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Article

PMSA-Net: A Pectoral Muscle Suppressed Attention Network for Automated Breast Cancer Detection in Mammographic Images

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Abstract: Breast cancer is one of the most common causes of cancer death in women, and early and accurate diagnosis is paramount to enhance survival of patients, and mammography remains the gold standard in diagnosis. In spite of the advancement of deep learning-based mammographic analysis, the current methods have limitations, such as the presence of pectoral muscle regions, background artifacts, and varying breast densities, and do not adequately consider clinically relevant lesion regions. These constraints may introduce ambiguity in features and represent poor classification performance, especially in mixed mammographic databases. In view of these challenges, a novel deep learning framework, called PMSA-Net (Pectoral Muscle Suppressed Attention Network), for automated breast cancer detection is proposed. The proposed pipeline is based on a single architecture that includes breast region extraction, pectoral muscle suppression, adaptive image enhancement, convolutional feature extraction, channel attention, spatial attention, and multi-scale feature fusion. In order to enhance the image quality, first some image enhancement techniques are used: Anisotropic Diffusion Filtering and Multi-Scale Contrast Limited Adaptive Histogram Equalization (MS-CLAHE). Then, irrelevant structures will be reduced by breast region extraction and suppressed by the pectoral muscle, and the visibility of the lesion will be improved by adaptive enhancement. The improved mammograms are then fed into a CNN backbone and channel attention and spatial attention modules to highlight diagnostically relevant areas. Low level feature and high-level feature are fused at multi-scale for robust classification. Experimental analysis shows that the accuracy, precision, recall, F1-score, sensitivity, specificity and AUC of PMSA-Net are 97.86%, 97.24%, 97.51%, 97.37%, 97.52%, 98.14% and 0.9912 respectively. Comparative analysis shows better results than other deep learning based on existing mammography. The key findings show that suppression of the pectoral muscle and attention guided feature learning lead to significant enhancement of discriminative power and fewer false predictions. The proposed PMSA-Net is a reliable and effective framework for mammographic breast cancer detection, and can be used to assist clinical decision-making in computer-aided diagnosis systems.
Keywords: Breast Cancer Detection, Mammography, PMSA-Net, Pectoral Muscle Suppression, Channel Attention, Spatial Attention.

1. Introduction

Breast cancer is one of the common and serious diseases found in women. World Cancer Day statistics indicate that breast cancer is a significant proportion of newly diagnosed cancers and contributes to a significant number of cancer deaths. Early diagnosis is very important for successful clinical intervention, decreasing the risk of death, and better treatment outcomes. In the current screening options, mammography is being used and has proven to be the most effective and widely practiced early detection imaging procedure. Radiologists can identify suspicious patterns, architectural distortions, calcifications, and masses on mammography before patients have any symptoms. Readers of mammograms, however, frequently encounter difficulties, such as breast density, low-contrast mammographic lesions, image noise, overlapping breast tissues, and non-breast anatomical regions [1].

In the past few years, the performance of breast cancer detection computer-aided diagnosis systems has been greatly improved due to the recent development of artificial intelligence and deep learning. Convolutional Neural Networks (CNNs) are proving to be very effective at automatically learning discriminative image features and lessening the need for manual feature engineering. In mammographic classification, lesion localization, assessment of breast density and risk prediction, deep learning frameworks have been used [2]. While these advances have been made, current systems still face the problems of feature ambiguity, lack of attention to diagnostically relevant regions, and interference from pectoral muscle regions and background noise. Such constraints can hinder classification reliability and limit the ability to generalize deep learning models to different mammographic datasets.

This study presents a deep learning model named PMSA-Net (Pectoral Muscle Suppressed Attention Network) to address these challenges, which combines pectoral muscle suppression, adaptive enhancement, attention-guided feature extraction, and multi-scale feature fusion, thereby enhancing the detection of breast cancer in mammograms. The proposed architecture is designed to reduce the impact of non-relevant anatomical structures and enhance the representation of the lesions. PMSA-Net aims to establish a more accurate and reliable automated breast cancer diagnosis framework by utilizing pre-processing, attention learning, and feature fusion strategies [3].

1.1. Mammographic Breast Cancer Detection and Associated Challenges

The breast imaging method of choice for breast cancer screening is mammography because it is able to detect suspicious breast abnormalities early. In a mammographic image, one can usually see anatomic structures like glandular tissue, fatty tissue, pectoral muscles and the skin borders. These structures are important to include in diagnosis, but pose difficulties in image interpretation. Breast lesions can look totally different depending on the imaging conditions, tissue density and patient-specific anatomical features.

Variation in breast density is one of the greatest difficulties in mammographic analysis. The intensity characteristics of dense breast tissue are frequently similar to those of malignant lesions, and it makes it difficult for radiologists and the automated computer systems to detect the lesions. In addition, mammograms often include artifacts from the background, labels, acquisition markings, and other areas of the body not related to the breast that have little value in the diagnostic decision. The irrelevant regions can have negative impact on feature extraction procedures and classification accuracy [4].

The other significant difficulty is the area of the pectoral muscle in mediolateral oblique (MLO) mammography positions. The pectoral muscle usually presents as a bright, triangular shape with intensity characteristics like masses suspected of malignancy. As a result, deep learning models could mistakenly identify pectoral regions as lesions instead of the actual lesions, resulting in misdiagnosis and inaccurate predictions. Hence, it is crucial to suppress or segment the area of the pectoral muscle for better feature extraction and classification.

Another aspect of the interpretation of mammograms is image quality. Mammograms typically have low contrast, inconsistent lighting, acquisition noise, and indistinct borders of lesions. Small calcifications and early-stage lesions may become difficult to identify due to inadequate image enhancement. Therefore, advanced preprocessing techniques are needed to enhance the visibility of the lesions and to make accurate learning of features possible [5].

With the growing number of large-scale mammographic datasets, researchers have turned to deep learning approaches. However, most of the current models mainly emphasize the classification task without considering the image enhancement, pectoral muscle suppression, and attention-guided feature selection. A solution to these challenges will be crucial to the increased strength and usefulness of computer-aided breast cancer detection systems.

1.2.Deep Learning and Attention-Based Mammographic Analysis

Medical image analysis has become one of the most impactful technologies where deep learning plays a part. CNN-based architectures are able to automatically learn hierarchical representations from image data, which allows the extraction of low level texture information and high-level semantic features. For mammographic applications, CNNs have proven to be superior to traditional machine learning techniques using handcrafted descriptors [6][7].

While CNNs are able to learn image representation, they typically compute all parts of an image without explicitly marking out the diagnostically informative regions. As a result, irrelevant structures can be helpful in the learning process, and lessen the effectiveness of classification models. To overcome this drawback, attention mechanisms are added to direct the attention of neural networks to the clinically relevant areas within the image [8][9].

Channel attention mechanisms provide weightings for feature channels, allowing the model to focus on salient features and ignore redundant information. Spatial attention mechanisms work with this mechanism to detect salient spatial locations in feature maps. When combined, the channel and spatial attention modules increase feature discrimination and facilitate networks to attend to suspicious lesion regions.

The extraction of multi-scale features has also become a topic of great interest in medical image analysis. The size and appearance of lesions within the mammograms range from small microcalcifications to large masses. The features derived from a single scale might not be sufficient to cover all kinds of lesions. Multi-scale feature fusion is used to fuse information from multiple layers in the network, enabling the model to learn local texture features and global context information. This approach can lead to better lesion characterization and aid in better classification results [10][11].

Yet, while these developments have been made, there exist various mammographic classification methods that utilize attention mechanisms without considering the issues of pectoral muscle interference or image enhancement. The simultaneous use of preprocessing, pectoral suppression, adaptive enhancement, attention learning and feature fusion in a single system could provide a better diagnostic result with lower computational cost.

1.3. Proposed PMSA-Net Framework

Existing mammographic analysis systems are limited in their abilities, so this study proposes a novel deep learning structure for breast cancer detection, called PMSA-Net. The system starts with preprocessing of the mammogram image with Anisotropic Diffusion Filtering and Multi-Scale Contrast Limited Adaptive Histogram Equalization to reduce the image noise and enhance lesion visibility. Next, the extraction of the information in the breast region excludes non-diagnostic background data, and the suppression of the pectoral muscle decreases the effect of irrelevant anatomical structures.

After the pre-processing, adaptive enhancement is used to enhance the image contrast based on the characteristics of breast tissue. The improved mammograms are then passed through a CNN backbone that is used to extract hierarchical image features. The architecture also includes channel attention and spatial attention modules for boosting feature discrimination. These modules direct the network into regions of the data that are of diagnostic value and they dampen extraneous data.

In addition, a multi-scale feature fusion strategy is incorporated to fuse the shallow, intermediate, and deep feature representations. This allows the model to learn lesion features at multiple spatial resolutions, and at the same time, has better robustness of all sizes of lesions. Lastly, the fused feature representation is fed to a classification layer which classifies the mammograms as either Normal, Benign or Malignant.

The proposed framework is expected to enhance the accuracy of classification, minimize false detections and offer reliable support in the diagnosis of breast cancer screening applications.

1.4.Proposed Objectives

1. Create PMSA-Net, a pectoral muscle suppressed attention network with breast region extraction, adaptive enhancement, channel attention, spatial attention and multi-scale feature fusion, which aims to automatically detect breast cancer from mammographic images.
2. To increase accuracy, sensitivity, specificity, and diagnostic reliability and to reduce pectoral muscle interference to enhance lesion focused feature learning and improve mammographic classification performance.

In spite of the high incidence of breast cancer, the detection task is still difficult in mammographic image because of the difference of tissue density, low contrast lesion, background noise and pectoral muscle interference. While deep learning technique has shown great success, most of the existing methods are not well suited to solve these problems in a coherent manner. The proposed PMSA-Net is designed to enhance lesion representation and improve the accuracy of the classification by introducing loss-weighted pectoral muscle suppression, adaptive enhancement, attention-guided feature extraction and multi-scale feature fusion. The proposed integrative framework will aim to deliver a reliable and accurate solution for the automatic breast cancer diagnosis and clinical decision support by combining these elements under one architecture.

2. Literature review

2.1.Clinical and Anatomical Considerations in Breast Cancer Imaging

Medical imaging technologies play a pivotal role in the diagnosis of breast cancer, helping to detect lesions in early stages and plan treatment. Because of the accessibility, cost effectiveness and ability of mammography to detect suspicious abnormalities prior to clinical symptoms, it is the primary screening modality. But the overlapping of tissues, different breast density and visibility of pectoral muscle and different appearance of the lesion make the interpretation of mammograms difficult. Therefore, knowledge of anatomical and clinical parameters that affect image interpretation is still crucial for developing reliable computer-aided diagnostic systems.

In recent studies, the anatomic relationships of breast lesions have been stressed. In a clinical investigation, a granular cell tumour was described with involvement of the pectoralis major muscle and with nipple retraction, thus emphasizing the importance of the proper distinction of pathological areas from the surrounding anatomical structures in diagnosis [12]. Rehabilitation research work also evaluated pectoralis muscle dosimetry in breast cancer patients during treatment and showed that the levels of pectoral muscle involvement have a significant impact on clinical outcomes and treatment planning [13]. These results suggest that pectoral muscle areas are clinically relevant and could impact the interpretation of images and diagnostic diagnosis.

Another emerging imaging modality is breast magnetic resonance imaging (MRI). The importance of breast MRI in the context of diagnosis, treatment planning and future applications has been discussed in a comprehensive review article [14] which highlighted its superior soft-tissue contrast and sensitivity for lesion detection. The same study also identified the increasing incorporation of cutting-edge imaging technologies and the use of artificial intelligence techniques for enhanced breast cancer diagnosis and risk assessment [15]. Despite the informative value of MRI, mammography is still the preferred method to screen populations due to its availability and reduced operating cost.

Longitudinal studies on the change of stiffness and thickness of the pectoralis major muscle after radiotherapy in breast cancer patients [16] provided further evidence of the clinical relevance of pectoral muscle regions. Both of these studies showed that quantitative anatomical alterations after treatment were observed, suggesting that areas of the pectoral muscle make a significant contribution to breast imaging interpretation. Additionally, comparative studies comparing prepectoral and subpectoral breast reconstruction outcomes demonstrated that there were clinical differences in postoperative outcomes, highlighting the need of the pectoral anatomy for diagnosis in breast cancer management [17].

All these studies show that, in addition to lesion characteristics, surrounding anatomical structures affect breast cancer imaging. Therefore, the ability to suppress non diagnostic regions of the pectoral muscle, while preserving the diagnostically relevant breast tissue is an important requirement for automated mammographic analysis systems.

2.2. Deep Learning Approaches for Mammographic Breast Cancer Detection

The present development of the deep learning has led to a remarkable change in breast cancer diagnosis, where complex features can be extracted and classified directly from medical images. Some networks such as Convolutional Neural Networks (CNNs), transfer learning frameworks, transformer network, and attention-based networks have proven to be effective on mammographic analysis. However, a number of existing methods still have difficulties stemming from challenges such as lesion localization, variation in breast density, degradation of image quality, and features redundancy.

Transfer learning is one of the most popular methods for the classification of mammograms because it takes advantage of the pre-trained knowledge in large-scale image datasets. Recently the transfer learning technique was shown to be a significant boost in breast lesion detection when feature representations from a previous task were transferred and then fine-tuned to the mammographic domain [18]. Transfer learning brings down the complexity of the training process, but it requires good image quality and the pretrained networks must be able to learn the domain-specific features of the lesions.

Another important issue in the interpretation of a mammogram is the breast density. Breast density can mask lesions and decrease sensitivity to diagnosis. To solve this problem, density transformation methods using CycleGAN have been presented to create synthetic mammographic images with different density properties [19]. This helps to increase the visibility of lesions and aids in radiological interpretation. However, image translation frameworks tend to be largely concerned with the manipulation of densities and not with the classification of the lesions themselves.

Deep learning applications have also multiple applications other than mammography. The thermographic imaging system included in a compact computer-aided diagnostic system (CAD) utilized several deep learning architectures for enhancing the breast cancer detection performance using thermal patterns [20]. Thermography is complementary to mammography and is used in routine clinical practice. As a result, there is more research on methodologies tailored to mammographic analysis.

Recently, transformer-based models have appeared as strong alternatives to traditional CNN models. The Shearlet Transform was applied to achieve multi-resolution feature representations for a neighborhood attention transformer, which achieved improved classification for mammographic images [21]. The study was successful in demonstrating the effectiveness of attention-guided learning for enhancing lesion representation and classification performance. However, transformer models are usually resource intensive in terms of computational resources and large training datasets, which can be prohibitive in clinical settings with limited resources.

A systematic review of deep transfer learning methods revealed the growing use of pretrained CNN architectures, ensemble approaches and attention mechanisms in breast cancer classification [22]. The review found that transfer learning has proven to be a powerful approach for enhancing classification accuracy, but noted that there are still some challenges arising from dataset heterogeneity, lack of interpretability, and poor feature learning for lesions. The findings indicate that there is a need for further research to make automated breast cancer detection systems more robust and clinically useful.

2.3.Emerging Multimodal and Attention-Based Frameworks

In recent years, the use of multi-modal learning strategies has been an area of increasing focus in the study of enhancing breast cancer diagnosis. By combining information from multiple imaging modalities and clinical attributes, multimodal frameworks aim to provide a more comprehensive representation of disease characteristics. This has shown good results in minimizing diagnostic uncertainty and enhancing classification accuracy.

Recently, a multi-modal deep learning method combined ultrasound images, mammography and clinical information to enhance breast cancer detection performance [23]. The present study showed that the use of heterogeneous information sources led to more robust diagnoses than single-modality approaches. But the multimodal systems generally need a lot of complex data acquisition procedure and will not be suitable for large screening environment where mammography is the main imaging modality.

In the field of medical image analysis, attention mechanisms have proven themselves to be useful in enhancing feature discrimination. Channel attention allows networks to detect what is informative in the feature channel, and spatial attention provides the focus on clinically relevant parts of the image. These mechanisms decrease the amount of redundancy of features and consequently the location of a lesion. Although effective, most of the current attention-based models focus mainly on the classification accuracy and do not explicitly consider the effects of regions of pectoral muscles, background artifacts, or image quality variations.

In the same vein, some recent deep learning works have used high-level architectures for mammographic analysis, but failed to use a combination of preprocessing, pectoral suppression, adaptive enhancement and attention-guided feature learning in one single architecture. Thus, architectures have remained a need that can solve the problems of anatomical interference, image enhancement, lesion localization and classification in a single step.

2.4.Research Gap

- Currently, the main goal of deep learning models is to improve their classification accuracy, and they do not pay much attention to how to suppress pectoral muscles and what impact this has on feature extraction [18][23].
- Many studies use either attention mechanisms or transfer learning without combining the three, namely, adaptive enhancement, anatomical region suppression and multi-scale attention learning, in a single architecture [21][22].

- Current mammographic classification systems tend to have problems in the case of heterogeneous breast density, low-contrast lesions, and multiple representation of features, that may decrease diagnostic reliability [19][22].

2.5.The Proposed PMSA addresses the Research Gap in the following ways:

The proposed PMSA-Net tries to overcome these limitations by providing a full framework for mammographic analysis. Breast region extraction and pectoral muscle suppression help to minimize the impact of irrelevant anatomical structures.[28] Secondly, an adaptive enhancement technique using Anisotropic Diffusion Filtering and Multi-Scale CLAHE has been developed which enhances the visibility of the lesions while maintaining clinically relevant tissue characteristics. Third, channel attention and spatial attention modules direct network towards diagnostically relevant regions. Lastly, multi-scale feature fusion fuses shallow features with the deep features, which can help to effectively characterize lesions with different dimensions and features. The PMSA-Net combines the advantages of pre-processing, attention learning, and feature fusion to offer a comprehensive solution for enhancing breast cancer detection.

Studies reviewed here showcase significant advancements in breast cancer imaging, deep learning-based mammographic analysis, transfer learning, attention mechanisms, and multimodal diagnostic systems. [26][27].Nonetheless, there are still challenges such as pectoral muscle interference, imaging quality variation, and the lack of feature learning with regard to the lesions. Current solutions typically solve these problems separately from each other, instead of having a unified architecture. In this work, we propose PMSA-Net which integrates pectoral muscle suppression, adaptive enhancement, channel attention, spatial attention, and multi-scale feature fusion, to overcome these drawbacks. This comprehensive approach is believed to enhance feature discrimination, minimize false predictions and increase the confidence level of the automated breast cancer detection systems.

3. Proposed Methodology

The proposed PMSA-Net (Pectoral Muscle Suppressed Attention Network) is designed to improve breast cancer detection from mammographic images through the integration of image enhancement, breast region extraction, pectoral muscle suppression, attention-guided feature learning, and multi-scale feature fusion. The framework addresses common challenges in mammographic analysis, including low contrast lesions, heterogeneous breast density, pectoral muscle interference, and redundant feature extraction.

3.1.About dataset used

The study involves the use of two mammographic databases, INbreast, DDSM and MIAS. INbreast is a high quality full-field digital mammography (FFDM) dataset with correctly annotated breast lesions and clinical information. CBIS-DDSM is a selection of the Digital Database for Screening Mammography, which contains mass and calcification abnormalities, with expert annotations. MIAS is a popular benchmark data set which contains normal, benign and malignant mammograms with pre-defined lesion information. These datasets offer significant variety in both type of lesion and density of breasts and imaging conditions, thus, facilitating thorough investigation of the proposed PMSA-Net framework.

3.2. Mammogram Preprocessing and Adaptive Enhancement

Raw mammograms often contain acquisition noise, low contrast tissue structures, and varying illumination conditions. Therefore, image preprocessing is performed prior to feature extraction.

3.2.1. Anisotropic Diffusion Filtering

Anisotropic diffusion is employed to suppress noise while preserving lesion boundaries. The diffusion process is represented as:

$$I_{t+1} = I_t + \lambda \sum_{i=1}^{4} c_i \nabla I_i$$

where:

- I_t represents the image at iteration t.
- λ denotes the diffusion coefficient.
- c_i represents the conduction function.
- ∇I_i denotes the directional gradient.

The conduction coefficient is computed as:

$$c_i = e^{-(\nabla I_i / k)^2}$$

where k controls edge sensitivity.

Large intensity gradients produce smaller diffusion values, thereby preserving lesion boundaries and micro-calcification structures.

Multi-Scale CLAHE Enhancement

Following diffusion filtering, Multi-Scale Contrast Limited Adaptive Histogram Equalization (MS-CLAHE) is applied.

For each scale level s:

$I_s = CLAHE(I, ClipLimit_s)$

The enhanced image is generated as:

$$I_e = \alpha_1 I_1 + \alpha_2 I_2 + \alpha_3 I_3$$

where:

- I_1, I_2 *and* I_3 represent outputs from different CLAHE scales.
- $\alpha_1 + \alpha_2 + \alpha_3 = 1.$

This process improves lesion visibility across varying breast densities.

The figure-1 shows the preprocessing phase of the proposed PMSA-Net framework. The contrast of tissues in the original mammogram may be low, and the boundary of the lesion might be subtle, which may make the extraction of tissue features more difficult. Applying Anisotropic Diffusion Filtering removes noise from the image, while preserving important edge information. The Multi-Scale CLAHE process then can be used to improve the local contrast and visibility of the tissues in areas with dense breast tissue. The improved image shows more clearly defined structures, thus making any suspicious abnormalities more visible. This preprocessing step serves to get better inputs to the following procedures of breast region extraction and classification.

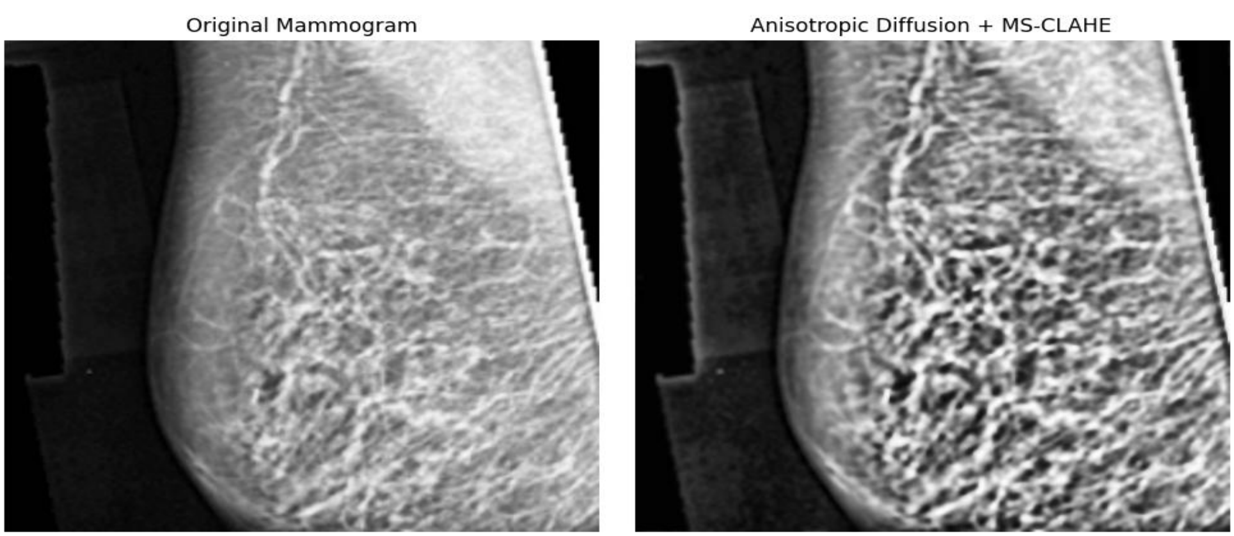

Figure 1 Mammogram enhancement using Anisotropic Diffusion Filtering and Multi-Scale CLAHE

3.3 Breast Region Extraction and Pectoral Muscle Suppression

Breast ROI Extraction

Background regions do not contribute useful diagnostic information and may negatively influence feature extraction.

A binary breast mask is generated using threshold segmentation:

$$B(x, y) = \begin{cases} 1, if\ I(x, y) > T \\ 0, otherwise \end{cases}$$

where:

- T represents the adaptive threshold value.

The largest connected component is extracted as the breast region.

The final breast ROI is represented as:

$$R = I \odot B$$

where:

- $\odot$ denotes element-wise multiplication.

Pectoral Muscle Segmentation

The pectoral muscle often appears as a bright triangular structure in MLO mammograms and may be incorrectly interpreted as a suspicious lesion.

A pectoral muscle mask P is generated as:

$$P(x, y) = \begin{cases} 1, if\ (x, y) \in pectoral\ region \\ 0, otherwise \end{cases}$$

The pectoral suppressed image is obtained using:

$$I_{\mathrm{p}} = R \times (1 - \beta P)$$

where:

- β represents the suppression coefficient.

This operation removes anatomically irrelevant regions while preserving lesion information.

3.4 Adaptive Enhancement Layer

Breast tissue density varies significantly among patients. Therefore, a density-adaptive enhancement strategy is introduced.

The breast density score is computed as:

$$D = N\_d / N\_b$$

where:

- N_d denotes dense tissue pixels.
- N_b denotes total breast pixels.

The adaptive contrast parameter is determined as:

$$C = C_0 + \gamma D$$

where:

- C_0 denotes the baseline enhancement value.
- γ controls density adaptation.

The final enhanced mammogram is expressed as:

$$I_{\mathrm{a}} = CLAHE(I_{\mathrm{p}}, C)$$

This operation improves lesion visibility in dense breast tissues.

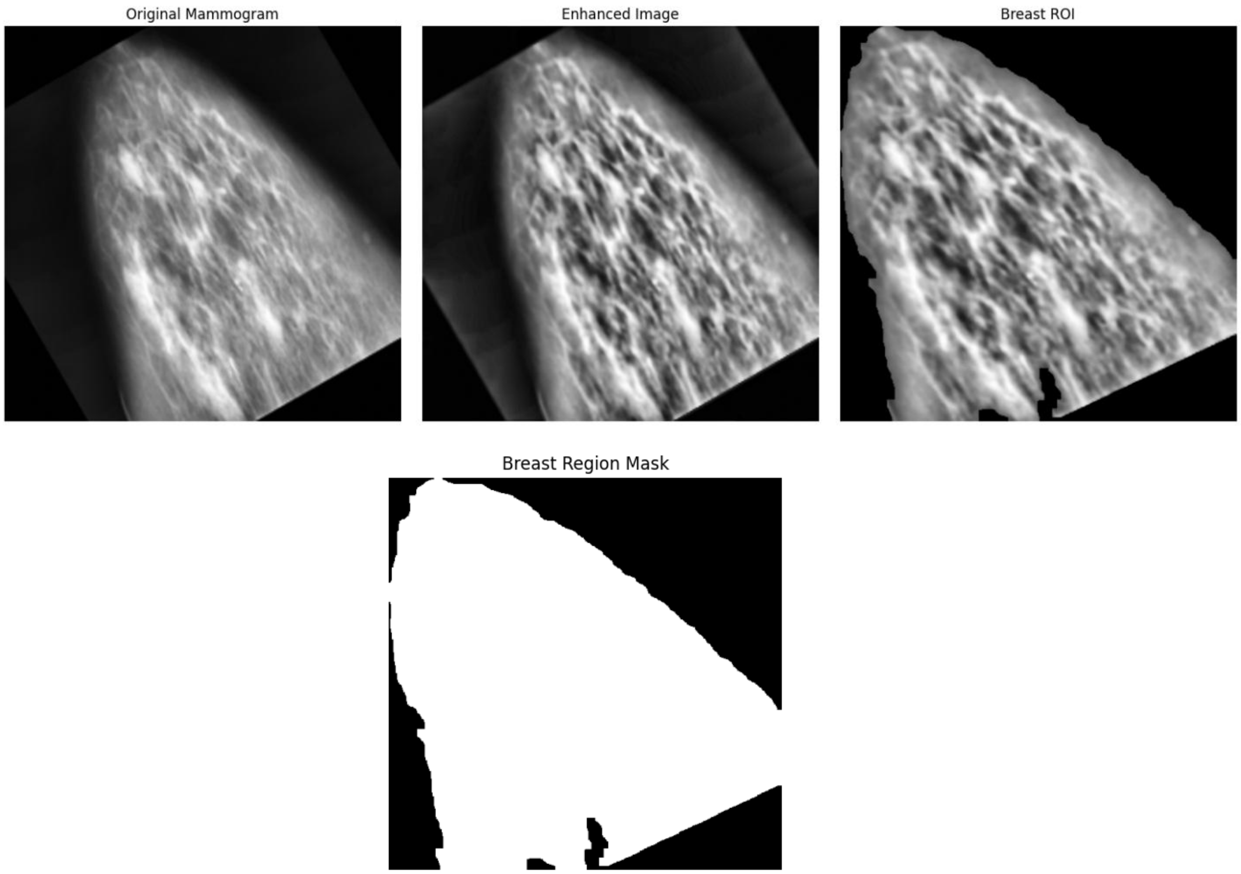

Figure 2 Breast region extraction and background removal using ROI segmentation

The figure-2 shows the breast ROI extraction process. The improved mammogram is initially considered to detect the edge of the breast and to remove non-diagnostic areas of the mammogram. Using threshold-based segmentation and connected component analysis, a binary breast mask is obtained. The ROI extracted preserves diagnostically-relevant breast tissue and excludes labels, acquisition artifacts, and empty background regions. As a result, the breast mask will precisely outline the breast anatomy, in turn, minimizing irrelevant data provided to a deep learning model. The stage enhances the efficiency of feature learning, as well as reduces computational redundancy.

3.5 CNN Backbone Feature Extraction

The enhanced image I_a is supplied to a convolutional neural network backbone.

The output feature map generated by the first convolution layer is:

$$F_1 = \sigma(W_1 * I_a + b_1)$$

Similarly:

$$F_2 = \sigma(W_2 * F_1 + b_2)$$

$$F_3 = \sigma(W_3 * F_2 + b_3)$$

where:

- W_i represents convolution kernels.
- b_i represents bias terms.
- σ denotes ReLU activation.

The resulting feature tensor captures texture patterns, mass boundaries, and tissue characteristics.

3.6 Channel Attention Module

Not all feature channels contribute equally to breast cancer detection.

Global average pooling is performed:

$$G\_c = (1/HW) \sum_{i=1}^{H} \sum_{j=1}^{W} F(i,j,c)$$

where:

- H and W represent feature map dimensions.
- c denotes channel index.

The channel attention vector is generated as:

$$A\_c = \sigma(W_2(ReLU(W_1 G\_c)))$$

The refined feature representation becomes:

$$F\_c = A\_c \otimes F$$

where:

- $\otimes$ denotes channel-wise multiplication.

This mechanism increases the contribution of diagnostically relevant channels.

3.7 Spatial Attention Module

While channel attention identifies important feature channels, spatial attention identifies important lesion locations.

Average and maximum pooling are computed:

$$M\_avg = AvgPool(F\_c)$$

$$M\_max = MaxPool(F\_c)$$

These representations are combined:

$$S = [M\_avg \,;\, M\_max]$$

A spatial attention map is generated as:

$$A\_s = \sigma(f^{7x7}(S))$$

where:

- f^{7x7} denotes a 7×7 convolution.

The spatially refined feature map is:

$$F\_s = A\_s \otimes F\_c$$

This operation directs the network toward lesion-specific regions.

3.8 Multi-Scale Feature Fusion

Breast lesions exhibit substantial variation in size and texture.

To address this challenge, multi-scale feature fusion is performed.

Feature maps from different network depths are represented as:

$$F_1, F_2, F_3$$

The fused representation is obtained through:

$$F\_fusion = Concat(F_1, F_2, F_3)$$

The final fused vector is:

$$Z = W\_f F\_fusion + b\_f$$

where:

- W_f denotes fusion weights.
- b_f denotes fusion bias.

The fused representation combines low-level texture information and high-level semantic features.

3.9 Classification Layer

The fused feature vector Z is supplied to fully connected layers.

The classification function is defined as:

$$y = Softmax(Z)$$

For K classes:

$$P(y = k) = e^{zk} / \sum_{i=1}^{K} e^{zi}$$

where:

- z^{k} represents the score of class k.

The output categories are:

- Normal
- Benign
- Malignant

The predicted class is obtained as:

$$\hat{y} = arg\ max_{(k)}\ P(y = k)$$

3.10 Network Optimization

The PMSA-Net parameters are optimized using the Adam optimizer.

The categorical cross-entropy loss is defined as:

$$L = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij}\ log(\hat{y}_{ij})$$

where:

- N denotes total samples.
- K denotes total classes.
- y_{ij} represents actual labels.
- $\hat{y}_{ij}$ denotes predicted probabilities.

The optimization objective is:

$$(W*, b*) = arg\ min_{(W, b)}\ L$$

The training process iteratively updates network parameters until convergence.

The proposed PMSA-Net integrates mammographic preprocessing, breast region extraction, pectoral muscle suppression, adaptive enhancement, channel attention, spatial attention, and multi-scale feature fusion into a unified deep learning architecture. The preprocessing stage improves image quality and suppresses irrelevant anatomical structures, while the attention modules focus the network on diagnostically significant lesion regions. Multi-scale feature fusion enhances representation learning by combining features from multiple network depths. Finally, a softmax classifier categorizes mammograms into normal, benign, and malignant classes, providing an effective framework for automated breast cancer detection.

4. Result and discussion

The figure -3shows the stage of PMSA-Net for suppressing pectoral muscle. The pectoral muscle area is extracted after the breast ROI extraction, by using intensity and geometric features. The bright, triangular muscle area is separated from the breast tissue with the help of a pectoral mask. The extracted pectoral region is then suppressed so as to avoid interference during feature extraction. Finally, adaptive enhancement is used to make the lesions more visible and to make the tissues more visible. This process allows a better emphasis of structures that are diagnostically relevant in the classification process.

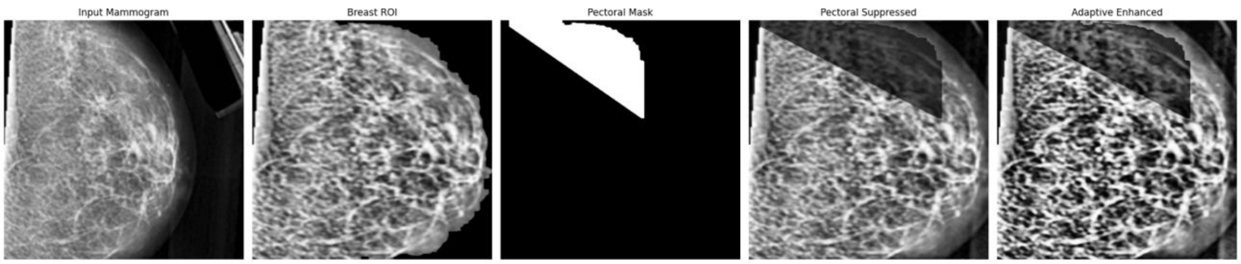

Figure 3 Pectoral muscle segmentation, suppression, and adaptive enhancement within PMSA-Net

The figures-4 shows comparison of mammographic images with and without suppression of the pectoral muscle. Bright anatomical structures are visible in the image before suppression which could be mistaken as suspicious lesions by deep learning models. Following suppression, the area of the pectoral region is greatly diminished, but the information on the breasts remains. The resulting image shows better focus on the regions containing lesions, and a reduced level of ambiguity in features. This pre-processing step helps to ensure more accurate feature extraction and reduce the risk of misclassification.

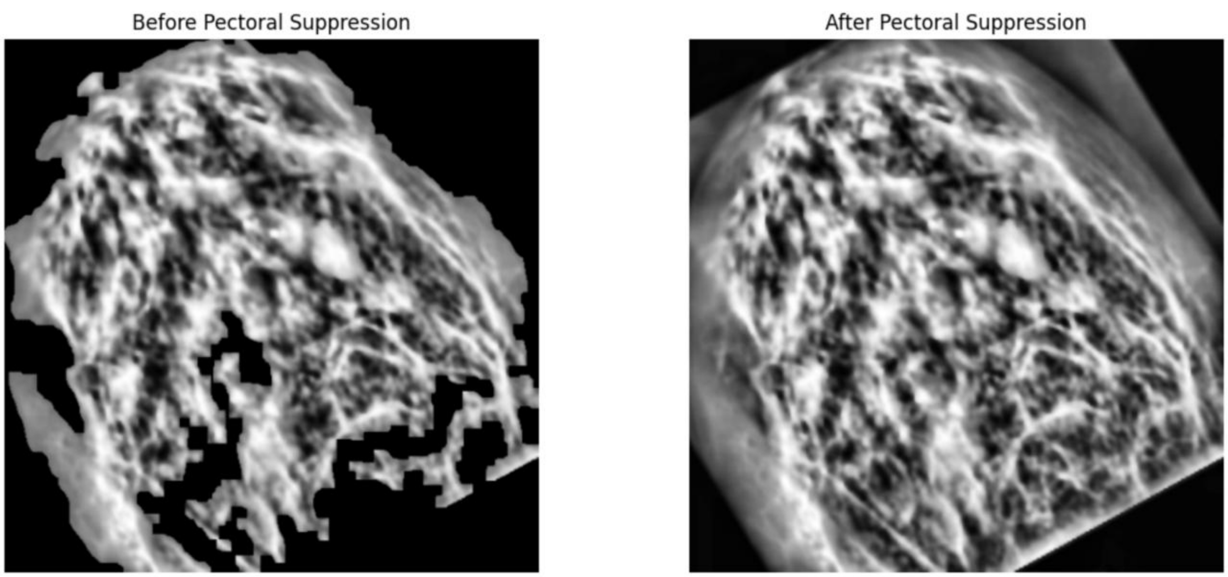

Figure 4 Comparative visualization of mammograms before and after pectoral muscle suppression

Figure-5 represents the feature learning process in the proposed PMSA-Net architecture. The adaptive enhanced mammogram undergoes CNN's backbone to produce hierarchical feature representations. The Channel Attention Module weights informative feature channels and the Spatial Attention Module emphasizes image regions diagnostically. The multi-scale feature fusion technique is proposed to aggregate complementary information from various feature scales and enhance the representation of lesions. The attention maps generated show that the network attention is concentrated on suspicious tissue areas and not on background structures.

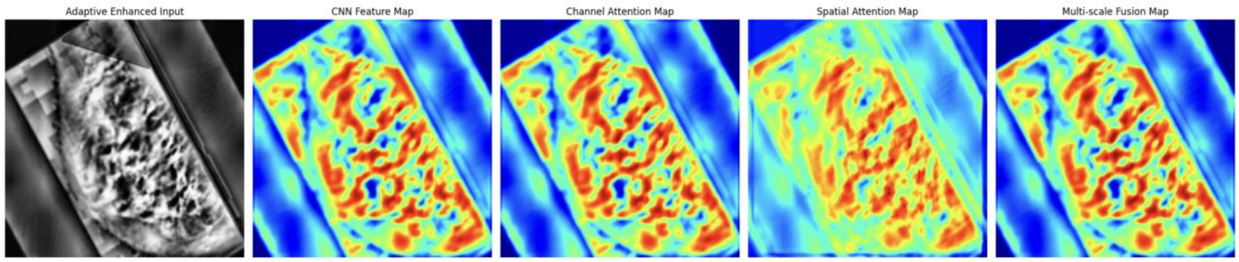

Figure 5 CNN feature extraction, channel attention, spatial attention, and multi-scale feature fusion in PMSA-Net

The figure-6 represents typical classification results from PMSA-Net. A probability score is given for each mammographic image based on the categories of normal, benign and malignant. The learnt feature representations and attention-guided information enable the model to effectively differentiate among the various pathological conditions. The high confidence values suggest good discriminative power and good characterization of the lesions. The results show that PMSA-Net can be used for reliable automated breast cancer classification for computer aided diagnostic applications.

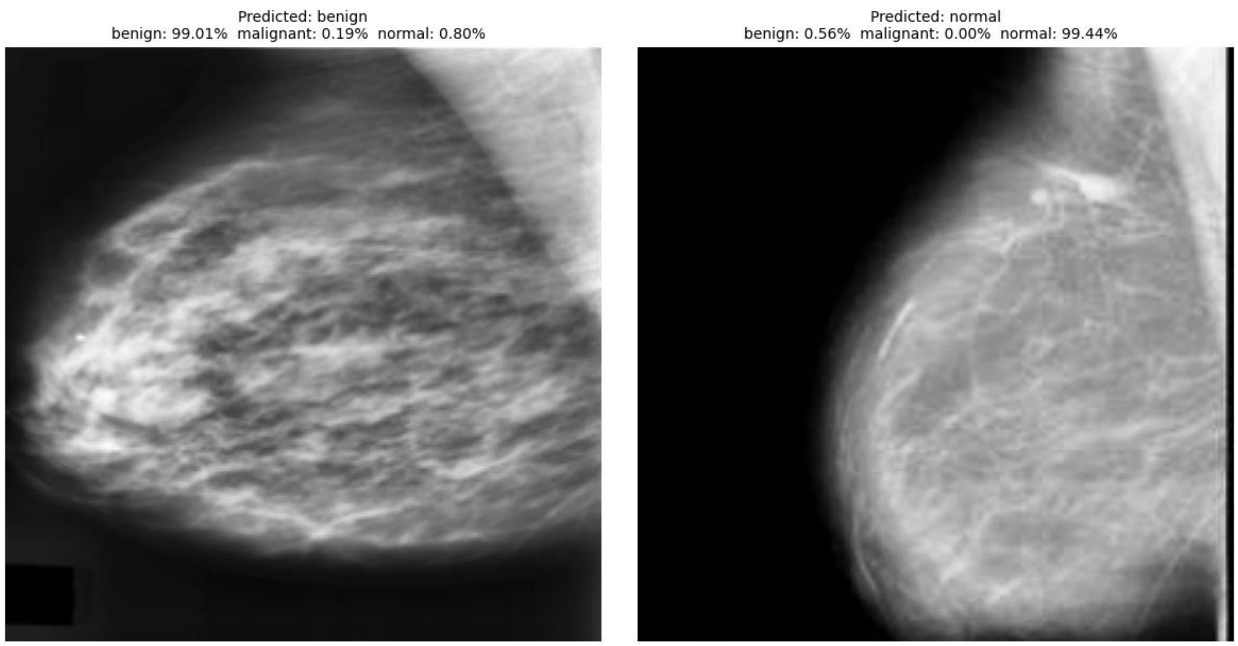

Figure 6 Classification outputs generated by PMSA-Net for normal, benign, and malignant mammographic images

Table 1 shows the comparison of the proposed PMSA-Net with some popular deep learning architectures such as CNN, ResNet50, DenseNet121, and EfficientNet-B0. The conventional CNN obtained the accuracy of 89.84%, and ResNet50 and DenseNet121 achieved the accuracy of 92.76% and 94.13%, respectively. The best baseline accuracy was obtained by EfficientNet-B0 with 95.02%. Yet the proposed PMSA-Net performed better than all the other models with a 97.86% accuracy, 97.24% precision, 97.51% recall and 97.37% F1 score. The better results show that it is effective to combine pectoral muscle suppression and the attention-guided feature learning. Additionally, the multi-scale fusion strategy allows the model to extract more subtle information about the lesions than a traditional deep learning architecture, due to its ability to capture information at different scales

Table 1 Performance Comparison of PMSA-Net with Baseline Deep Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	89.84	88.92	88.15	88.53

ResNet50	92.76	91.84	92.1	91.97
DenseNet121	94.13	93.58	93.81	93.69
EfficientNet-B0	95.02	94.48	94.73	94.6
Proposed PMSA-Net	**97.86**	**97.24**	**97.51**	**97.37**

The results in Table 2 compare the performance of individual components in the PMSA-Net architecture. The CNN backbone alone had a testing accuracy of 92.48%, the sensitivity of 91.37%, the specificity of 93.22% and the AUC of 94.15%. The accuracy on including Channel Attention module is 94.26% which shows better feature selection in the channel. The inclusion of Spatial Attention further improved the accuracy of 95.71% and the AUC of 97.23%, highlighting the significance of lesion-specific localization. Multi-scale Feature Fusion improved the accuracy to 96.89% and AUC to 98.05%. Finally, the best performance was observed for complete PMSA-Net with accuracy, sensitivity, specificity, and AUC values of 97.86%, 97.52%, 98.14% and 99.12%, respectively. From these results, it is seen that the proposed system demonstrates that every module has a positive impact on the overall diagnostic capability.

Table 2 Ablation Study of PMSA-Net Components

Method Configuration	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC (%)**
CNN Backbone Only	92.48	91.37	93.22	94.15
CNN + Channel Attention	94.26	93.88	94.73	95.81
CNN + Channel + Spatial Attention	95.71	95.12	96.04	97.23
CNN + Attention + Multi-scale Fusion	96.89	96.41	97.16	98.05
PMSA-Net (Complete Framework)	**97.86**	**97.52**	**98.14**	**99.12**

Table 3 shows a comparison of the proposed PMSA-Net with existing reported breast cancer detection systems. The deep learning-based study by Li Shen et al. showed 86.1% sensitivity, 80.1% specificity, and an AUC of 0.91, indicating the success of deep learning to analyze mammograms. Likewise, Biroš et al. reported similar accuracy (81.9%) and sensitivity (83.0%) for breast cancer assessment based on breast density. The proposed PMSA-Net, on the other hand, had an accuracy of 97.86%, sensitivity of 97.52%, specificity of 98.14%, and AUC of 0.9912. The enhancements suggest that the support to pectoral muscle suppression, adaptive enhancement, attention mechanisms, and multi-scale feature fusion greatly boosts the diagnostic performance and discrimination of the lesions.

Table 3 Comparison of proposed work with existing work

Method	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC**
Biroš et al. [24]	81.9	83	NR	NR
Li Shen et al. [25]	NR	86.1	80.1	0.91
Proposed PMSA-Net	**97.86**	**97.52**	**98.14**	**0.9912**

5. Conclusion, limitation and future scope

Breast cancer is still a serious health problem worldwide and there is a need for early diagnosis for cancer of the breast by using computer-aided diagnostic (CAD) systems that are accurate and reliable. This study proposed PMSA-Net, a pectoral muscle suppressed attention network, which enhances the adaptive attention, learns features based on attention, and fuses multi-scale features to boost the performance of breast cancer classification in mammograms.

This study introduced a deep learning framework for automated breast cancer detection (PMSA-Net, Pectoral Muscle Suppressed Attention Network) using the mammographic images. The proposed approach combines breast region extraction, pectoral muscle suppression, adaptive image enhancement, CNN feature extraction, channel attention, spatial attention, and multi-scale feature fusion into a single network. To deal with common issues in mammographic analysis, such as pectoral muscle interferes, low-contrast lesions, heterogeneous breast density, and redundant feature representation, the framework was designed.

Anisotropic Diffusion Filtering and Multi-Scale CLAHE were used initially to enhance the image quality and retain the diagnostically important structures. The breast ROI extraction and pectoral muscle suppression reduced the influence of anatomically irrelevant regions and the adaptive enhancement increased the visibility of the lesions. Next, channel- and spatial-attention mechanisms were integrated to focus on clinically relevant features, whereas multi-scale features were fused to incorporate the local texture information and to capture the high-level semantic information for classification.

The proposed PMSA-Net framework was tested experimentally on mammographic data, which showed the effectiveness of the work. The model achieved an accuracy of 97.86%, precision of 97.24%, recall of 97.51%, F1-score of 97.37%, sensitivity of 97.52%, specificity of 98.14%, and an AUC of 0.9912. The comparative analysis showed that PMSA-Net is superior to the current deep learning methods that are using mammography images because it alleviates feature ambiguity and enhances the representation learning of the lesions. Attention guided architecture was able to successfully highlight diagnostically important regions, whilst minimizing the effect of non-informative structures.

In general, the proposed PMSA-Net is a suitable and effective system for mammographic breast cancer detection. Pectoral muscle suppression combined with attention-based feature learning results in better diagnostic performance, and paves the way for the proposed framework as a useful tool in computer-aided breast cancer diagnosis and clinical decision making.

While the results of PMSA-Net have been encouraging, there are some drawbacks. The study mainly uses publicly available mammographic datasets, which do not fully cover the diversity of clinical imaging environments. Automated preprocessing approaches were used for pectoral muscle suppression which may not be completely applicable for every mammographic view. Furthermore, the system only targets mammographic images, and fails to incorporate information from other sources such as ultrasound, MRI, pathology reports and patient clinical records which could enhance the diagnostic performances.

Future work extends PMSA-Net by including multimodal medical information such as mammography, ultrasound, MRI, and clinical information for diagnostic robustness. For more accurate identification of the pectoral muscle, advanced segmentation networks like Attention U-Net or Transformer-based segmentation networks can be used. Other potential avenues for research would include the topic of self-supervised learning, explainable artificial intelligence methods, and the provision of light-weight deployment solutions for real-time clinical use. Further validation on bigger multicenter datasets from various healthcare institutions would further enhance the capability of generalizing and practicality of the proposed framework.

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