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IMPROVE EARLY DIAGNOSIS OF BREAST CANCER FOR ENHANCING THE X-RAY MAMMOGRAM

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ABSTRACT

The region growth algorithm is used in practice to accomplish the approach of removing pectoral muscle explained here. The Mini MIAS dataset is used to evaluate the suggested methods. Using the breast boundary extraction approach to a dataset of 322, the segmentation accuracy increased to 98.7 percent. Measures of enhancement, absolute mean brightness error, the combined enhancement measure, and discrete entropy are used to assess the contrast enhancement technique. When applied to 14 photos depicting various masses, quantitative assessments revealed that the suggested contrast enhancement approach provided the best balance of contrast improvement and local detail retention. Many CAD approaches have been created to enhance the identification of primary signs of this illness, including masses and micro calcifications, in order to improve radiologists' diagnostic performance. Lesions that take up physical space are called masses, and their characteristics, including form, structure, borders, and density, help to characterize them. A malignant tumor has an indistinct and irregular border that becomes more speculated upon with time, while a benign neoplasm has a smooth margin and regular shape. Low contrast and considerable blurring characterize the appearance of masses and benign glandular tissue on X-rays because of their small variances in X-ray attenuation. Microscopic calcium deposits, or micro calcifications, may be seen as bright spots on a mammography.

KEYWORDS: Mammogram images- histogram equalization- contrast enhancement- breast border- pectoral muscle

INTRODUCTION

When it comes to female cancer mortality, breast cancer is by far the most common. There were 2.1 million new instances of breast cancer in 2018, resulting in 626,679 deaths. 1 The first step in the diagnostic approach to reduce mortality from breast cancer is adequate access to detection using imaging. While mammography has been widely regarded as the most effective method for detecting breast cancer at an early stage, it is not always practical, particularly in low-resource areas. One possible explanation for this is the difficulty in attracting and keeping qualified technicians and radiologists, in addition to the high initial cost of equipment. According to 2014 data, highly developed regions of the globe have ranging from 40 to 600 mammography units per

1 million women between the ages of 50 and 69, whereas most of sub-Saharan Africa and about many developing regions in Asia have between 12 and 41 units on average. 2 Diagnostic digital mammography has been shown to have an estimated overall sensitivity and specificity of 87.8% and 90.5%, respectively, in the United States, where 70% of women get mammography. 3,4 The reported sensitivity of mammography in low- and medium-income countries (LMICs) varies from 63 percent to 95 percent, with a greater sensitivity noted when investigating palpable lumps and a lower sensitivity seen in situations with thick breasts.

The global prevalence of breast cancer has not changed. It is the leading tumor in industrialized nations and ranks second or third in low-income regions. 1 Worldwide, breast cancer rates continue to rise, making this illness a major public health concern. Breast cancer survival rates are correlated with the disease's stage at diagnosis and therapy. The prognosis improves if the tumor is found early. Asymptomatic women have a 95.1% chance of surviving for 20 years or more if they undergo routine breast cancer screening, which may uncover clinically non-palpable tumors. 2 A lumpectomy and radiation therapy instead of a mastectomy and less systemic chemotherapy are two examples of the less invasive treatments made possible by early discovery of breast cancer.

One in eight women in North America will be diagnosed with breast cancer at some point in their lives, making it the most frequent disease among females today. Around 215,919 new instances of invasive breast cancer and roughly 40,110 fatalities are expected in the United States in 2004. Early detection is key to successful treatment of breast cancer. As of right now, screening mammography is the best imaging option for spotting breast cancer in its earliest stages. Unfortunately, there are still certain limits to mammography despite technological advancements. Loss of 3D data associated with projection images (i.e., features of interest are obscured by overlying and underlying structures in the projection radiographs), limited sensitivity leading to an inappropriately high rate of "missed" cancers, and an inherent inability to prove that a suspicious abnormality is benign or malignant are all examples of these shortcomings. Because of these shortcomings, mammographers overlook around 10% of all lesions. It's expected that radiologists find around two-thirds of these missed tumors in hindsight. The total yield of breast malignancies per breast biopsy is around 10 to 50%, while roughly two-thirds of tumors referred for biopsy turn out to be benign. Because of this, other imaging techniques, such as MRI, ultrasound, CT, etc., are being studied for their potential to identify and diagnose breast cancer at an earlier stage.

LITERATURE REVIEW

Farouk A. K. Al-Fahaidy (2022) One of the leading causes of illness and mortality among women worldwide is breast cancer. Breast cancer affects around one in eight American women and one in ten European women, according to the most recent scientific studies. The problem with this illness is figuring out how to create a stress-free and quick diagnostic procedure. The use of a computer-aided diagnostic (CAD) tool to analyze mammography pictures of the breast is one promising approach of detecting breast cancer at an early stage. The initial goal of this study was to provide a way for efficiently identifying breast cancers from mammography images using a machine learning methodology. The second objective of this research was to use the first step's suggested approach as the basis for creating a computer-aided diagnosis (CAD) software application for the detection of breast cancer. Following the Mammographic Image Analysis Society's (MIAS) five-step procedure for the proposed method, images are preprocessed, segmented with the seeded region growing (SRG) algorithm, features are extracted with different feature's extraction classes, and the most important and effective features are selected with the Sequential Forward Selection (SFS) method. Finally, the Support Vector Machine (SVM) algorithm is used as a binary classifier. The first classifier is used to determine if the picture is normal or abnormal, and the second classifier determines whether the abnormality is malignant or benign. To evaluate and refine the efficacy of the proposed technique, it is applied to the MIAS dataset of mammography images in a split-sample design, with 70% of the dataset used for training and 30% used for testing. The suggested approach and the GUI CAD tool are put into practice with the help of MATLAB software. The suggested technique has been proved to be very effective in practice, with an experimental accuracy of 100% when categorizing normal and abnormal mammography pictures and an accuracy of 87.1 when classifying benign and malignant tumors.

Basurto-Hurtado, J.A.; Cruz-Albarran, I.A. (2022) As 16% of all malignant lesions identified in women occur in the breast, it is one of the leading causes of mortality for women globally. In this regard, early detection of these lesions is crucial for optimizing the likelihood of a successful treatment and subsequent recovery. Although a number of books cover certain aspects of this field, none of them provide a comprehensive overview, including everything from picture creation through interpretation. In this study, we provide a thorough state-of-the-art assessment of the picture creation and processing methods used to identify breast cancer, presenting and discussing many promising prospects. To produce cutting-edge alternatives with the accuracy, precision, and dependability needed to reduce misclassifications, new approaches should thoughtfully integrate AI-concepts with the category data.

Koshy, Soumya&Anbarasi, L. & Jawahar (2022) Among women, breast cancer is the most frequently diagnosed malignancy. Mass screening and early identification of breast cancer are both facilitated by computer-assisted diagnosis. The development of AI for diagnosing breast cancer is being fueled by recent breakthroughs in deep learning. Histopathology, mammography, thermography, and ultrasound-based pictures are only few of the many imaging modalities used to identify breast cancer. This study aims to discuss recent research on the efficacy of deep learning methods for categorizing breast cancer. Methods This paper summarizes the different imaging modalities, publicly accessible datasets, augmentation methods, preprocessing methods, transfer learning methodologies, and deep learning techniques employed by researchers for early diagnosis of breast cancer. The study also provides an in-depth analysis of the successes and failures of current deep learning algorithms as well as suggestions for where the field should go next. Results Accuracy, sensitivity, specificity, area under the curve (AUC), and F-measure are only few of the performance measures that have been used to evaluate the many approaches developed thus far. Classification and analysis of breast cancer detection using histological images have both reached accuracy rates of over 90% in several studies. Conclusion This review has highlighted several gaps that need to be addressed before breast cancer can be reliably identified using image analysis. Inaccurate data labeling caused by observer fluctuations with respect to image segmentation datasets, computation time, and Memory overhead has to be investigated in the future to provide a better CAD system.

Abdallah, Yousif et al (2018) The classification of breast normal tissues and diseases relies heavily on the quality of the mammogram, and here is where image enhancement comes in.

Mammograms may be enhanced and have more clinical use thanks to digital image processing tools. This study presents an algorithm for improving contrast, reducing noise, inspecting textures, and cutting up images. In order to maintain their integrity, the mammography pictures are retained at a high resolution. The primary goals of such techniques are the improvement and refinement of picture intensity and the removal of image noise. Since breast lesions vary in density according on their nature and the surrounding tissues, some lesions improved more than others. Correspondence and matching ratio were employed to calculate computational speeds. Statistically, the findings were 96.3 8.5 ($p>0.05$). The results demonstrated that the suggested image enhancement and segmentation techniques were effective in reducing the severity of breast lesions.

MATERIALS AND METHODS

Images from the widely used public Mini-MIAS dataset were used to evaluate the suggested preprocessing methods (Suckling et al., 1994). There are a total of 161 unique mammograms in this data collection, all of which were acquired using MLO technology. Cases ranging from normal to malignant are included in this data collection. Each patient's mammograms are grouped together in pairs; the right mammograms have even filename numbers, while the left mammograms have odd filename numbers. Images are all 1024x1024, with an 8-bit grayscale resolution, and a pixel size of 200 microns.

Contrast Enhancement

Histogram Equalization

A digital image's histogram is defined by the frequency distribution of the image's intensity levels. The histogram may be written as a discrete function g(rk) = nk for a digital picture with gray levels in the range [0, L1], where rk is the kth gray level and nk is the number of pixels in the image with gray level rk. Histogram equalization's fundamental principle is to create a more consistent intensity distribution by recalibrating each pixel's intensity value. Histogram equalization involves transforming each intensity level, rk, into a new intensity, sk, using the formula:

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} p(r_k) \qquad (1)$$

Brightness preserving Bi-Histogram Equalization (BBHE)

Traditional HE has been adapted into BBHE. The original image's brightness is maintained by dividing the histogram into two halves depending on the mean intensity value in this approach. Each of these two sub-histograms is then normalized separately.

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Adaptive histogram equalization (AHE) was developed since the histogram equalization method improved images without taking local context into account. Nevertheless, the standard AHE improves pictures by integrating processes that provide big values for areas with almost uniform intensity distributions with numerous peaks. This oversaturates the original picture in places where there is noise and dramatic contrast. By inserting a user-defined clip level to restrict the local histogram in such a manner that the optimal amount of enhancement may be reached, CLAHE is a variant of AHE that successfully addresses this issue.

Unsharp Masking (US)

Traditional US enhances images by eliminating a low pass filtered version of the picture from the original. The primary goal here is to emphasize the already-sharp parts of the source picture. Yet, noise amplification and edge enhancement may both be outperformed by focusing on sharper edges.

Histogram Modified-Local Contrast Enhancement (HM-LCM)

Contrast enhancement of mammography images is described as a two-stage process in (Sundaram et al., 2011). In the first step, we modified the histogram of the entire image with a uniform histogram mapping function. In this step, we worked toward the goal of getting the modified histogram as close to a normally distributed histogram as possible. The second step included using a local contrast enhancement approach to improve local details. The approach relied on the local variance and mean to develop a local improvement filter. Formerly, the best results were achieved by the use of histogram-based thresholding.

RESULTS

Breast Border Extraction

Three hundred twenty photos from the small MIAS dataset are processed using a breast boundary extraction approach. A line of length 10 and 15 degrees was used as a structural element for the final morphological procedure. In addition, a 2-radius disk has been selected as the structural element for the morphological erosion procedure. After the breast's border is finally pinpointed, all pixels that fall outside of it are covered with a 0 so that only those inside the breast may be seen. In all but the rarest of instances, labels and even some artifacts will emerge beyond the breast border. Masking this region will get rid of the labels and artifacts. For breast boundary extraction, our technique performed really well. The suggested approach successfully recognized borders in 318 of the 322 photos. Unfortunately, owing to the existence of artifacts, only partly proper borders were recognized in the case of 4 photos. The findings are derived from the

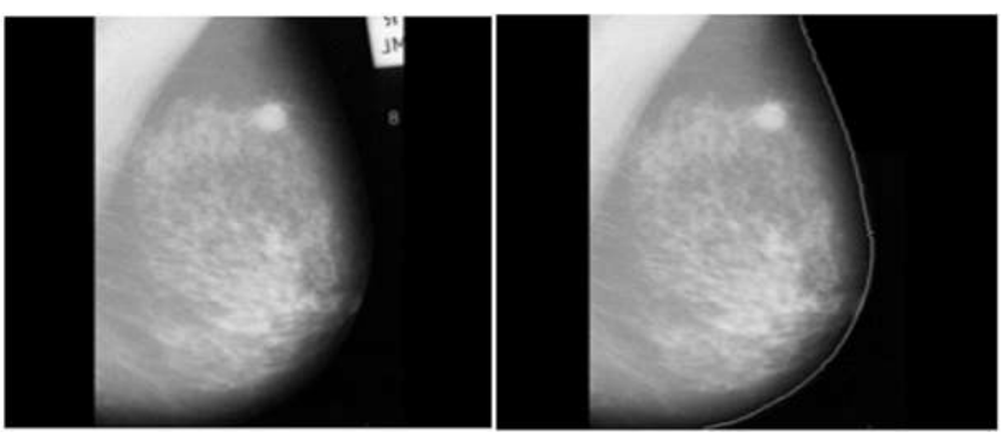

Figure 1. (a) Original Mammogrammdb202 (b) Mammogram with Extracted Breast Border

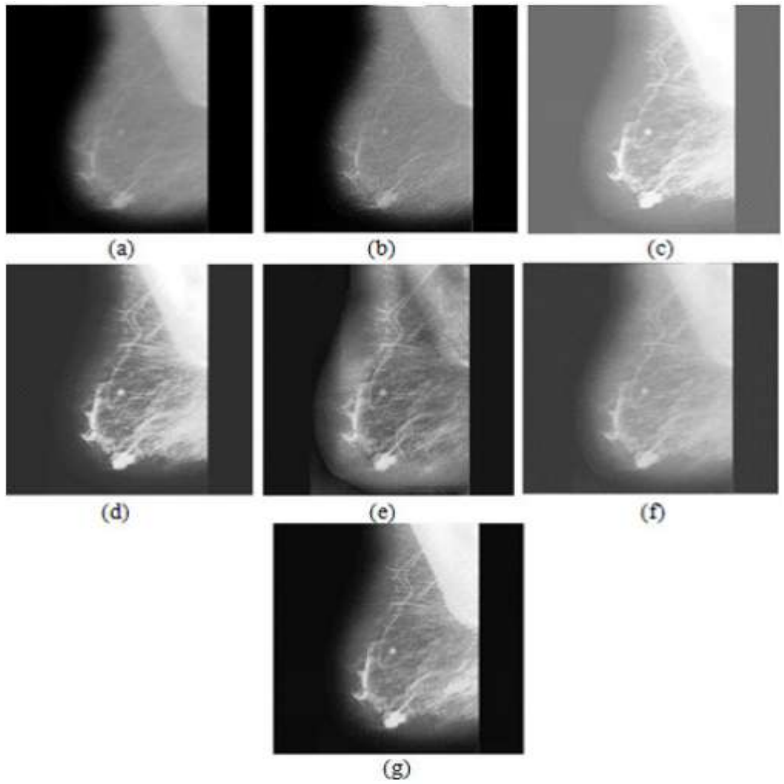

Figure 2. (a), Original Image mdb005; (b), Result of US; (c), Result of HE; (d), Result of BBHE; (e), Result of CLAHE; (f), Result of HM-LCM; (g), Result of BHMANF

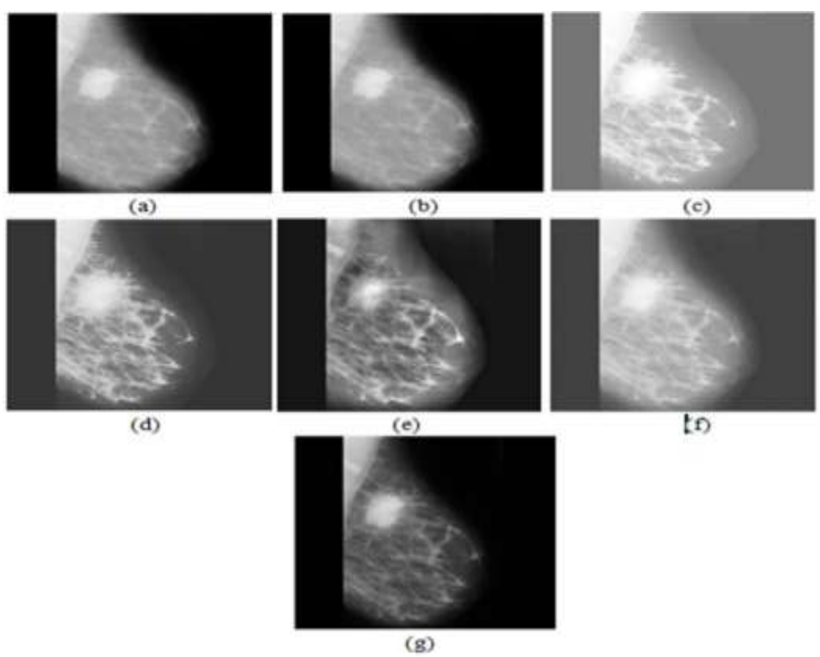

Figure 3. (a), Original Image mdb184; (b), Result of US; (c), Result of HE; (d), Result of BBHE; (e), Result of CLAHE; (f), Result of HM-LCM; (g), Result of BHMANF

Table 1. Comparison of Breast Border Extraction Techniques

Author(s)	Methods applied and performance measure achieved	Number of Images	Detection Accuracy
M´endez and Tahoces., (1996)	Intensity Gradient Based	322	89%
Mario et al., (2009)	Region Growing	40	100%
Raba et al., (2005)	Histogram based threshold, Gaussian Filter	320	98%
Ferrari et al., (2000)	Active Contour	84	0.96 completeness and correctness
Proposed	Morphology	322	98.75

Performance measure of Contrast Enhancement

If the processed picture can be shown to contain the needed information, it is considered an improvement over the original image. In this research, we evaluate the effectiveness of the suggested approach by

Table 2. Combined Enhancement Measure Discrete Entropy Values of Enhanced Images with Different Techniques

	CEM						Entropy						
Original File Name	HE	BBHE	CLAHE	US	HM-LCM	BHM-ANF	Original	HE	BBHE	CLA-HE	US	HM-LCM	BHM-ANF
mdb005	2.847	2.298	1.486	1.737	2.353	1.317	5.176	3.966	4.124	5.417	5.188	5.433	5.189
mdb023	3.362	2.229	1.500	1.742	3.229	1.505	5.104	4.044	4.564	5.548	5.154	5.607	4.964
mdb025	4.283	2.313	2.252	1.741	3.117	1.234	5.410	3.987	5.009	5.542	5.415	5.562	5.009
mdb028	8.327	3.039	2.233	1.740	5.402	1.204	5.580	4.220	4.907	5.691	5.590	5.651	4.907
mdb058	5.908	2.591	1.753	1.740	3.929	1.369	4.232	3.052	4.122	4.406	4.235	4.396	4.122
mdb063	6.086	2.992	2.177	1.752	4.277	2.084	4.119	2.896	6.998	4.409	4.118	4.163	4.033

mdb069	6.853	3.062	2.017	1.747	4.774	1.941	5.519	4.280	4.868	5.662	5.514	5.629	5.868
mdb178	3.281	2.268	1.824	1.741	2.394	1.341	3.085	2.028	2.985	3.203	3.086	2.924	3.685
mdb184	10.334	3.802	3.092	1.722	8.330	1.286	4.900	3.673	4.618	5.163	4.909	5.101	4.668
mdb186	3.436	2.298	2.190	1.738	3.281	1.607	3.536	2.659	3.481	3.778	3.583	3.441	3.481
mdb190	9.756	3.531	1.830	1.748	6.330	1.568	5.135	4.049	4.574	5.454	5.133	5.374	4.874
mdb193	3.297	2.202	2.173	1.744	2.504	1.418	5.195	3.953	4.995	5.447	5.195	5.314	4.995
mdb204	4.246	2.359	1.945	1.738	5.298	1.021	5.422	4.263	4.587	5.683	5.433	5.599	5.487
mdb206	2.885	2.391	1.318	1.736	2.394	1.449	5.035	3.822	4.722	5.296	5.035	4.947	4.722
Average	5.350	2.670	1.985	1.741	4.115	1.453	4.818	3.635	4.611	5.050	4.828	4.939	4.715

On quantitative measurements and visual perception. State-of-the-art contrast enhancement methods such as HE, BBHE, CLAHE, and US are used to evaluate the suggested approach. In order to assess the efficacy of the suggested technique, 14 mammography images from the Mini MIAS dataset are used in this research. Images of both benign and malignant masses, made up of various tissues, may be seen in these mammograms.

Many quantitative metrics are used to assess the efficacy of contrast enhancement methods in practice. Enhancement Measure (EME), Absolute Mean Brightness Error (AMBE), Combined Enhancement Measure (CEM), and Discrete Entropy are some of the quantitative measurements employed in this investigation (H). Table 2 and Table 3 provide the performance matrices for EME, AMBE, CEM, and H, respectively.

We have isolated the nodules and calculated the total number, median size, and standard deviation of mammographic nodules.

Table 3. Mean value of nodules

Image no.	Size of main nodule	Mean Value	Classification (Staging)
1.	230 mm	0.0575993	T3
2.	8mm	0.00380899	T1b
3.	1mm	0.00043653	T1mi
4.	195mm	0.0481018	T3
5.	48mm	0.0131076	T2

CONCLUSION

For women, breast cancer ranks high among the leading causes of mortality. This means that cancer may be prevented with the help of routine screening and prompt treatment. This research examines the efficacy of a CAD-based system for making diagnoses from mammography images.

The procedures include preprocessing, segmentation, feature extraction, feature selection, and classification. In this study, we provide a fresh method for determining whether or not a mammography shows a breast cancer tumor. In our study, we use a gradient magnitude Sobel filter and other fundamental image processing operations to identify and classify nodule forms depending on their contextual context.

To effectively identify breast cancer masses in mammography, we used a novel method that combines the Sobel filer and Sobel mask. According to the grading system, this tool may help physicians make earlier diagnoses of breast cancer.

The prognostic risk assessment may be enhanced by using more criteria in future studies, such as the number of invaded axillary nodes, calcifications, disease extent, etc.

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