Proceedings of the Fifth International Conference on Intelligent Computing and Control Systems (ICICCS 2021)
IEEE Xplore Part Number: CFP21K74-ART; ISBN: 978-0-7381-1327-2

2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS) | 978-1-6654-1272-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICICCS51141.2021.9432381

# *Implementation of Fuzzy Logic in Identification of Calcification in Mammogram Image*

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**ABSTRACT**

**Mammogram is a specialized medical imaging tool used for finding the presence of Microcalcification in the women's breast. Microcalcification generally refers to an initial form of breast cancer. A mammogram image helps the doctor to understand the approximate number of calcifications identified in the breast. Many analytical methods have been proposed to identify the extent of MC in the mammogram image. Those analytical methods can help in Computer Aided Detection (CAD) of MC. To encircle the Microcalcification locations, many commercial software have been developed. The proposed system uses Fuzzy logic for segmentation and Gray Level Co-Occurrence Matrix to extract features based on texture for identifying MC from the mammogram images. Comparison of ground truth image with the extracted features is done to find the segmentation accuracy. The accuracy of the algorithm is analyzed by PSNR metric in identifying the calcification in mammogram.**

**KEYWORD: Fuzzy logic, gray level co-occurrence matrix, mammography, segmentation accuracy.**

## I. INTRODUCTION

This research presents the implementation technique to extract features from the mammogram of the breast image using wavelets. These features are used for training firefly algorithm. Segmentation of the mammogram is done with trained weights values. All the images obtained through segmentation is compared with the original image in data set. Mammographic Image Analysis Society Digital Mammogram Database is used in this research work to identify the detection of calcification. This research is focused mainly on the accuracy of detection of Microcalcification in mammogram to detect cancer. Their view on literature shows clearly that, there is further scope in increasing the accuracy detection. The literature gap found here is to develop a new hybrid optimization algorithm to improve accuracy in detection of MC. El-Naqa et al.,[1], proposed Support Vector Machine (SVM) classifier prepared through supervised learning for discovery of microcalcifications in the computerized mammogram images. Tzikopoulos et al.,[2] proposed an automated segmentation and classification technique. Jebathangam et al.,[3] has proposed a combination of wavelet, K-Means for segmentation and GLCM for feature extraction. The training of the algorithm is done by using the features extracted. The proposed system is used to identify the presence of calcification as malign or benign. Muhammad Tulha et al[6] has used histogram equalization for image enhancement of the database images and has used Artificial Neural Network algorithm for benign and malignant classification. The features were extracted using Haralick Texture Features.

## II FEATURE EXTRACTION USING WAVELETS

The Daubechies wavelets changes are described practically like Haar wavelets by ascertaining the showing contrasts and midpoints to methods for scalar things with scaling signs and wavelets, the most differentiation between them includes in how these scaling signs and wavelets are characterized. The Daubechies wavelet type has recurrence reactions that are adjusted yet non - direct. Daubechies wavelets use windows which cover, along these lines the high frequency coefficient offers a hint of all the high frequency changes. Thusly Daubechies wavelets are mostly used for removing the noise and for compressing the pictures, and incorporate enhancement of images and for recognizing the signals. To compress the mammogram image the following step has to be followed

- Loading the image which requires compression.
- Application of the transform: On several levels the image is transformed to wavelet space from data space.
- Selecting the threshold: The threshold is selected such that a assured part of the total coefficients is preserved. This type of choosing the threshold is called as quantile thresholding.
- Finally, the compression is performed.

The sum of overall time of the signal which is multiplied by shifted and scaled version of the wavelet is defined as the continuous wavelet transform (CWT). Wavelet coefficients which are the functions of position and scale are the results of continuous wavelet transform. The constituent wavelets of the original signal are obtained by multiplying each of the coefficients with the appropriate scaled and shifted wavelet. To analyze the image to obtain various information, the image is decomposed using wavelets.

**Scaling:**
Scaling a wavelet simply means compressing it or stretching it. Scaling is equal to the frequency band. Low scale compressed wavelet rapidly changes the details and has high frequency. High scale stretched wavelet changes slowly and has low frequency.
**Shifting:**
Shifting a wavelet is hastening the wavelet or delaying the wavelet. Statistically, it is delaying a function by k.

## III FUZZY LOGIC FOR MAMMOGRAM SEGMENTATION

The information is divided into different clusters, such as each data component fits into one of the clusters in hard clustering, whereas in Fuzzy clustering a data element can fit in to one or more clusters. It reveals the relationship quality between the cluster group and each element. The vagueness and the uncertainty in the digital mammogram image can be handled by Fuzzy c-means algorithm. More flexibility is provided by using membership values for usage in practical applications. A transfer function called Fuzzy Inference System is used to map the input data with the target output. This algorithm assigns membership function for each data point corresponding to the cluster center. The membership of each data point is given by assigning it to the nearest cluster. The summation of each data point will be equal to one.

$$\mu_{ij}=1/\sum_{k=1}^{c}(d_{ij}/d_{ik})^{(\frac{2}{m}-1)}$$

$$v_j = \left(\sum_{i=1}^{n}(\mu_{ij})^m x_i\right) / \left(\sum_{i=1}^{n}(\mu_{ij})^m\right), \forall j = 1, 2, \ldots.c$$

The optimal function is

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \left\|x_i - v_j\right\|^2$$

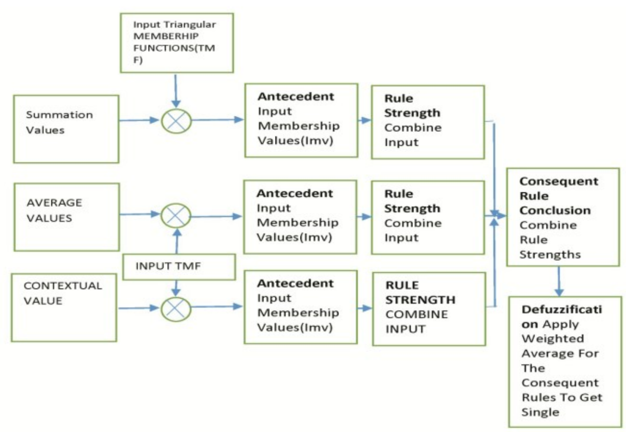



**Figure 1 Fuzzy Inference System**

Mammogram segmentation is done by the following steps:

1) Training fuzzy logic with the statistical features acquired from the wavelet decomposition.
2) Segmenting the mammogram image using the statistical features attained from the wavelet decomposition.

## IV. MICROCALCIFICATION DETECTION BY TEXTURE ANALYSIS

The architecture of proposed model in detecting the MC from the images is given in Figure 2. Segmented images attained from the proposed wavelet and Fuzzy logic algorithms are given as inputs to the detection module to identify the MC.

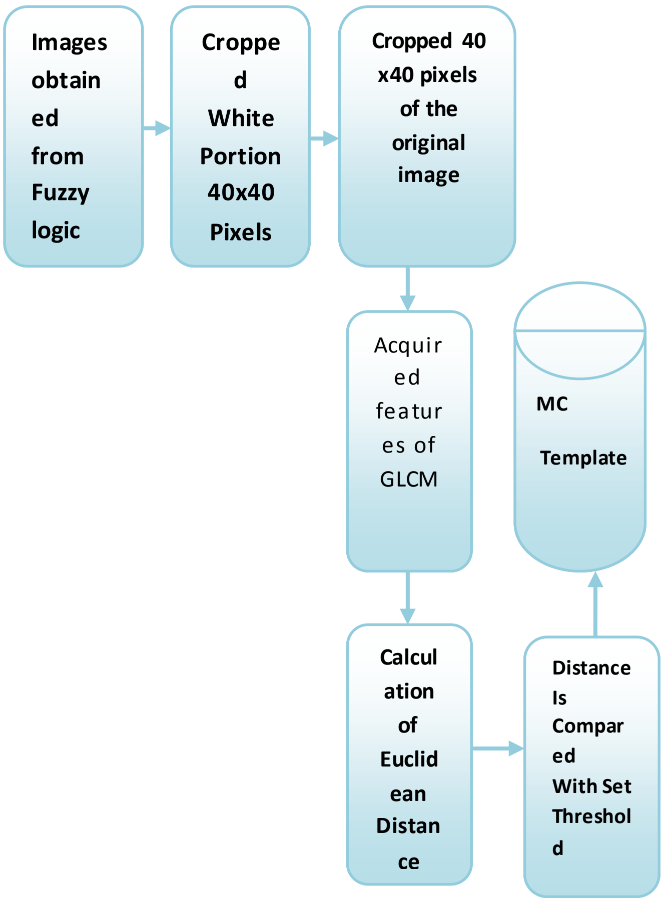
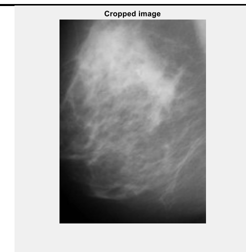
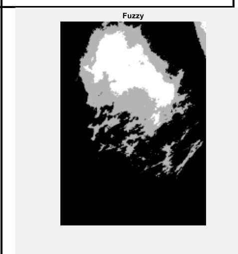
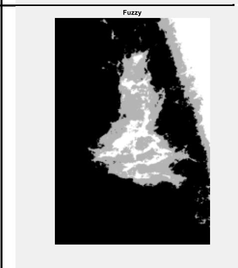
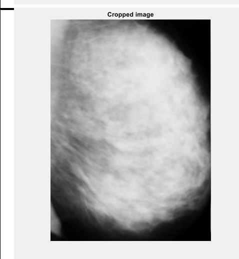
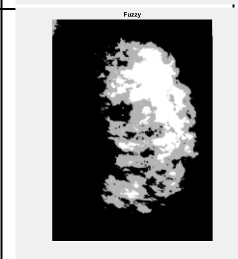
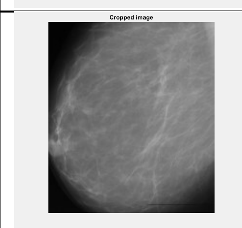
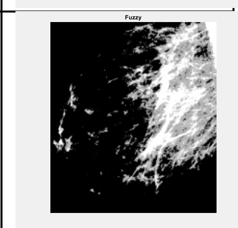
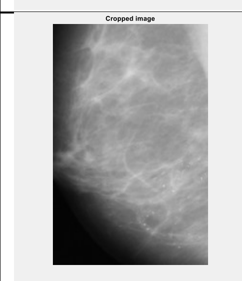
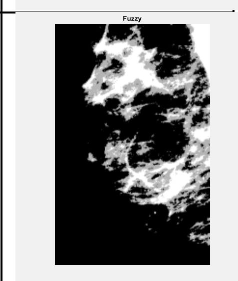


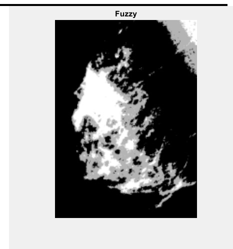
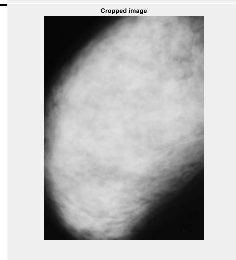
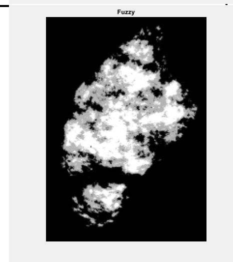
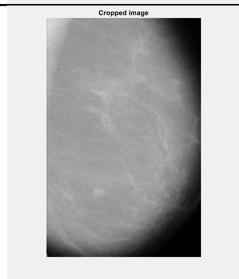
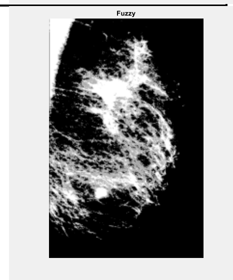

**Fig.2 Proposed MC Detection Architecture**

## V Results

The below figure shows the segmented images using Fuzzy logic and the original cropped image from MIAS data base along with the image number for each image

**SEGMENTED IMAGES USING FUZZY LOGIC**

| MIAS Image number | Original image-Cropped | Fuzzy |
|---|---|---|
| 209 |  |  |
| 213 |  |  |
| 216 |  |  |
| 231 |  |  |
| 245 |  |  |

| | | |
|---|---|---|
| 249 |  |  |
| 253 |  |  |
| 256 |  |  |

## VI PERFORMANCE EVALUATION METRICS

### A) Full-Reference Quality Metrics

Full-reference quality metrics relate the input image alongside a original reference image with no misrepresentation.

### B )No-Reference Quality Metrics

If there is misrepresentation in the original reference image then no reference quality metrics is used. It calculates quality scores created on the basis of image statistics.

### C) Test Chart Based Quality Measurements

Standard quality measurement can be performed by edge spatial frequency response (eFSR).

The research work showed a accuracy of 95% sensitivity and specificity of 86% and 96% respectively. By comparing the segmented image of the proposed method with the original segmented image in database the results prove that the technique proposed in this research work will be able to accurately detect the tumour in mammogram images

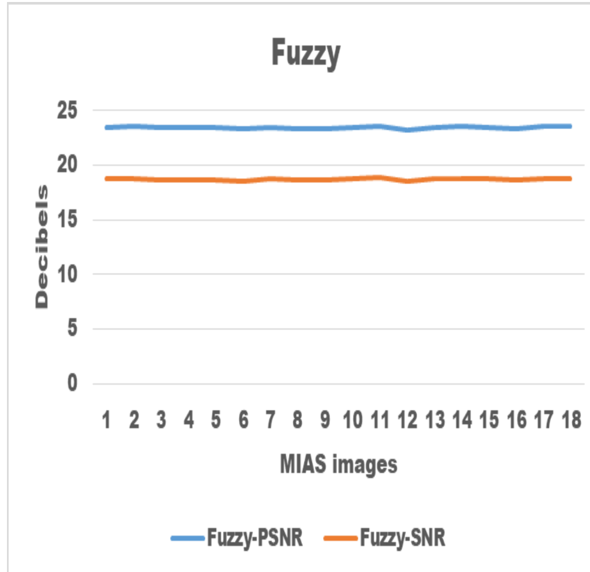



**Figure 3: Difference in the Fuzzy segmented mammogram image and the ground truth image**

## VII CONCLUSION:

In this work wavelets and fuzzy logic algorithm are implemented using images from mammographic image analysis (MIAS) mammogram database. The proposed model elaborates the results of the segmentation using fuzzy logic algorithm with respect to the peak signal noise ratio. The effectiveness of the fuzzy logic algorithm in identifying the MC depends upon the number of rules used in fuzzy logic algorithm training. The accuracy of the algorithm in identifying the calcification is analyzed by PSNR metric

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