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AN EFFICIENT IMAGE PROCESSING METHODS FOR MAMMOGRAM BREAST CANCER DETECTION

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ABSTRACT

Nowadays it is immediate need for best pre-screening tool to identify the abnormality of the mammogram images in the earlier stage itself. In this paper it is discussed about a tumor segmentation and classification algorithm from mammogram. The proposed approach concentrates on the result of two issues. One is the way to recognize tumors as suspicious regions may be very weak contrast to the background and the next is the way to concentrate properties which classify tumors. The proposed technique follows step by step procedures such as (a) Image Enhancement (b) Tumor Segmentation. (c) The extraction of properties from the segmented tumor region. (d) The utilization of SVM classifier. The improvement could be characterized as change of the image originality to a superior and more reasonable level. The mammogram enhancement can be obtained by removing the noise and improve the quality of the image using speckle noise removal and EM algorithm respectively. The most well-known division technique utilized is Modified Watershed Segmentation method. The features are extracted from the segmented tumor region and classify the regions utilizing the SVM classifier. The technique was tried on 100 mammographic images using MIAS and Apollo hospital based images. The system attained an Accuracy of 98%.

Keywords: *Mammogram, MIAS Database, Cancer Detection, Benign, Malignant, Mammogram Segmentation.*

1. INTRODUCTION

Breast tumors are uncontrolled and anomalous multiplications of cells. Some start in the breast itself, in which case they are termed essential. Others spread to this area from someplace else in the body through metastasis, and are termed as optional. Essential breast tumors don't spread to other body locales, and might be dangerous or amiable. Optional breast tumors are constantly threatening. Both sorts are possibly crippling and life debilitating. Tumors in the bosom initially begin creating from the breast tissue itself. It is significantly more basic in ladies than in men. Bosom malignancy represents 22.9% of diseases amongst ladies around the world. Its survival rates are much lower in creating countries. The motivation behind why there is center upon breast tumors is on account of numerous ladies overlook the vicinity of knots in their breasts. This irregularity later turns dangerous and has a tendency to be all the more destructive.

Therapeutic Image investigation and transforming has extraordinary essentialness in the field of pharmaceutical, particularly in noninvasive medication and clinical study. Therapeutic imaging methods and examination apparatuses empower both specialists and radiologists to touch base at a particular determination. Restorative Image Processing has risen as a standout amongst the most imperative devices to distinguish and also diagnose different issue. Imaging helps the specialists to envision and examine the picture for understanding of anomalies in interior structures. Mammograms distinguish indicators emitted from typical and anomalous tissue, giving clear pictures of generally tumors. It has turned into a generally utilized strategy of fantastic medicinal imaging, utilized broadly within breast imaging, where delicate tissue contrast and non-obtrusiveness are clear focal points.

In this paper it is motivated that detecting and classifying the breast cancer accurately and comparing with the existing systems. Few methods are combined to have more accuracy in

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this paper and the methods are Speckle Noise Removal, Watershed Segmentation method, EM algorithm, GLCM method and SVM classification. Since all the methods used in this paper are benchmark approaches and they proved individually good in the early studies.

2. RELATED WORKS

This section provides a survey about various methods and techniques applied for image processing, tumor detection and tumor classification. Author Fatima Eddaoudi Et al [1]. Proposed Mass detection threshold and classified using SVM classifier. For detection the main factor take is Thresholding. The region of interesting segmented are classified to normal and abnormal tissue using Haralick features calculated from the co-occurrence matrix. The test of these methods on mammograms of MIAS databases showed better performance in detecting masses compared to the methods proposed in the literature. Tingting Mu et al. [2] proposed a new approach strict two-surface proximal (S2SP) classifier for tumor classification where this method uses 22 features of the segmented tumor portion. The earlier detection of breast cancer using self-similar fractal method [3] was proposed by BhagwatiCharan Patel et al. Where the aim of this paper [3] is presenting a method for medical image enhancement based on the well-established concept of fractal derivatives. The concept of a fractal is most often associated with geometrical objects satisfying two criteria: self-similarity and fractional dimensionality. The method was tested over several images of image databases taken from BSR APPOLO for cancer research and diagnosis, India. Olfati.E et al. [4] discussed Eigen factors for comparison and classification and the results were compared with GA based results. A swarm intelligence technique based support vector machine classifier (PSO_SVM) is proposed for breast cancer diagnosis in [5].

In the proposed PSO-SVM, the issue of model selection and feature selection in SVM is simultaneously solved under particle swarm (PSO optimization) framework. A weighted function is adopted to design the objective function of PSO, which takes into account the average accuracy rates of SVM (ACC), the number of support vectors (SVs) and the selected features simultaneously. Furthermore, time varying acceleration coefficients (TVAC) and inertia weight (TVIW) are employed to efficiently control the local and global search in PSO algorithm. Mammography feature analysis and mass detection in breast cancer images was introduced by Patel,B.C., et al[6]. KarthikeyanGanesan et al.[7] discussed various methods, issues and challenges of computer aided diagnosis. A CAD system with SVM classification combined LDA classification was proposed by Alolfe.M.A in paper [8]. Osareh.A et al. [9] proposed Machine Learning techniques to diagnose breast cancer. Cheng-Hong Yang et al. [10] used GA to detect the associated geno-type frequencies. Jinshan Tang et al. [11] developed a CAD system for cancer detection and diagnosis. The techniques used are applied for various stages like finding, locating, detection and classification. Mohammad SametiRabab et al. [12] applied feature extraction method which was used to check the tumor is benign or malignant. A Fuzzy SVM method was used in a CAD system for mass detection by Xiangjun Shi et al. in [13]. Amir Fallahi et al. in [14] proposed an automatic system for detection of breast cancer using data preprocessing and Bayesian network where in this study, Relief algorithm is used for reducing the dimension of breast cancer database then a pre-processing is done on the data and ultimately Bayesian network classifier is used for classification. HosseinRabbani et al. proposed speckle noise removal method for enhancing the image for better mass detection in [15].

The overall literature survey says that there are various methods are already used on medical images. The various classification techniques applied are classifying the images with less number of features. Due to less number of features the classification accuracy is also less and it is limited on the type of input images.

3. EXISTING SYSTEM

In the existing system the Mammogram breast cancer detection was applied image processing threshold, edge-based and watershed segmentation methods. Also the author present a case study based on the detection time and simplicity [10]. The limitation of the study is all the three methods applied are commonly using threshold value for their main functionality. Also for classification the selected features were not providing clarity and not using standard classifier or feature extraction method. But in this paper the detection, feature extraction and

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classification are used standard method, multi database based images.

But in this paper the complete set of 322 images are taken from MIAS database combined with some real time images also.

4. PROPOSED APPROACH

Tumor Detection in Mammogram images is divided into three stages. The stage-1 involves the enhancing the image, the stage-2 involves the tumor segmentation and the stage-3 involves the feature extraction and classification. The noise removed using speckle noise removal method. The tumor area is segmented using the Modified Watershed Segmentation method and binary operations. Finally the features of tumor area are extracted using GLCM feature extractor and it is used to measure the properties of the segmented image and classified using SVM classifier. The complete functionality of the proposed approach is depicted in Figure-1.

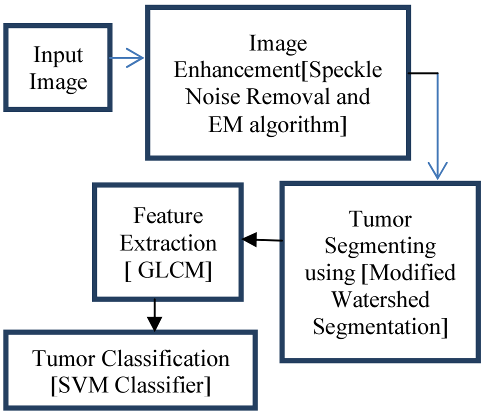

Figure-1: Overall Functionality Of Proposed Approach

The input image is taken from BSR APPOLO for cancer research and diagnosis, India and comparing with the MIAS database. The input image may be a color image or gray scale image or any kind of images. If necessary the image can be converted from one color space into another color space. [Ex: RGB-to-GRAY].

4.1 Noise Removal

The mammogram is perused from the record and preprocessed by evacuating the noise utilizing Speckle Noise Removal Method. For more exact output, the mammogram image is upgraded utilizing EM algorithm. Also change the mammogram into gray scale if the input image is in RGB color

4.2 Speckle Noise Removal

Speckle Noise is a granular noise that intrinsically exists in and decreases the quality of the dynamic radar and engineered aperture radar images and therapeutic images. Reducing noise from the therapeutic images, a satellite image and etc., is a challenge for the experts in DIP. A few methodologies are there for noise reduction [12]. By and large speckle noise is usually found in engineered aperture radar images, satellite images and therapeutic images.

An inalienable normal for MRI imaging is the presence of speckle noise. Speckle noise is an arbitrary and deterministic in a image. Speckle has negative impact on ultrasound imaging, Radical diminishment interestingly determination may be in charge of the poor successful determination of ultrasound as contrasted with MRI. If there should arise an occurrence of medicinal written works, speckle noise is otherwise called texture. Generalized model of the speckle [13] is represented as,

$$\boldsymbol{g(n,m) = f(n,m) * u(n,m)\varepsilon\,(n,m)} \quad ------ (1)$$

Where, $g(n,m)$ is the observed image, $u(n,m)$ is the multiplicative image part and $\varepsilon\,(n,m)$ is the added image part segment of the speckle noise. Here n and m means the axial and parallel indices of the image samples. For the ultrasound imaging, just multiplicative image part of the noise is to be considered and added image part of the noise is to be disregarded. Thus, mathematical equation (1, 2) could be altered as;

$$\boldsymbol{g(n,m) = f(n,m) * u(n,m) + \varepsilon(n,m) - \varepsilon(n,m)}$$

Therefore,

$$\boldsymbol{g(n,m) = f(n,m) * u(n,m)} \qquad -(2)$$

In this paper the speckle noise could be evacuated by then again select any sub alternative of average filter, wavelet filter and TV filter and so on. Depends on the image and the image information the noise evacuation filter might be chosen. Before evacuating the noise the image size is expanded and cushioned as piece sort of sub-images, and filter connected, consequently the noise gets cleared totally.

4.3 Image Enhancement

In this paper, a firmness improvement method exploiting EM procedure is proposed. By energetically giving a priori probability delivery suited for a specific application environment

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currently considered, the proposed method provides a general framework for rendering good image quality at the designated firmness for a large class of image development procedure.

In the EM procedure, assumed, unobservable “complete data set” is working to ease the procedure of maximizing the likelihood function of the measured data. The actual cunning consists of a sequence of irregular anticipation steps and expansion steps. This iterative process has the necessary possessions of maximizing the likelihood function defined on the unhurried data monotonically, and meeting to a worldwide maximum at a unique point. A graphic illustration of the solicitation of the EM algorithm to firmness enhancement faced in the perusing process is showed in Figure-2. A glowing light source pulled by a resulting apparatus from top to bottom produces light on the shallow of the scanned hardcopy. The concentration of the light reproduced is then noticed by an array of light sensors. However, the intensity recorded by any specific sensor is affected not only by the area restricted by scanner firmness, but also adjacent areas due to the dispersal of light. The proposed method exploiting EM technique can be used to recompense the above effect, reinstate the innovative density, or increase firmness if desired.

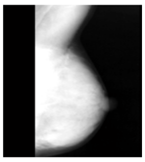

Figure-2: Enhanced Image Using Em Algorithm

The enhanced image using EM algorithm is depicted in Figure-2. The brightness of the image is increased and the tumor portion and the normal portion in the breast image are very clear on the image. The figure-2 is a resultant image where the EM algorithm is developed in Matlab and produced.

4.4 Tumor Segmentation

Image separation is the separation of an image into sections or groups, which agree to dissimilar objects or parts of images. Every pixel in an image is owed to one of a quantity of these groups. A good separation is typically one in which:

- Pixels in the same group have similar grey scale of multivariate values and form an associated section.
- Adjacent pixels which are in dissimilar groups have dissimilar values.

The IWS technique is motivating when you have to describe an area which has neither texture nor gray level unity. Furthermore, this region should have ambiguous outlines and it should be problematic to section even by using human eyes. It is need to provide inner and outer indicators by using mouse clacks. Additionally your model is detailed; more precise will be the final separation. For the cancers we work on, the minimum number of clacks was of three inside and five outside, but it should depend on your image type.

The images we have are frequently deafening and real tumor borders are ambiguous. Instead of annoying to obtain improbable “perfect” separation, our method has a more realistic approach: we add an ambiguous area with a tumor probability between 0 and 1. In order to do this, we use iteratively the watershed technique.

A principal watershed is computed from the two early indicators as showed in the top Image. In the case of the semi-automatic approach, these initial indicators are provided by an operator using mouse clicks. These clicks locate pixels which are automatically linked by lines. The pixels which belong to these lines are all considered as markers. This operation is needed two times: a first time for the inside marker set and a second time for the outside marker set.

The resulting watershed which is shown in white between the two markers on the top of the Image is considered as a third marker for a second watershed which gives three regions (inside, fuzzy and outside) as you can see in the middle of the Image shown in figure-3.

In the middle of the Image, we can see the new segmentation and its three areas:

- ✓ Inside the white inner line, the tumor assuredly exists.
- ✓ Between the white inner line and the green outer line, the tumor occurrence is powerfully possible. The probability of occurrence decreases when moving from the red line to the green one.
- ✓ Outside the green exterior line, there is no tumor.

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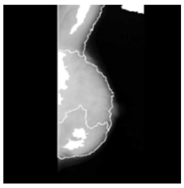

Figure-3: Iterative Modified Watershed Segmentation

4.5 Feature Extraction using GLCM

In gray level co occurrences matrices, the number of rows and columns are equal to the number of gray levels. Indexing and retrieving the visual contents in an image can be obtained by Feature Extraction method. The GLCM is a $L \times L$ square matrix of the gray scale image I of spatial dimension $M \times N$ with gray level in the range $T = [t_{i,j}] L \times L$ .It can be represented by $T = [t_{i,j}] L \times L$ matrix. Every element in the matrix specifies the number of transitions among all pair of gray values in a specific manner. Every pixel in the image at spatial co-ordinate (m, n) including its gray value specified by f(m, n), it deliberates all its nearest adjacent pixels in the locations of

$$(m+1, n), (m-1, n), (m, n+1) \text{ and } (m, n-1)$$

The co-occurrence matrix is formed by comparing gray level changes of f (m, n) to its corresponding gray levels,

$$f(m+1, n), f(m\text{-}1, n), f(m, n+1) \text{ and } f(m, n\text{-}1).$$

There are various co-occurrence matrix are possible and it duly depends on the gray level I follows the gray level j. The co-occurrence matrix by considering horizontally right and vertically lower transitions can be given as

$$t_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} \delta$$

where

$$\delta = 1 \text{ if} \begin{Bmatrix} f(m,n) = i \text{ and } f(m,n+1) = j \\ f(m,n) = i \text{ and } f(m+1,n) = j \end{Bmatrix}$$

$$\delta = 0 \text{ otherwise}$$

Normalizing the entire number of transitions in the co-occurrence matrix, a desired transition probability P_{ij} from gray level I to gray level j is obtained as follows.

$$P_{i,j} = \frac{t_{i,j}}{\sum_{i=1}^{L} \sum_{j=1}^{L} t_{i,j}}$$

Using the feature extraction method the texture properties of the mammogram images are extracted. These feature values are used by the classifier after some times to categorize the images accurately.

Textural features are the characteristics of the surface of mammogram images and the relationship among the nearest neighbor pixels on the surface. There are several textural features available a mammogram, but in this scenario the mean, standard deviation, entropy and homogeneity of the pixels are calculated and compared for evaluating the performance of the proposed approach. The spatial distribution of the gray level features can be obtained from Co-Occurrence matrix of the image. The below table shows the extracted features which are treated as most important-features used to classify the tumor regions.

For our proposed work 50 normal images and 50 tumor affected images (totally 100 images) are taken as input images and their features are extracted and the classification results are shown below.

Table-1: Feature Used To Classify

Feature	Description	Formula
RegionSize [area]	*Theregionsizeaofthe segmentedportion [tumor]fromthe mammogramimage isthenumberofpixels insidetheregion.*	$a = \sum_{i=1\,ton} i$
Mean [Radius]	*Thesumof theR, G, B valuesdivided by 3.*	$\mu R = \frac{\sum_{i\in\Omega} R(i)}{a}$ $\mu G = \frac{\sum_{i\in\Omega} G(i)}{a}$ $\mu B = \frac{\sum_{i\in\Omega} B(i)}{a}$
Standard Deviation [Texture]	*Thestandarddeviation oftheRGBvalues insidetheregion [σR, σG, σG]. Theyare calculatedas*	$\sigma R = \frac{\sqrt{\sum_{i\in\Omega}(R(i)-\mu R)^2}}{a}$ $\sigma G = \frac{\sqrt{\sum_{i\in\Omega}(G(i)-\mu G)^2}}{a}$ $\sigma B = \frac{\sqrt{\sum_{i\in\Omega}(B(i)-\mu B)^2}}{a}$
Mean RGB	*Theaverage value oftheMean ofthe RGBvalues.*	$\mu_R^a = \frac{\sum_{i\in\Gamma} R(i)}{a^a}$ $\mu_G^a = \frac{\sum_{i\in\Gamma} G(i)}{a^a}$ $\mu_B^a = \frac{\sum_{i\in\Gamma} B(i)}{a^a}$
Uni − formity	*Similarity orthe uniqueness amongthe pixels.*	$U = \sum_{i=0}^{n-1} p^2(intensity)$
Entropy	*Unpredictable information in theimageis entropy.*	$p(intensity) log_2 p\,(intensity)$

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extracted and the classification results are shown below.

4.6 SVM classification

Several features are extracted and only 6 features are taken to classify the tumor. One is area and 5 textural features. The SVM classifier is employed to tumor or non-tumor in the mammogram images. The selected features feed as input to SVM classification parameters and it classifies the normal and abnormal categories.

Algorithm Proposed algorithm ( )

{

1. $Let\ I\ be\ the\ input\ mammogram\ image$
2. $I\ =\ add\_noise(I, noise\ type)$
3. $I\ =\ remove\_noise(I, filter\ type)$
4. $[m\ n]\ =\ imagesegmentation(I, thresholdvalue)$
5. $KL\ =\ featureExtraction(m)$
6. $Train1\ =\ SVM - classifier(KL);$
7. $Result\ =\ Train1$
8. $Result\ is\ Tumor\ or\ Non - Tumor$

}

5. EXPERIMENT RESULTS

To investigate the efficiency of the proposed approach, the algorithm is programmed in MATLAB 2012a software and run on entire datasets. Tumor detection was gathered from the result set. The results of the proposed approach are shown in the following Figure-4 and Figure-5 clearly.

5.1 Performance Evaluation

To run a normal image in MATLAB software takes a minimum of 14 second using PC with core i5 processor and 4 GB RAM. All the database images are individually called for training and testing the detection as well as classification processes. The sample of each data set is divided into 50% of training and 50% of testing categories. Finally SVM classifier is trained with the training data set. Then the each testing image is compared with the trained images and classify.

The results of the proposed approach are shown in the following Figure-4 and Figure-5 clearly.

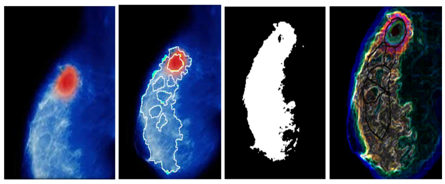

Figure-4: Original Image, Watershed Segmentation, Negative Image, Tumor Detected For Color Image

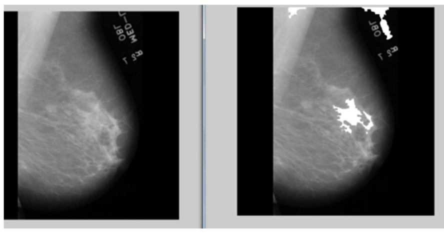

Figure-5: Breast Cancer Detection For Mammogram

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

$$\boldsymbol{Sensitivity}(\%) = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}} \times \mathbf{100\%}$$

$$\boldsymbol{Specificity}(\%) = \frac{\boldsymbol{TN}}{\boldsymbol{TN + FP}} \times \mathbf{100\%}$$

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

Where $TP \rightarrow True\ Positive; TN \rightarrow True\ Negative; FP \rightarrow False\ Positive;$

$FN \rightarrow False\ Negative; N \rightarrow is\ the\ total\ Number\ of\ images$

The input image and the gray scale based enhanced image used in the experiment is shown in the following Figure-4. The following table shows the GLCM matrix obtained from the DR image where all these values in matrix represent the features of the image.

$$\begin{bmatrix} 672180 & 1207 & 659 & 0 & 0 & 0 & 0 & 0 \\ 712 & 2106 & 1786 & 11 & 0 & 0 & 0 & 0 \\ 954 & 1105 & 475216 & 14994 & 5 & 0 & 0 & 0 \\ 199 & 175 & 14590 & 238704 & 7291 & 6 & 0 & 0 \\ 1 & 22 & 23 & 7248 & 46694 & 1472 & 0 & 0 \\ 0 & 0 & 0 & 8 & 1470 & 9038 & 194 & 0 \\ 0 & 0 & 0 & 0 & 0 & 194 & 3736 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

A sample GLCM Matrix for Mammogram Image

5.2 Co-Occurrence Matrix

The textural features such as gray level, contrast, homogeneity, correlation and energy are also calculated from the GLCM. The tumor segmentation results for sample images of Apollo.

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Table-2: Classification Specificity Results

Total No. of Images	TP	FP	Sensitivity
80	78	2	97.50%

$$Sensitivity = \frac{TP}{TP+FN} = \frac{78}{(78+2)} = 97.5\%$$

$$Specificity = \frac{TN}{FP+TN} = \frac{20}{(0+20)} = 100\%$$

$$Accuracy = \frac{Tp+TN}{P+N} = \frac{(78+20)}{(50+50)} = 98\%$$

$$Where\ P = TP+FN$$

N =FP+TN

Total Number of Images	TN	FN	Specificity
20	20	0	100.00%

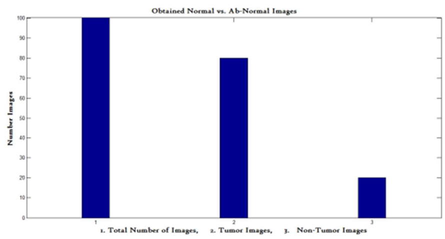

Figure-6: Obtained Normal Vs Abnormal Tumor Images

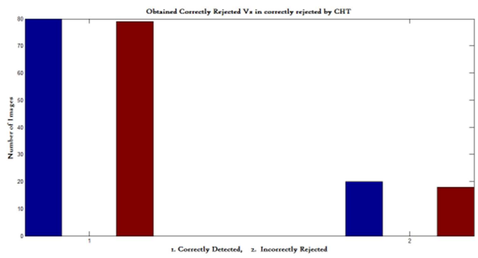

Figure-7: Obtained Correctly Detected Vs. In-Correctly Rejected Images

6. CONCLUSION

In this paper, the various steps involved in Automatic Tumor detection were implemented. The proposed approach in this paper with Image Enhancement [Speckle Noise Removal and EM algorithm], Modified Watershed Segmentation, Feature Extraction [GLCM] and SVM classification proved its performance via performance metrics such as Sensitivity is 97.5%, Specificity is 100% and its Accuracy in classification is 98%. Our system gives the better performance when compared with existing methods, so it is very helpful to the medical people in detecting tumor. Also this proposed approach can help rural people to find out the tumor occurrence in MRI in case of emergency situations. In future, it is concentrated on automatic detection of tumor with Classification in MRI images.

6.1 FUTURE WORK

Further we are incorporating the above algorithms for the development of CAD system for early detection of breast cancer and a Model for Fractal Images.

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