

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





Abstract: Radiologists generally use mammogram images for extracting masses or cancer-affected breast issues using texture features of the images by segmenting techniques. The most commonly used technique in this process is the region of interest (ROI). However, this method fails for an extensive collection of mammogram image databases. To address this issue, this paper proposes a multi-ROI (M-ROI) technique. This method not only reduces the limitations of ROI but also identifies suitable texture features. This paper also evaluated the efficiency of the proposed M-ROI method using first-order and second-order statistical techniques. ues

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

I. INTRODUCTION

Texture features of mammogram images are typically obtained by segmenting the images into two regions: cancer and non-cancer. These two regions exhibit distinct patterns and shapes. Segmentation is a powerful technique for detecting such irregularities in images. Using a segmentation technique, we generally divide the image by extracting edges or boundaries. In mammogram images, ill-defined [11] masses contain more intensity compare to other regions. Additionally, these regions contain circular-based objects. Textures play a crucial role in the analysis of images. This task can be completed in two steps. In the first step, we segment the image, and in the second step, we extract the texture features from the segmented parts in the first step [13]. Textures play a crucial role in the analysis of images.

ROI is one of the most potent and valuable techniques for segmenting and detecting various regions in mammogram images. However, some limitations exist when using this technique. One of these limitations is not suitable for a massive number of images [2]. To overcome this issue, this paper proposes M-ROI-based texture features. The efficiency of the proposed method is also evaluated; these regions contain circular-based objects.

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Textures play a crucial role in the analysis of images. This task can be completed in two steps. In the first step, we segment the image, and in the second step, we extract texture features from the segmented image using statistical techniques and 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 the 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 provided in Sections 4 and 5, respectively.

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

In Contrast, the stretching method can improve image intensity by increasing the range of values. The range of upper and lower intensities is needed before stretching. For example, in grey images, 0 and 255 are the lowest and highest values, respectively. The EQ1 can be used to enhance pictures in the contrast stretching method.

$$\mathbf{p}_{\text{out}} = (\mathbf{p}_{\text{in}} - \mathbf{c})(\frac{\mathbf{b} - \mathbf{a}}{\mathbf{d} - \mathbf{c}}) + \mathbf{a}$$
(1)

Where 'a and 'b' represent lower and upper, respectively, and 'Pin' refers to the pixel intensity.

Without affecting the nature of the image, we can alter the contrast of the image using the histogram equalisation method [7]. In this method, a transformation procedure is applied to transform grey pixels between the input and output images, maximising the contrast of the picture. Eq 2 represents the transformation from input to output ima. ges

$$\mathbf{D}_{\mathrm{B}} = \mathbf{f}(\mathbf{D}_{\mathrm{A}}) \tag{2}$$

Another analyzing technique for representing the image is the Wavelet transformation [3]. This method utilises a double filter bank, specifically a Laplacian pyramid representation, for the coefficients in a smooth contour of the input mammogram images. These pyramids capture not only discontinuities but also provide a record of discontinuities. There are numerous filters for reducing the blurriness of edges in images.



The median filter is one such filter that works on a 3-by-3 or 4-by-4 neighbourhood of the current pixel to replace it with the median value. The advantage with this method is that it does not reduce sharpness [9] it reduces noise. Mean filter [4] is another way for reducing noise. In this method, instead of using the median value, replace it with the current pixel intensity and the mean value of the neighbourhood of the pixels. The advantage of this method is that the output image generated with it contains less noise and minimal highfrequency details.

The methods so far generally improve the quality of the input images, but do not meet the actual requirements for mammogram images. These images require improvement in clarity so that structures within the image appear with clear boundaries and edges. To overcome the limitations of current enhancement methods, this paper proposes the IMEM method, with more details provided in the following section.

II. BACKGROUND STUDY

The area of the image that contains the tumour or any suspicious part is called the Region of interest (ROI) [2]. To identify the ROI from the given input mammogram images, the initial preprocessing technique is used to suppress any noise within the image. After preprocessing, it becomes very easy to identify the ROI which contains the tumour or breast abnormalities [12] within the input mammogram images. Normal breast tissue resembles abnormalities within the mammogram images, making it very difficult to identify those masses. Additionally, these masses are composed of overlaying parenchymal tissues, not isolated densities. Therefore, numerous techniques have been developed to address 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 the texture, spatial or morphological domains [1].

The key characteristics of ROI are extracted in the feature extraction phase. These characteristics are analysed to classify either malignant or benign tumours [8] mass lesion or micro-calcifications, further in the classification step. Similarly, like other pattern recognition methods, region segmentation is used to identify suspicious regions, which are then used to extract features and build classifiers, all of which are fundamental steps in the proposed model.

One of the most essential roles in image processing is texture. Since it carries more information, it plays a crucial role in the medical image processing domain as well. These textures help detect suspicious regions within the image itself. So many methods exist for extracting [1] these features using gray level or level of granularities of the mammograms.

Practical texture features are extracted using ROI segmentation of the input mammogram images. Since it has some limitations, it requires a large number of training samples to build the model. So, the proposed M-ROI extends

the current ROI model for resolving these cases. More details about our proposed M-ROI are discussed in the next section.

III. MULTI-ROI SEGMENTATION

The proposed M-ROI is an iterative process, but the basic functionality with regular ROI remains the same. The proposed M-ROI is more flexible in terms of ROI's from a vast image collection. Additionally, it proposed a swift M-ROI technique compared to regular ROI methods. The resulting output using the proposed M-ROI increases the properties of the textures, which are very helpful for detection [14] of abnormalities. Therefore, we can achieve high classification accuracy for mammogram inputs.

In our proposed M-ROI model, boundary selection is made using the intensity distribution of mammogram images. These distributions are used for the massive collection of input images. This approach first computes the probability of image intensity and then calculates the mean of these probabilities. Next, we map the input image PI to produce a binary image, which we will denote as 'BPI'. In BPI, there are pixels whose threshold value is greater than 'I'. Let 'BIr' be the binary mask of M-ROI. This 'BIr' actually generates the shape of the image. Let it be.

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

MROI(i) =
$$\frac{1}{n} \int \int (\phi_{M}(x) - \phi_{r}(N)) dx$$
 (3)

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

MROI (i) denotes the 'ith image selected region over the 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 a horizontal line and a vertical line along the pixel position (x_1,y_1) and draw lines along the pixel position (x_2,y_2) . These lines represent the boundary of the mammogram area and the region of interest (ROI) of the mammogram image.

4. Locate a rectangular ROI of the 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 mammogram images processed, and experimental





values are tabulated and compared to conclude.





(a) Segmentation 1 (c) ROI result (b) Segmentation 2 Fig. 1.4: Multi-ROI Segmentation Results for 'mdb004' image in iteration 4



Segmentation 1

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

The proposed model M-ROI efficiency is 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 neighbouring pixels is considered in these, but it provides beneficial information from the image [13]. Let I(x,y) and M x N be the image and its size, respectively. Let equations 4 to 8 represent the features using first-order statistics, which are the mean, standard deviation (SD), kurtosis, skewness, and entropy, respectively.

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

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

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

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

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

Texture Features using second-order statistics

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

The regularity of the image can be described using the Energy feature, which can be expressed using Equation 9.

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

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

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

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

Equation 11 represents contrast, which is the difference between the minimum and maximum intensities of neighbouring pixels.

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

Equation 12 represents the correlation of the pixel within the neighbourhood.

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

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

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

IV. RESULTS AND DISCUSSIONS

In this paper, we propose M-ROI for extracting texture features from a vast collection of mammogram images. Initially, this method evaluates average values from abnormal and standard types of mammograms. After that, it selects the shape from the non-selected region of the ith mammogram image. These shapes are obtained using the integrated difference between the regular or abnormal mammogram image and the shape of the selected non-region. Next, applied texture features to the resulting shapes of M-ROI. In the case of regular ROI features, they are extracted directly from the selected mammograms themselves. In this paper, we calculated both texture features from the normal ROI and proposed the M-ROI. We listed

these results in Tables 1 and 2.

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A median filter and morphological algorithm are used for segmenting images, as shown in Fig. 2.

IMEM segmentation yields better results for input mammograms, as shown in Fig. 3

 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 the 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 Tables 1 and 2 above, we can observe the improvement in texture features using the proposed M-ROI. This is possible since the proposed M-ROI uses accurate shapes from the huge input mammogram.ams



Fig. 2: Comparisons of Texture Features with preprocessing Wavelet techniques



Fig. 3: Comparisons of Texture Features with preprocessing IMEM

Figs. 2 and 3 show the texture feature results obtained after the proposed M-ROI on pre-processed wavelet and IMEM images, respectively. It indicates the efficiency of the proposed M-ROI. These Figures also illustrate the best cancer detection, highlighting the textual properties using the 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 on the results obtained from segmentation procedures. Using a 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 large mammogram images. Ultimately, this approach yielded more accurate texture and shape feature information from the input mammogram images, enabling the detection of breast cancer.

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Authors Contributions	All authors have equally participated in this article.

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