Detection of Microcalcifications in Digital Mammogram Using Curvelet Fractal Texture Features

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ABSTRACT

In this work, an attempt is made to Segment and find features of the segmented mammogram Images and finally mammogram images are classified as normal and abnormal. The mammogram images used for this work are considered from MIAS Database. The database includes 322 digitized films and all the images are of size 1024x1024. It consists of 322 images (208 normal images and 114 abnormal images). Initially, mammogram images are subjected to pre-processing using Discrete Cosine Transform to enhance the edges of the mammograms. Then, sharpened images are cl using the Fuzzy C-means Clustering algorithm. After segmentation, Curvelet coefficient and fractal Dimension values are obtained using Discrete Curvelet Transformand Fractal textures respectively. The average values of obtained curvelet coefficient and fractal dimension values for both normal and abnormal mammogram images are compared. Finally, The mammogram images are classified using an Ensemble Fully Complex-Valued Relaxation Network Classifier. The Classifier is used foe the classification of the mammogram images as normal and abnormal.

Keywords: Mammography, DCT, MIAS, SFTA, FCRN, Fuzzy – C Means.

INTRODUCTION

Image processing refers to the processing of images using mathematical operations to extract an enhanced image or to obtain some meaningful information which can be used for processing later from it. Image processing system treats the image as two-dimensional signals and then applied to standard signal processing techniques to them. The applications of image processing can be extended to satellite and medical imaging too. The root cause to use the technique of image processing is classified into five major groups and are visualization, image sharpening and restoration, image retrieval, measurement of pattern, and image recognition to distinguish the objects in an image. In the past, image processing was largely done using analog devices. Whereas digital image processing refers to the process of converting a normal image to a digital image by making use of computer. The digital image is consists of finite number of elements, each of which is in a particular location and values which are generally represented in terms of a matrix, and those elements are known as pixel elements or pixels which overcomes the traditional analog problems such as noise in the image, distortion during processing, the inflexibility of the system to change, and difficulty of implementation.

Image pre-processing

Image pre-processing is one of the preliminary steps required to ensure the accuracy of the subsequent steps. It involves major corrections in the images like distortion, degradation, and noise introduced during acquisition. This process results in a corrected image that is as close as possible, both geometrically and radiometrically, to the radiant energy characteristics of the original scene. The main aim of using pre-processing is to improve the quality of image data that reduces unwanted distortion and enhances features important for further processing. Discrete Cosine Transform sharpening is one of the pre-processing methods and it helps to enhance the image. When compared to the Discrete Fourier Transform, it helps to obtain a more concentrated histogram.

Image segmentation and feature extraction

Segmentation is the process of splitting or fractioning a picture into semantically interpretable regions. Segmentation aims to distort the image into parts that are significant with relevance to a selected application. Image segmentation typically accustomed locate objects in images. The concept of feature extraction is used to define the obtained set of features that are used for efficient representation of data which is crucial for analysis and categorization. The five types of features used for processing using the algorithm include binary object features, RSI invariant features, histogram features, texture features [3], and spectral features are used for while classification. A discrete curvelet transform could be a new pictorial representation and may be used for the method which codes the edges of the image more effetely than wavelet transform [1]. As a matter of fact, the curvelet has useful geometric features that set them except for wavelet [7]. The curvelet transform coefficients are used as a feature vector while the mean square error is reduced in curvelet for accuracy. To implement and manipulate curvelet transform in various field of applications, a quick, accurate and precise discrete curvelet transform which holds good on digital data is mandatory. Fractal analysis is beneficial in image processing for characterizing various factors like shape, size and grey-scale complexity [11]. Breast tissues mass are present with grey-scale characteristics that toggles between the benign masses and malignant masses in mammograms. Fractal dimensions and previously developed shape factors are accustomed to classify the breast masses as benign and malignant.

Mammogram Images

The deformity in mammograms are often segregated into calcifications, well-interpreted masses, speculated masses, indistinct masses, architectural malformation, and symmetry. Calcifications are minor mineral settles within the breast tissue, which would look like tiny acne in the films. Microcalcifications are more of a tiny spot of a calcium within the breast tissues [6]. They either appear randomly or in groups. The mammogram images of microcalcifications helps the radiologist to evaluate the stage of cancer [19].

Figure 1: **Mammogram image with micro-calcifications**

METHODOLOGY

Mammogram images are subjected to various processing techniques like pre-processing, segmentation, feature extraction, and classification. Sharpening is performed to reinforce the contrast of the image and sharpened images are segmented using fuzzy C-means Clustering. The segmented images are then wont to obtain the features of the affected region using Curvelet transform and Fractal textures [7]. These images are then classified using Fully Complex Valued Relaxation Network.

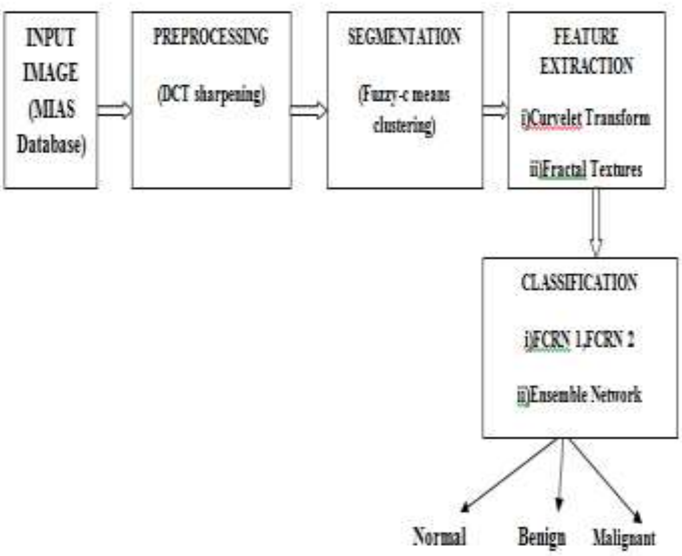


Figure 2. **Block Diagram of the Proposed System**

2.1 Discrete Cosine Transform Sharpening

Generally, mammographic Image enhances the pictures into various parts (or spectral sub-bands) of varying importance (about the image's visual quality). DCT transforms the sample input from the spatial domain into the frequency domain. Fuzzy C-means Clustering: Fuzzy C-means is in a position to retain more information from the first image and segregates the image by grouping patterns with similar data points in feature space into clusters [5]. FCM partitions a collection of n objects x in Rd dimensional space into c(1<c<n) fuzzy clusters with y= {y1, y2…, yn) cluster centres/centroids [20]. The fuzzy clustering of objects are used for implementation by a fuzzy matrix U with n rows and c columns in which n is the number of data objects and c is the number of clusters. The U^{th}, element in the i^{th} row and j^{th} column in U, indicates the range of association or membership function of a i^{th} object with j^{th} cluster. The

objective of using the FCM algorithm is to minimize the following equation.

$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} U_{ij}^{m} d_{ij}$---- (1)

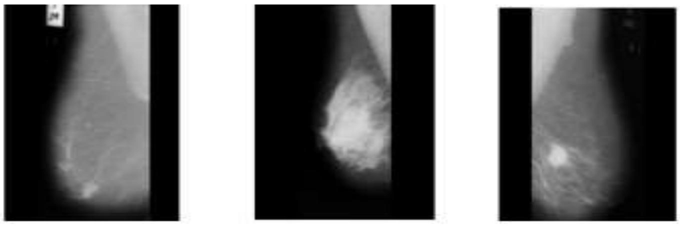
2.2 Feature Extraction

2.2.1 Curvelet via Wrapping

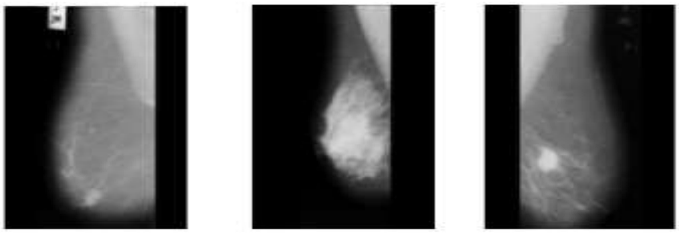
Discrete curvelet transform is a new technique of image representation approach which codes, and edges the image more efficiently than the existing technique known as wavelet transform. The Curvelet Transform coefficient of the object is used for the purpose of feature vector [12].

2.2.2 Fractal Analysis

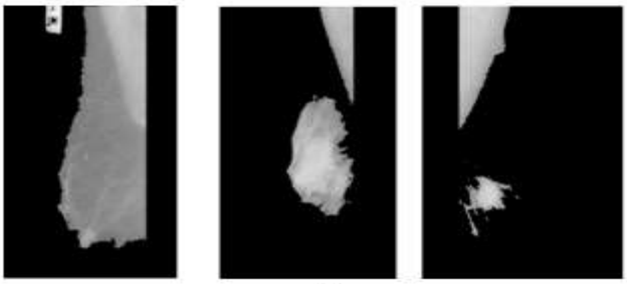
Fractal dimension elaborately denotesthe structural detailsas the scale of measurement changes [2]. Fractal geometry uses many techniques to define fractional dimensions and the most commonly known approach is the Harsdorf's dimension [14].



(a)



(b)



(c)

Figure 3: Segmentation of Image using FCM (a) Input mammogram image (normal and abnormal) (b) Pre-processed image with DCT sharpening and (c) Segmented image using fuzzy C-means Clustering.

2.2.3 Ensembled Fully Complex valued Relaxation network classifier

Complex-valued neural network has a good yield for the generalization approach than the real-time available neural networks. The projection-based learning algorithm implemented by FCRN is implemented for the estimation of the optimal result which would weight as a better result to apply for the system of linear equations,requires less power and consumes really minimal computational effort to generalize any desired function with greater accuracy compared to other algorithms which isregarded as a major advantage over the existing ones available. Below Figure shows Fully Complex – Valued Relaxation Network (FCRN) based Ensemble Classifier [15].

The input image is pre-processed and segmented and these segmented images are accustomed to extract all the features. These features are curvelet coefficients and fractal dimensions [13]. The features obtained for every mammogram image are given to two FCRN networks for processing and the output from each FCRN network is analysed and the beat performer is chosen [16]. The output from the FCRN network is given to the ensemble network and the results are merged for final output. Finally, mammogram images are classified as normal, benign, and malignant.

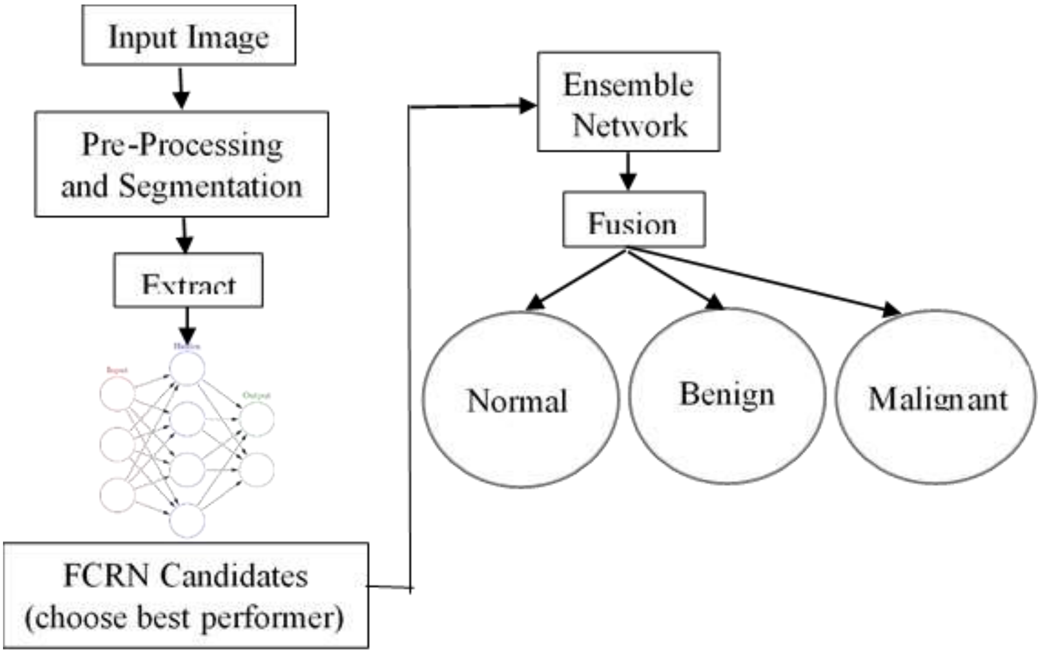


Figure 4: FCRN Based Ensemble Classifier

RESULT AND DISCUSSION

Generally, the fractal dimension values of abnormal images should be high compared to normal images. Similarly, the curvelet coefficient values of abnormal images should be less compared to normal images.

Table 1: Curvelet Coefficients and Fractal Dimensions of Abnormal Mammogram Images

Image number	Fractal Dimensions	Curvelet Coefficients
mdb146	1.9777	0.9739
mdb151	1.9961	0.8800
mdb153	1.9966	0.9758
mdb156	1.9678	0.9654
mdb201	1.9747	0.9520
mdb210	1.9692	0.9711
mdb215	1.9630	0.9645
mdb133	1.9956	0.9205
mdb112	1.9667	0.9585
mdb008	1.9584	0.9413
Average	1.9766	0.9503

Table 2: Curvelet coefficients and fractal dimensions of normal mammogram images

Image number	Fractal dimensions	Curvelet coefficients
mdb022	1.9210	0.9876
mdb033	1.8891	0.9875
mdb035	1.8913	0.9895
mdb044	1.9018	0.9860
mdb053	1.8940	0.9864
mdb071	1.8971	0.9864
mdb085	1.9181	0.9876
mdb086	1.9085	0.9894
mdb177	1.8799	0.9878
mdb224	1.8960	0.9873
Average	1.8997	0.9876

The results show the fractal dimension and curvelet coefficient values between the normal and abnormal images which are classified. On comparing the values of fractal dimension, the image having the low fractal dimension value is classified as normal and the image having high value is considered as abnormal. The average fractal dimension value for normal and abnormal images are 1.8997 and 1.9766. On comparing the values of the curvelet coefficient, the image having a higher value is considered as normal and less value as abnormal. The average curvelet coefficient values for normal and abnormal images obtained are 0.9876 and 0.9503.

3.1 Validation

Table 3: Performance measures of normal and abnormal Images

Image number	Sensitivity (%)	Specificity (%)	Accuracy (%)
mdb033	94.4053	82.1452	90.1355
mdb153	87.3479	81.4824	87.5572
mdb201	80.1011	78.9365	81.0426
mdb086	91.5763	88.0511	95.2588
mdb112	83.1638	82.0408	82.6739
mdb035	90.9251	96.1047	96.1047
mdb177	89.1238	93.5018	93.5018
mdb146	92.3475	86.7852	86.7852
mdb085	86.9251	90.9148	90.9148
mdb022	94.3811	90.4618	90.4618
Average	89.0297	87.0424	89.4436

CONCLUSION

In this paper, it is attempted to segment the affected region (micro clarifications) in mammogram images and also to classify the images using Fully Complex –valued Relaxation Network (FCRN) Ensemble Classifier. The features are extracted using curvelet transform and fractal textures. Quantitative features extracted are used in the FCRN ensemble classifier for the classification of normal and abnormal images with an accuracy of 89%.

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