An Automated Detection and Classification of Suspicious Lesions in Mammograms

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Abstract— **Breast cancer is the most common cancer among the Indian women and it ranges from 25 to 31% of all cancers among Indian women. It is better to treat this dreadful disease at the earliest in order to save invaluable lives. For this sake, we developed a system that automatically detects and classifies the suspicious lesions present in the mammograms. The results are accurate because two levels of segmentations namely coarse and fine segmentation are employed. Coarse segmentation is done with the help of histogram based fuzzy c means technique, which is known for its accuracy, since it takes degree of truth and false into account. After obtaining the local sketch of the suspicious region, fine segmentation is applied in order to improve the rough representation of coarse segmentation and this is achieved by window based adaptive thresholding method. Finally, the outcome of fine segmentation is superimposed over the coarse segmentation to arrive at the perfect result. Then, the first order and run length features are extracted and the image is classified as normal, benign or malignant. Also, the type of lesion is identified by the maxvote algorithm and it proves 95% of accuracy.**

Keyword- Mammograms, segmentation, feature Extraction, classification

I. INTRODUCTION

Breast cancer is the cancer that is a type of malignant tumour and grows in the cells of breast. Mostly, breast cancer is common among women but in very rare occasions it can be found in men too. The cancer cells of malignant tumour spreads up to the nearby area, if not treated at the right time. Breast cancer is the most common cancer among the Indian women and ranges from 25 to 31% of all cancers in India.

The average age of the occurrence of breast cancer is 30-50 years and previously it was 50-70. The severity or aggressiveness is directly proportional to the age of the person. The survey of Globocan (WHO) in the year of 2012, reports that the death count of breast cancer patients in India is 70,218 and stood first in the death rate. China ranked second with the death count of 47,984 and United States ranked third with 43,909 deaths [15].

The earlier the cancer is detected, the easier it is to cure it. Thus, early detection of cancer is necessary. Mammography is the best reliable technique for the detection of breast cancer, since it can detect 85 to 90% of all kinds of breast cancer. The abnormalities cited in a mammogram are masses and calcifications. Calcifications are the deposits of calcium. The cancer can be categorized as benign or malignant and this is determined by the shape of the mass.

Usually, benign tumours are round or oval in shape and a malignant tumour can be observed with a partially rounded mass with a spike or an irregular outline [7]. Breast cancers can be detected earlier with the help of mammograms and can help physicians to diagnose and deal with it. The abnormalities present in the mammograms are detected and extracted in order to arrive at the correct diagnostic results. Some grayscale based segmentation mehods are found to be effective in extracting the exact edges of the homogenous grayscale regions.

The appearance of breast cancer is not stable at their early stages. Hence, the physicians may not be able to locate the abnormalities. In such cases, this automated system helps the physicians to detect the abnormalities easily. A tumor detection algorithm has to identify the lesion and is needed to be accurate with reduced number of false negatives.

In the proposed system, wavelet lifting transform is done twice on an image and the sub-images of lower frequency are obtained at various resolutions. The suspicious lesions are localized from the roughest representation through the histogram based fuzzy c-means technique. Then, the rough representation is improved by the window based adaptive thresholding in order to arrive at the fine segmentation.

After fine segmentation of an image, the first order features such as Mean, Standard deviation, Skewness and Kurtosis are extracted. Also, the run length features such as Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Non-uniformity (GLN), Run Percentage (RPC), Run Length Non-Uniformity (RLN), Low Gray-level Run Emphasis (LGRE) and High Gray level Run Emphasis (HGRE) are extracted.

Finally, non-linear SVM is employed to classify an image as normal or benign or malignant. Also, the type of lesion is also identified by the maxvote algorithm. This combines the shape, texture and colour, in order to achieve more reliable results in classifying between the types of lesions. Also, the detection process is upgraded to multiresolution.

The sensitivity, specificity, jaccard distance and accuracy are then calculated by taking True Positive, True Negative, False Positive and False Negative into account. After this, we compare the proposed system with Fuzzy C means, K-Means, Otsu and Adaptive Thresholding methodologies. The remaining section of this paper is organized as follows. Section II carries the review of literature and section III presents the proposed methodology. Section IV deals with the performance analysis and finally concluding remarks are presented.

II. REVIEW OF LITERATURE

Mencattini A. et al. have proposed a new algorithm for mammographic image enhancement and denoising a mammographic image. Denoising is based on wavelet transform in this work [1]. Cao A.Z. et al. in [2] has investigated a Robust Information Clustering (RIC) algorithm, incorporating spatial information for breast mass detection in digitized mammograms. The detection system of this work employs RIC algorithm based on the raw Region of Interest (RoI) extracted from the global mammogram by two steps of adaptive thresholding.

The algorithm is claimed as robust in the sense that both the peak and valley of image intensity histogram are estimated and the pixels corresponding to valley in the histogram are clustered adaptively to the content of the image. Cascio D. et al. have proposed an algorithm for the detection of mass lesions in mammographic images. The algorithm follows the edge-based threshold operator strategy for segmenting the masses. The discriminating performance of the algorithm is verified by a supervised neural network [3].

In [5], Kom G. et al. have proposed an algorithm for detecting suspicious masses from mammographic images. In [6], te Brake G.M. et al. have proposed two different methods for segmenting the suspected regions. Initially, the segmentations of masses were compared to the annotations made by the radiologist; secondly, a number of features were computed for all the segmented areas as normal and abnormal. Based on this, the regions are classified with the neural network.

Eltonsy N.H. et al. have proposed a technique in [8] for the automated detection of malignant masses in screening mammography. This technique is based on the presence of concentric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region. Mammographic areas with high concentration of concentric layers, with progressively lower average intensity are considered as suspicious deviations from normal parenchyma.

Singh S. et al. have proposed a novel set of metrics in [9], which measure the quality of the image enhancement of mammographic images in a computer-aided detection framework. This aimed at finding masses automatically using machine learning techniques. Saurabh Sharma et al. have presented a new algorithm for detecting suspicious lesions in mammograms by using adaptive thresholding [10].

Balakumaran T. et al. have come up with the algorithm to detect microcalcification in mammograms. This work proposes an algorithm that involves mammogram quality enhancement by using multiresolution analysis, which is based on the dyadic wavelet transform and microcalcification detection by fuzzy shell clustering [11]. In [12], Ted C. Wang et al. have proposed an algorithm that detects microcalcifications in digital mammograms. This is done by employing wavelet based sub-band image decomposition. The proposed method of this work is robust that it does not require the use of heuristics or the prior knowledge of the size and resolution of the mammogram.

Xhang X.P. have proposed a wavelet-packet multiscale image segmentation in [13]. This work is combined with a multiscale region based segmentation method and a new generic systematic scheme is generated. Using this scheme, suspicious tumour areas with exact boundaries are obtained on the basis of multiscale analysis in both grayscale and space. In [14], Xhang X.P et al. have developed an analytical model for the segmentation of targets. This is done by a novel multiresolution analysis in concert with a Bayes classifier, in order to identify the possible target areas. A method is developed in this work, which adaptively chooses the thresholds to segment targets from the background. This is done by a multiscale analysis of the image probability density function.

In the proposed work, we exploit the histogram based fuzzy C-means technique for implementing the coarse segmentation and only after this; the fine segmentation is carried out. Thus, the rough representation is improved and the accurate result can be obtained. Then, the image is classified as normal, benign or malignant by extracting the run length and first order features.

III. PROPOSED METHODOLOGY

In this work, we propose an algorithm that detects suspicious lesions in mammograms, so as to simplify the work of a physician or a radiologist. The proposed system proves its accuracy which when compared with Fuzzy C means, K-Means, Otsu and Adaptive Thresholding methodologies. The work flow followed in this work is presented below. In the proposed system, wavelet lifting transform is done twice on an image and the sub-images of lower frequency are obtained at various resolutions.

The suspicious lesions are localized from the roughest representation through the histogram based fuzzy c-means technique. Then, the rough representation is improved by the window based adaptive thresholding in order to arrive at the fine segmentation. Then, the first order and run length features are extracted, in order to classify an image into normal, benign or malignant.

A. Wavelet Lifting Transform

The lifting method supports to generate an infinite number of discrete biorthogonal wavelets originating from a single entity. This lifting scheme designs perfect reconstruction filter banks by beginning, from the nature of the wavelet transform. A single lifting step is described by the three basic phases. They are split, predict and update.

The split phase is responsible for splitting the signal into several disjoint components, which is shown in eqn 1. The predict operation can also be denoted as dual lifting step. In this, the samples of odd polyphase component are replaced by the difference between the odd polyphase component and the predicted value, which is presented in eqn 2.

The update phase is also known as primal lifting step. Update is the even polyphase component, which is based on the linear combination of sample difference obtained from the predict step and is given in eqn 3.

$$Split: \lambda_k \leftarrow f(2k), \gamma_k \leftarrow f(2k+1) \quad (1)$$

$$Dual\ Lifting\ (Predict):$$

$$\gamma_k \leftarrow \gamma_k - {}^1\!/_2\,(\lambda_k + \lambda_{k+1}) \quad (2)$$

$$Primal\ Lifting\ (Update):$$

$$\lambda_k \leftarrow \lambda_k + {}^1\!/_4\,(\gamma_{k-1} + \gamma_k) \quad (3)$$

The equations for performing inverse lifting transform are given below.

$$Inverse\ Primal\ Lifting\ (Undo\ Update):$$

$$\lambda_k \leftarrow \lambda_k - {}^1\!/_4\,(\gamma_{k-1} + \gamma_k) \quad (4)$$

$$Inverse\ Dual\ Lifting\ (Undo\ Predict):$$

$$\gamma_k \leftarrow \gamma_k + {}^1\!/_2\,(\lambda_k + \lambda_{k+1}) \quad (5)$$

$$Merge:$$

$$f(2k) \leftarrow \lambda_k, f(2k+1) \leftarrow \gamma_k \quad (6)$$

In this work, we have performed wavelet lifting transform twice on an image.

B. Histogram based Fuzzy C Means Method

In this work, the coarse segmentation is done by means of histogram based fuzzy c means technique. This technique is employed as it doesn't follow a blind or strict mechanism to group pixels. It takes the degree of truthfulness and false into account and group pixels accordingly.

This allows the pixels to be in more than one group, such that no pixel is missed out. Since, we are detecting lesions; this would be the optimal choice of grouping. Each pixel has a degree of membership to be a part of each group.

The threshold is calculated by adding the average color intensity with the subtraction of the maximum value of color from the minimum value of color and is given by

$$TH(i,j) = \delta + cd \quad (7)$$

$$cd = icol_{max} - icol_{min} \quad (8)$$

where δ is the average intensity, $icol_{max}$ and $icol_{min}$ are the maximum and the minimum intensity respectively. The fuzzy centroid is calculated by the following formula at the kth step.

$$C_j = \frac{\sum_{i=1}^{n}(u_{ij})^m x_i}{\sum_{i=1}^{n}(u_{ij})^m} \quad (9)$$

where C_j is the fuzzy centroid for j=1,...ni; where ni is the total number of groups or clusters, m is the fuzzy parameter and n is the total number of pixels. Main thing here is, this algorithm allows a pixel to be in multiple groups.

C. Window based Adaptive Thresholding Method

Local segmentation serves well with perfect results than the global segmentation since the rough representation is already provided with the coarse segmentation. The adaptive threshold is calculated by eqn 7,8. This adaptive thresholding method separates the foreground from the background with a non-uniform illumination. By employing this method, we arrive at a fine segmentation. Then, the outcome of fine segmentation is superimposed over the outcome of the coarse segmentation. This is done by the below given condition

$$N = \begin{cases} 1 & if\ Fs = 1\ or\ Cs = 1 \\ 0 & otherwise \end{cases} \quad (10)$$

where Fs is the fine segmented result and Cs is the coarse segmented result.

The suspicious lesion is detected based on the superimposed result. Then, the morphological operator is used to remove the unwanted portions of an image and is given as

$$E = N - H \quad (11)$$

$$D = E - H \quad (12)$$

where N is the superimposed result and H is the structuring element. E is the erosion and D is the dilation operators.

Thus, a mammogram image is effectively segmented in order to detect the suspicious lesions and also the unnecessary portions of an image are eliminated. In this work, the outcome of fine segmentation is superimposed over the coarse segmentation, such that no single pixel is left out and the result is accurate and is shown in the next section.

D. Feature Extraction

Feature extraction is a type of dimensionality reduction from which the region of interest can alone be extracted. In this work, the first order features such as Mean, Standard deviation, Skewness and Kurtosis are extracted. Also, the run length features such as Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Non-uniformity (GLN), Run Percentage (RPC), Run Length Non-Uniformity (RLNU), Low Gray-level Run Emphasis (LGRE) and High Gray level Run Emphasis (HGRE) are extracted and are presented below.

1) First Order Statistical Features: With respect to the pixel count that represents the local feature, the statistical methods are classified. In this work, first order statistical features are incorporated in order to estimate the properties of individual pixel values. Mean, standard deviation, skew and kurtosis are extracted and are presented in this section.

Mean is given by the following.

$$F_{01} = \mu = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{n} p[i,j] \quad (13)$$

Where 'N' is the number of pixels in an image, 'i' and 'j' are the initial values of the row and column of an image, 'm' and 'n' are the final value of the row and column of an image and p[i,j] is the matrix value of the image.

Standard Deviation (σ) is another first order statistical feature which is given by

$$F_{02} = \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{m}\sum_{j=1}^{n}(p[i,j]-\mu)^2} \quad (14)$$

Standard Deviation is the mostly used statistical measure of diversity in images.

Skewness is the measure of the asymmetry of the probability distribution of a real valued random variable. This value can be positive or negative. Usually, darker and glossier surfaces are positively skewed rather than lighter and matte surfaces and is given by

$$F_{03} = \frac{1}{(N-1)\sigma^3}\sum_{i=1}^{m}\sum_{j=1}^{n}(p[i,j]-\mu)^3 \quad (15)$$

Kurtosis is a measure of the shape of the probability distribution of a real-valued random variable.

Kurtosis can be given by

$$F_{03} = \frac{1}{(N-1)\sigma^4}\sum_{i=1}^{m}\sum_{j=1}^{n}(p[i,j]-\mu)^4 \quad (16)$$

2) Run Length Statistical Features: These features capture the coarseness of the texture both horizontally and vertically. A run can be defined as a string of consecutive pixels, which have the same gray level intensity along a specific linear orientation [15]. Fine textures contain more short runs with similar gray level intensities, whereas coarse textures have long runs with different gray level intensities.

A run length matrix p is defined as when each element p(i,j) represents the number of runs with pixels of gray level intensity equal to 'i' and length of run equal to 'j' along a specific orientation. After calculating the run length matrices along each direction, several texture properties are calculated to capture the texture properties and differentiate among different texture features.

In this work, seven features are extracted from the run-length matrices. The run length statistics extracts the texture information of an image from its gray level runs. Consecutive pixels of the same gray value in a given direction constitute a run. The number of runs of different lengths and gray values, arranged according to the lengths and gray levels form a 2D matrix p(i,j) called gray level run length matrix.

A run-length matrix p(i,j) is defined as the number of runs with pixels of gray level i and run length j. Let M be the number of gray levels and N be the maximum run length and N_r be the total number of runs in the image.

3) Short Run Emphasis (SRE): SRE measures the distribution of short runs. SRE depends on the occurrence of the short runs as large runs are expected on fine textures and is given by

$$RL_{01} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p[i,j]}{j^2} \quad (17)$$

Where p[i,j] specifies the number of runs of length 'j' and gray level 'i', occurring in the image region, 'N' indicates the number of gray levels, 'M' represents the number of run length groups and the total number of runs in an image is given by

$$n_r = \sum_{i=1}^{M}\sum_{j=1}^{N} p[i,j] \quad (18)$$

4) Long Run Emphasis (LRE): LRE measures the distribution of long runs and is dependent on the occurrence of long runs and is expected large for coarse structural textures and is presented below

$$RL_{02} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p[i,j] * j^2 \quad (19)$$

5) Gray Level Non-uniformity (GLN): GLN measures the similarity of gray level values throughout the image. The GLN value will be small, if the gray values resemble the same throughout the image and are given by eqn.20.

$$RL_{03} = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N} p[i,j]\right)^2 \quad (20)$$

6) Run Percentage (RPC): Run percentage measures the homogeneity and the distribution of runs in an image along a specific direction. RPC is the largest when the length of runs is 1 for all gray levels in specific direction.

$$RL_{04} = \frac{n_r}{p[i,j]*j} \quad (21)$$

7) Run Length Non-uniformity (RLN): RLN measures the similarity of the length of runs throughout the image. RLN is smaller if the run lengths are alike throughout the image.

$$RL_{05} = \frac{1}{n_r}\sum_{j=1}^{N}(\sum_{i=1}^{M} p[i,j])^2 \quad (22)$$

8) Low Gray Level Run Emphasis (LGRE): LGRE measures the distribution of low gray level values. The value of LGRE is large for the image with low gray level values and is calculated by eqn.23.

$$RL_{06} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} \frac{p[i,j]}{i^2} \quad (23)$$

9) High Gray Level Run Emphasis (HGRE): HGRE measures the distribution of high gray level values. The value of HGRE is large for the image with high gray level values and is calculated by eqn.24.

$$RL_{07} = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p[i,j] * i^2 \quad (24)$$

Thus, seven run-length statistical features are extracted.

E. Image Classification

This work employs a non-linear Support Vector Machine (SVM) classifier to distinguish between the normal, benign or malignant cancer. This exploits a non-linear mapping, in order to transform the original training data into a higher dimension. In this dimension, it searches for a decision boundary, so as to separate the tuples of one class from the other. Non-linear SVM is employed in this work because it fits the maximum margin hyperplane in a transformed feature space. Some of the merits of SVM are its simplicity, efficiency, robustness and its increased performance.

F. Proposed Algorithm

Here, the suspicious lesions are detected by following the steps given below.

Step-1: Initially, the image is applied wavelet lifting transform twice and the low frequency subimages at various resolutions are reaped out of it.

Step-2: I0 is the original mammogram that has the finest resolution and I1, I2 be the subimages of the low resolution of the original image, where I0,I1 and I2 collectively represent the multiresolution of the original mammogram.

Step-3: Initially, the coarse segmentation is done by employing histogram based fuzzy means C technique, in order to obtain the rough sketch so as to locate the suspicious lesions.

Step-4: The so-produced rough sketch of the coarse segmentation is further improved by the fine segmentation, such that this system can arrive at a perfect result.

Step-5: This fine segmentation is done by window based adaptive thresholding method.

Step-6: Then, the outcome of fine segmentation is superimposed over the coarse segmentation result and is presented in Fig 1.

Step 7: Extract first order features such as mean, standard deviation, skewness and kurtosis as given in section 3.3.1.

Step 8: Extract run length features such as SRE, LRE, GLN, RPC, RLN, LGRE, HGRE as presented in section 3.3.2.

Step 9: Image classification is done by SVM in order to distinguish between normal, benign and malignant cancer.

Step 10: Finally, the type of lesion is detected by the maxvote algorithm.

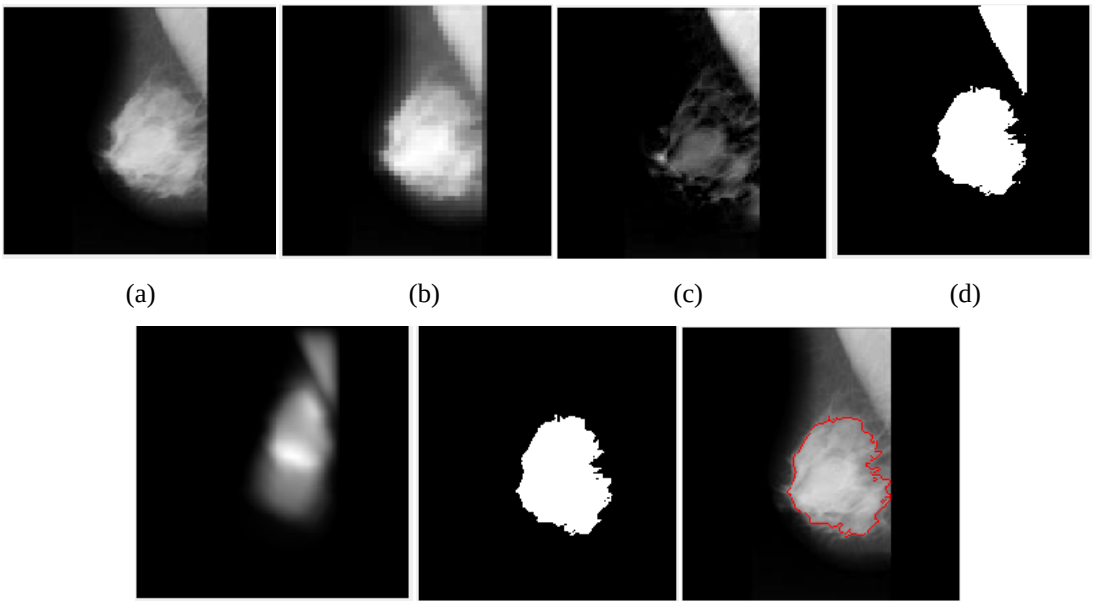

Fig 1: (a) Original Image, (b) After applying Wavelet Lifting Transform twice, (c) Image after Morphological Filtering, (d) Coarsely Segmented Image, (e) Convoluted Image, (f) Fine segmented image, (g) Detecting cancer cells.

Maxvote algorithm is proposed to detect the type of lesions. This algorithm takes shape, texture and colour into account. The CIRC lesion is usually in the shape of round or oval. The center of the MISC lesion will be having a higher gray level values, when compared to the background region.

The ARCH type of lesion can be detected with the texture feature and hence all the three features such as shape, colour and the texture are taken into consideration and finally the process of voting will be taken place. This is to determine the dominance of the feature. If the shape feature is dominant than colour and texture, then the lesion is detected to be CIRC. If colour is dominant than shape and texture, then the lesion must be MISC, whereas if texture is dominant over the shape and colour, then the lesion is of type ARCH.

IV. Performance Analysis

This work is tested over MIAS Mini Mammographic Database with 322 images and Matlab is employed for simulating this work. The proposed work shows its excellence over Fuzzy C means, K-Means, Otsu and Adaptive Thresholding methodologies and the experimental results are shown in this section.

The performance of this method is tested with measures such as sensitivity, specificity, accuracy and jaccord distance. All these measures can be taken into account only if True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are in hand. The above mentioned parameters are computed in the following way.

A. True Positive (TP)

True Positive (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation (25).

$$TP = \frac{Number\ of\ Correctly\ classified\ images}{Total\ number\ of\ images} \times 100 \quad (25)$$

B. True Negative (TN)

True Negative (TN) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation 26.

$$TN = \frac{Number\ of\ falsely\ classified\ images}{Total\ number\ of\ images} \times 100 \quad (26)$$

C. False Positive (FP)

False Positive (FP) is the proportion of negatives cases that were correctly rejected as negative, as calculated using the equation.

$$FP = \frac{Number\ of\ correctly\ rejected\ images}{Total\ number\ of\ images} \times 100 \quad (27)$$

D. False Negative (FN)

False Negative (FN) occurs in a case where an tumour affected image is misclassified as normal.

$$FN = \frac{Number\ of\ incorrectly\ rejected\ images}{Total\ number\ of\ images} \times 100 \quad (28)$$

With the above mentioned parameters, the accuracy, jaccord distance, sensitivity and specificity are calculated and the results are shown in graphs. From the experimental results, it is evident that the proposed system works well than the others.

E. Accuracy Rate

The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual (true) value and the corresponding graph is presented in Fig 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (29)$$

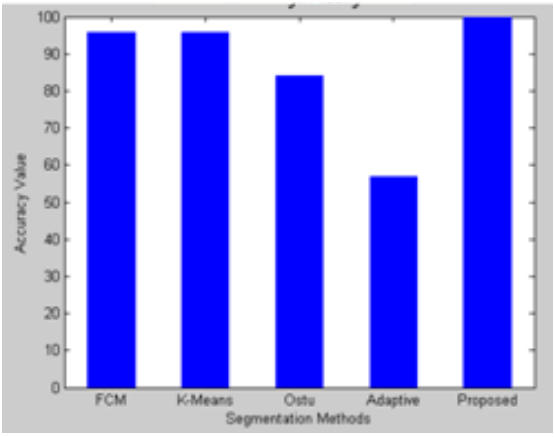

Fig.2. Segmentation Accuracy

F. Sensitivity

Sensitivity also called the true positive rate or the recall rate in some field's measures the proportion of actual positives which are correctly identified such as the percentage of sick people who are correctly identified as having the condition and the corresponding graph is presented in Fig 3.

$$S_e = \frac{TP}{TP+FN} \quad (30)$$

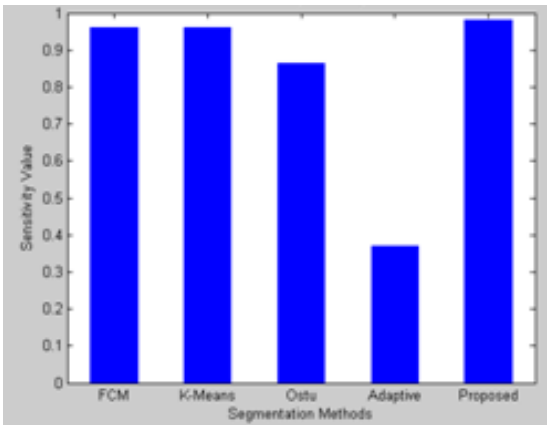

Fig 3: Sensitivity Analysis

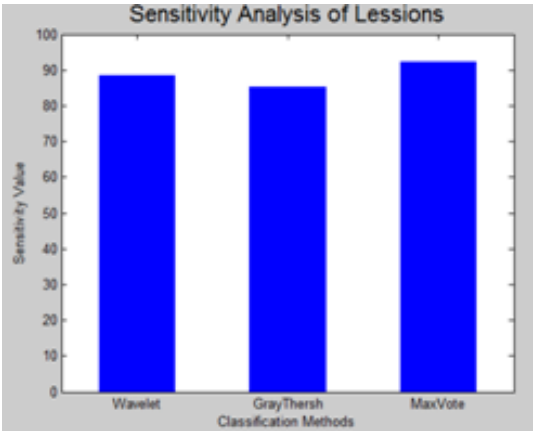

Fig 4: Sensitivity Analysis of Lesions

The existing methods of detecting lesions of mammograms are wavelet and graythresh methods consider texture and the colour intensity respectively. The proposed maxvote algorithm considers all the three features such as colour, texture and shape which arrives at perfect detection of lesions and it proves 95% of accuracy and is shown in Fig 4.

V. CONCLUSION

In this work, a system that automatically detects suspicious lesions is presented. This work utilizes the lifting wavelet transform so as to process the image effectively. This work exploits two levels of segmentation namely coarse and fine segmentation. The coarse segmentation is accomplished by the histogram based fuzzy c segmentation and the fine segmentation is achieved by the window based adaptive thresholding method. Finally, the fine segmented outcome is superimposed over the outcome of coarse segmentation. Then, the first order and run-length statistical features are extracted and finally, the image is classified with SVM as normal, benign or malignant. The type of lesion is also detected by the maxvote algorithm.

REFERENCES

[1] A. Mencattini, M.Salmeri, R. Lojacono, and F.Caselli,"Mammographic Images Enhancement and Denoising for Microcalcification Detection Using Dyadic Wavelet Processing",IMTC 2006 - Instrumentation and Measurement Technology Conference Sorrento, Italy 24-27 April 2006.

[2] A.Z.Cao, Q.Song, and X.L.Yang, “Robust information clustering incorporating spatial information for breast mass detection in digitized mammograms,” Comput. Vis. Image Understand., vol. 109, no. 1, pp. 86–96, Jan. 2008.

[3] D.Cascio, F. Fauci, R. Magro, G. Raso, R. Bellotti, F. De Carlo, S. Tangaro, G. De Nunzio, M. Quarta, G. Forni, A. Lauria, M. E. Fantacci, A. Retico, G. L. Masala, P. Oliva, S. Bagnasco, S. C. Cheran, and E. Lopez Torres,"Mammogram Segmentation by Contour Searching and Mass Lesions Classification With Neural Network",IEEE TRANSACTIONS ON NUCLEAR SCIENCE, VOL. 53, NO. 5, OCTOBER 2006.

[4] D.H.Xu, A.Kurani,. Furs t J.D., & D.S.Raicu, "Run-length encoding for volumetric texture", The 4th IASTED International Conference on Visualization, Imaging, and Image Processing - VIIP 2004, Marbella, Spain, September 6-8, 2004.

[5] G.Kom, A.Tiedeu, and M.Kom, “Automated detection of masses in mammograms by local adaptive thresholding,” Comput. Biol. Med., Vol. 37, No. 1, Jan. 2007, PP. 37–48.

[6] G.M.te Brake and N.Karssemeijer, “Segmentation of suspicious densities in digital mammograms,” Med. Phys., vol. 28, no. 2, Feb. 2001, pp. 259–266.

[7] Mariam Biltwani, Nijad Al-Najdawi, Sara Tedmori, "Mammogram enhancement and segmentation methods: Classification, Analysis and Evaluation", The 13th International Arab Conference on Information Technology ACIT'2012 Dec.10-13, ISSN: 1812-0857.

[8] N.H.Eltonsy,G.D.Tourassi, and A.S.Elmaghraby, “A concentric morphology model for the detection of masses in mammography,” IEEE Trans. Med. Imag., vol. 26, no. 6, Jun. 2007, PP. 880–889.

[9] S.Singh and K.Bovis, “An evaluation of contrast enhancement techniques for mammographic breast masses,” IEEE Trans. Inf. Technol. Biomed., vol. 9, no. 1, Mar. 2005, PP. 109–119.

[10] Saurabh Sharma, Ashish Oberoi,"A new approach for Classification and Detection of Suspicious Lesions in Mammograms based on AdaptiveThresholding", International Journal of Computer Science and its Applications, ISSN 2250 - 3765, PP. 336-340.

[11] T.Balakumaran, Dr.ILA.Vennila, and C.Gowri Shankar,"Detection of Microcalcification in Mammograms Using Wavelet Transform and Fuzzy Shell Clustering", (IJCSIS) International Journal of Computer Science and Information Security, Vol. 7, No. 1, 2010.

[12] Ted C. Wang and Nicolaos B. Karayiannis,"Detection of Microcalcifications in Digital Mammograms Using Wavelets",IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 17, NO. 4, AUGUST 1998.

[13] X.P.Zhang, “Multiscale tumor detection and segmentation in mammograms,” in Proc. IEEE Int. Symp. Biomed. Imag., Jul. 2002, PP. 213–216.

[14] X.P.Zhang and M.D.Desai, “Segmentation of bright targets using wavelets and adaptive thresholding,” IEEE Trans. Image Process., vol. 10, no. 7, Jul. 2001, PP. 1020–1030.

[15] http://www.breastcancerindia.net/