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BREAST CANCER SEGMENTATION AND CLASSIFICATION USING ADAPTIVE CLUSTERING TECHNIQUE

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ABSTRACT

Breast cancer has become the most common form of cancer diagnosed in women and is a leading cause for cancer death worldwide. Mammogram is the best and contemporary option for the early detection of breast cancer in women. Noise present in mammogram images has an adverse effect on image processing and analysis works. The primary objective of preprocessing stage is to improve the quality of mammogram image by removing the noise and unwanted portions present in the image so as to convert the image into some meaningful representation, thus making it easier to interpret the minute details present in an image. The proposed framework follows a step by step methodology such as (a) Image denoising (b) Image Enhancement (c) Segmentation of tumor portion using AMS MEM framework (d) Feature extraction (e) Classification. The noises present in the image were removed using various filtering methods and an automated scheme for segmentation is proposed. various feature were extracted and the classification is done using SVM classifier. The accuracy obtained in this proposed work was 98.13%.

Keywords- Breast cancer, Mammogram, Preprocessing, Segmentation, Feature extraction, Classification

I. INTRODUCTION

Breast cancer has become the common type of cancer affecting the woman nowadays. Cancer is the uncontrolled growth of cells in the breast region. It is the major cause of cancer death in women, after lung cancer. It has been estimated that New Female Breast Cancer Cases and Deaths by Age during 2015 was 1,658,370 new cancer cases diagnosed and 589,430 cancer deaths [15]. Detection and diagnosis of breast cancer at earlier stage can increase the chances for successful treatment and recovery of the patient. Among the various imaging modalities like Magnetic Resonance image (MRI), Ultrasound, Digital mammograms, Microwave imaging and Infrared Thermography, Digital mammography is found to be the most commonly used method for breast cancer detection. The mammogram images undergo various processes which includes preprocessing, image enhancement, tumor segmentation, feature extraction and finally classification. The captured images are usually subjected to various kinds of noises. The primary objective of preprocessing is to remove the irrelevant portions in an image and to enhance the image quality for further processes. In this paper, Adaptive median

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filter and Anisotropic diffusion filter [8] is used in image denoising to remove Salt and pepper noise and Gaussian noise respectively [12]. The denoising stage is followed by image enhancement which is performed using Mean adjustment and Histogram equalization methods. Image segmentation [10] is done using Adaptive Mean Shift Modified Expectation Maximization (AMS MEM) framework [2][4]. The various feature descriptors such as GLCM (Gray Level Co-occurrence Matrix), Discrete Wavelet Transform (DWT) and Framelet Feature Extraction is utilized. Finally the classification is performed using SVM classification algorithm. The design and implementation of the proposed framework is done using MATLAB [5][11].

II. RELATED WORK

Numerous algorithms have been proposed by various authors for Breast cancer segmentation and classification. Various denoising and image enhancement methods have been adopted for implementing this segmentation and classification procedure. All of these algorithms proved efficient and classification results. Few of them are discussed below; M.Sucharitha *et al* has developed an adaptive mean shift methodology to classify the brain voxels where the MRI image space is represented by a high-dimensional feature space called as space. The output of AMS consists of various modes. After pruning intensity based clustering techniques called k-means clustering algorithm is utilized to produce better results [4]. Blagojce Jankulovski *et al* has developed a techniques for automated mammography image classification process. Various feature extraction methods like LBP, GLDM, GLRLM, Haralick, Gabor filters were used. The images were classified using several machine learning algorithms like support vector machines, random forests and k-nearest neighbor classifier. The best results were obtained when the images were described using GLDM together with the support vector machines B.Monica Jenefer *et al* proposed an efficient method of segmentation and classification for mammogram images. The mammogram enhancement can be obtained by denoising the image and improving the quality of the image using speckle noise removal and EM algorithm. The well-known division technique used is Modified Watershed Segmentation method. The features are extracted from the segmented tumor region using GLCM and classification is performed using SVM classifier [12] Neeta V. Jog *et al* gave an efficient segmentation and classification technique for mammogram images. This paper utilizes GLDM, (Gray Level Difference Method), LBP (Local Binary Patterns), GLRLM (Grey level Run Length Method), Harralick, Gabor texture features extraction methods along and K-NN classification algorithms [10] Snehal A. Mane *et al* proposed a method of mammogram image segmentation and classification. It used weiner filter for image denoising .The image is segmented into smaller areas to capture the region of interest and feature extraction is performed using Gabor wavelet method. In the feature extraction phase each image is assigned with a feature vector to recognize it. These vectors are used to distinguish the image. Finally classification is done using SVM classifier. Bagwati charan patel *et al* developed a novel method for accomplishing mammographic feature analysis through the detection of tumor, in terms of their size and shape with experimental work for early breast tumor detection. By using preprocessing noise are remove and then segmentation is applied to detect the mass, post processing is applied to find out the benign and malignant tissue Size of tumor is also detected in these steps. The occurrences of cancer nodules are identified clearly

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Naishil N. Shah *et al* proposed an efficient method for early detection of breast tumor. Noise present in the mammogram images is removed using -median filtering and image enhancement is done using Histogram based region isolation shifting method .Segmentation is performed using morphological filtering. Linear & kernel based classifiers are used for classification. Although the existing system tends to provide efficient segmentation results, the accuracy obtained by these methods are low and can further be improved .The proposed framework provides more accurate segmentation and classification results compared to the existing work [11].

II. PROPOSED METHODOLOG

2.1 Digital Mammogram

Mammography is widely used an effective screening modality for tumor segmentation and classification. The proposed algorithm is to mainly separate the cancer portion from remaining healthy tissues and to evaluate the various performance metrics. The breast image with different levels of cancer cells are shown below in Figure1.The images are taken from MIAS database.

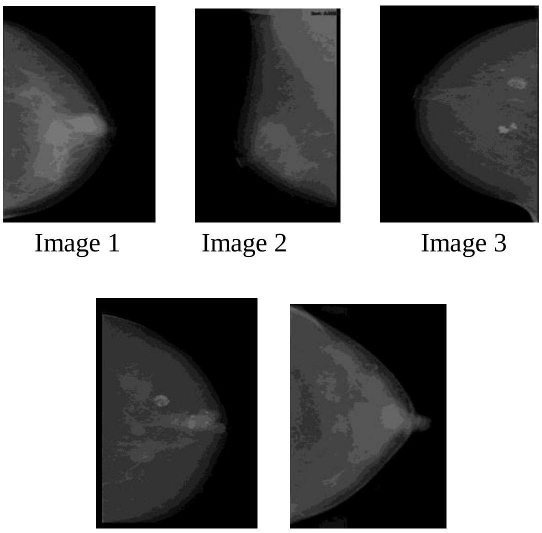

Image 1 Image 2 Image 3

Image 4 Image 5

Figure 1. Breast Mammogram images with cancer

The proposed techniques undergoes the following steps

1) Preprocessing
   a) Denoising
   b) Image enhancement
2) Segmentation
3) Feature Extraction
4) Classification

Figure 2 shows the block diagram of the proposed system.

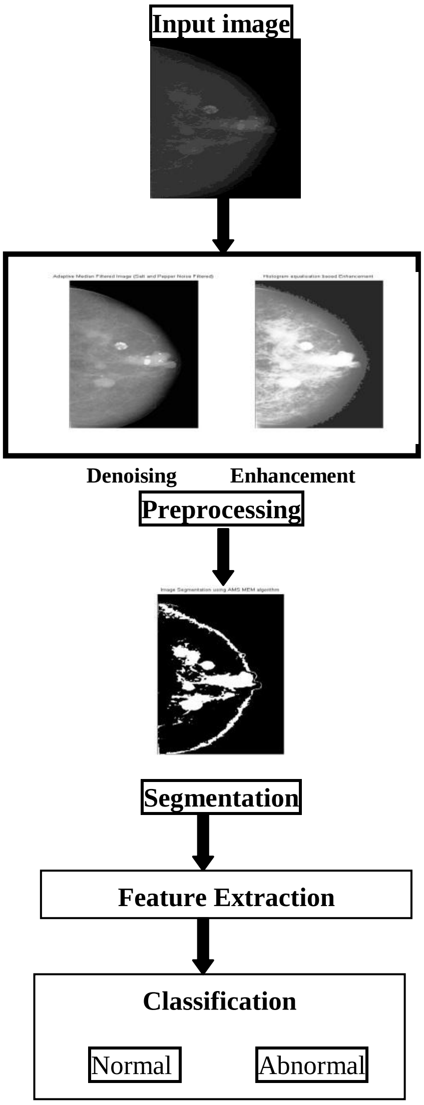

Figure 2. Block Diagram

3.2 Image Preprocessing

Image distortion is a crucial problem in image processing. Preprocessing involves noise removal and image contrast enhancement of Mammogram image. The reliability of optical inspection significantly increases in image preprocessing

A. Denoising

Image is degraded due to various types of noise such as Gaussian noise, Poisson noise, Speckle noise, Salt and Pepper noise and many more are fundamental noises. These noises may be due to noise sources present in capturing devices or may be introduced due to inaccuracy in the image capturing devices like cameras, scattering, misaligned lenses, weak focal length, scattering etc. The noises that are predominant in mammogram images are salt and pepper noise and Gaussian noise. The denoising filters used in this paper are Adaptive median filter, Anisotropic diffusion filter [8]. The adaptive median filter works as follows. Initially it calculates

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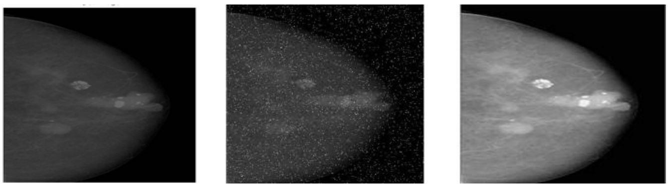
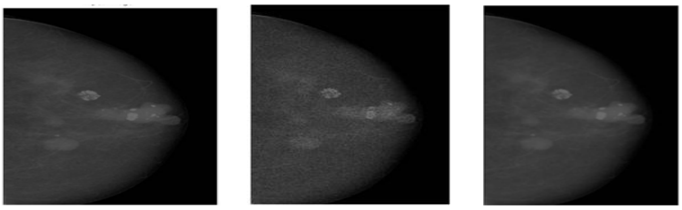
the minimum, maximum, median values of the sub-image window. If the selected pixel is noise, then the pixel will be replaced using previously calculated median value. If the median is itself noise, then the size of the sub-image window is increased and the minimum, maximum and median values are recalculated and the pixel is again checked as mentioned before. The anisotropic diffusion filter works by creating a scale space where the image generates a parametrized family of more and more blurred version of original image based on the diffusion process [12]. The image is filtered and various quality metrics are evaluated. The output of the filters are shown in Figure 3and 4.



Input image   salt and pepper noise   Adaptive median filter output

Figure 3. Output of Adaptive median filter



Input image   Gaussian noise   Anisotropic diffusion filter

Figure 4. Output of Anisotropic diffusion Filter

The Table 1, shows the comparison of various image quality metrics and the corresponding graph is plotted in figure 5, The plot of various image quality metrics are shown below;

Table 1 Comparison of various image denoising filters

FILTER (TECHNIQUE)		PSNR	MSE	SSIM	ENTROPY
ADAPTIVE MEDIAN FILTER	IMAGE 1	34.157	2.496e-5	0.9849	4.292
	IMAGE 2	34.110	2.523e-5	0.9891	4.725
	IMAGE 3	35.954	1.650e-5	0.9914	4.109
	IMAGE 4	35.755	1.728e-5	0.9844	4.498
	IMAGE 5	34.397	2.362e-5	0.9848	5.465
ANISOTROPIC DIFFUSION FILTER	IMAGE 1	42.472	3.680e-6	0.9722	4.545
	IMAGE 2	41.161	4.976e-6	0.9757	4.932
	IMAGE 3	41.371	4.741e-6	0.9728	4.259
	IMAGE 4	42.781	3.426e-6	0.9681	4.667
	IMAGE 5	41.924	4.174e-6	0.9639	5.549

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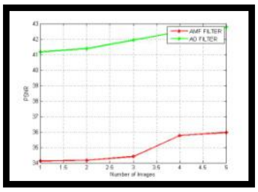
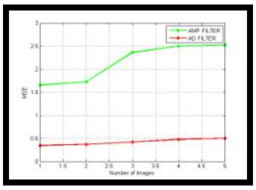
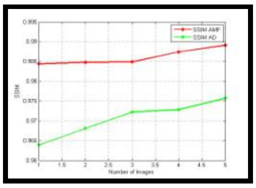
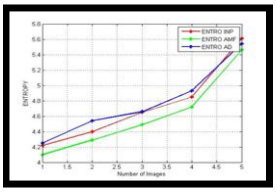
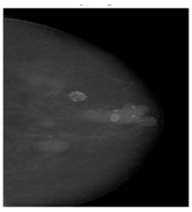
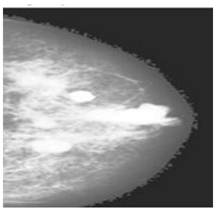
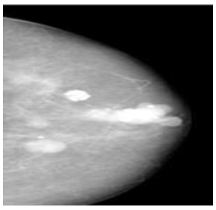
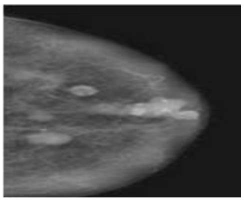
   

PSNR PLOT **MSE PLOT** **SSIM PLOT** **ENTROPY PLOT**

Figure 5. Plot of input Mammogram images Vs Quality metrics for various filters

A. Image Enhancement

Image enhancement is the process of improving the image quality for human visual perception. This is done to enhance the minute details present in an image for further processing [7]. There are many methods used for image enhancement. Histogram Equalization and mean adjustment method are the most widely used techniques. In the mean adjustment method, the mean value of the image pixel is calculated and thereby the contrast is adjusted for the image using intensity thresholding procedure. The results obtained are shown in Figure 6.

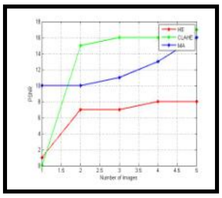
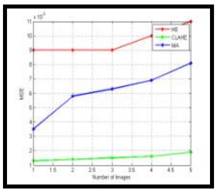
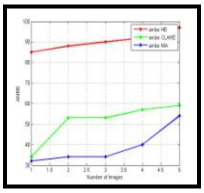
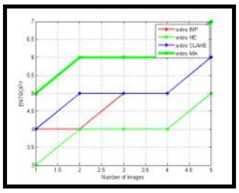
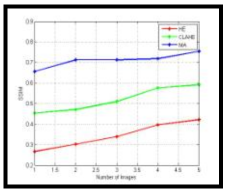
Input Image Histogram Equalization Mean adjustment Contrast Limited Adaptive HE

Figure 6. Image Enhancement output

The following Table, Table 2 shows the comparison of various image quality metrics of image enhancement. Various image quality metrics are compared and tabulated, and their plot is shown below in Figure 7.

Table 2 Image quality metrics

ENHANCEMENT TECHNIQUE	PSNR	MSE	AMBE	ENTROPY	SSIM
HISTOGRAM EQUALIZATION	7.7825	0.0108	92.457	4.1613	0.3022
CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION	16.368	0.0015	34.909	4.6282	0.5099
MEAN ADJUSTMENT	9.0660	0.0081	34.909	5.5272	0.6562

PSNR PLOT **MSE PLOT** **AMBE PLOT** **ENTROPY PLOT** **SSIM PLOT**

Figure 7. Plot of input Mammogram images Vs Quality metrics for various Equalization methods

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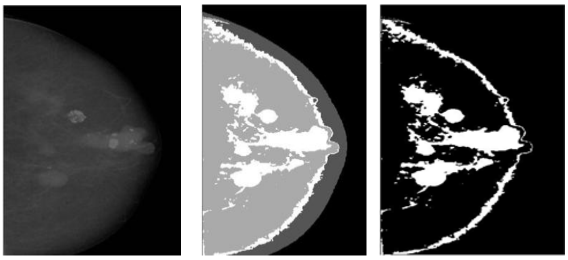
3.3 Segmentation

Image segmentation is the process of dividing a digital image into multiple segments. The main objective of segmentation is to simplify and change the image representation into something that is easier to analyze. It is typically used to Locate tumors and other pathologies present in images. Image segmentation is the process of labeling every pixel in an image so that pixels with the same label share certain characteristics[5]. There are numerous segmentation techniques used to segment the image. Segmentation can be done by Region Based Segmentation, Edge Based Segmentation, Threshold Segmentation, and Clustering Based Segmentation. The method proposed in this paper is Adaptive Mean Shift Modified Expectation Maximization (AMS MEM) Algorithm. In the method we first perform image region segmentation by using the AMS algorithm, and we then treat those regions as nodes along the image plane and apply a graph structure to represent them [1].The final step is to apply the MEM method to partition these regions. The AMS algorithm is a robust feature-space analysis approach which can be applied to discontinuity preserving smoothing and image segmentation problems The algorithm starts by assigning the number of cluster. After converting the image into m*1 format the mean value of the image is calculate so as to find the location of the column image. The centroid is calculated using k-means algorithm. Further the expectation of cancer pixel is calculated and those pixels are maximized simultaneously by suppressing the unexpected pixels. The resultant is then normalized to avoid non cancer pixels to be segmented and finally the cancerous portion is segmented leaving behind the non-cancerous portion. The segmentation results are shown in Figure 8.



Input Image Clustered Image Segmented image

Figure 8. Adaptive Mean Shift Modified Expectation Maximization segmentation

Advantage of Proposed algorithm is that it has good for convergence of gradients of the image pixels. It is the fastest algorithm when compared to the k means algorithm and k Means algorithm. The Mean shift AMS MEM algorithm can have linear convergence and the speed is based on how many information is lost .Mean shift AMS MEM algorithm is applicable for RGB color space images. The exact segmentation of the tumor of Mammogram is possible.

3.4 Feature Extraction

Feature extraction is the method of simplifying the amount of resources required to describe a large set of data accurately. In image processing, a various features can be used to extract the visual information from a given image. Since the mammography images are specific, not all the visual features can be used to correctly describe the relevant image patch. All classes of suspected tissue are different by their shape and tissue composition [6][9].

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(a) First order Feature Extraction

The following Table, Table 3 shows the First order features of various images

Table 3 First order features

FEATURES	IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4	IMAGE 5	IMAGE 6	IMAGE 7	IMAGE 8	IMAGE 9	IMAGE 10	IMAGE 11	IMAGE 12	IMAGE 13	IMAGE 14
MEAN	23.2952	80.8804	50.4178	62.9503	0.1731	71.3420	73.6029	22.9355	50.3270	14.5901	20.2479	18.9460	83.7974	9.343
STD	73.4686	118.6715	101.5609	86.6927	109.9529	114.4664	115.5482	72.9557	101.4919	59.2250	68.9438	66.8752	119.777	47.908
MEDIAN	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VARIANCE	2.947e7	4.238e7	4.743e7	2.146e7	3.921e7	4.6876e7	4.5087e7	2.1336e7	4.6431e7	2.2762e7	2.2714e7	2.0564e7	4.4757e7	1.5418e7
COVARIANCE	1.1022e3	2.1633e3	1.811e3	1.044e3	1.883e3	3.3160e3	2.9283e3	611.1461	1.2120e3	496.0826	478.7257	421.4043	2.613e3	7.863e3
MINIMA	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MAXIMA	255	255	255	255	255	255	255	255	255	255	255	255	255	255
MODE	0	0	0	0	0	0	0	0	0	0	0	0	0	0

(b) Feature Extraction using GLCM

The most widely used feature descriptor is GLCM. The gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix takes into account the spatial relationship of pixels. This relationship is defined as the pixel of interest and pixel to its immediate right. Each element (I, J) in the resultant GLCM will be simply the sum of the number of occurrences of the pixel with value I in the specified spatial relationship to a pixel with value J in the input image. The Following GLCM features were extracted in our work: Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity Energy, Entropy, Homogeneity, Maximum probability , Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation, information measure of correlation, Inverse difference normalized. The following table, Table 4 contains the various GLCM features for dataset consisting of 12 mammogram images obtained from MIAS database.

Table 4 GLCM Features

FEATURES	IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4	IMAGE 5	IMAGE 6	IMAGE 7	IMAGE 8	IMAGE 9	IMAGE 10	IMAGE 11	IMAGE 12	IMAGE 13	IMAGE 14
AUTOCORRELATION	6.6404	20.8324	12.8073	8.7072	16.2329	18.5050	19.0178	6.4460	13.2343	4.4807	5.6150	5.3073	20.1580	3.1916
AMPLITUDE	0.2630	0.3322	1.3593	1.4268	0.7385	0.3272	0.3757	0.4674	0.4071	0.2639	0.7918	0.7463	3.3977	0.2880
CORRELATION	0.9678	0.9844	0.9127	0.8743	0.9596	0.9835	0.9813	0.9419	0.9738	0.9502	0.8896	0.8893	0.843	0.9177
CLUSTER PROMINENCE	2.3344e3	2.8839e3	2.9822e3	2.6080e3	3.0653e3	3.0245e3	2.9897e3	2.2605e3	3.1298e3	1.6661e3	1.9914e3	1.9013e3	2.574e3	1.137e3
CLUSTER SHADE	185.8338	333.7616	279.6517	222.0122	312.2905	326.8286	328.2803	180.0908	291.6531	127.3824	157.4727	149.3962	307.517	85.3629
DISSIMILARITY	0.0376	0.0475	0.9142	0.2038	0.1055	0.0467	0.0537	0.0668	0.0582	0.0377	0.1131	0.1066	0.4854	0.0411
ENERGY	0.8282	0.5599	0.6552	0.7401	0.6125	0.5898	0.5815	0.8265	0.6749	0.8865	0.8377	0.8475	0.4925	0.9228
ENTROPY	0.3367	0.6649	0.6182	0.5132	0.6357	0.6328	0.6454	0.3514	0.5429	0.2489	0.3501	0.3333	0.8823	0.1887
HOMOGENITY	0.9947	0.9941	0.9757	0.9715	0.9868	0.9942	0.9933	0.9917	0.9927	0.9953	0.9859	0.9867	0.9393	0.9942
MAXIMUM PROBABLITY	0.9057	0.6792	0.7879	0.8518	0.7448	0.7162	0.7072	0.9051	0.7984	0.9400	0.9124	0.9181	0.9320	0.9600
SUM OF SQUARES	6.7209	16.4740	13.4123	9.0898	11.4803	18.5767	19.1347	6.6924	13.3899	4.5691	5.9651	5.6308	21.78	3.2965
SUM OF AVERAGES	3.2827	6.4441	4.7749	3.8712	5.4671	5.9264	6.0457	3.2622	4.7640	2.8028	3.1135	3.0401	6.6348	2.5190
SUM VARIANCE	24.7496	75.5873	47.2272	32.6813	59.2245	67.2967	69.1165	24.1211	48.5144	16.8723	21.2564	20.1172	73.6553	12.1581
SUM ENTROPY	0.3330	0.6603	0.5990	0.4930	0.6252	0.6281	0.6401	0.3447	0.5372	0.2452	0.3339	0.3227	0.834	0.1847

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DIFFERENCE VARIANCE	0.2630	0.3322	1.3593	1.4268	0.7385	0.3272	0.3757	0.4674	0.4071	0.2639	0.7918	0.7453	3.3977	0.2880
DIFFERENCE ENTROPY	0.0334	0.0406	0.1268	0.1317	0.0782	0.0401	0.0450	0.0539	0.0481	0.0335	0.0827	0.0788	0.2519	0.0360
INFORMATION MEASURES OF CORRELATION (1)	0.9006	0.9352	0.7584	0.6490	0.8644	0.9336	0.9260	0.8400	0.9061	0.8664	0.7388	0.7401	0.6100	0.8094
INFORMATION MEASURES OF CORRELATION (2)	0.9975	0.8304	0.7281	0.6490	0.7874	0.9969	0.9964	0.9955	0.9961	0.9975	0.9925	0.9929	0.7344	0.4757
INVERSE DIFFERENCE NORMALIZED (INN)	0.9975	0.9968	0.9871	0.9864	0.9930	0.9763	0.9707	0.9046	0.9474	0.9536	0.8807	0.8782	0.9676	0.9973
INVERSE DIFFERENCE MOMENT NORMALIZED(IDN)	0.9977	0.9971	0.9880	0.9874	0.9935	0.9971	0.9967	0.9959	0.9964	0.9977	0.9930	0.9934	0.9699	0.9975

(c) Feature Extraction using famelet transform

Framelets has two or more high frequency filter banks, which produces more sub bands in decomposition. Framelet sub bands, which mean changes in the coefficients of one band can be compensated by the coefficients of other sub bands. After the decomposition, the coefficient present in one particular sub band is said to have correlation with coefficients in the other sub band, which means, changes in one particular coefficient can be compensated using its related coefficient in the reconstruction stage which produces less noise in the original image.

(d) Feature extraction using 2D Wavelet Transform

Feature extraction is the primary stage of classification in which features present in each image is separately extracted from image by wavelet which considers the best method to extract weighted pixels present in images to enhance results [13]. To decompose data into different frequency components Wavelets mathematical functions are used and then each component is studied having resolution matched to its degree. DWT is an implementation method for wavelet obeying some defined rules and discrete set of wavelet translations. The scale limit is then discredited according to the translation limit (τ). The following equation describes the scale and translation of the wavelet.

Where m, n Є Z, so Z is the set of all integers. Equation 1 shows the family of wavelet function.

$$\Psi\ m,\ n\ (t) = 2m/2\ (2m\ t - n) \qquad \text{------------ (1)}$$

The equation 2 and 3 shows DWT crumbles a signal x (t) into a family of synthesis wavelet are given as follows.

$$x(t) = \Sigma m\ \Sigma n\ Cm,n\ \Psi m,n(t) \qquad \text{------------ (2)}$$

$$Cm,n = (x(t)\ ,\ \Psi m,n\ (t)) \qquad \text{----------- (3)}$$

x[n] is the discrete time signal mentioned in the equation 4, decomposition of wavelet on ***I*** is given below

$$x[n] = \Sigma\ i{=}1\ to\ i\ \Sigma\ k \in Z\ ci,\ kg\ [n - 2ik] + \Sigma\ k \in z\ dI,K\ hi\ [n - 2I\ k] \qquad \text{------------ (4)}$$

Where wavelet coefficients are given by ci,k, i = 1 ……….. *I.* and Scaling coefficients are *di* and k

i = 1 ……….. I.

The wavelet is given by equation 5 and wavelet scaling coefficients are given in equation 6.

$$ci,k = \Sigma n\ x[n]\ gi^*\ [n - 2ik] \qquad \text{---------- (5)}$$

$$di,k = \Sigma n\ x[n]\ hI^*\ [n - 2Ik] \qquad \text{----------- (6)}$$

Where, * represents complex conjugate and gi* [n – 2ik] represents discrete wavelets and h*I** [n – 2*I*k] represents scaling sequence.

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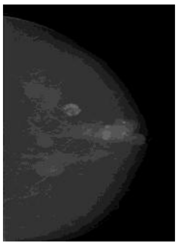
DWT has been used to extract the wavelet coefficient from image at different directions and scales. Wavelet decomposition results in four sub bands which are as follows.

- Horizontal (LH)
- Vertical (HL)
- Approximated (LL)
- Diagonal (HH).

Approximated sub band (LL) is further decomposed at different scales while (LH, HL, HH) includes characteristic of an image. Discrete Wavelet transform gives local frequency information. LL is lower frequency component band. If LL band is further decomposed into next level then LL band will be distributed into further four parts and each part will have about $N/2 \times N/2$ coefficients .In second level $N/2 \times N/2$ coefficients are further decomposed into four parts containing $N/4 \times N/4$ coefficients each and in the successive level same procedure will be repeated.



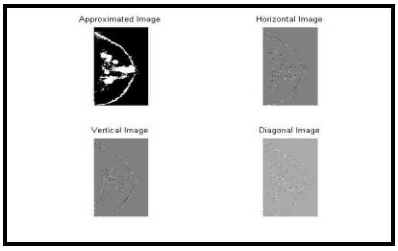


Figure 9. DWT Plot

The following table, Table 5 Lists the DWT and framelet features for various mammogram images

Table 5 DWT and Framelet transform features

FEATURES	IMAGE 1	IMAGE 2	IMAGE 3	IMAGE 4	IMAGE 5	IMAGE 6	IMAGE 7	IMAGE 8	IMAGE 9	IMAGE10	IMAGE 11	IMAGE 12	IMAGE 13	IMAGE 14
DWT (APPROXIMATED IMG)	46.3933	125.0593	100.6074	65.6605	84.9882	142.3641	146.8758	45.7682	100.4238	29.1438	40.4453	37.8448	166.9887	18.5774
DWT (HORIZONTAL IMG)	0.0349	0.1478	0.0086	-0.0226	0.0920	0.0693	0.1967	0.0877	0.1882	-0.0035	0.0226	-0.0136	0.1552	-0.0403
DWT (VERTICAL IMG)	-0.0965	-0.2586	-0.0086	-0.3283	0.0241	-0.5052	-0.4430	-0.9171	-0.4883	0.0021	0.3236	0.3821	-0.7347	-0.6455
DWT(DIAGONAL IMG)	-0.0062	0.0041	0.0685	-0.0226	-0.0439	0.0297	-0.0014	0.0085	-0.0099	-0.0120	0.0057	0.0177	0.1552	-0.0202
FRAMELET TRANSFORM FEATURE	0.2595	4.2684	0.5203	0.3549	0.7326	0.7939	2.6411	0.2997	2.6101	0.1425	0.4025	0.4892	2.405	0.2118

3.5 CLASSIFICATION

There are numerous algorithms available for automated classification. Among them the most powerful classification procedure is SVM (Support Vector Machine) classifier. SVM is a most widely used technique for data classification. A classification task involves with training and testing data which consist of some data instances. The standard SVM is a non-probabilistic binary linear classifier which takes in a set of input data, and predicts, for each given input.

Performance Evaluation

To evaluate the performance of this proposed work certain evaluation metrics such as sensitivity, specificity and accuracy are computed using the following equations given below:

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \times 100\% \qquad \text{Specificity (\%)} = \frac{TN}{TN+FP} \times 100\%$$

$$\text{Accuracy (\%)} = \frac{TP+TN}{N} \times 100\%$$

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Where TP – True Positive, TN – True Negative, FP –False Positive, FN – False Negative, N – Total number of images.

SVM classifier proved its performance through the various performance metrics such as Sensitivity is 98.446 %, Specificity is 95.238 % and its Accuracy of classification is 98.131%. The following table, Table 6 shows the comparison of accuracy obtained using various methods.

Performance measures

Sensitivity	98.446 %
Specificity	95.238 %
Accuracy	98.131 %

Table 6 Comparison of accuracy for existing and proposed method

AUTHOR	ACCURACY OBTAINED (%)
Belal K. Elfarra [6]	89% - 96.3%
Neeta V. Jog [10]	95.83%
Bin Zheng [14]	87%
B. Surendiran [16]	87%
Proposed method	98.13%

IV. CONCLUSION

The main drawback of the standard EM for image segmentation is that the objective function does not take into account of the spatial information in the image, but deal with images as the same as separate points. Therefore, as mentioned in many literatures the standard EM algorithm is sensitive to noise and a noisy pixel is always wrongly classified because of its abnormal feature. In this paper, we proposed a new AMS MEM that incorporates the spatial information into membership function in order to improve the segmentation results. In the new spatial function two contribution factors were used. The first one was with regards to distances between central pixels with neighbor pixels. The second factor was calculated according to value difference of central pixel with neighbor pixels. Using these contribution factors caused that spatial function is made of according to distance and value pixels. The new method was tested on Mammogram images and evaluated by using various cluster validation functions. Preliminary results showed that the effect of noise in segmentation was considerably reduced with the new algorithm than with the EM. Further, the various spatial and shape based features were extracted. These image derived features provide useful information for early detection of masses.

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