Breast Cancer Classification and Precise Diagnosis using Breast MRI Data

Vidya K[1], M Z Kurian[2]
[1]Research scholar, Sri Siddhartha Academy of Higher Education, Tumakuru
[2]Registrar, Sri Siddhartha Academy of Higher Education, Tumakuru

Abstract- **Precise diagnosis of the Breast cancer plays a pivotal role in deciding the treatment whether it is surgery or neo adjuvent chemotherapy. Accurate detection will avoid the unnecessary procedure and the removal of the breast. High resolution Magnetic Resonance Imaging (MRI) has been strongly incorporated as the imaging modality to measure the size of the tumor and hence the staging of the cancer in order to choose the best treatment for the patient. Therefore, Detection of the tumor from the breast MRI and its classification performed by Computer Aided Diagnosis (CAD) based techniques has been a helping hand to the radiologist in taking the decision about the tumor. The aim of the proposed work is to segment and detect the tumor section from the MRI slices. This is done by initial thresholding followed by filtering and then extraction of foreground and background objects assisting in reliable classification. A statistical based approach is used for extracting the feature set followed by supervised learning classification. The detected tumor is extracted and compared with the data which is marked by the radiologist (ground truth data). Performance parameters such as sensitivity, specificity, accuracy and F values are calculated. Tumor is extracted from all the MRI slices of a patient and then its dimension is calculated at its widest part to know the stage for further treatment. Spearman correlation coefficient of 0.7079 is obtained by comparing the extracted tumor with radiologist data. Study outcome is also compared with the existing classification.**

***Index Terms*— Magnetic Resonance Imaging, Classifier Malignant/Benign tumor, Breast cancer.**

I. INTRODUCTION

Breast cancer is the second most common cancer seen in women across the world. It is the major cause of mortality among women[1]. According to highly reliable sources, approximately 287,850 women have been reported for invasive breast cancer and 51,400 women are found to be diagnosed with in-situ breast cancer in the year 2021. These statistics show that breast cancer is an alarming disease condition where still medical science is lagging behind in early detection of the disease [2]. Even though there are lot of advancements in medical image processing in terms of soft computing and hardware-based techniques which has assisted disclosing various valuable information about the disease condition, still it encounters exponential challenges in the detection of cancer [3]. Medical imaging can assist in minimizing the mortality rate and helps in precise clinical diagnosis. At present, Mammography is used as the standard mechanism for diagnosing breast cancer as it can make out the difference between the infected tissue and normal breast tissue. But however, it is found that the degree of sensitivity of Mammogram is reduced in case of patients having dense breast tissue. Apart from Mammogram Ultrasound is also used for capturing the disease condition. This is mainly operator dependent for the diagnosis. Magnetic Resonance Imaging (MRI) is one of the best options to investigate the radiological image of the breast [4][5]. The images that are constructed on the basis of potential radio waves and magnetic fields in MRI helps in investigation of bones, tissues and organs with higher accuracy. Also, these images with high resolution are generated without any radiation. But there are many cases where MRI images also introduce ambiguity which will affect the identification and classification process. There are various research work being carried out towards breast cancer identification and classification [6]-[10]. The significant factors in classification are prominent grade of tumor, form of histopathological, current stage of tumor and others, which are more clinical in nature [11]. An effective and precise segmentation of the tumor and its classification is to be performed in order to assist in determination of treatment. Even the smallest mistake may lead to wrong treatment at the cost of the patient's life. There are various forms of classification algorithms used in medical image processing which deal with the extraction of the infected region of the breast and then classifying it as cancerous or non-cancerous [12][13][14][15][16].

There are many problems associated with all these classification approaches. First problem is associated with preprocessing where majority of the existing studies have less focused. Usually, MRI images have higher possibility of having multiplicative noise. This has to be addressed. Second problem is the mechanism used for processing the image has to retain maximum information after the processing is done. Once the tumor is extracted and classified, its size is estimated [17] and then the stage of the cancer is noted according to TNM (Tumor, Node and Metastasis) staging data. In measuring the size of invasive tumors MRI shows high accuracy, unless there is an associated Ductal in-situ component. Therefore, the proposed study presents an implementation of a classification technique which focuses on accuracy and computational efficiency. The system uses the True positive(TP) and False positive(FP) as the parameters to calculate the accuracy from multiple observations. Then the extracted tumor dimension is measured in centimeters which decides the stage of the cancer which further helps in deciding the treatment. In this work breast MRI of the benchmark images of the reference database (RIDER) is considered for the assessment. Ten Axial MRI slices are considered for each patient and every image is separately examined with the considered methodology and then the performance is validated.

Discussion about the existing literatures on different techniques of segmentation and classification is done in the next Background section followed by problem identification and proposed solution. Section II explains about the algorithm implementation followed by Result discussion in section III. Section IV discus the summary of the contribution of the proposed research work towards improving the classification performance of breast cancer and then effectively staging the cancer.

A. Background

There are various techniques adopted for segmentation and classification of disease condition pertaining to medical image dataset. Human factor has a significant effect in the cancer detection process. Work carried out by Singh et al.[18] in this direction explains about exponential transform followed by feature extraction of the suspected region. An accuracy of 97 percent is achieved and compared with the existing techniques. Tariq Sadad et al.[19] proposed a method to detect the malignancy of the breast tumor through CADx (Computer Aided Diagnostic tool for detection) by making use of marker-controlled Watershed for segmentation and the Decision tree, k-nearest neighbor (KNN), and Ensemble decision tree model are utilised to separate cancerous and non-cancerous tumors. Results were compared.

Various segmentation methods are discussed by Epimack Michael et al[20]. They have grouped segmentation methods into three groups. (i) Classical segmentation includes region-, threshold- and edge-based segmentation.(ii) Machine learning segmentation and (iii) supervised, unsupervised and deep learning segmentation. Prabhpreet Kaur et. Al [21], proposed a method for accurate diagnosis of the disease and help in outcome predictions in mammograms. K-means clustering is used for feature selection and deep neural network along with multi class space vector machine is used for classification which improved the accuracy compared to decision tree model. Deepika S et.al[22] have compared various methods, Classification and Regression Tress(CART), Linear Support Vector Machines(SVM), Gaussian Naive Bayes(NB) and k-Nearest Neighbors (KNN). Space vector machine is found be the best for breast data. Sung Eun Song et al.[23] showed that by making use of the proper threshold Computer Aided Detection(CAD) and MRI can detect the breast lesion more accurately. For both invasive cancer and Ductal carcinoma insitu (DCIS) with 30 percent threshold, correlation coefficient was found to be highest between tumor size in imaging and pathology. Luciana Karla et al,[24], have discussed the evaluation of breast tissue from MR image and hence calculated the size of the breast by experts. Since the size assessment is the first stage in cancer diagnosis, if the assessment is accurate, medical experts will be able to provide better treatment for breast cancer patients. Uniayal et al .[25] have presented a radio frequency time sequence features and machine learning framework to classify the breast lesions into cancerous and non-cancerous. The presented RF time sequence technique helps to generate maps during the classification of breast lesions. Through space vector machines, the technique generates a characteristic curve of suspicious breast tissues. The accurate classification will reduce the number of biopsies. Beevi et al.[26] have suggested a deep belief network based multi classifier system for accurate detection of mitosis cells in breast image. The experimental outcome and performance score demonstrates that the performance of the presented technique provide better results as compared to another state of-the-art method. Odajima and Pawlovsky[27] have used KNN algorithm for diagnosis of breast cancer. Pawlovsky and Nagahashi[28] have enhanced the KNN performance further to increase the mean accuracy of breast cancer diagnosis. Alpaslan et al.[30] have used KNN algorithm for classifying masses of breast cancer. Hybridisation of KNN algorithm with support vector machine was seen in the work of Bouazza et al.[31] towards solving classification problems in gene expression.

Literatures also show that artificial neural network has been adopted in various researchers in solving breast cancer classification. Usage of feed forward as well as back propagation was investigated by Saini and Vijay[29] toward analyzing mammograms. From the literatures available it is found that lot of work being carried out towards addressing classification problems in radiological images. Usage of the convolution based neural network is reported in Bardou et al.[32]. The authors have also used the support vector machine for training in order to enhance the diagnosis process. Hence there has been various work carried out by existing researchers towards solving the classification problem of breast cancer.

B. Problem Identification

- MRI generates huge amount of data which is superior and high-resolution images. But its interpretation is highly subjective which rises the variability in clinical conclusion about the disease among different observers.
- Fully automated techniques to perform detection and classification of stages of cancer for MRI images are very less.
- Even now many false positives are seen in identification stages.

Therefore, the problem statement of the proposed study is identified as to develop a simple and cost-effective model that address the classification problem in breast cancer and thereby comparing the correlation between the tumor size measured with the propose method and the radiologist data.

II. METHOD

The purpose of the proposed study is to present a classification approach in order to distinguish malignant and benign condition by developing a simple analytical model as shown in Figure 1. to perform reliable extraction of feature from the MRI data followed by classification. The study will consider investigating breast MRI images from The Cancer Imaging Archive (TCIA)-RIDER dataset. The initial part of the study will perform the preprocessing operation to be carried out, which is expected to make the image suitable for classification. Then a simple analytical formulation will be carried out that will assist in extracting potential statistical features. The next part of the study will be to develop a classifier that can perform better distinction. This approach will use supervised learning technique for better compatibility with both linear and nonlinear classification feasibility. A probabilistic distribution model will be used for enabling computational tractability. The final outcome of the model lead to the classification result as to malignant or benign. Once the cancerous tumor is extracted from all the MRI slices of a patient by applying the above methodology staging of the cancer is done by measuring the dimension of the tumor at its widest part.

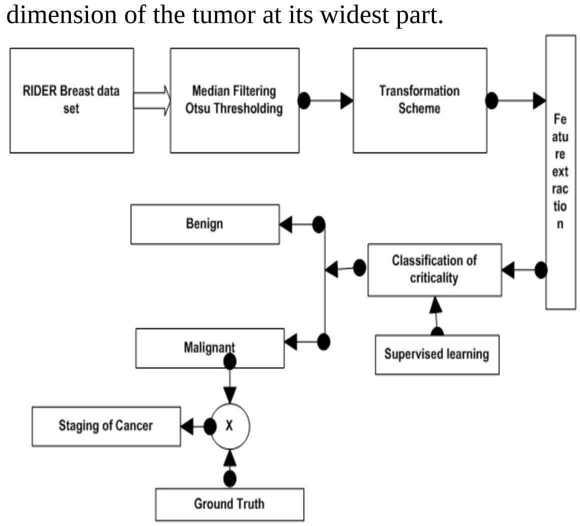
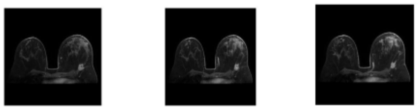


Figure 1. Architecture of proposed method



(a) (b) (c)

(a) (b) (c)

Figure 2. Three slices of Axial breast MRI image depicting the tumor of case 1 and case 2

A. TCIA –RIDER dataset

In this work, the breast MRI images from RIDER-TCIA dataset [33] is considered for the assessment. RIDER is chosen for this study because it is a registered dataset and has been used by various previous works. This dataset also included Ground Truth (GT) segmentation, which has been identified manually by expert radiologists. GT is used as a benchmark for performance evaluation of segmentation methods in this study. All images are 288x288 pixels. They are read in DICOM format and converted into 8-bit grey level scale. Axial images are considered for the evaluation. For each patient 10 slices are collected for the investigation along with their GT. Figure 2 shows 3 slices of case 1 and case 2 containing the tumor. The image (b) in each case contains the tumor at its maximum size which has to be detected and extracted to diagnose the staging of the cancer.

B. Filtering and Thresholding

Pre-processing is mainly responsible to increase the eligibility criteria of MRI image towards better classification process owing to the complexities related to the form of the medical image. This stage always includes the removal of noise from the data. The filter which is used is a nonlinear channel which tends to keep the sharpness of the edges while getting rid of the noise [34]. Increasing the size of the window will improve the efficiency of the filter in the noise removal. This filter makes use of mxn neighborhood and arrange them in an increasing order. The middle value of the neighborhood is selected, and the central pixel of the neighborhood is replaced with this value. Thus, the principal function of these filters is to force points with distinct intensity levels to be more like their neighbors. Isolated clusters consisting of pixels which are either dark or light when compared to their neighbors and also having an area of mxm/2 are eliminated by mxm filter. Forcing the pixel value to the median intensity of the neighbors is the meaning of 'elimination'. When this filter is applied to gray scale image, median of the gray values inside the mask is assigned to all the pixels in the mask. If the filter is applied to a logical image, then the central pixel will be assigned a true value if there are more true pixels than false pixels inside the mask. Filtering is followed by thresholding.

Otsus thresholding is found to be more suitable in enhancing these MRI images. This type of thresholding gives a good result when number of pixels in each class are close to each other. Since it directly operates on gray level histogram it is the most referenced thresholding method. It is fast and produces an optimized threshold. It is a variance-based technique. Threshold value is found when the weighted variance between the foreground and background pixels is the least. This method will iterate through all the possible values of threshold and then measure the spread of background and foreground pixels. Then find the threshold where the spread is least. Algorithm for Otsu's thresholding will iteratively search for a threshold that will minimize the inter class variance. Therefore, threshold is the weighted sum of the variances of two classes[35].

$$\sigma^2(t)=\omega_{bg}(t)\sigma_{bg}^2(t)+\omega_{fg}(t)\sigma_{fg}^2(t)$$

where $\omega_b g(t)$ and $\omega_f g(t)$ are the probability of number of pixels in each class (background(b_g) and fore ground(f_g)) at threshold **t** and σ_2 represents the color values.

$$\omega_{bg}(t) = P_{bg}(t)/P_{total}$$

$$\omega_{fg}(t) = P_{fg}(t)/P_{total}$$

$$\sigma^2(t) = \Sigma(x_i - x^-)^2/(N - 1)$$

x_i is the value of the pixel at i in the group b_g or f_g

x^- is the average of all the pixels in the group b_g or f_g

N is the total number of pixels in the image.

$P_{bg}(t)$ is the total countof pixels in the background(b_g) at threshold **t**.

$P_{fg}(t)$ is the total count of pixels in the foreground(f_g) at thresold t.

P_{total} is the total count of pixels in the image process.

C. Transformation Scheme

This transformation scheme will make the input image furthermore compatible for performing classification. This scheme is meant for transformation as well as the segmentation together for obtaining better compatible image. In this stage the thresholded image is applied with a two-dimensional filter of pre-defined form where Sobel operator is used in order to emphasize the edges during the filtering process. Therefore, the edge-based information that is significant in assisting the determination of the stage of the disease in classification is retained. Sobel mask used for the filtering process is given by the following 3x3 matrix.

$$Gx = \begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad Gy = \begin{bmatrix} -1 & -2 & -1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

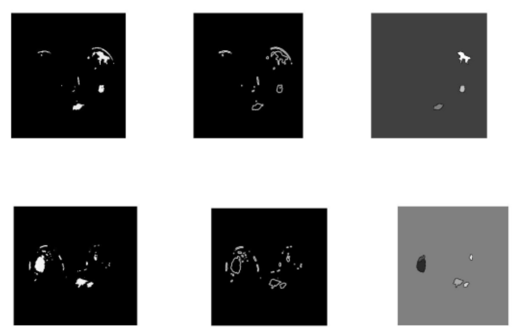
Gx and Gy are applied to the thresholded image. Finally gradient magnitude is obtained.

Marker based watershed is applied to the gradient magnitude. Watershed lines are external markers which pass along the highest points between neighboring markers. Hence these lines are nothing but the edges. Therefore, gradient magnitude is obtained first before applying watershed segmentation. Regions which are characterized by small variations in intensity often represented by a small gradient value. Along with preventing over segmentation this is another reason for applying watershed on the gradient magnitude. Further smaller morphological operations are carried out in order to introduce the Markers (Markers are connected components belonging to the image). 1) Indexing the foreground objects 2) Removal of dark spots (to address false positives) 3) Applying maximum image region to extract better foreground information 4) Cleaning of the edges 5) Elimination of blobs with less pixel information. The backgrounds are also indexed followed by applying watershed algorithm in order to obtain the better version of segmented image. Finally transformed image is obtained.

D. Classification of criticality

This is the last stage of the proposed method. In this stage classification of the criticality of the stages of the tumor of the breast cancer from MRI image is performed. This should maintain increased amount of accuracy in the detection. Imprecise diagnosis of the disease will lead to selection of imprecise treatment by the specialist. Therefore, multiple statistical information is obtained first to extract more information which will improve the accuracy of classification. Various descriptive statistical parameters like Mean, Variance, Kurtosis, Skewness, M2/M3/M4 moments and also Area and Perimeter are extracted. Support vector machine is applied on these extracted features as the proposed methodology uses supervised learning approach to perform classification which has supportability for both linear and non-linear classification. Since it is a binary classifier output will be 1 for benign tumor and 2 for malignant tumor. The primary contribution of this proposed method is that it is nearly similar to existing optimization-based algorithms that uses evolutionary based approaches.

III. RESULTS AND DISCUSSION



(a) (b) (c)

Figure 3. (a) filtered and threshold image (b) gradient magnitude (c) watershed image (both case 1 and case 2)

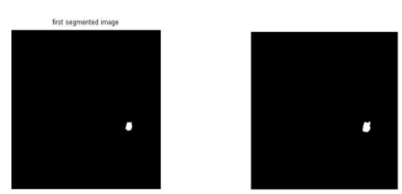


Figure 4 (a) Extracted tumor (b) Ground truth image (both case 1 and case 2)

The evaluation of this proposed system is carried out considering the DICOM format of the images taken from TCIA-RIDER. All the images are grayscale in the dataset. The data set for ten patients is considered where each patient data will have 10 slices (images) containing the tumor. Each slice is analysed using the proposed method and tumor is extracted. Tumor with largest area is considered and its width is calculated at its widest part. Fig 3 shows the Threshold image , gradient magnitude and watershed image of the slice consisting of the largest tumor for case 1 and case 2 considered above respectively.

Fig 4 shows the tumor extracted and the respective ground truth image. In case of case 1 the tumor found to be 2.49cm which is T2 stage and the tumor of case 2 found to be 3.41cm which is also in T2 stage according to TNM staging data

Performance analysis of is done by calculating various parameters like True positive, True negative, False positive and False negative. Accuracy, precision and sensitivity are calculated from these parameters. Between the tumor extracted and the ground truth performance parameters are calculated and listed in the Table 1 below. Table 2 contains the parameters calculated over all the MRI images considered for each case.

Spearman correlation coefficient is calculated to compare the correlation between the measured tumor extent over all the slices and the radiologist data and is equal to 0.7079.

Table 1. Performance parameters calculated between extracted tumor and GT

TP	TN	FP	FN	Jaccard
186	82712	1	45	0.8334
507	82215	3	219	0.8196

Table 2. Average performance parameters calculated over all the samples

Sensitivity	Specificity	Accuracy	NPV	Precision
0.7936	0.9999	0.9980	0.9981	0.9804

The outcome of the proposed study (classifier) was compared with more frequently used neural network and KNN algorithm. For this purpose, the proposed framework continues the similar steps till the transformation stage for existing system with the last step of classification being performed separately by feed forward network and KNN algorithm in order to maintain similar test bed environment for comparative performance analysis. The outcomes are assessed with respect to Accuracy, Sensitivity and Precision as in Fig 5. The proposed system has better sensitivity, slightly better accuracy than KNN.

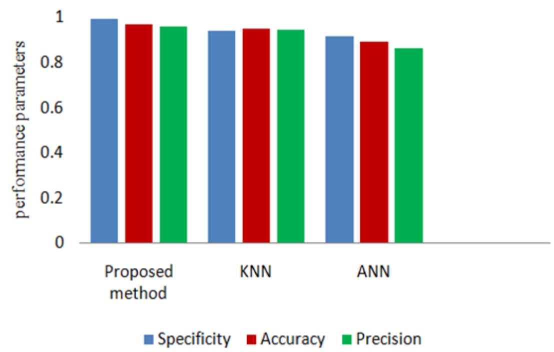


Figure 5. Comparative analysis of the proposed method with other existing techniques

IV. CONCLUSION

In this paper a framework that address the problem of classification of breast cancer with respect to criticality of the masses(benign and malignant) is presented. This method will significantly assist in increasing the accuracy level. Staging of the cancer also helps the specialist to take the proper decision about the treatment. This work can be extended for other imaging applications. The proposed method can be further extended for classifying other variants of malignant lesions.

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