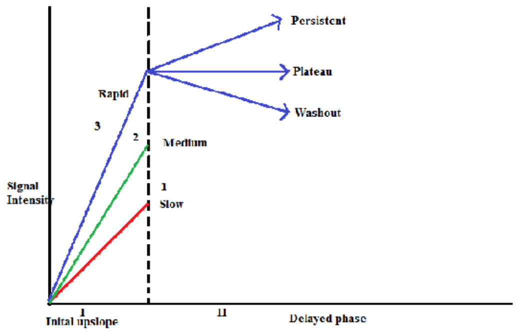


Fig. 1. Kinetic parameter based on intensity criteria response

B. Markovian Random Function and Markovian RandomField
Markov random fields (MRFs) have been widely generated in the field of image processing is for computer vision problems, like image segmentation [10], surface reconstruction [6] and depth inference [5]. As this a understanble and easy algorithm to implement makes this a efficient algorithm.Different steps of the algorithm are Convert the image to 2D gray-level, finding the intensities based on the Gaussian distributions and segments are labeled,
EM-Algorithm:Used to find the parameter set,
MAP-Estimation:Used for finding the sum of energy function and to minimize the energy value. The difference between MRF and HMRF is that, in

HMRF, the parameter set is affected in an unsupervised manner. In a HMRF image segmentation bugs are formed, there is no training set, and assumption for no prior knowledge is known about the foreground/background intensity distribution. Thus, a natural proposal for solving a HMRF problem is to use the EM algorithm, where parameter set _and label configuration X are learned alternatively. It is a mathematically simple model and can be computed efficiently. This method only uses the intensity parameter for segmentation.

1) Intensities based on the Gaussian distributions: In MRF based problems are usually done with the parameter set $\theta = \theta_l | l \in L$ from the training data. For example,in image segmentation problems, prior knowledge of the intensity distributions of the foreground and the background might be consistent within a dataset, especially domain specific dataset. Thus, we can learn the parameters from some images that are manually labeled, and use these parameters to run the MRF to segment the other images.

Y = $(y_1,\ldots..y_N)$ is the image ,where $y_i$is the gray-level intensities. Each part is considered as labels

X = $(x_1\ldots\ldots x_N)$,where x_i ∈ L According to the

MAP-criterion: X_ = argmax P(Y |X,θ)P(X),where P(X) is the distribution and $X^*$is the label configuration.

P(yi|xi)- Gaussian distribution.θ_{xi}-parameter of Gaussian distribution, where

θ_{xi}= (μi,σi)

θ(Parameter set) = ($\theta_l | l\epsilon L$) by this the parameters Are found.

P(Y |X,θ) = ΠiP(yi|xi; θxi)

2) EM Algorithm: Here the steps of this algorithm is Practiced for detecting the parameter set and which based on the algorithm steps illustrated below.Before that this algorithm consists of E-step and M-step.Where E-step is based on the iterations and M-step is based on the maximizing of the energy functions.

– Start with initial parameter set $\theta_{(0)}$.
– Calculate the likelihood P(t)(yi|xi;θxi).
– Using current parameter set $\theta_{(t)}$ to estimate the labels.
– $X_{(t)}$ = argmax $_{x\epsilon x}$P(Y |X,$\theta_{(t)}$)P(X)
= argmin$_{X\epsilon x}$U(Y |X,$\theta_{(t)}$) + U(X)
– U(X)-Prior energy function.
– Calculate the distributions for all labels for all y_i pixels.
– $P_{(t)}(y_i) = \sum_{l\epsilon L}$G(yi,$\theta_l$)P(l|$x_{(t)N(i)}$)
– where
– Use $P_{(t)}$(l|y_i) to update.

$$\frac{\sum_l P(t)(l|y_i)y_i}{\sum_i P(t)(l|y_i)} = \mu_l^{t+1}$$

$$(\sigma_l^{t+1})^2 = \frac{\sum_i P(t)(l|y_i)(y_i-\mu_l^{t+1})}{\sum_i P(t)(l|y_i)}$$

These are steps of the m-file type algorithm called EMalgorithm.Based on which the dataset _ is calculated andthe region of interest is detected.

3) MAP Estimation: This estimation is done for the Detection of the prior energy function and also which isused for the final step of the algorithm.This is based on the neighborhood pixel comparison just like in the case of the median filter.

– To start with initial estimate $X_{(0)}$ from EM algorithm.
– Provided $X_{(k)}$,for all 1≤i < N ,x_i^{k+1}=1
$argmin_{l\in L} U_{(y_i|l)} + \sum_{j\in Ni} V_c(1,x_j^k)$

– Repeat from the second step until U(Y |X ,θ)+U(X) stops changing significantly or a maximum k is achieved.

4) GMM-Based HMRF: Gaussian mixture model (GMM) made to make a powerful enhancement modelingthe complex distributions than one single Gaussian distribution.A Gaussian mixture model with g componentscan be represented by parameters:

θ_l= (μ_l,1,σ_l,1,ω_l, 1)…….(μ_l, g,σ_l, g,ω_l, g)
comparing.
_G_{min}(Z; θ_l) = $\sum_{c=1}^{g} \omega_l$,c
G(Z;$\mu_l, c, \sigma_{l,c}$) the M-step ofthe EM-algorithm the changes to a Gaussian mixturemodel fixes a problem. The GMM fitting problem itselfcan be also solved using an EM-algorithm. In the Estep,we determine which data should belong to whichGaussian component; in the M-step, we re-compute theGMM parameters.

C. Parameters used in Database

– T1:Based on the longitudinal movement of protons.
– T2:Based on the transverse movement of protons.
– PD(Proton Density):based on the density of the protonthat hits the surface.
– Gradient Echo:Based on the gradient field to produce transverse movement in protons.

D. Density Estimation

This is done for the condition to detect and classify the fatty and watery regions of the breast anatomy and which deals with the simple path of the volume detection.

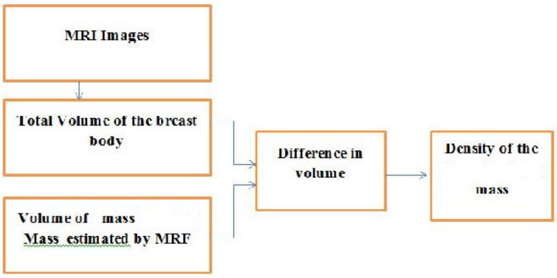


Fig. 2.Density Estimation

III. RESULTS AND DISCUSSIONS

Here it is seen that the extracted tumor based on the watershed segmentation in which the image that showingthe regional maxima is then implemented based onthe kinetic parameter as it is plotted with the positiongives that the tumor part shows a increase in washoutparameters.

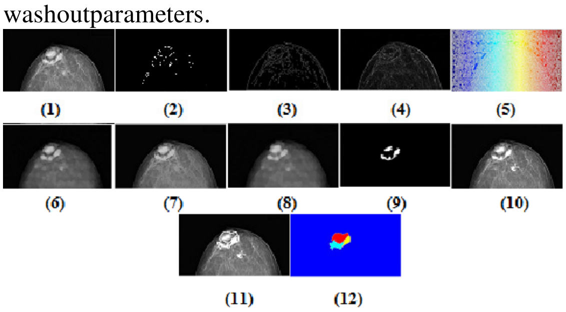


Fig. 3. (1)Input image(2)Edged by Canny(3) Edged Image(4)Gradient-magnitude(5)Watershed-Transform Gradient(6)Opening,Operator(7)Openingby reconstruction(8)Closing(9)Regional maxima of opening -closing by reconstruction(10)Regional maxima superimposed in input image(11)Markers andboundaries superimposed in input image(12)Colored watershed label matrix.

The above response deals with a graph showing the efficiency of specificity,accuracy and sensitivity ofthe work based on the different parameter of MRI.

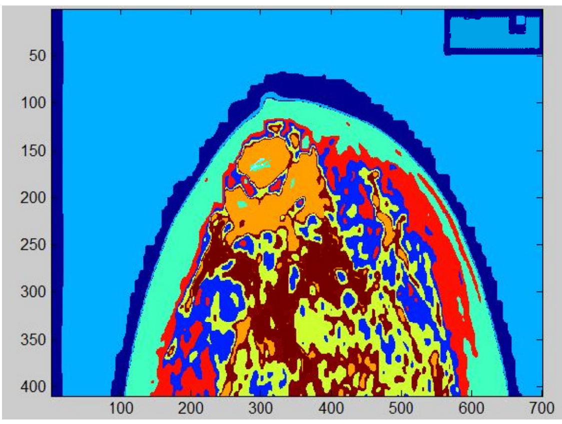


Fig. 4. Markovian based segmentation result

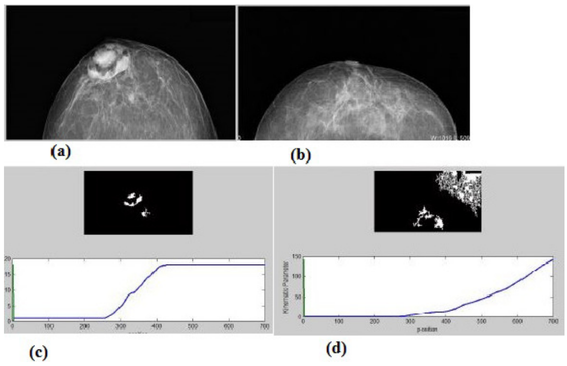


Fig. 5.Malignant and benign detection by kinetic morphology.

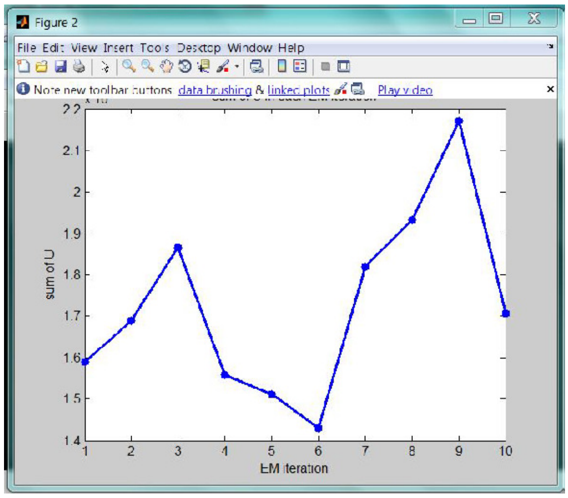
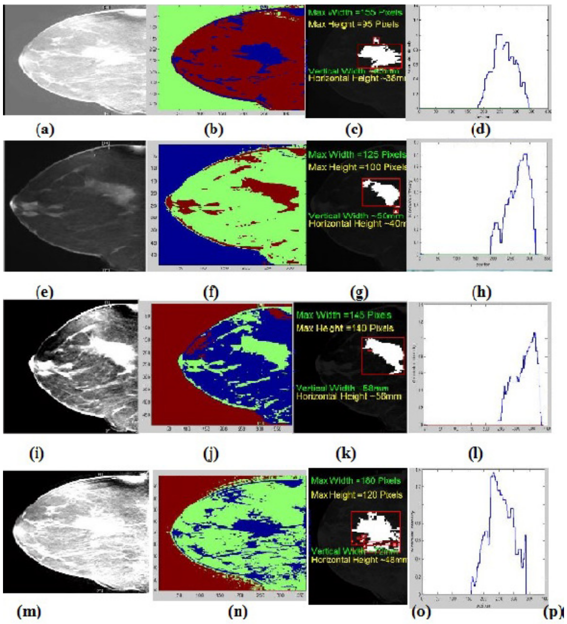


Fig. 6. Response Showing the sum of energy vs iteration



(a)(b)(c)(d)are the output of T1-MRI,(e)(f)(g)(h) are theoutput of T2-MRI,(i)(j)(k)(l) are the output of PD-MRI,(m)(n)(o)(p) are the output of Gradient-MRI

Comparison of Results	
Method	Accuracy (%)
Proposed Method	96.98
Discriminant Analysis	87.11
ANN	95.45
Decision Tree	92.89
Logistic Regression	93.78
SVM	95.79
KNN	94.78

Fig. 7. Comparison on proposed method

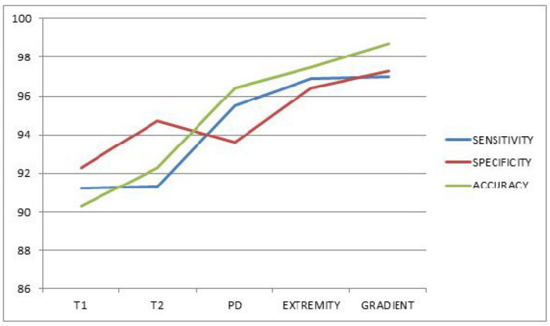


Fig. 8. Efficiency Analysis

IV. CONCLUSION

A general introduction of the potential and challenges of breast carcinoma detection was given. With digital imaging taking part in an progressively outstanding rolewithin the diagnosis and treatment of diseases, the matterof extracting clinically useful data has become vital.For instance, mammography facilitates to outline thecharacter and extent of diseases, aiding the diagnosisand treatment. Therefore, segmentation of those featuresbecomes a key challenge for correct analysis, visualization and quantitative comparison. This has been themost focus of this treatise, i.e., segmentation of normaland abnormal features. From each range and varietyof algorithms used for carcinoma detection it had beenclear that there's no gold customary that solves entiredownside. It's been dedicated to the preprocessing andoutline of mammogram databases wont to appraise the Strategies.a number of the pictures were discarded bydoctors before the identification. However such pictureswere images within the database to ascertain the enclosedof the developed system. Images that suffered from non-uniform illumination and poor contrast were subjected topreprocessing before they are subjected to segmentation. This algorithm focuses to segment the image depth wise.Here the identification of malignant and benign cells isdone more easily and also to increase the efficiency of the mammogram images.A k-mean clustering in a modifiedway is also called markovian function method. In which

Sl.No	T1	T2	PD	Extremity	Gradient	Density
Patient-1	6.2195	2.6641	4.098	9.7796	9.997	6.5254
Patient-2	8.1581	3.903	5.755	12.7588	14.265	9.004
Patient-3	10.5266	2.299	7.3632	12.7875	17.9177	9.9543

Fig. 9.Density Estimation of three different patients.

the relative signal enhancement technique is also done forhigh dynamic range images. Markovian random functioncan be used in the depth segmentation. For every imagewithin the database the region of interest is well defined.Thus validation prevents over fitting and goes how tomake sure the relevance of the results to a wider set ofimages.As a future work the density can be calculatedbased on the sternum as the center,relatively removingthe fatty masses and unwanted lesions of regions areremoved and the density of the fibro-glandular mass canbe obtained

.

ACKNOWLEDGMENT

I would also like to extend my whole hearted gratitudeto the HOD of the Electronics and Communication DepartmentDr. R.Ibrahimkutty, PG Coordinator Prof. AjithChandran M.C. who was always ready to help me withideas and suggestions for rectifying the mistakes thatcrept up from time to time during the completion this venture. I also extend my whole hearted gratitudeto my guide Nissa Surling who was always ready tohelp me with ideas and helped me a lot in rectifying themistakes' would also like to thank my friends and lastbut not the least the staff of ECE department for theirwhole hearted support and encouragement.The authors would like to thank... more thanks here.

REFERENCES

[1] Bram Platel, RoelMus, Tessa Welte, NicoKarssemeijer, and RitseMann"Automated Characterization of Breast Lesions Imaged Withan Ultrafast DCE-MR Protocol",IEEE Transactions on MedicalImaging, Vol. 33, NO. 2, February 2014.

[2] Arpana M.A, PrathibaKiran"Feature Extraction Values for DigitalMammograms "International Journal of Soft Computing andEngineering (IJSCE) ISSN: 2231-2307, Volume-4, Issue-2, May2014.

[3] Yiping Liu, Hui Liu, Zuowei Zhao, Lina Zhang, Xiang Liu,"A NewActive Contour Model-Based Segmentation Approach for AccurateExtraction of the Lesion from Breast DCE-MRI "Department ofBiomedical Engineering, Dalian University of Technology, 116024,China 2013 IEEE.

[4] Vishnukumar K. Patel, Prof. Syed Uvaid, Prof. A. C.Suthar"Mammogram of Breast Cancer Detection Based UsingImage Enhancement Algorithm "International Journal of Emerging
Technology and Advanced Engineering,ISSN 2250-2459, Volume 2, Issue 8, August 2012.

[5] Pradeep N, IEEE Member "Segmentation and Feature Extractionof Tumors from Digital Mammograms",Computer Engineering andIntelligent Systems www.iiste.org ISSN 2222-1719 (Paper) ISSN2222-2863, Vol 3, No.4, 2012.

[6] Zaheeruddin , Z. A. Jaffery and LaxmanSingh"Detection and Shape Feature Extraction of Breast Tumor in Mammograms "Proceedingsof the World Congress on Engineering 2012 Vol II WCE2012, July 4 - 6, 2012, London, U.K.

[7] Aarthi.R, Divya.K, Komala.N, Kavitha.S, Application of FeatureExtraction and Clustering in Mammogram Classification usingSupport Vector Machine, IEEE 978 1 4673 0671, 2011.

[8] Feng Zhao, Licheng Jiao, Spatial improved fuzzy cmeans clusteringfor image segmentation, International Conference on Electronic andMechanical Engineering and Information Technology, IEEE 2011,pp 4791-4794.

[9] Jacob Levman and Anne L. Martel"Computer-Aided Diagnosis ofBreast Cancer from Magnetic Resonance Imaging Examinations by Custom Radial Basis Function Vector Machine",32nd Annual International Conference of the IEEE EMBS Argentina, August 31 - September 4, 2010.

[10] Shyr-Shen Yu, Chung-Yen Tsai, Chen-Chung Liu, A breast regionextraction scheme for digital mammograms using gradient vectorflow snake, New Trends in Information Science and Service Science (NISS), 2010 4th International Conference , IEEE2010.

[11] Mohammad Sameti, RababKreidieh Ward, Jacqueline Morgan-Parkes, and BrankoPalcic,Image Feature Extraction in the LastScreening Mammograms Prior to Detection of Breast Cancer, IEEEJournal of selected topics in signal processing, VOL. 3,NO.1 FEBRUARY 2009.

[12] Laxman Singh, R. B. Dubey, Z. A. Jaffery, Z. Zaheeruddin, Segmentation and Characterization of Brain Tumor from MR Images, 2009 IEEE Int. Conf., Computer Society, 2009, pp. 815-819.

[13] S. H. Lee1, J. H. Kim1, K. G. Kim, J. S. Park, S. J. Park, W. K.Moon "Optimal Clustering of Kinetic Patterns on Malignant BreastLesions:Comparison between K-means Clustering and Three-timepointsMethod in DCE-MRI".29th Annual International Conferenceof the IEEE EMBS France August 23-26, 2007.

[14] PawaelTadejko, WaldemarRakowski, Mathematical morphologybased ECG feature extraction for the purpose of heartbeat classification,in proc. IEEE Int. Conf., Computer Society, 2007, pp.322-327.

[15] Jacob Scharcanski and Claudio Rosito Jung, 2006. Denoising and enhancing digital mammographic images for visual screening, Computerized Medical Imaging and Graphics 30, pp. 243254.

[16] item R.M. Rangayyan, L. Shen, Y. Shen, J.E.L. Desautels, H. Bryant, T.J. Terry, N. Horeczko and M.S. Rose, 1997.Improvementof sensitivity of breast cancer diagnosis with adaptive neighbourhoodcontrast enhancement of mammograms, IEEE Trans. Inform.Technol.Biomed. 1, pp. 161-170.

[17] M. Veta, A. Huisman, M.A. Viergever, P.J.Diest, J.P.W. Pluim,Marker Controlled Watershed Segmentation of Nuclei in HEStained Breast Cancer Biopsy Images,IEEE Int. Symposium on Biomed.Imag., 2011, pp. 618-621.

[18] A. Tsai, A. Yezzi, W. Wells, C. Tempany, D. Tucker, A. Fan, W.E.Grimson, A. Willsky, A shape-based approach to the segmentationof medical imagery using level sets, IEEE Trans. Med. Imaging 22(2) (2003) 137154.

[19] Nithya. K, Aruna.A, Anandakumar.H, Anuradha.B, "A SurveyOn Image Denoising Methodology On Mammogram Images";INTERNATIONAL JOURNAL OF SCIENTIFIC TECHNOLOGYRESEARCH VOLUME 3, ISSUE 11, NOVEMBER2014.

[20] Roopashree.S, SachinSaini, RohanRanjanSingh,"Enhancementand preprocessing of image using filtering," International Journalof Engineering and Advanced Technology (IJEAT), ISSN: 22498958, Volume-1, Issue-5, June 2012.

[21] A.M.Khuzi, R.Besar and W.M.D. Wan Zaki, Texture features selection for masses detection in digital mammogram, 4th Kuala Lumbur International Conference on Biomedical Engineering, proceedings,pp.629-632, 2008.

[22] A.MohdKhuzi, R.Besar, Wan Zaki and NN.Ahmad,Identificationof masses in digital mammogram using gray level cooccurrencesmatrices, Biomedical Imaging and Intervention Journal, 2009.

[23] IndraKantaMaitra, Sanjay Nag and Samir Kumar Bandyopadhyay,Identification of abnormal masses in digital mammography images,International Journal of Computer Graphics, Vol.2, No.1, 2011.

[24] J.Padmavathi, A comparative study on breast cancer predictionusing RBF and MLP, International Journal of Scientific and EngineeringResearch, Vol.2, Issue.1, 2011.

[25] JinchangRen, Dong Wang and Jianmin Jiang, Effective recognitionof MCCs in mammograms using an improved neural classifier,Engineering Applications of Artificial Intelligence, 24, pp.638-645,2011.

[26] AlirezaOsareh and BitaShadgar, A computer aided diagnosis system for breast cancer, International Journal of Computer ScienceIssues, Vol.8, Issue-2, 2011.

[27] L.Vincent and P.Soille, Watersheds in Digital Spaces: An EfficientAlgorithm based on Immersion Simulations, IEEE Trans. Patternand Machine Intell., vol.13, pp.583- 598, June 1991.

[28] Stephen S. Wilson, Theory of Matrix Morphology, IEEE Transactionson Pattern Analysis and Machine Intelligence, vol. 14, no.6,pp. 636-652, June 1992.