International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-12 Issue-1, May 2023

A Robust Method for Extracting Texture Features of Segmented Mammogram Images using M-ROI Technique

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Abstract: ***Radiologists generally uses mammogram images for extracting masses or cancer effected breast issues using texture features of the images by segmenting techniques. The most commonly used technique in this process is region of interest (ROI). But this method fails for large collection of mammogram image database. To address this issue this present paper proposed multi-ROI (M-ROI) technique. This method not only reduces limitations of ROI but also finds the very suitable texture features. This paper also evaluated the efficiency of the proposed M-ROI method using first order and second order statistical techniques***

Index Terms: Benchmarked Images, Multi-ROI Segmentation, Region of Interest, Texture Features

I. INTRODUCTION

Texture features of the mammogram images are generally obtained by segmenting images into two regions i.e. cancer and non-cancer respectively. These two regions contain different patters or shapes. Segmentation is very powerful technique to detect such irregularities in the images. Using segmentation technique, we generally divide the image from extracting edges or boundaries. In mammogram images ill-defined [11] masses contain more intensity compare to other regions. And also, these regions contain circular based objects. Textures are very important in the analysis of the images. This task can be completed in two steps. In first step we segment the image and in second step we extract the texture features from the segmented parts in the first part[13]. Textures are very important in the analysis of the images.

ROI is one of most powerful and useful technique for segmenting and detecting various regions in the mammogram images. But there are some limitations using this technique. One of these limitations is not suitable for huge number of images [2]. To overcome this issue this paper proposed M-ROI based texture features. The efficiency of the proposed method is evaluated also, these regions contain circular based objects.

Manuscript received on 16 May 2019 | Revised Manuscript received on 12 April 2023 | Manuscript Accepted on 15 May 2023 | Manuscript published on 30 May 2023.
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Textures are very important in the analysis of the images. This task can be completed in two steps. In first step we segment the image and in second step we extract the texture features from the segmented using statistical techniques of the extracted features using Multi-ROI features.

The main features of the proposed method are:

1. Used ROI and proposed M-ROI for segmenting the mammogram images on large data sets.
2. Segmented images are used to extract texture features
3. In depth texture analysis for abnormal images
4. Extracted statistical features from ROI and proposed M-ROI segmentation are compared

This paper is organized as follows. Section 2 deals with the Background study of the present study. The proposed method details are given in section 3. The results and conclusions are given in Section 4 and 5 respectively.

The efficiency of the proposed segmentation mainly depends upon the illumination of the mammogram image. This problem mainly arises from the images having Low contrast. So we first need to enhance these images to improve the efficiency of the method. Contrast stretching [6] is one method for enhancing the image to improve the efficiency.

In Contrast stretching method image intensity can be improved by stretching range of values. The range upper and lower of intensity are needed before stretching. For example, in gray images 0 and 255 are lowest and highest values respectively. The eq1 can be used to enhance image in contrast stretching method.

$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a \qquad (1)$$

Where ‘a’ and ‘b’ represents lower and upper respectively and ‘Pin’ refers the pixel intensity.

Without effecting nature of the image we can alter the contract of the image using histogram equalization method [7]. In this method transformation procedure applied to transform gray pixels between input and output images and maximizes the contrast of the image. Eq 2 represents transformation from input to output images

$$D_B = f(D_A) \qquad (2)$$

Another analyzing technique for representing the image is Wavelet transformation [3]. This method uses double filter bank i.e. Laplacian pyramid representation for coefficients in a smooth contour for the input mammogram images. These pyramids capture not only discontinuities but also provides record of discontinues. There are so many filters for reducing the blur of edges in the images.

Median filter one such filter which works on neighborhood of 3-by-3 or 4-by-by of current pixel to replace with the median value. The advantage with this method is without reducing sharpness [9] it reduces noise. Mean filter [4] is another way for reducing noise. In this method instead of median value replace with current pixel intensity with the mean value of the neighborhood of the pixels. The advantage with this method is output image generated with the method contains less noise with minimum high frequency details.

The methods so far generally improve the quality of the input images but not improve the actual requirement for the mammogram images. These images require the improvement in the clarity so that structures within the image appear with boundaries and edges as well. To remove the limitations of the current enhancement methods this paper proposed the IMEM method and more details are given in the following section.

II. BACKGROUND STUDY

The area of the image with contains the tumor or any suspicious part is called Region of interest (ROI) [2]. To identify the ROI from the given input mammogram images initially performs the preprocess technique to suppress any noise within the image. After preprocessing it becomes very easy to identify the ROI which contains the tumor or breast abnormalities [12] within the input mammogram images. Normal breast tissues resemble with the abnormalities with in the mammogram images and so very difficult to identify those masses. And also these masses are overlay parenchymal tissues not isolated densities. Therefore, so many techniques have been developed to resolve these issues. Region growing [4], Markov Random Fields [5], Fractal modeling [5], Tree structured wavelet transform [6], Adaptive density-weighted contrast enhancement [6], Morphological operations [3] and Dynamic programming-based techniques are some examples to resolve these issues.

In the detection of early breast cancer using segmented ROI characteristics heuristics and associated features are extracted from the input mammogram images. These features are extracted from either texture, spatial or morphological domains [1].

The key characteristics of ROI are extracted in feature extraction phase. These characteristics are analyzed to classify either malignant, benign tumors [8] mass lesion or micro-calcifications further in the classification step. So like other pattern recognition, region segmentation to identify suspicious regions, use these regions to extract features and building classifiers are basic steps in the proposed model.

One of the important or basic role in the image processing is texture. Since this carries more information so plays very important major role in medical image processing domain also. These textures useful for detection of suspicious regions with in the image itself. So many methods exist for extracting [1] these features using gray level or level of granularities of the mammograms.

Effective texture features are extracted using ROI segmentation of the input mammogram images. Since it has some limitations that it requires huge number of training samples for building model. So, the proposed M-ROI extends current ROI model for resolving these cases. More details about our proposed M-ROI are discussed in detail in next section.

III. MULTI-ROI SEGMENTATION

The proposed M-ROI is an iterative process but the basic functionality with regular ROI is same. The proposed M-ROI more flexible in terms of ROI's from huge image collection. And also proposed M-ROI very fast technique compared to regular ROI methods. The resulted output using proposed M-ROI increases the properties of the textures which are very helpful for detection [14] of abnormalities. So we can achieve high classification accuracy of the mammogram inputs.

In our proposed M-ROI model boundary selection made using intensity distribution of mammogram images. These distributions are used for huge collection of input images. This approach first computes the image intensity probability and then find mean probability. Next maps input image PI to produce binary image let us say 'BPI'. In BPI contains pixels whose threshold value greater than 'I'. Let 'Blr' be the binary mask of M-ROI. This 'Blr' actually generates shape of the image. Let it be ' '.

The following equation 3 represents the M-ROI intensity data term

$$\mathrm{MROI(i)} = \frac{1}{n}\iint(\phi_M(x) - \phi_r(N)).dx \quad (3)$$

where 'n' represents the input mammogram images size, ' ' and denotes the shape of considered input images and shape of remaining part of input mammogram image 'i' respectively.

MROI (i) denotes the 'i' image selected region over set of input images.

A. Algorithm M-ROI

Input: n- Number of Images;
mammogram_image[ ] - array of images={1,2,3,….n};
Output: J- Set of MROI Images

Method:

1. for i = 1 : n
2. I= read(mammogram_image[i]);
3. Scan the image 'I' and determine the upper-leftmost pixel and lower-rightmost pixel and record positions as (x_1,y_1) and (x_2,y_2) respectively. Draw horizontal line and vertical line along the pixel position (x_1,y_1) and draw lines along the pixel position (x_2,y_2). These lines represent boundary of mammogram area and region of interest (ROI) of mammogram image.
4. Locate rectangular ROI of mammogram image based on positions of (x_1,y_1) and (x_2,y_2), this ROI image is stored as ROI(i)
5. Sum=Sum + avg(intensity (ROI(i)));
6. end for
7. ROIAVG=(1/n) * Sum
8. for i=1 to n
9. MROI(i) = ROIAVG – ROI(i)
10. end for

MROI Segmentation for five sample mammograms images processed and experiment values are tabulated and compared conclusions.

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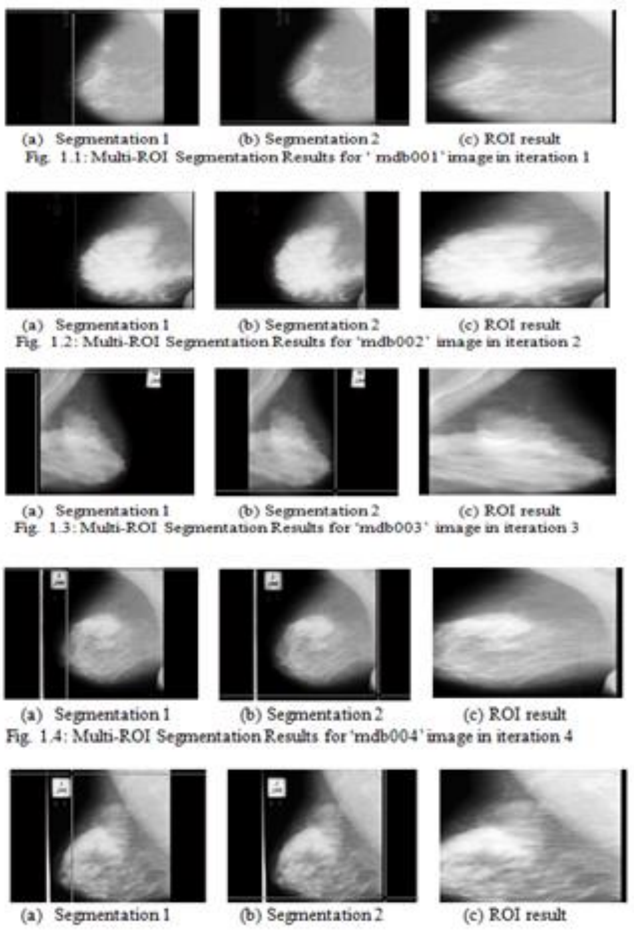

Fig. 1: M-ROI segmentation on five sample images

The proposed model M-ROI efficiency evaluated using First-order and second-order statistics.

Texture Features using First order statistics

These features are computed directly from the original image itself. No relation from the neighboring pixels not considered in these but provides very useful information from the image[13]. Let I(x,y) and M x N be the image and its size respectively. Let equations from 4 to 8 represents the features using first order statistics which are represents mean, standard deviation(SD), kurtosis, skewness, and entropy respectively.

$$\text{mean}(\mu) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)}{MxN} \tag{4}$$

$$\text{s tan dard\_deviation}(\sigma) = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - u}{MxN}} \tag{5}$$

$$\text{kurtosis} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - \mu^4}{MxNx\sigma^4} \tag{6}$$

$$\text{skewness} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - \mu^3}{MxNx\sigma^2} \tag{7}$$

$$\text{entropy} = \frac{1}{MxN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)(-\ln(I(x,y))) \tag{8}$$

Texture Features using second order statistics

These features depend on the relation between neighborhood [10] of considered pixel location. Energy, contrast, variance, correlation, homogeneity are some features in the second order statistics.

The regularity of the image can be described using Energy feature and it can be described using equation 9.

$$\text{energy} = \sum_{i,j=0}^{n-1} P(i,j)^2 \tag{9}$$

Where P(i,j) represents the relative frequency between two pixels in the neighborhood of (dx,dy).

Equation 10 represents the variance of all pixels of input database.

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2 \tag{10}$$

Equation 11 represents contrast which difference between minimum and maximum intensity of neighboring pixels.

$$\text{contrast} = \sum_{i,j=0}^{n-1} (i-j)^2 P(i,j) \tag{11}$$

The Equation 12 represents correlation of the pixel within the neighborhood.

$$\text{Correlation} = \sum_{i,j=0}^{n-1} \frac{(ixj)P(i,j) - \mu_i\mu_j}{\sigma_i\sigma_j} \tag{12}$$

Equation 13 represents the homogeneity using Angular second moment (ASM)

$$\text{Homogeneity} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \{P(i,j)\}^2 \tag{13}$$

IV. RESULTS AND DISCUSSIONS

In this paper we proposed M-ROI for extracting texture features from huge collection of mammogram images. Initially this method evaluates average values from abnormal and normal type of mammograms. After that selects the shape from the i^{th} mammogram image non-selected region. These shapes are obtained using integrated difference between normal or abnormal mammogram image and shape of selected non-region. Next applied texture features on resulted shapes of M-ROI. In case of normal ROI features extracted directly from the selected mammograms itself. In this paper we calculated both texture features from normal ROI and proposed M-ROI. We listed these results in Table 1 and Table 2. Median filter and morphological algorithm are used for segmenting images as in fig.2.

IMEM segmentation gives better results for input mammograms as in fig. 3

Retrieval Number: 100.1/ijrte.A1821058119
DOI: 10.35940/ijrte.A1821.0512123
Journal Website: www.ijrte.org

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TABLE 1. Texture feature values using median enhancement on input Mammograms

Texture feature	Median filter Enhancement in preprocessing	
	Normal-ROI	M-ROI
Mean	0.003491214	0.0038198
SD	0.08973586	0.2512398
Entropy	2.96258	2.966469
Variance	0.008047208	0.0080230186
Smoothness	0.912928	0.9324845
Kurtosis	12.01304	11.866092
Skewness	1.0039368	1.0681011
Contrast	0.2891463	0.2867568
Correlation	0.13448869	0.1517984
Energy	0.7973156	0.7891899
Homogeneity	0.9425088	0.9394648

TABLE 2. The values of Texture feature using morphological enhancement on input Mammograms

Texture feature	Morphological filter Enhancement in preprocessing	
	Normal-ROI	M-ROI
Mean	0.003491316	0.003368146
SD	0.08973598	0.08974516
Entropy	2.96241	2.953132
Variance	0.008047196	0.00802452
Smoothness	0.912935	0.9180522
Kurtosis	12.01304	12.045874
Skewness	1.0039384	1.0752846
Contrast	0.2891548	0.2830924
Correlation	0.13448966	0.160724
Energy	0.7973144	0.7911768
Homogeneity	0.9425092	0.9406992

From the above tables one and two we can observe the improvement in the texture features using proposed M-ROI. This is possible since proposed M-ROI uses accurate shapes from the huge input mammograms

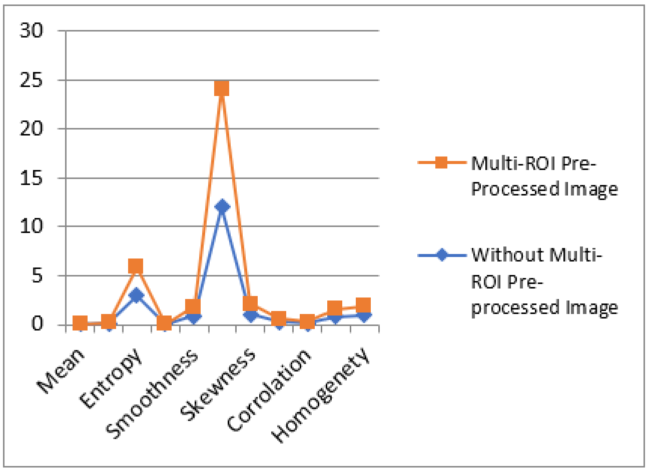

Fig. 2: Comparisons of Texture Features with pre-processing Wavelet techniques

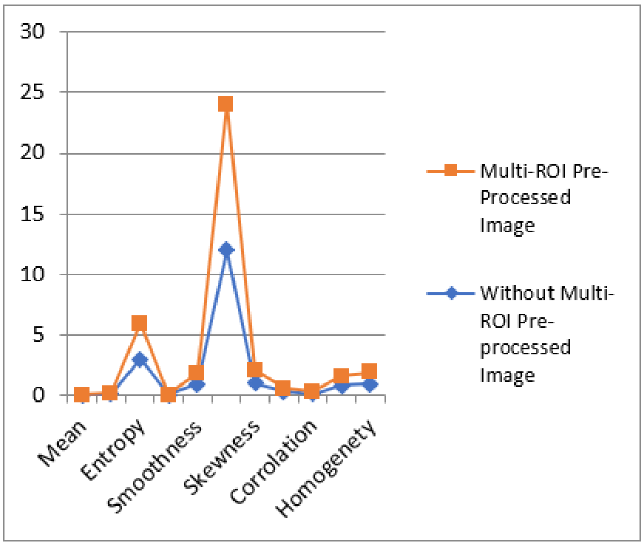

Fig. 3: Comparisons of Texture Features with pre-processing IMEM

Fig 2 and Fig 3 shows the texture feature results obtained after proposed M-ROI on pre-processed wavelet and IMEM images respectively. It clearly indicates the efficiency of the proposed M-ROI. These Figures also illustrate the best cancer detection with highlighting the textual properties using proposed M-ROI.

V. CONCLUSION AND FUTURE SCOPE

In this paper we proposed a new method called M-ROI for segmenting and extracting texture features of mammogram images to detect breast cancer. The performance of the textures depends upon results obtained from segmenting procedures. Using normal ROI we can obtain shapes without any knowledge from input mammograms. To overcome this problem the proposed method M-ROI derives universal shapes using huge mammogram images. And ultimately achieved more accurate textures and its shape features information from the input mammogram images to detect breast cancer.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	The data can be accessed from KAggle data sets https://www.kaggle.com/datasets/kmader/mias-mammography
Authors Contributions	All authors have equal participated in this article.

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