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Enhancing Detection of Microcalcifications using FADHECAL for Early Stage Breast Cancer

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Abstract

Microcalcifications (MCCs) are reliable early signs of breast cancer. However, the small size of calcifications and low radiation factors used in digital mammograms cause low and poor quality mammogram images in detecting MCCs. This paper presents an image enhancement technique called Fuzzy Anisotropic Diffusion Histogram Equalization Contrast Adaptive Limited (FADHECAL) to enhance the details of MCCs in mammogram images by reducing the image noise while conserving contrast and brightness. A total of 23 mammogram images with MCCs were retrieved from the Mammographic Image Analysis Society's database. The enhancement performance of FADHECAL was compared with Recursive Mean-Separate Histogram Equalization, Histogram Equalization and Fuzzy Clipped Contrast-Limited Adaptive Histogram Equalization. Image quality measurement tools of absolute mean brightness error (AMBE), structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR) were used. The results showed that FADHECAL had the most superior results among other enhancement techniques, with 6.302 of AMBE, 20.453 of PSNR and 0.851 of SSIM. The proposed FADHECAL exhibited a high accuracy of 91.30% for the detection of MCCs. Hence, FADHECAL can be used as an ideal tool for identifying MCCs in early-stage breast cancer.

***Keywords**:* breast imaging, fuzzy inference system, image analysis, mammography, medical image processing

1. Introduction

Breast cancer is one of the top causes of death in women worldwide (Nounou *et al*., 2015; Suppaya *et al*., 2020; Ravi and Ismail, 2021). Based on the 2020

Global Cancer Statistics, 11.7% of breast cancer cases were diagnosed, with approximately 19.3 million new cases (Sung *et al.*, 2021). According to the American Cancer Society, a total of 276,480 new cases of breast cancer were expected to be diagnosed in 2020 among women in the United States, with an estimated death rate of 15% (Viale, 2020). One of the main contributions is inappropriate imaging tools used for early detection or during breast screening examination (Suradi *et al.*, 2021a). Besides, poor quality mammogram images will reduce the early detection rate of breast cancer and the patient's chances of survival (Mohd Hashim *et al.*, 2020).

Breast cancer can be classified by the size of lesions and their growth rate (Bonfiglio *et al.*, 2018; Suradi *et al.*, 2021b). The breast lesions may manifest as carcinoma in situ in the mammary lobules or the intermediate ducts. The lesions may also have a great potential to spread the cancer cells to their surroundings. Microcalcifications (MCCs) are a reliable early sign of breast cancer (Mordang *et al.*, 2018; Mahmood *et al.*, 2021). These MCCs consist of small grains or calcium deposits with diameters between 0.1 and 1 mm (Albiol *et al.*, 2017). MCCs can be seen as white dots, which are usually overlying the breast tissues in the mammogram images. Therefore, the detection of MCCs in mammogram images is complex, especially due to the variant of size, diameter, or shape (Ur Rehman *et al.*, 2021). Based on the Breast Imaging Reporting and Data System (BI-RADS), MCC is categorized by the description of the morphology and its distribution. The categories include benign, intermediate concern and malignant (Rao *et al.*, 2016). The morphology of MCC is the most crucial factor in the differentiation between benign and malignant. The intermediate concern term is used to identify the MCC in the form of amorphous or coarse heterogeneous, which is not fully ready to identify as benign or malignant (Yu *et al.*, 2011). In BI-RADS, the distribution of MCC can be categorized as scattered, regional, cluster and segmental (Bent *et al.*, 2012).

Digital mammograms are one of the radiological examinations to investigate any abnormalities within the breast tissues. It can be used as the initial step or first-line screening method to identify the early stages of breast cancer lesions (Rodríguez-Ruiz *et al.*, 2019). Digital mammograms use low-exposure protocols to ensure minimum radiation dose for the patients. However, the use of low-exposure protocols has led to low contrast performance of mammogram images, especially when detecting the MCCs. During image acquisition, impulse noise can distort mammogram images (Rajaguru *et al.*, 2020). Consequently, numerous image enhancement techniques have been evolved and introduced in digital mammograms. Image enhancement is the most common image processing technique used in digital images that involve image manipulation to improve or maintain the image features and reduce image noise appearances (Suradi and Abdullah, 2021b). The image enhancement techniques involve modifying the intensity and contrast appearances to highlight the fine details or any suspected abnormalities (Quintanilla-Dominguez *et al*., 2011).

The main factor to detect breast cancer at an early stage is the proper process of acquisition of mammogram images (Almalki *et al*., 2022). Over the past years, image enhancement techniques in mammogram images have been discussed, such as Histogram Equalization (HE) (Gonzalez *et al*., 2009), Contrast Limited Adaptive Histogram Equalization (CLAHE) (Pisano *et al*., 1998; Sondele and Saini, 2013), Recursive Mean-Separate Histogram Equalization (RMSHE) (Akila *et al*., 2015), Fourier transform (Senthilkumar and Umamaheswari, 2015), nonlinear unsharp masking (Panetta *et al*., 2011) and fuzzy logic-based enhancement (Sondele and Saini, 2013; Jenifer *et al*., 2016; Suradi and Abdullah, 2021a).

However, the aforesaid image enhancement techniques still have limitations (Singh and Kaur, 2017). For example, the HE technique can only stretch the histogram pixels, which causes the change in level saturation but is not able to properly enhance the images (Sengee and Choi, 2008). Although it is the frequently used technique for enhancing contrast in mammogram images (Rahmati *et al*., 2010; Moradmand *et al*., 2012; Majeed and Isa, 2020), CLAHE enhancement has a major disadvantage – the manual setting up of the clip-limit value for the enhancement process. As a result, CLAHE cannot improve the details because of high noise appearances in the homogeneous regions (Lee *et al*., 2019). Therefore, a combination of two or more image enhancement methods has been proposed.

Jenifer *et al*. (2016) developed a technique using the combination of fuzzy and histogram-based algorithm called the Fuzzy Clipped Contrast-Limited Adaptive Histogram Equalization (FC-CLAHE) algorithm, which has shown positive results with better enhancement of breast lesions. Suradi *et al*. (2021a) developed image enhancement techniques for mammogram images based on the combination of fuzzy-based algorithm, filter algorithm and histogram algorithm technique of image enhancement to improve the structure of breast masses details while reducing the image noise in the mammogram images. However, the study is limited to breast masses only. Microcalcifications are early signs of developing breast cancer. Breast masses or tumors are usually larger and brighter compared with MCCs that are physically smaller and scattered around the breast tissue (Mustra *et al*., 2012). The presence of MCCs in low-contrast mammogram images may lead to delayed detection of breast cancer. Therefore, continuous improvement is still needed to further enhance and reduce noise in mammogram images, especially for the detection of MCCs as an early stage of breast cancer.

The proposed image enhancement technique for mammogram images by Suradi *et al*. (2022), the FADHECAL, was used in this study to further enhance the details of breast cancer lesions in mammogram images, especially in the region of interest (ROI) of MCCs. This FADHECAL can minimize the noise in the mammogram images while conserving the contrast and brightness, especially enhancing the presence of MCCs.

2. Methodology

2.1 Source of Mammogram Images

A total of 322 mammogram images containing ground truth were retrieved from the Mammographic Image Analysis Society's (MIAS) database (Clark, 2012). Of these, 207 cases were normal, 64 were benign, and 51 were malignant. These mammogram images were then filtered to only include the mammogram images with MCCs. Finally, only 23 of those mammogram images contained MCCs with various background tissues and abnormalities.

2.2 Image Enhancement Technique for Mammogram Images

The FADHECAL is a hybrid image enhancement technique that combines fuzzy-based and histogram-based enhancement techniques (Suradi *et al*., 2022). A Fuzzy Clipped Inference System (FCIS) is employed in the FADHECAL technique to automate the clip-limit selection for the enhancement procedure. The prior approach of manually selecting the clip limit can be replaced by this automatic option. An anisotropic diffusion filter (ADF) is embedded in this technique to minimize the impulse noise that occurs during image acquisition while conserving the details of mammogram images. The steps of this FADHECAL technique are shown in Figure 1.

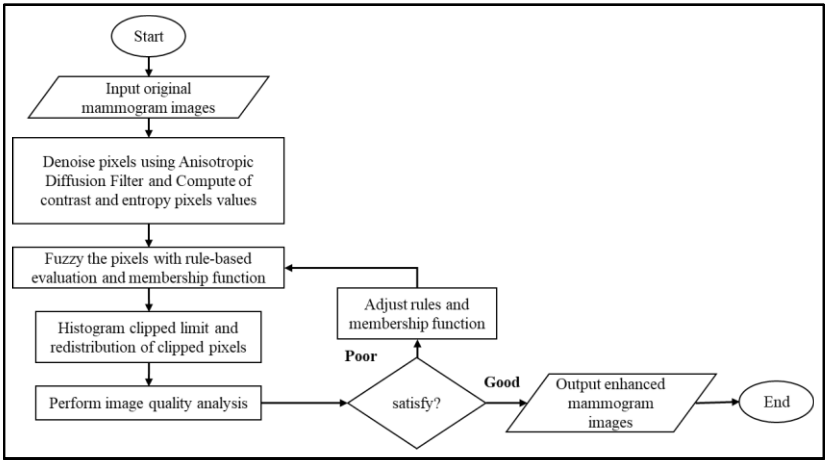

Figure 1. The FADHECAL image enhancement technique adopted from Suradi *et al*. (2022)

The ADF model, which was previously proposed by Perona and Malik (1990), works by increasing the diffusion in the homogeneous areas and reducing the nearly strong gradient corresponding to the edges. Equation 1 represents the ADF model (Suradi *et al*., 2022).

$$\frac{\partial I(x,y)}{\partial t} = div\big(g(|\nabla I(x, y)|)\nabla I(x, y)\big) \tag{1}$$

where $div(.)$ and ∇ represent the divergence and the gradient operators, respectively, while $g(|\nabla I(x, y)|)$ is a decreasing function that plays a crucial role in controlling the diffusion process.

The FCIS is designed with two input measures: contrast (C) and entropy (E). The fuzzy sets of C are low (C_1), medium (C_2), and high (C_3), while the fuzzy sets of E are small (E_1) and big (E_2). The Fuzzy Histogram Clipped Limit (FHCL) is the FCIS output metric. Contrast and entropy were used to detect any abnormalities. The contrast and entropy of the digital mammogram images can be calculated using Equations 2 and 3, respectively (Suradi *et al*., 2022).

$$Contrast,\ C = \frac{1}{W \times H}\sum_{w=1}^{W}\sum_{h=1}^{H} Y^2(w, h) \tag{2}$$

where H and W represent the height and width of the image, respectively, while $Y(w, h)$ is the pixel of the image grey level at (w, h).

$$Entropy,\ E = \sum_{i,j=0}^{N-1} P(i,j)(-\ln P(i,j)) \qquad (3)$$

The probability of a possible outcome is represented by $P(i, j)$. The summation range $i, j = 0$ to $N - 1$ essentially means that each cell in the matrix should be measured.

The triangular membership function was utilized to construct the rules of FCIS and classify the FHCL into low clip limit (CL_1) and high clip limit (CL_2). Table 1 shows the rules of automatic selection for clipping enhancement parameters using FCIS rules (Suradi *et al*., 2022). For the overall FCIS output, the output of each rule was combined into a single fuzzy set. Figure 2 shows the overall result of FCIS with the aggregation of rule consequences (Suradi *et al*., 2022). The FCIS had a defuzzification result of 0.0185. As a result, with the provided values of C = 0.325 and E = 0.444, the FHCL was 0. 0185. The FADHECAL enhancement technique used Equation 4 to calculate the new clip limit that depended on the C and E of the input mammogram images (Suradi *et al*., 2022).

Table 1. The rules of automatic selection for clipping enhancement parameters using FCIS rules

Rules	Description
1	If contrast *(low)* and entropy (*Small)*, FHCL *(high)*
2	If contrast (*medium)* and entropy (*small)*, FHCL *(high)*
3	If contrast (*low)* and entropy (*big)*, FHCL *(high)*
4	If contrast (*high)* and entropy (*small)*, FHCL *(low)*
5	If contrast (*medium)* and entropy (*big)*, FHCL *(low)*
6	If contrast (*high)* and entropy (*big)*, FHCL *(low)*

$$FADHECAL = \left[\frac{\varphi}{256}\right] + \left[FHCL.\left(\varphi - \left[\frac{\varphi}{256}\right]\right)\right] \qquad (4)$$

where *FHCL* is for fuzzy histogram clip limit, which ranged from 0 to 0.1; [.] stands for truncating value to the nearest integer; and φ is the result of dividing the block size by the total number of blocks. The pixel intensity range was 0 to 255, as indicated by the 256 values.

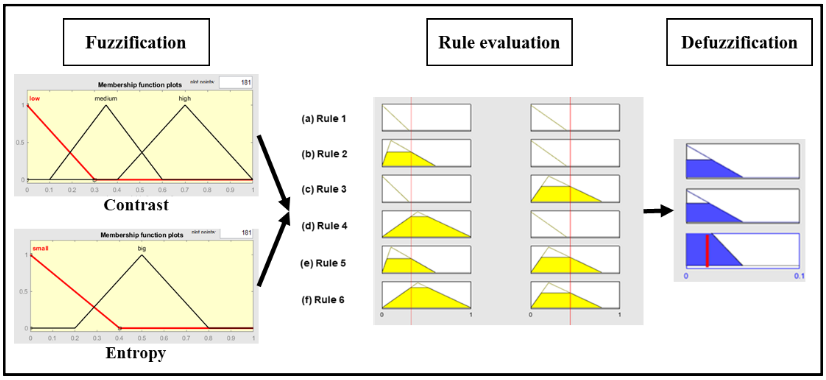

Figure 2. Fuzzy clipped inference system

2.3 Image Quality Analysis

The effectiveness of the FADHECAL enhancement technique on the ROI of MCCs in mammogram images was evaluated using image quality analysis. The following parameters were used: (i) absolute mean brightness error (AMBE); (ii) peak signal noise ratio (PSNR) and (iii) structural similarity index measure (SSIM).

2.3.1 AMBE

The absolute difference in brightness between the original and enhanced mammogram images is known as the AMBE. This value indicates the amount of image brightness that has been disrupted. AMBE can be calculated using Equation 5.

$$AMBE\ (x,y) = |E(y) - E(x)| \tag{5}$$

where $E(y)$ is the mean grey level of the enhanced mammogram image while E(x) indicates the mean grey level of the original mammogram image.

2.3.2 PSNR

The PSNR is a performance metric that can be used to evaluate the image quality of the enhanced mammogram image. The values of PSNR represent the ratio between the maximum possible power of the signal and the power of distorting noise that affects the quality of its representation. Equation 6 defines the PSNR.

$$PSNR = 10 \log_{10} \frac{R^2}{MSE} \tag{6}$$

where R represents the highest pixel values and MSE defines the mean squared error.

2.3.3 SSIM

The SSIM, which can be defined using Equation 7, is an image quality evaluation that can be used to assess the similarity between original and enhanced mammogram images.

$$SSIM\,(x, y) = \frac{(2\mu_x\mu_y + C_1)\,(2\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu_y{}^2 + C_1)\,(\sigma_x{}^2 + \sigma_y{}^2 + C_2)} \tag{7}$$

Let x and y as the original mammogram image and the enhanced mammogram image, respectively; μ indicates the mean of the image intensity; and σ and C are the standard deviation and the constant, respectively.

2.4 Image Quality Assessment for Detecting Microcalcifications in Enhanced Mammogram Images

Accuracy assessment for enhanced mammogram image quality is a crucial step to defining the accuracy of detecting MMCs in enhanced mammogram images. The detection of MMCs in enhanced mammogram images was verified with ground truth from the MIAS database. The accuracy percentage of the proposed technique was measured using Equation 8. After applying the proposed image enhancement technique to all the selected mammogram images, quantitative analysis was carried out by employing the accuracy of the proposed image enhancement technique to detect MMCs as follows:

$$Accuracy\ \% = \frac{Detected\ true\ positive\ MMCs\ in\ the\ enhanced\ mammogram\ images}{Total\ of\ mammogram\ images} \times 100\% \tag{8}$$

3. Results and Discussion

The resulting enhanced mammogram images were analyzed qualitatively and quantitatively. The performance of FADHECAL was tested on the selected mammogram images containing only MCCs that were extracted from the

MIAS database. The results were compared with three image enhancement techniques, namely HE, RMSHE and FC-CLAHE.

3.1 Performance of Mammographic Image Enhancement Techniques

The visual quality or qualitative analysis is always subjective and depends on human perception. In this study, qualitative analysis was included to assess the performance of enhancement techniques in addition to quantitative analysis. The red circles in Figure 3 represent the location of the MCCs in the mammogram images. Figure 4 shows the magnification of the ROI of MCCs from Figure 3 in detail and clear manner. Figure 3a shows an example of the original mammogram image. The image is presented in low contrast and smoothed textures. Thus, the details of dense tissue and suspected breast lesions cannot be observed. Figure 3b shows an overly enhanced image by using the HE technique. The dense tissue is too bright because the HE redistributes the histogram and normalizes the brightness of the whole image. Consequently, the MCCs in Figure 4b cannot be demonstrated appropriately.

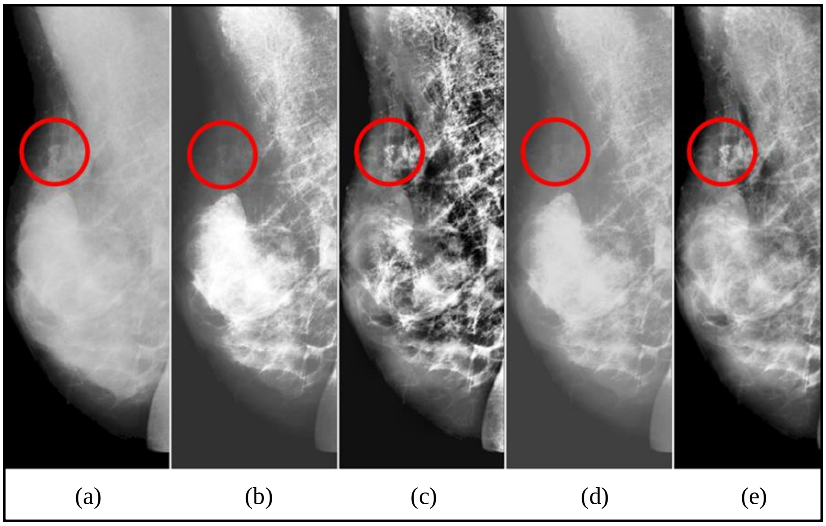

Figure 3. Mammogram images with ROI of MCCs in the red circle: original mammogram image (a) and enhanced mammogram images – HE (b), FC-CLAHE (c), RMSHE (d) and proposed technique (FADHECAL) (e)

Figure 3c shows the enhanced image produced by FC-CLAHE. The results showed an improvement when preserving the details and local information although there was an increase in brightness and contrast. However, the saturation region is seen near the suspected MCCs (also seen in Figure 4c) and thus, may lead to misinterpretation. The RMSHE may decrease the image quality of enhancement for mammogram images, particularly around the mass. Figure 4d shows the resulting image of unclear MCCs in the ROI. The image then grows dark and fades (Figure 3d).

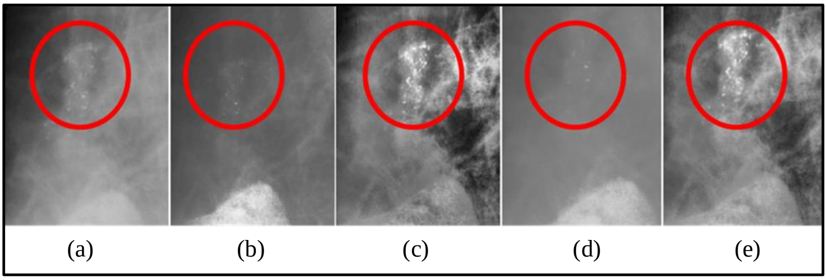

Figure 4. Magnification of the ROI of MCCs from Figure 3: original mammogram image (a), HE (b), FC-CLAHE (c), RMSHE (d) and proposed technique (FADHECAL) (e)

Figures 3e and 4e show the most superior results of FADHECAL among other enhancement techniques. The edges of the MCCs' cluster are more apparent than in the original image. The overall brightness is improved by processing the image based on the FHCL. The fuzzy clipped inference system manages the conflicting requirement of histogram clipped limit to increase the brightness appropriately and without blurry effect.

3.2 Image Quality

For quantitative analysis, three measures of image quality analysis were used to support the qualitative performance. Table 2 shows the average results of image quality analysis for images with MCCs. The enhanced images using FADHECAL showed the lowest AMBE values (6.302) than HE, FC-CLAHE and RMSHE. The low values of AMBE indicated a high-quality image while preserving the brightness. The FADHECAL also obtained the highest PSNR values (20.453) than other enhancement techniques. These values indicated that the resulting images produced had good quality with no amplification of noise during the process. The values of SSIM showed the presence of the real image. Among other enhancement techniques, FADHECAL had shown the highest SSIM values (0.851). Figure 5 shows the comparison results of image quality analysis for mammogram image enhancement techniques.

Table 2. Average results of the image quality analysis

Mammographic image enhancement techniques	Image quality analysis (average)		
	AMBE	PSNR	SSIM
HE	25.192	16.963	0.681
FC-CLAHE	12.504	14.360	0.421
RMSHE	17.987	18.625	0.722
Proposed technique (FADHECAL)	6.302	20.453	0.851

3.3 Accuracy of Image Quality Assessment for Detecting Microcalcifications in Enhanced Mammogram Images

The results showed the proposed image enhancement technique had obtained a good performance for the detection of MMCs with 91.30% of accuracy. All the results were validated with the ground truth from the MIAS database. Morphology and distribution of MMCs in mammogram images are crucial indicators in breast cancer screening at an early stage. Of the 23 selected mammogram images, only two mammogram images with MCCs were not detected by the proposed image enhancement technique due to the dense breast tissue. Figure 5 shows the comparison of mammogram images with the ROI of MCCs after image enhancement process using FADHECAL in red circle.

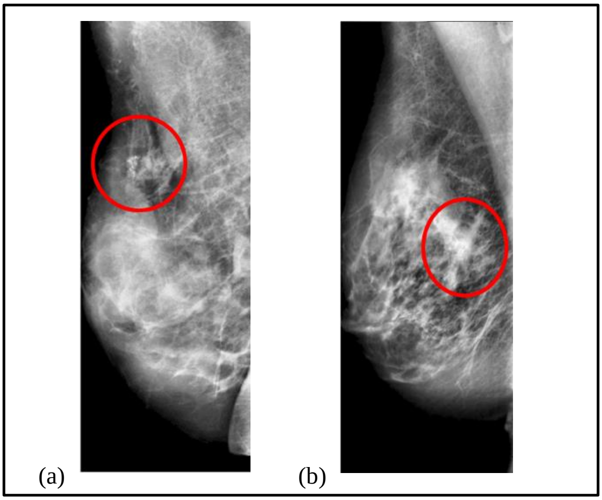

Figure 5. Detectable (a) and undetectable (b) mammogram images with the ROI of MCCs after image enhancement process using FADHECAL

4. Conclusion and Recommendation

The proposed image enhancement technique (FADHECAL) improved the detection of breast cancers, especially MCCs. It can highlight the MCCs clusters than background dense tissue sufficiently. Also, the resulting images of FADHECAL showed the most superior performance of image enhancement with the least noise production compared with other previous techniques. Its accuracy in detecting the presence of MCCs showed an excellent result (91.30%). In essence, FADHECAL can be used as an ideal platform for identifying the characteristics of MCCs at an early stage of breast cancer. To further improve the accuracy of FADHECAL, a case study needs to be carried out in the future using a higher number of mammogram images with MCCs from a local database.

5. References

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