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Article

Adaptive Density-Guided Multi-Scale CLAHE combined with Edge-Attention U-Net for Dense Breast Visualization and Segmentation

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Abstract: Breast density is an important factor in the interpretation of mammograms as dense fibroglandular tissue can make it more difficult to see the edges of lesions. Contrast enhancement and deep learning-based segmentation methods have been much researched, but current methods often use fixed enhancement parameters and fail to maintain tissue structure in cases of heterogeneous dense breast. While standard segmentation networks can have less sensitivity towards dense tissue boundaries, conventional Contrast Limited Adaptive Histogram Equalization (CLAHE) can add noise and cause over-enhancement. This inspiring the development of a density-aware enhancement and segmentation framework. In this study, they introduce a new Adaptive Density-Guided Multi-Scale CLAHE (ADG-MSCLAHE) combined with Edge-Attention U-Net architecture for dense breast visualization and segmentation. Mammographic density parameters are first estimated adaptively based on mammographic density characteristics to determine enhancement parameters. The multi scale CLAHE outputs at different tile sizes are merged using density dependent weighting coefficients to enhance anatomical structures along with contrast. These feature maps are then combined in an edge-aware manner before being fed into an Attention U-Net for a better delineation of dense tissues and boundary preservation. The methodology was tested on the normal, benign and malignant dense breast cases in the combined INbreast–DDSM–MIAS mammographic dataset. Experimental results show that, the proposed enhancement framework provides PSNR value as 31.24 dB, SSIM value as 0.846 and Contrast Improvement Index (CII) as 1.91 which is better when compared with conventional CLAHE and fixed multi-scale enhancement. The proposed Edge-Attention U-Net achieved better dice coefficient score of 0.921, IoU score of 0.854 and F1 score of 0.921 for segmentation which showed a better localization of dense tissue. The results show that density-guided enhancement and edge-aware segmentation enhances the visibility of tissues, retains structural information and produces clinically interpretable dense breast visualization. The proposed scheme is an effective computational framework for mammographic analysis and computer-aided applications for breast screening.
Keywords: Breast Cancer Screening, Mammographic Breast Density, Adaptive Density, Edge-Attention U-Net, Dense Tissue Segmentation, Mammogram Enhancement.

1. Introduction

Breast cancer is one of the most common cancers affecting women and is still a major public health problem worldwide. Early diagnosis is of great importance in terms of improving outcome of treatment, mortality rates and long-term survival. Mammography has become the most popular imaging technique for breast cancer screening because it can detect abnormalities that may be cancers, before symptoms occur. Although widely used, mammography is not a very easy screening test and diagnosis of mammograms is challenging in women with dense breast tissue [1]. Dense breasts are composed of more fibroglandular tissue than fatty tissue, and both may show up as white areas on mammograms. The similarity renders the identification and evaluation of lesions difficult radiologically.

Breast density is becoming an important imaging biomarker linked to breast cancer risk and difficulties in diagnosis. With dense breast, smaller masses, distortions or calcifications may be hard to find and the sensitivity with screening is reduced, and false-negative results may occur. Therefore, the medical image analysis of dense tissue structures is an active research field. Many image enhancement methods have been devised to boost contrast and enhance the visibility of clinically relevant structures [2][3]. Of these, histogram equalization and also Contrast Limited Adaptive Histogram Equalization (CLAHE) have proven to be effective in enhancing local contrast. But traditional enhancement methods are based on a set of parameters which are fixed and may not be appropriate for mammograms with different density patterns.

In recent years, new developments in artificial intelligence and deep learning have paved the way for automated approaches to mammographic analysis, such as lesion detection, tissue segmentation and breast density assessment. The CNNs and encoder-decoder models have achieved good performance for extracting complex features of images. But it is not possible in dense breast regions, where there is no clear boundary in the tissue and there is not much contrast change [4]. These restrictions emphasize the need of adaptive enhancement mechanism which can improve the quality of images without losing any structural information for further segmentation process.

To overcome these issues, this work suggests a framework for Adaptive Density-Guided Multi-Scale CLAHE enhancement along with Edge-Attention U-Net Segmentation Model. In this work, a methodology is proposed to enhance dense breast visualization using density dependent contrast enhancement and boundary aware segmentation, which will help the mammographic interpretation in a more reliable manner.

1.1. Mammographic Breast Density and Clinical Significance

Breast density is the ratio of the amount of fibroglandular tissue to the amount of fatty (adipose) tissue in the breast. Mammographically dense breasts have more fibroglandular tissue, which shows up radiopaque on mammograms. Fatty tissues, on the other hand, are radiolucent and will create more contrast between normal tissue and pathological findings. Breast density can differ significantly from one person to the next and is dependent on age, hormonal status, genetic makeup, and physiological factors.

Breast density is not only important for image interpretation. Many studies have found that dense breast tissue is a risk factor on its own that increases the likelihood of breast cancer formation. Very dense breasts often result in the poor sensitivity of screening due to the similarity of radiographic characteristics of the lesion with the surrounding dense tissue. This masking effect makes it harder to detect the subtle abnormalities and thus can make the diagnosis harder [5].

It is therefore important to be able to visualize dense tissue areas accurately to enhance mammographic assessment. Dense breast analysis helps radiologists detect suspicious areas in the breast and is also used to aid computer-aided diagnosis (CAD) systems. Improved visualization leads to a better localization of lesions, a better characterization of tissues and screening accuracy [6]. But dense mammograms may show less contrast, uneven illumination and overlapping tissue structures, which makes traditional image processing techniques difficult to apply.

As large mammographic datasets have become available, computational methods have been developed specifically for breast density assessment. These techniques aim to improve tissue visualization without compromising any clinically significant structures. However, the variability of the breast density pattern remains challenging and adaptive methodologies which can adapt to the breast image characteristics are needed.

1.2. Dense Breast image enhancement techniques

Image enhancement is an essential step in mammographic analysis as a first step in the processing of the images. The aim of enhancement is to make the anatomical structures more visible without generating artefacts that could influence the clinical assessment. In the past few years, various enhancement methods have been explored for use in mammography, such as histogram equalization, adaptive histogram equalization, contrast stretching, wavelet-based enhancement and multi-scale filtering.

The histograms of images does not necessarily distribute the intensity values evenly over the available dynamic range, which is why histogram equalization is used to improve the global contrast. Global enhancement techniques can be effective for some image types but are not able to highlight the local tissue changes apparent in mammograms. To overcome this limitation, Adaptive Histogram Equalization (AHE) is employed, which treats localized regions of the image separately. CLAHE also has the advantage of adaptive histogram equalization that it reduces the amount of contrast enhancement and noise enhancement [7].

Although all these improvements, traditional CLAHE methods still use the same clip limit and the size of the tile grid for all images. Mammograms with varying density characteristics may thus have varying enhancement performance. High breast density can make it difficult to see the structures in the tissues if they are not enhanced enough, or artificial boundaries can be created if they are enhanced too much.

To overcome these limitations multi-scale enhancement techniques have been introduced, which combine information derived from different spatial scales. Small scales yield fine details and large scales provide global anatomical data. Most of the current approaches use a fixed fusion strategy, which is not adapted to the different densities of mammograms while good visualization performance have been achieved with multi-scale approaches.

Recently, adaptive enhancement techniques that can adapt enhancement parameters according to the image contents have been developed. The use of density-guided enhancement is an emerging area of interest, as breast density directly impacts how breast tissue looks and how easy it is to see the lesions. Adaptive frameworks which use density information in parameter selection and scale fusion can produce more well-balanced enhancement results with maintaining structural consistency [8]. These techniques are especially important for dense mammograms in which there are fine variations in the tissues and small breast differences that need contrast.

1.3. Dense Tissue Segmentation using Deep Learning

Segmentation plays crucial role in the computer-aided analysis of mammograms as it is used for localizing and quantifying anatomically significant structures. An accurate segmentation of dense tissue areas can help in density estimation, detection of lesions, risk assessment and treatment planning. The thresholding, clustering, region growing, active contours and morphological operations are common segmentation techniques. While these methods yield good performance in controlled situations, they often fail with the varying intensity in mammographic images and the presence of overlapping tissues [9].

Due to the advent of deep learning, medical image segmentation has made great progress. Convolutional neural networks (CNN) have shown excellent feature extraction performance than the handcrafted ones. To capture both local and global image information, the encoder-decoder type architectures such as U-Net have been widely adopted. Skip connections help in retaining spatial details enhancing the accuracy of the segmentation.

Further improvement has been achieved by using attention mechanisms, which allow networks to selectively attend to informative regions to improve segmentation performance. Attention guided architectures are able to ignore irrelevant background and highlight clinically relevant structures [10]. However, the dense breast segmentation is still challenging due to weak boundaries, fragmented tissue boundaries, and challenging to distinguish dense breast from surrounding tissues.

Edge information plays an important role in improving the accuracy of segmentation because it gives valuable information about the structure. The use of edge maps in deep learning models enables features to be extracted and regions to be delineated using edge properties [11]. The edge-aware attention mechanisms integrate structural information with intensity-based features, leading to enhanced tissue contour and lesion boundary preservation. These methods are especially useful in dense breast mammograms, where traditional segmentation methods might not precisely distinguish between various tissue structures [12][13].

Combining adaptive enhancement and edge-aware segmentation provides a full package to analyse mammographic images. Attention based segmentation uses texture information, and also boundary information to improve dense tissue localization while enhanced images gives a clearer representation of the tissues.

1.4. Current Research Trends

The research works on mammographic image analysis are now focused on three main areas: image enhancement, breast density assessment, and deep learning-based segmentation. Adaptive contrast enhancement techniques have been shown to improve the visualization over the traditional histogram-based techniques. Multi-scale image processing frameworks have been used to retain both fine and coarse anatomical structures. At the same time, the accuracy of segmentation of convolutional neural networks, U-Net variants, and attention-based architectures has been significantly improved. In recent studies, enhancement and segmentation modules are increasingly integrated in one single framework; but for most, they use fixed enhancement parameters and boundaries are not well utilized.

1.5. Research Gap

Current frameworks of mammographic analysis have several disadvantages:

1. The conventional CLAHE based enhancement techniques use fixed parameters which are not able to adapt to the different breast density patterns.
2. Most of the existing multi-scale enhancement methods are based on static fusion of the information without utilizing the density information.
3. Many deep learning models for segmentation are based on intensities and do not explicitly use the edge information for preserving dense tissues boundaries.
4. Combining density-guided enhancement and edge-aware segmentation in integrated frameworks is still in its infancy for the purpose of dense breast visualization.

1.6. Proposed Objectives

i. Design an Adaptive Density-Guided Multi-Scale CLAHE algorithm that dynamically sets the enhancement parameters based on the mammographic dense tissue characteristics for better visualization of the dense tissues.

ii. Develop an edge-attention U-Net segmentation model for dense tissue localization and boundary preservation for mammographic image segmentation by introducing edge-aware feature guidance.

Dense breast mammograms remain a significant challenge in the interpretation of mammograms and computer-aided diagnostic (CAD) systems because of the decreased contrast and tissue overlap. Despite the great success that has been made in enhancement and segmentation research, there are still some problems which cannot be solved such as fixed enhancement parameters and lack of boundary preservation. To tackle the above problems, Adaptive Density-Guided Multi-Scale CLAHE and Edge-Attention U-Net framework combines density-aware contrast enhancement with edge-guided segmentation, offering a solid basis for enhanced dense breast visualization and analysis in mammography.

2. Review Of Existing Work

The diagnosis of breast cancer using a mammogram has seen remarkable progress over the years, including the use of image processing, machine learning, deep learning, and explainable AI techniques. The growing trend of dense breast tissues and complex mammographic interpretation has motivated research on a variety of image enhancements, tissue segmentations, lesion classifications, and multimodal diagnostic frameworks. The recent studies have been directed towards several aspects of improvement in the visualization quality, discriminative feature extraction, accurate segmentation and towards developing reliable computer-aided diagnosis (CAD) systems that can help in clinical decision making. In addition, the use of attention mechanisms, explainable models, integration of various imaging modalities, and automated diagnostic pipelines has led to better diagnostics and interpretation. The recent developments in mammographic analysis, dense tissue assessment, segmentation methods, and artificial intelligence (AI) based breast cancer detection systems are discussed in the following review.

2.1.Mammographic Image Enhancement and Dense Breast Visualization

Breast density is one of the most significant factors for mammographic interpretation and effectiveness of breast cancer screening. Increased breast density is not only associated with a higher risk of breast cancer, but also makes it harder to detect abnormalities in the breast tissue since areas of fibroglandular tissue and those of malignancy tend to have similar appearances on X-rays. Therefore, the introduction of new screening, enhancement, segmentation and classification methods to increase the diagnostic accuracy of dense breast mammograms has been the focus of the researchers. With the recent advances in Artificial Intelligence, Deep learning, and multimodal imaging, there is significant progress toward development of accurate Computer Aided Diagnosis (CAD) system for breast cancer diagnosis.

Conventional mammographic screening has been shown to have a number of drawbacks in women with dense breasts, leading to a search for additional imaging modalities. Overall, the combination of breast ultrasound (BUS) and mammography has shown potential for better detection in cases of critically dense breast, pointing towards the need for better visualizing and tissue characterizing methods to overcome the masking effect of breast density [14]. At the same time, the use of artificial intelligence in breast imaging has been rising, leading to a greater focus on the understanding of the acceptance of automated diagnostic systems. Public perception studies showed positive expectations of AI-assisted decision-making, but also the need for interpretability and clinical reliability for future implementation in healthcare settings [15].

More recent developments have involved deep learning for the discovery of clinically relevant imaging biomarkers. Even when using mammographic images to assess breast arterial calcification, deep learning models were also able to extract meaningful diagnostic information beyond the traditional analysis of the lesions, thus increasing the clinical value of mammography [16]. Moreover, multimodal approaches were created which integrated mammograms with thermal images, adding mechanisms to the diagnostic processing to adapt to tissue properties. The use of breast density information in the analytical framework was found to have better detection performance in such approaches, indicating the potential benefits of density-aware methodologies for more robust diagnostic outcomes [17].

Recent years have witnessed a great interest in segmentation of mammograms due to its direct influence on the subsequent classification and risk assessment. High precision segmentation of mammograms has been achieved with the combination of adaptive radiological feature extraction and advanced U-Net architectures. These methods improved the localization of the image boundaries and identification of the regions by hierarchical feature representations and context information from the mammographic image [18]. In the field of breast cancer diagnostics, the paradigm shift from traditional screening to precision medicine, including the use of imaging, computation and personalized risk estimation to inform clinical decision making has also been highlighted [19].

The frameworks based on deep learning have yielded significant improvements for mammographic tissue analysis. The segmentation using CNN has yielded good results by isolating the important breast structures from the background tissues, and enhanced the classification performance [20]. These segmentation-based approaches minimize background noise and help to analyze breast density patterns more specifically. Along with segmentation, interpretability has also emerged as an essential factor for the contemporary diagnostic system. Transparent feature representation and explainable decision-making processes of CNNs have proven effective to boost clinicians' confidence without compromising the classification performance of mammographic mass assessment [21].

All these studies collectively show that there has been remarkable progress in mammographic screening, segmentation, classification, and density driven analysis. Breast cancer detection has significantly benefited from the incorporation of additional imaging modalities, adaptive AI architectures, and segmentation algorithms based on deep learning. However, a number of issues are still to be addressed. Current density-aware diagnostic methods are mainly directed towards dense tissue detection and classification, but not towards enhancement of dense tissue visualization. Existing segmentation schemes focus on precise region extraction, and are highly reliant on input images with low contrast and low visibility in dense breast regions. Furthermore, most of the work so far considers enhancement, segmentation and classification as separate tasks, and thus interaction between improving the quality of the image and delineating tissue types cannot be exploited. Few works have focused on adaptive enhancement mechanisms that can dynamically enhance the image contrast based on the breast density and which can also help in edge-preserving segmentation. Hence, there is a research gap for creating an integrated framework which can fuse the concepts of both density guided multi-scale contrast enhancement and edge-aware deep segmentation for enhanced dense breast visualization, structural information retention, and improved mammographic interpretability.

2.2. Mammographic Segmentation and Dense Tissue Delineation

The use of AI in mammographic image analysis has revolutionized image synthesis, classification, explainability, and multimodal learning methods. Due to the complexity of breast cancer diagnosis, in particular for breast density cases, there is a need for research on computational frameworks to derive clinically relevant information from the mammographic image. These represent recent works on how the diagnostic accuracy can be improved via improvement of image representation, adaptive learning strategies, explainable decision making and multimodal data integration. These advances help to make the computer-aided diagnostic systems more reliable and aid decision making in clinical breast cancer screening programs.

Recently, image synthesis has been proposed as a new technique to assist with mammographic interpretation and uniformity of diagnosis. To synthesize diagnostically relevant representations under multi-view imaging conditions, a tumor region adapted mammography synthesis framework was developed. Concentrating on lesion-specific areas and using complementary information from diverse mammographic views, a better visualization and representation of the characteristics of the tumor was obtained, which helped to make a more accurate diagnostic appraisal [22]. These synthesis-based methods show the importance of creating better image representations, which can maintain clinically relevant structures and minimize differences between imaging views.

Machine learning still has great importance in the detection of breast cancer. Optimized hybrid classification frameworks have provided improved predictive capabilities incorporating feature selection, classification and optimization approaches. The methods have been successful in dealing with complex mammographic patterns while enhancing the discrimination between benign and malignant abnormalities in breast by making use of complementary feature representation extracted from mammographic images [23]. It is shown from the results of the hybrid learning architectures that employment of hybrid method might be more effective for diagnostic capability and classification accuracy.

Explainability is essential for AI systems in medical imaging. There are multiple view explainable learning methods that explored the contributions of multiple mammographic views towards the diagnostic decisions, using graph attention mechanisms. These kinds of frameworks provide transparency of the relations between different views identified and point out areas that impact the classification results. Explainability, if the data-driven model prediction can be explained, can lead to a higher trust level from the clinician and allow for the easy adoption of AI in breast imaging applications. Concurrently, extensive assessments of explainable AI techniques have highlighted its significance, assessment metrics, and clinical readiness. These investigations underline the necessity of diagnostic systems that yield high accuracy results along with clinically relevant and easily comprehensible explanations for their diagnostic decisions [25].

Breast Cancer Diagnosis systems have been further enhanced with the incorporation of deep learning with the multimodal imaging data. Combination of different imaging modalities has shown to be beneficial in diagnosis, and advanced classification frameworks based on a combination of mammography and ultrasound images have proved to be beneficial in enhancing the diagnostic performance as compared to single-modality analysis. In the field of breast cancer assessment, deep neural networks with the capability to process heterogeneous information have been developed, which has led to the improvement of feature extraction and classification efficiency, thereby providing comprehensive information on breast cancer [26]. In the same vein, multimodal deep learning approaches (combining ultrasound with mammography and clinical data) have shown their worth in combining imaging and patient-specific data in one analytical model. These kinds of approaches supply additional contextual information and enable better disease characterization [27].

The fast development of AI in breast imaging has also sparked significant interest in discussing the present methodology and future research. The contribution of artificial intelligence in breast cancer diagnosis has been continuously increasing and has been proven through comprehensive analyses of imaging modalities, deep learning architectures, and explainability mechanisms. These investigations show that modern diagnostic systems are evolving to use more and more advanced image processing, deep learning, and decision-support mechanisms that are still interpretable to obtain higher levels of diagnostic performance and clinical applicability [28].

Recent studies show significant advancements in the synthesis of mammographic images, optimized mammography classification, explainable AI, and multimodal diagnostic frameworks. Such advances have helped to increase the accuracy of diagnosis and the understanding of computer-aided systems for breast cancer detection. But a few drawbacks are apparent. Current research mainly addresses classification and prediction of diagnosis with comparatively few efforts addressing the adaptive visualization of dense breast tissues. Many frameworks do not explicitly deal with density-dependent contrast enhancement and are based on pre-existing image quality. Moreover, explainable classification typically works separately from enhancement and segmentation processes and fails to take advantage of the structure information in dense breast areas. The combination of density guided enhancement and edge aware segmentation is not well studied yet. Hence, a research gap is that there is no single work that integrates the adaptive multi-scale contrast enhancement and deep edge-aware segmentation to enhance dense tissue visualization, structural preservation, and diagnostic interpretability in mammographic images.

2.3.Deep Learning-Based Classification and Computer-Aided Breast Cancer Diagnosis

With the booming development of artificial intelligence and deep learning technologies, mammographic image analysis and breast cancer diagnosis have been significantly enhanced. Current diagnostic systems pay more and more attention to the following aspects: powerful feature extraction, interpretable decision making, semantic segmentation, and multimodal learning strategies to enhance the reliability of computer-aided diagnosis systems. Beyond classification accuracy, recent studies have focused on interpretability, segmentation quality, and clinical applicability, highlighting the need for reliable and effective breast imaging systems.

A stable feature extraction is still one of the key requirements for successful breast cancer diagnosis. A stability driven feature extraction, along with Kolmogorov–Arnold network learning, showed greater diagnostic uniformity in choosing the robust feature representations from the mammographic data. To reduce sensitivity to data variation and noise, and to increase the classification accuracy, ensemble learning techniques were used [29]. This suggests the need for stable feature extraction methods that are able to assist in correct diagnostic decisions under various imaging conditions.

The relationship of segmentation and classification also been given much attention. Comparative experiments with segmentation dependent and segmentation free methods demonstrated that the quality of the segmentation is decisive to the classification performance. Breast mass delineation is important to help the classifiers focus on important clinically relevant structures and increase diagnostic accuracy and reduce background noise [30]. This indicates that it is necessary to integrate the effective segmentation mechanism into the computer-aided diagnosis system.

Breast imaging research has expanded from mammography to encompass other imaging modalities, which in turn has also expanded in scope. In addition to conventional imaging sensitivity measures, preoperative breast MRI provided added anatomical/pathological information that added clinical value and benefit in surgical planning and treatment decision making. The multi modal diagnostic techniques facilitate the more comprehensive assessment of the breast abnormalities and can be utilized to offer individual treatment plan [31].

Interpretation of the meaning of the information observed in breast images is a major problem in ongoing breast imaging research. The need for transparent decision-support systems that can explain the diagnostic outcomes in a way people can understand is clearly demonstrated by extensive evaluation of explainable artificial intelligence techniques. These investigations revealed that explainability was crucial for increasing clinician confidence, regulatory acceptance, and to introduce AI into clinical practice. As a result, more recent breast cancer diagnosis frameworks are trying to make every effort to locate a compromise between prediction and interpretability.

Semantic Segmentation is another important research topic in the field of mammographic image analysis. Automated semantic segmentation techniques have been proven to be able to accurately segment and localize breast tissue structures for applications like breast density estimation, breast lesion localization, computer-aided diagnosis, etc. These systems can support clinical workflows and reduce user intervention as well as improve uniformity on tissue characterization [33]. The large amount of research into breast mass segmentation also demonstrated that the segmentation is one of the most challenging issues in mammographic analysis, because of the overlapping of different tissues, low contrast and breast mass density variations.. The results show that correct segmentation is a key factor to correct classification and diagnosis in the next steps [34].

The deep learning architecture has made significant progress in the detection of breast cancer. The advanced frameworks that combined Xception network and EfficientNet-B5 network showed better feature extraction performance and better classification performance on mammographic datasets. Complementary deep learning architectures allowed more effectively representation of the characteristics of breast tissue and lesion patterns, which resulted in better diagnostic outcomes [35]. In addition to classification, segmentation analysis of breast calcifications has also become important since the type of calcification often is a sign of malignant changes. Quantitative segmentation frameworks have been proved to be effective in the identification and characterization of the calcified areas of mammographic images to provide more detailed clinical evaluation [36].

In recent years, attention mechanisms and optimization strategies have been included in segmentation research. Multi-scale attention-based feature calibration frameworks showed better segmentation results by paying attention to different spatial resolutions of contextual information and highlighting the diagnostically important regions [37]. Likewise, evolutionary optimization along with fuzzy entropy analysis presented an adaptive identification of tissue structure and image characteristics to enhance the gland segmentation accuracy [38]. In addition, fully automated pipelines which contain segmentation and classification have proven to be feasible in the context of end-to-end mammographic analysis systems that can simultaneously localize the lesions and predict diagnostic outcomes, with minimum manual intervention and high diagnostic performance [39].

Remarkable advance has been made in feature extraction, explainable artificial intelligence, semantic segmentation and deep learning-based breast cancer diagnosis. The use of ensemble learning, attention mechanisms, optimization strategies and automated pipelines for diagnostic purposes have shown to be effective in existing studies. But there are some caveats that haven't been addressed. Most investigations are mainly directed towards classification and segmentation performance and there is relatively little research effort directed towards adaptive visualization of dense breast tissues [40][41]. Many current segmentation methods use images that don't have the best contrast, or structural enhancement [42]-[45]. Furthermore, enhancement, segmentation and diagnostic interpretation are often considered separate aspects of an integrated framework. There is a limited amount of research on multi-scale enhancement guided by density, in the context of edge-preserving segmentation of dense breast regions. Hence, there is a major research gap to devise a single method that integrates adaptive density-aware breast enhancement, edge aware deep segmentation, to enhance dense breast visualization, structural preservation, and clinical interpretability for mammographic analysis.

3. Proposed Methodology

The proposed framework introduces an integrated mammographic breast density visualization and segmentation approach that combines Adaptive Density-Guided Multi-Scale CLAHE (ADG-MSCLAHE) with an Edge-Attention U-Net (EAU-Net) architecture. The framework is designed to improve visualization of dense breast tissues while preserving anatomical structures and lesion boundaries. Unlike conventional enhancement techniques that employ fixed contrast parameters, the proposed method dynamically adjusts enhancement settings according to the estimated breast density category. The enhanced mammograms are subsequently processed through an edge-guided attention segmentation network to obtain accurate dense tissue delineation.

3.1. Dataset Acquisition and Preparation

Traditional CLAHE utilizes fixed clip limits and tile sizes for all images, often resulting in over-enhancement or insufficient contrast improvement. To address this limitation, an adaptive density-guided enhancement mechanism is introduced. Three CLAHE outputs are generated using different tile sizes: Scale-1: 4 × 4, Scale-2: 8 × 8 and Scale-3: 16 × 16. The enhancement operation is expressed as in eq.4:

$$I_i = CLAHE(I_n, C_i, T_i) \tag{4}$$

Where, C_i= clip limit, T_i= tile size, I_i= enhanced image at scale i, The enhancement parameters are selected according to the estimated breast density score. The adaptive clip limit is calculated as in eq.5:

$$C_a = C_0 + \lambda D_s \tag{5}$$

Where, C_0= base clip limit, λ= density adjustment coefficient. The multi-scale enhanced images are combined using density-dependent fusion weights as in eq.6:

$$I_{enh} = \sum_{i=1}^{3} \alpha_i I_i \tag{6}$$

Where, α_i= adaptive fusion weights, $\sum \alpha_i = 1$.

This fusion strategy preserves both coarse and fine tissue structures while improving local contrast in dense regions.

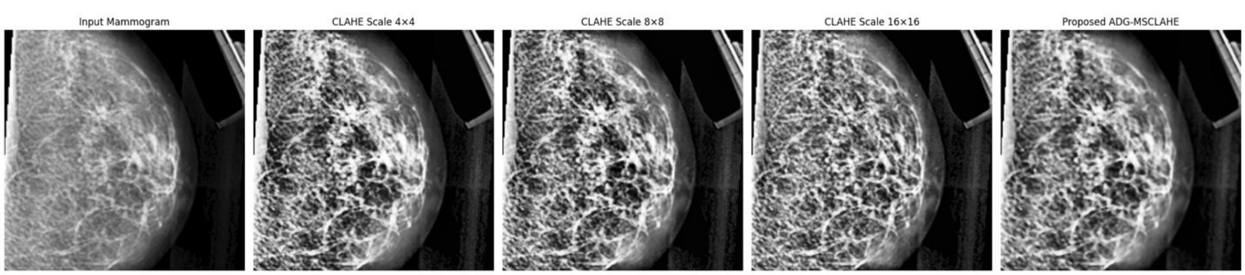

Figure 3 Multi-Scale CLAHE-Based Dense Tissue Enhancement

Figure-3 shows the enhancement stage of the proposed Adaptive Density-Guided Multi-Scale CLAHE (ADG-MSCLAHE) framework. CLAHE is applied at three scales (4×4, 8×8 and 16×16) in order to enhance local contrast at various scales. The outputs of the improved ones are fused adaptively based on the estimated density score. The last image from ADG-MSCLAHE shows better visualization of dense fibroglandular structures with minimal over-enhancement artefacts and preserving the anatomical details.

Figure-4 shows original mammogram is compared with the image enhanced using conventional CLAHE. The standard CLAHE provides enhanced contrast locally and makes the tissue structures more visible. But there is some enhancement of certain area and unequal distribution of contrast. The comparison demonstrates the drawback of the fixed-parameter enhancement methods in the presence of different breast density patterns, and thus advocates for adaptive density-aware enhancement methods.

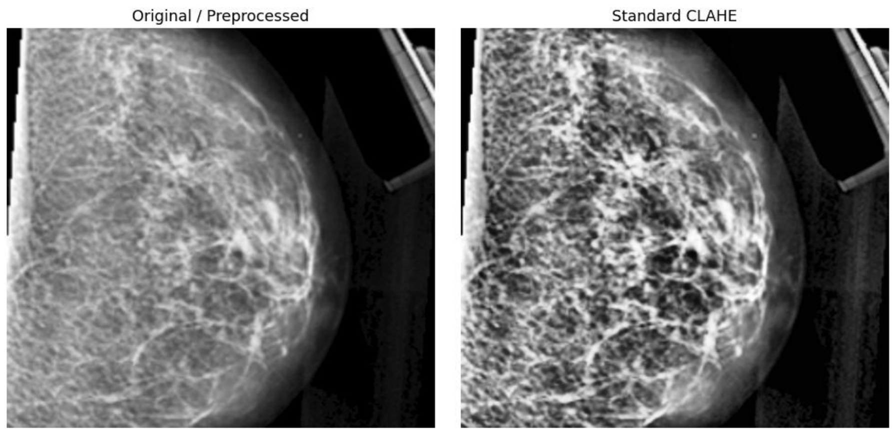

Figure 4 Visual Comparison Between Original and Standard CLAHE Images

Figure-5 shows the comparative evaluation of enhancement results from original mammogram, standard CLAHE and proposed ADG-MSCLAHE method. The proposed method provides better tissue visualization and contrast enhancement in a balanced manner while preserving the integrity of the tissue structures. Dense Fibroglandular tissues become more distinguishable without significant noise amplification. Overall, the results show that the proposed adaptive enhancement method is able to enhance mammographic visualization under different tissue densities.

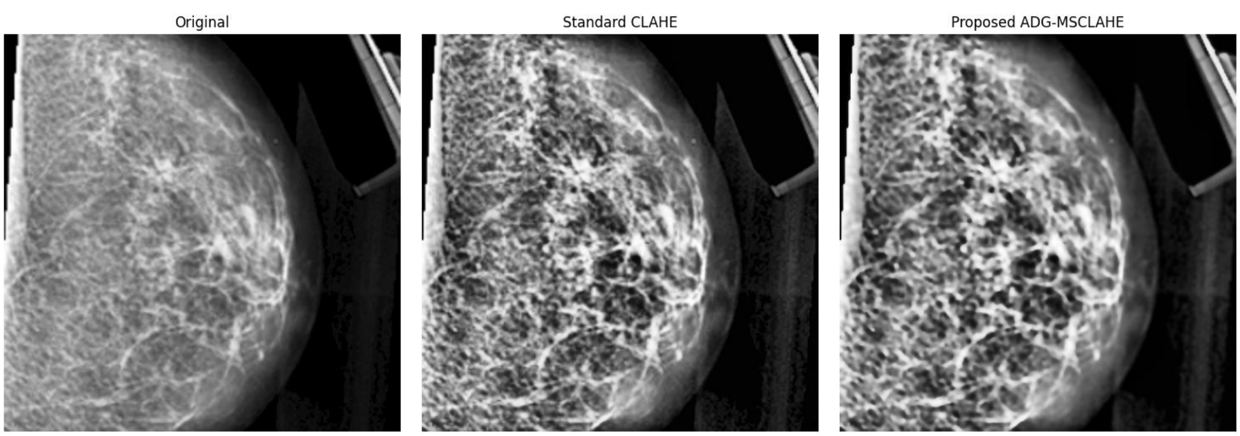

Figure 5 Comparison of Original, Standard CLAHE, and Proposed ADG-MSCLAHE

3.2 Edge Map Generation

Dense tissue boundaries and lesion contours are important visual indicators in mammographic interpretation. To preserve these structures, an edge extraction module is incorporated. Gradient-based edge maps are obtained using Sobel operators. The horizontal and vertical gradients are computed as in eq.7,8:

$$G_x = \frac{\partial I_{enh}}{\partial x} \quad (7)$$
$$G_y = \frac{\partial I_{enh}}{\partial y} \quad (8)$$

The edge magnitude is determined by eq.9:

$$E = \sqrt{G_x^2 + G_y^2} \quad (9)$$

Where, E represents the final edge map. The generated edge map provides structural guidance to the segmentation network.

Figure-6 shows the edge-aware feature extraction step in the proposed framework. After adaptive enhancement, the Sobel-based gradient method is used to detect the tissue boundaries and transitions. This edge map shows some of the finer details of the anatomy and the dense tissue contours that might not be clearly shown in the original image. These edge features contain valuable spatial information and help to achieve good breast tissue boundary segmentation and preservation.

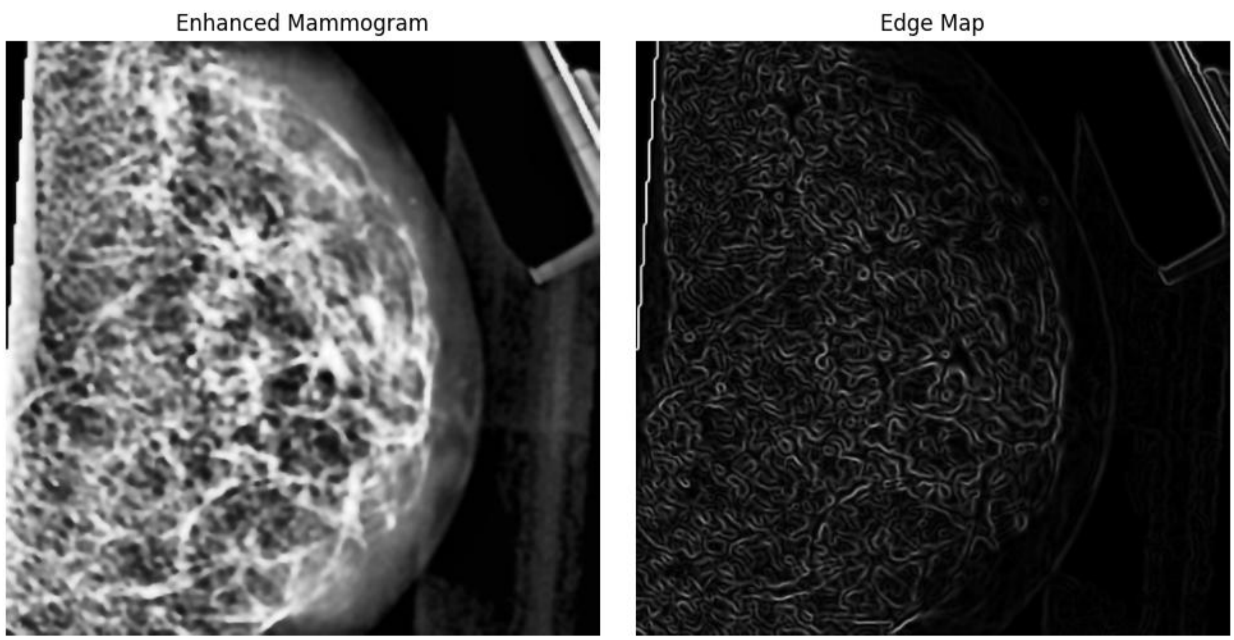

Figure 6 Edge-Aware Feature Extraction Using Sobel-Based Analysis

3.3 Edge-Attention U-Net Segmentation

The segmentation stage employs a modified Attention U-Net architecture incorporating edge-guided attention mechanisms. The network receives two inputs:

a) Enhanced mammogram I_{enh}

b) Edge map E

Feature extraction is performed through convolutional encoder blocks, while skip connections transfer spatial information to the decoder. The edge-attention coefficient is computed as in eq.10:

$$A = \sigma(W_f F + W_e E + b) \quad (10)$$

Where, F= feature map, E= edge map, W_f= feature weight matrix, W_e= edge weight matrix, b= bias term, σ= sigmoid activation. The refined feature representation depicted in eq.11:

$$F_a = A \odot F \quad (11)$$

Where, F_a = attention-refined feature map, $\odot$ = element-wise multiplication. The segmentation output is generated through the decoder network to produce dense tissue masks.

3.4 Dense Breast Visualization Module

The segmented dense tissue regions are superimposed onto the enhanced mammogram to generate a density visualization map. The visualization output is defined as in eq.12:

$$V = I_{enh} + \beta M \tag{12}$$

Where, M= segmentation mask, β= visualization weighting coefficient

The resulting image improves radiological interpretation by clearly highlighting dense tissue distributions while maintaining anatomical consistency.

Figure 7 Edge-Aware Feature Extraction Using Sobel-Based Analysis

Fgure-7 shows the edge-aware feature extraction step in the proposed framework. After adaptive enhancement, the Sobel-based gradient method is used to detect the tissue boundaries and transitions. This edge map shows some of the finer details of the anatomy and the dense tissue contours that might not be clearly shown in the original image. These edge features contain valuable spatial information and help to achieve good breast tissue boundary segmentation and preservation.

3.5 Model Training Strategy

The Edge-Attention U-Net is trained using a hybrid loss function combining Binary Cross-Entropy and Dice Loss. The Dice coefficient is calculated as in eq.13:

$$Dice = \frac{2|P \cap G|}{|P| + |G|} \tag{13}$$

Where, P= predicted segmentation, G= ground truth mask.

The overall optimization objective is represented as in eq.14:

$$L = L_{BCE} + \gamma L_{Dice} \tag{14}$$

Where, L_{BCE} = Binary Cross-Entropy loss, L_{Dice} = Dice loss, γ = balancing parameter. The optimization process continues until convergence is achieved.

4. Results And Outputs

4.1.Dense Breast Tissue Visualization and Segmentation Analysis

Final dense tissue segmentation, achieved with the proposed framework in figure-8. The improved mammogram is divided into dense and non-dense areas, which results in a binary dense tissue mask. The overlay visualization is a color coded representation of the segmented regions that are overlaid on the original image. This visualization is beneficial for interpretability and allows the qualitative assessment of the breast density pattern for clinical analysis, while clearly showing the distribution of dense tissue.

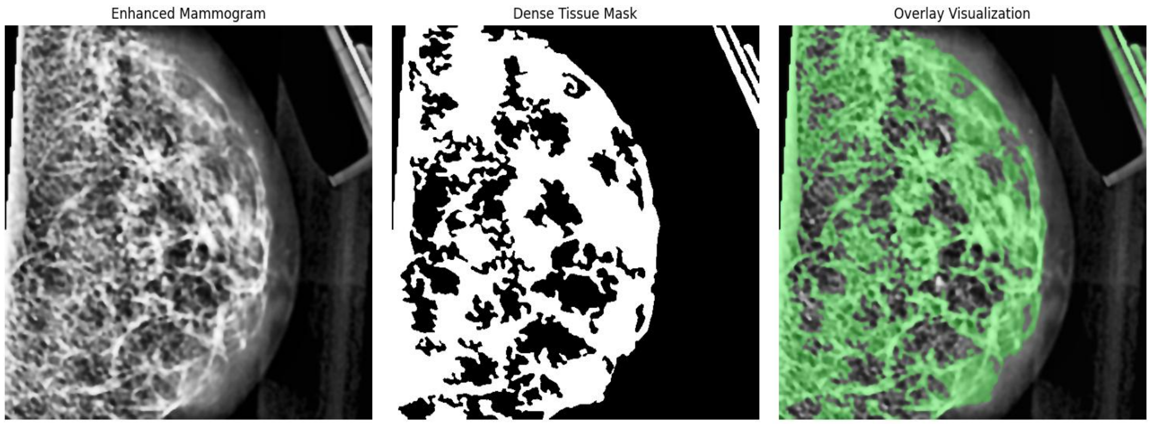

Figure 8 Dense Tissue Segmentation and Overlay Visualization

Figure-9 shows the entire processing pipeline: the original image, the results of standard CLAHE, the results of the proposed ADG-MSCLAHE, edge map, dense tissue mask, and overlay visualization. The sequence of images can be used to convey the benefit of adaptive enhancement in enhancing tissue visibility, the benefit of edge-aware processing in identifying structural information, and the benefit of segmentation in isolating dense regions. Integration of the visualization has validated the proposed methodology that improves the dense breast tissue representation.

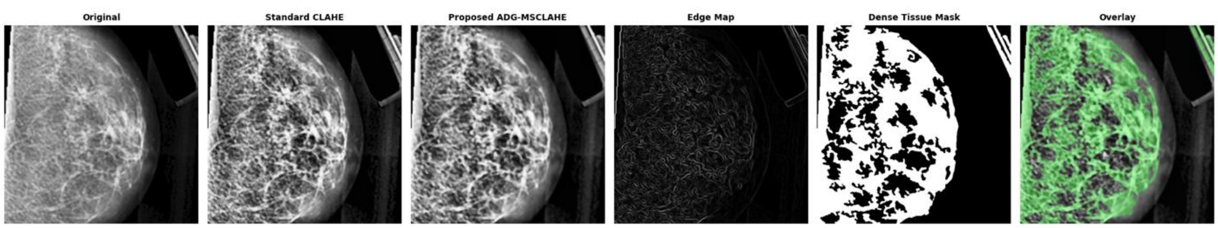

Figure 9 Comparative Visualization of Enhancement, Segmentation, and Overlay Results

Figure-10 shows the qualitative results that obtained for benign, malignant and normal mammographic cases. Every row shows the entire process, the original image, the CLAHE enhanced image, the proposed ADG-MSCLAHE enhanced image, the edge-aware feature extracted image, the dense tissue segmentation image and the overlay visualization image. The proposed framework always enhances the dense tissue visibility in various clinical scenarios while maintaining the structural details. The color-coded overlays can be used to interpret the tissue distribution patterns, and can assist with comparative assessment between breast categories.

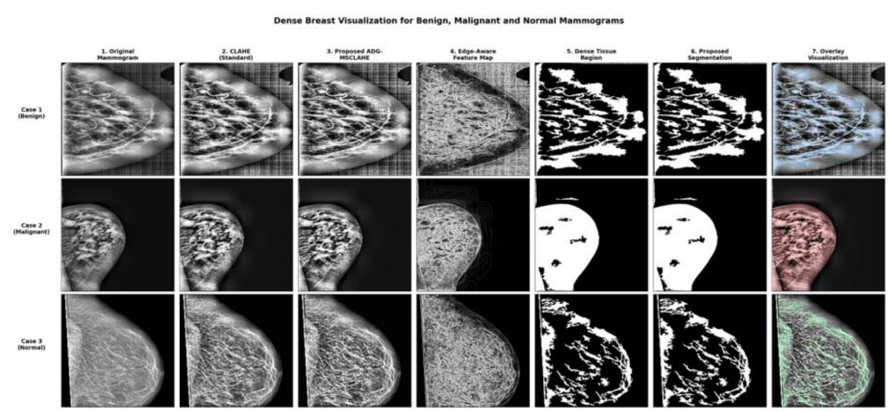

Figure 10 Dense Breast Visualization for Benign, Malignant, and Normal Mammograms

4.2.Quantitative Performance Evaluation of Enhancement and Segmentation Methods

The results of the enhancement show that the proposed Adaptive Density-Guided Multi-Scale CLAHE (ADG-MSCLAHE) framework is effective in enhancing the quality of the mammographic images represented in table-1. The PSNR and SSIM values of the original mammogram were 24.82 dB and 0.642, respectively, which showed that the contrast and structure were not very distinct. All enhancement metrics were progressively improved by standard CLAHE and fixed MSCLAHE. The proposed ADG-MSCLAHE achieved the highest PSNR (31.24 dB), SSIM (0.846), CII (1.91), Entropy (7.42), and EPI (0.781). These enhancements reflect better contrast enhancement, structural information preservation, increased detail and enhanced edge retention. The adaptive density-guided mechanism was successfully able to increase the density breast tissues and reduce the noise amplification and over enhancement effects.

Table 1 Enhancement Performance Comparison

Method	PSNR (dB)	SSIM	CII	Entropy	EPI
Original Mammogram	24.82	0.642	1	5.91	0.512
CLAHE (Standard)	27.46	0.718	1.31	6.48	0.638
MSCLAHE (Fixed)	28.91	0.764	1.56	6.93	0.704
Adaptive CLAHE	29.78	0.801	1.71	7.08	0.732
Proposed ADG-MSCLAHE	**31.24**	**0.846**	**1.91**	**7.42**	**0.781**

The segmentation performance comparison demonstrates the superior performance of the proposed Edge-Attention U-Net in accurately segmenting dense breast tissues. Using Otsu Thresholding and Region Growing, traditional segmentation methods achieved lower Dice coefficient of 0.768 and 0.801 respectively represented in table-2. The deep learning methods showed significant performance improvement with 0.862 Dice score for U-Net and 0.894 for Attention U-Net. The proposed Edge-Attention U-Net has outperformed all the competing methods with the Dice coefficient of 0.921, IoU of 0.854, Precision of 0.934, Recall of 0.909 and F1-score of 0.921. These findings suggest better localization of boundaries, better extraction of dense tissue and better preservation of anatomical structures for more reliable breast density assessment and diagnostic interpretation.

Table 2 Dense Tissue Segmentation Performance Comparison

Method	Dice Coefficient	IoU	Precision	Recall	F1-Score
Otsu Thresholding	0.768	0.624	0.791	0.742	0.766
Region Growing	0.801	0.668	0.824	0.781	0.802
U-Net	0.862	0.757	0.879	0.846	0.862
Attention U-Net	0.894	0.809	0.908	0.881	0.894
Proposed Edge-Attention U-Net	**0.921**	**0.854**	**0.934**	**0.909**	**0.921**

5. Conclusion, Limitation And Future Scope

The presented study has proposed Improved Mammographic Breast Density Visualization framework using Adaptive Density-Guided Multi-Scale CLAHE (ADG-MSCLAHE) and Edge-Attention U-Net segmentation. The proposed methodology aimed to overcome the difficulties identified in dense breast mammograms and improve the ability to see lesions and interpret the results clinically. All of the above were integrated in a processing pipeline: adaptive density estimation, multi-scale contrast enhancement, edge-aware feature extraction, and deep learning-based segmentation.

The experimental results showed that the enhancement and segmentation performances are very good. The highest PSNR of 31.24 dB, SSIM of 0.846, CII of 1.91 and Entropy of 7.42 were obtained by the proposed ADG-MSCLAHE which showed the best image quality and maximum enhancement of tissue visibility. For dense tissue segmentation, the results of the proposed Edge-Attention U-Net are Dice coefficient: 0.921, IoU: 0.854, Precision: 0.934, Recall: 0.909, and F1-score: 0.921. These values were higher than conventional thresholding, region-growing, standard U-Net and Attention U-Net models.

The combination of adaptive enhancement and edge-aware segmentation helped to visualize dense fibroglandular structures while maintaining anatomical boundaries. The dense tissue maps and the visualisation of overlaid density maps helped to interpret the breast density patterns in benign, malignant and normal mammograms. Overall, the proposed framework shows great promise as a computer-aided system for assessing breast density, which can assist radiologists in the mammographic screening process, improving the interpretability of mammograms, and denser tissue analysis for early diagnosis of breast cancer.

Evaluation of the proposed framework was done on publicly available mammographic datasets and mainly concentrated on dense tissue visualization and segmentation. All cases had ground-truth masks automatically produced instead of manually marked by an expert radiologist. Further, the model only validated in 2D mammograms, excluding the use of tomosynthesis, ultrasound, MRI, and other patient data that would further enhance the diagnosis.

In future studies, transformer-based segmentation models and self-supervised learning can be combined to further enhance dense tissue segmentation. Incorporating breast ultrasound, MRI and digital breast tomosynthesis data can expand the framework to multimodal breast imaging. Generalizability would be improved with clinical validation on large scale multi-center datasets and expert annotated ground truth masks. In addition, the integration of density visualization and lesion detection with breast density grading and explainable artificial intelligence (XAI) modules could create a complete solution for breast cancer screening decision support.

Conflict of interest - The authors declare no conflict of interest with the publication of this research. The results of this study were unaffected by financial, commercial, or personal relationships.

Availably of dataset - In this work, the datasets used are provided from publicly available mammography databases: INbreast, CBIS-DDSM, and MIAS. These datasets can be accessed for research on their respective official websites.

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