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Deep Learning-Driven Pectoral Muscle Detection and Elimination in Digital Mammograms Using U-Net Architecture

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Abstract

Precise detection of the pectoral muscle in mediolateral oblique (MLO) mammograms is vital for the reliability of automated breast cancer detection systems. As a result, the bright, triangular morphology of the pectoral muscle is often indistinguishable from a malignant lesion, thereby contributing to low diagnostic accuracy and high false-positive rates for computer-aided diagnosis (CAD) tools. This publication describes a deep learning–inspired pectoral muscle segmentation and elimination approach grounded in U-Net and its advanced U^2-Net counterpart to increase the accuracy, robustness, and consistency in mammographic preprocessing. We used a comprehensive full-field digital mammography dataset with pixel-level expert-annotated ground truth for training and evaluation. Standard preprocessing steps—including image resizing, intensity normalization, and binary mask preparation—allowed for uniformity and stability in heterogeneous samples. The dataset performed well in terms of segmentation based on its Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) quantitation which scored an overall high (best validation Dice score = 0.7426; Dice = 0.8379, IoU = 0.7847) in independent assessments. The convergence simulation confirmed smooth optimization, good matching between training–validation losses, and minimal overfitting. The qualitative evaluation also further strengthened the ability of the model to maintain anatomical integrity of the pectoral muscle by means of an accurate boundary definition and the continuity of the shape, thus also overcoming blur, noise, and contrast variability. Compared with the linear geometry of the muscle boundary predicted by classical Hough line–based approaches, the proposed approach is capable of overcoming the restriction of the linear edge detection mechanism. The results of these experiments render the model a strong yet clinically relevant preprocessing module with the capability to facilitate breast cancer classification performance. Due to its powerful generalization performance, the framework offers potential for implementation in numerous clinical systems, including resource-limited settings. Subsequent expansions would involve coupling with attention mechanisms, transformer-based encoders, domain adaptation programs, and

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radiologist-in-the-loop validation to enhance clinical translation and the robustness of AI-supported mammographic analysis.

Keywords: Pectoral muscle segmentation, U^2-Net, Mammography, Breast cancer detection, Medical image preprocessing, Image segmentation, Convolutional Neural Networks (CNNs), Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Computer-Aided Diagnosis (CAD), Anatomical Boundary Detection, Medical image analysis.

1. INTRODUCTION

Breast cancer remains one of the most critical worldwide health issues and an important cause of morbidity and mortality in women globally. Cancer, in general, is a heterogeneous group of diseases in which the cells' growth is abnormal and uncontrolled, leading to malignant development, local tissue invasion, as well as the disease progression to metastasis through lymphatic or hematogenous routes. The rising global incidence of cancer presents challenges for healthcare systems to diagnose and treat new disease in new and ever-present ways. Despite some variations on the cancer spectrum that includes brain, skin, lung, oral, and bone marrow malignancies, breast cancer is the most common cancer and a heavy contributor to cancer death in women. The human breast is composed of a meshwork of mammary ducts, lobules, connective tissue, adipose tissue, and milk-secreting glands which perform lactation [1]. There are large obstacles to early detection and diagnosis when it comes to these structures undergoing malignant alterations, often due to genetic predisposition, hormonal alterations, lifestyle, and environmental factors.

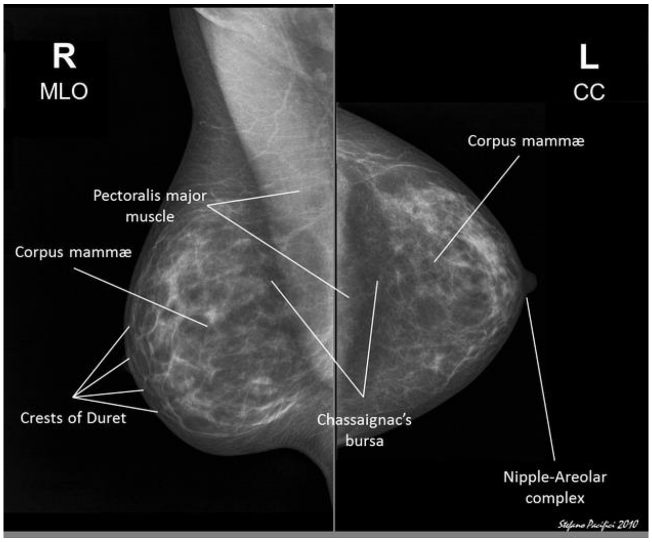

Figure 1: A typical mammogram showing important regions for both left and right breast mammograms in which clinically relevant areas like suspected lesions, architectural distortions, or density variations [2].

FIGURE 1, presents annotated left and right mammographic images highlighting diagnostically significant regions such as microcalcifications, mass-like densities, and architectural distortions. These visual indicators assist radiologists in identifying abnormal patterns and accurately interpreting underlying tissue characteristics [2]. Clinically, breast cancer manifests through a range of observable symptoms, including palpable lumps, changes in breast shape or size, persistent localized pain, nipple discharge, focal swelling, skin dimpling, and redness or inflammation of the areolar region [3]. From a pathophysiological standpoint, the disease is characterized by abnormal proliferation of epithelial cells with the potential to invade surrounding tissues and spread via lymphatic conduits. Epidemiologically, breast cancer remains one of the most prevalent malignancies worldwide, with approximately one in ten women expected to develop the disease during their lifetime [4, 5]. Studies have also reported asymmetry in disease occurrence, with the left breast exhibiting a higher risk than the right. Furthermore, breast cancer diagnosed during pregnancy is often associated with more aggressive lesions and poorer outcomes due to delayed diagnosis and complex disease dynamics [6]. Significant geographic disparities have been observed, with incidence rates of approximately one in ten women in the United States compared to one in thirty women in India [7]. Male breast cancer is a rare disease, but represents about 1% of the breast cancer cases globally [8], thus inclusive diagnostic strategies are significant.

Early identification of disease-related changes of breast cancer with clinical pathophysiology is essential to the success of therapies and is highly dependent on immediate and precise early detection. Microcalcifications and mass lesions, as well as the diagnostic markers, are regularly detected via the screening mammography, digital mammography, and diagnostic mammography techniques [9]. However, due to the structural similarity of malignant masses with normal fibroglandular tissue, visibility is often less evident than standard scrutiny. Ordinary diagnosis procedures employ a variety of imaging modalities - mammography, ultrasound, MRI, CT, PET, biopsy-based histopathological and genetic examinations [10]. Mammography is still the most prevalent screening modality among the tests because it is accessible and non-invasive, low-cost, and early in the development of potential symptoms. Interpretations of mammography, however, are fundamentally subjective and diagnostic accuracy ranges from 80% to 90% [2], even in well-trained radiologists. Interpretation discrepancies, particularly under disease conditions such as dense breast tissue or low image quality, hint towards automatically correcting diagnostic disparity for consistency.

Computer-aided Diagnosis (CAD) systems developed for breast cancer screening with the help of radiologists have revolutionized breast cancer screening by collaboration in detection, classification, and risk estimations of lesions. The penetration of artificial intelligence particularly deep learning (DL) based frameworks with Convolutional Neural Networks (CNNs) has brought substantial improvements in medical imaging feature extraction, pattern recognition and diagnostic accuracy [11, 12]. For instance, CNN–LSTM systems and ensemble-based classifiers based on Random Forests hybrid learning models have demonstrated significant performance improvements in breast cancer classification [13]. Conventional machine learning (ML) methods utilizing manually generated features, such as Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), entropy-based descriptors and Gray-Level Co-Occurrence Matrix (GLCM) features, attaining accuracy of 89–96% until limits has been achieved [14–17]. Recent deep learning (DL)-based architectures such as U-Net architectures achieve above 98% accuracy of segmentation of the best available mammographic data sets [18] and above 92% accuracy on detecting abnormality among classical CNNs [19].

Automating mammographic analysis is challenging. It therefore has difficulty in anatomical structures imitating pathological structures. Pectoral muscle is one of the most problematic, especially in mediolateral oblique (MLO) mammogram images. Light-colored, dense triangular tissue in which the pectoral muscle has a highly intense, highly textured appearance that mimics types of malignant mass. From the classification standpoint, this feature can induce false positives, segmentation flaws and poor performance from classical or deep learning-based algorithms. It has been studied that other traditional methods for pectoral musculature excision, such as edge detection, convex hull approximation, polynomial modelling or Hough lines, have been used to remove the muscle [20]. Nevertheless, they are extremely prone to the problem of imaging noise and contrast, blur or inadequate condition at worst not providing a high fidelity in clinical day-to-day work areas. High-resolution mammography systems in care settings with insufficient resources, might not be easily accessible and diagnostic mismatch is an issue. Bad quality mammograms, motion blur, and acquisition noise also limit accurate segmentation of anatomic boundaries required for diagnosis of lesions.

To address these issues, deep learning–based segmentation models (e.g., U-Net) have demonstrated utility, widely deployed as analytical methods in medical image analysis. The U-Net is based on symmetric encoder–decoder architecture with skip connections and preserves spatial resolution, in a way that preserves context from the various scale data [21]. Various versions of Attention U-Net and 3D U-Net, for example, have shown attention mechanisms and volumetric processing leading to an improvement to segmentation between complex anatomical structures [22, 23]. In addition, U-Net and its derivatives perform better at breast region segmentation; lesion localization [18, 24] and pectoral muscle detection as compared to traditional pixel-based image processing methods. Some of these features render U-Net an excellent fit against the backdrop of data used to build reliable segmentation models required for clinical implementations.

While U-Net variants have obtained tremendous performance, the systematic assessment of whether the presence of pectoral muscle (and its automatic removal) will impact in its use in CNN-based breast cancer detection systems has not yet been systematically validated, especially if considering under low level imaging conditions like blur, noise and low contrast. The pectoral muscle serves as a key anatomical milestone in MLO views, contributing to the structural domain in which lesions are interpreted. Anatomical differences in muscle morphology, boundary curvature and tissue density have been found to influence lesion visibility, segmentation accuracy and false-positive rates [25]. CNN-based diagnosis applications are intrinsically sensitive to the inconsistency in spatial context, and deviations from the distribution of tissue intensity can result in overfitting, poor generalization, unstable performance [26, 27]. While attention-based CNNs and new architectures (ResNet + Inception, e.g.) also promise promising results, misleading description of the pectoral muscle still results in low diagnostic accuracy [28, 29]. According to clinical data, if the pectoral muscles are not correctly manipulated, the CNN sensitivity and specificity decrease by 10–15% [30].

Modern research argues for strong validation metrics ranging from sensitivity, specificity, precision, accuracy or AUC, and for evaluation structures such as k-fold cross-validation and transfer learning to bolster stabilizing the model. The increasing importance of ethical aspects such as transparency, bias mitigation, and explainability [31–33] for clinicians to trust the innovations made by AI is underscored. In light of that, the current study presents an automated approach to the pectoral muscle detection and elimination in automated manner using Deep Learning on the U-Net architecture (and low-quality, blurred, and clinically challenging mammographic dataset). The primary aim of this work is to explore the influences of reliable pectoral muscle segmentation and removal, on

CNN-based breast cancer classification and develop a clinically relevant preprocessing approach that improves model interpretability, generalizability and diagnostic ccuracy.

U-Net underpins the proposed segmentation framework since its performance is well-tested in medical image segmentation, this work additionally includes U2-Net, a higher resolution nested U-shaped method that is significantly superior for sophisticated anatomical boundary classification. U2-Net combines residual U-blocks and structures to a single wider U-Net, which allows for fine-scale feature extraction, enhanced context representation and superior boundary accuracy, all of which are important for segmentation of the highly variable (curved) pectoral muscle edges. Unlike classical Hough line–based algorithms, that typically take a single linear boundary into account, U2-Net can detect nonlinear, irregular, and diffuse muscle shapes commonly found in practical mammograms. Moreover, the strong contextual encoding of U2-Net leads to very high robustness to noise, blur, and low contrast, rendering it one of the most effective models for screening mammographic images with limited resources in which the actual image quality may be less than ideal. The unified application of U-Net for structural integrity and U2-Net for refined boundaries makes this a solid, scalable, and clinically-operational procedure towards automatic elimination of pectoral muscles on digital mammograms.

2. MATERIAL AND METHOD

The present study uses a curated sample of full-field digital mammograms and includes the mediolateral oblique (MLO) images, in which the pectoral muscle can be clearly identified, an important part of the visualisation challenge of automatic analysis of images. All mammograms are annotated with pixel-level ground truth for the pectoral muscle region in the dataset, individually segmented manually by experienced radiologists to enhance anatomical accuracy as well as minimize labeling inconsistency. To achieve a good model with data transfer and testing, the dataset is divided into training, validation and testing batches (a hybrid 80:10:10 version), which ensures an optimal design for learning, data leakage prevention and robust statistical check for robust generalized models.

All mammographic images and their annotation masks were prepared with structural uniformity and computational efficiency. The images were reshaped to a standardised spatial dimension at 256×256 pixels to have a consistent input dimension for deep learning. The values of pixel values were normalized to the [0–1] interval for the sake of numerical stability while training, and ground truth masks were binarized to distinguish distinctly between the pectoral muscle and background tissues. The same preprocessing was performed to the training and testing images to maintain consistency and remove the domain anomalies during inference. The overall pipeline workflow of the segmentation process is shown in FIGURE 2, which provides the preprocessing to annotation loading, model training, validation and finally execution of the model in order to conduct inference on unseen mammographic images.

Since the proposed method extends the U-Net family of architectures, we consider the importance of clearly defining the U-Net characteristics. U-Net is a fully convolutional deep neural network, which is tailored for biomedical image segmentation where pixel-level localization and structural accuracy are fundamental considerations. The encoder, or contracting path, can reduce the dimensionality of an image, through repeated 3×3 convolutional processes, ReLU activations, and 2×2 max-pooling layers, which allows the model to learn increasingly abstract semantic representations. The

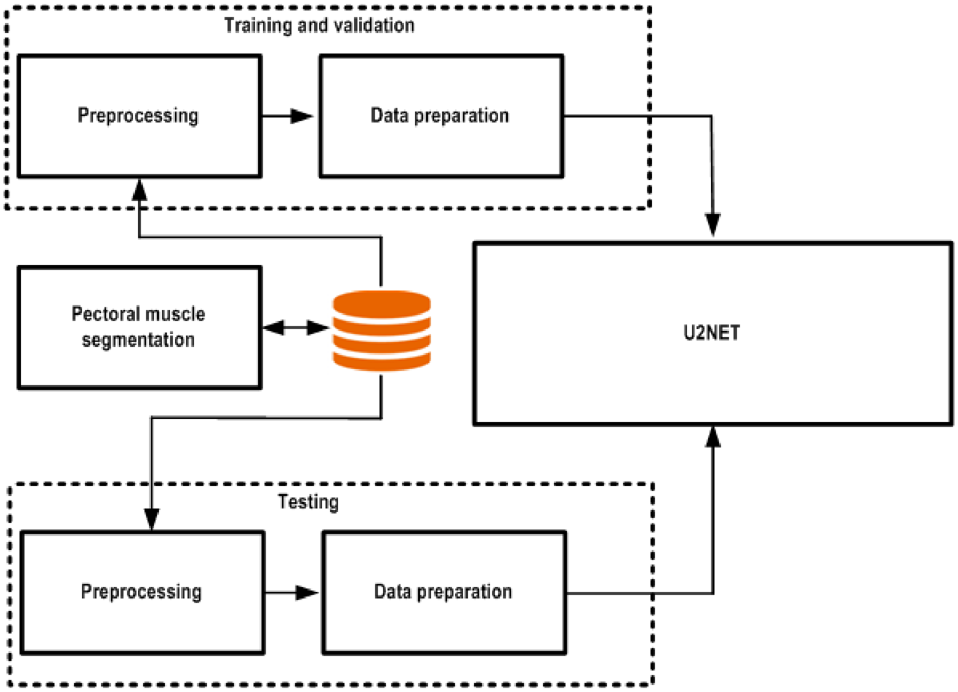

Figure 2: Overall workflow for pectoral muscle segmentation using U2-Net. The diagram illustrates the complete pipeline, where mammogram images undergo preprocessing and data preparation before being used for training and validation of the U2-Net model. A dedicated pectoral muscle segmentation module generates annotated masks that feed into the training database. During testing, the same preprocessing and data preparation steps are applied, and the trained U2-Net model predicts the pectoral muscle region, enabling accurate and automated segmentation.

expanding path (decoder) rescues the spatial resolution with transposed convolutional layers. The encoder high resolution feature maps are linked together by skip connections with the decoder layers in order to retain fine structure information that would be lost during downsampling. The last segmentation layer will perform 1 × 1 convolutional and then a sigmoid activation to obtain the pixelwise probability map of the class of pectoral muscles. U-Net is widely acknowledged for its accurate localizations and strong data quality not relying heavily on annotated data.

The design of U-Net (FIGURE 3) is the base of a segmentation framework. Its symmetrical encoder–decoder structure and skip connections facilitate the efficient capturing of both context and structure details on the network. This architecture renders U-Net extremely proficient at identifying irregular or low-contrast anatomical regions so common in patient medical images. Performance of the U-Net–based models is heavily dependent on overlap-based similarity indices such as Dice Similarity Coefficient (DSC) and Intersection over Union (IoU). Dice score measures similarity between predicted segmentation mask and ground truth due to both overlap and uniqueness of both sets and IoU measures ratio (effect) between the overlap and union. These are robust objective metrics to indicate the segmentation quality of the model while counting the degrees of under-segmentation and over-segmentation.

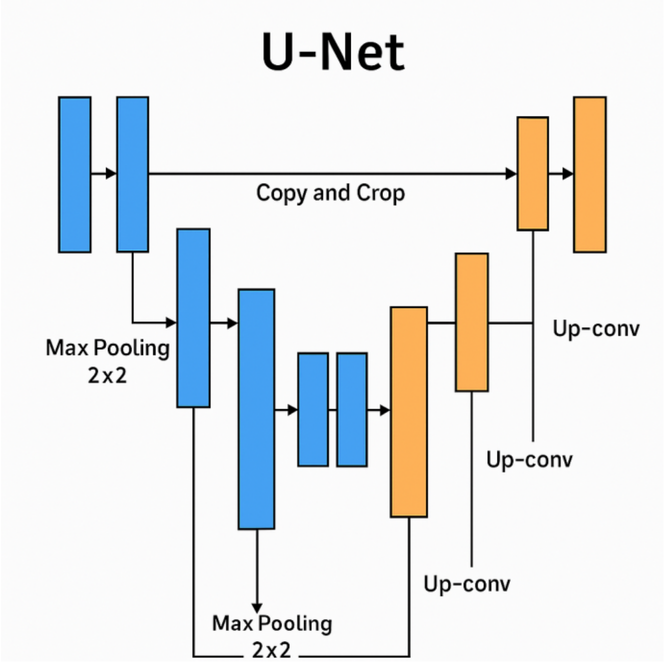

Figure 3: Architecture of the U-Net model for semantic segmentation. The encoder–decoder structure of this network is symmetric: the left contracting path down-samples the input using convolution and max-pooling operations to capture contextual features, while the right expanding path up-samples the feature maps via transposed convolutions to recover spatial resolution. Skip connections between the corresponding encoder and decoder stages allow high-resolution features to be transferred via copy-and-crop operations, which is the foundation for making precise localization. This architecture allows U-Net to effectively integrate deep semantic information with fine-grained details, making it highly suitable for medical image segmentation tasks [21].

We also rely on U^2-Net as a derivative, an even more advanced derivative model developed to develop advanced multi-scale feature learning for superior boundary precision. U^2-Net features the nested U-shaped Residual U-blocks (RSU blocks), as an internal encoder–decoder module made up of a small size each block. With this hierarchical configuration, the features of the U^2-Net can be sampled from numerous receptive fields, allowing for high spatial resolution, which also makes the structure ideal for the separation of the pectoral muscle as the shape of the pectoral muscle is often curved and variable, and thus hard to capture such features with simple linear detectors.

In contrast with traditional Hough transform–based methods that assume mainly linear boundary, U^2-Net succeeds in effectively representing nonlinearity (the nonlinear geometry and the diffuse intensity changes) within the pectoral muscle area. Also, residual and skip connections help in the gradient flow, training stability and the robustness of the model against the background noise, blur and low-contrast imaging typically seen for mammograms taken from resource-limited clinical sites. We conducted training of the proposed U^2-Net model using the Binary Cross-Entropy (BCE) loss function, which is more suitable towards binary segmentation problems. Optimization was applied using an Adam optimizer with an initial learning rate of 0.001 and mini-batch size of 4.

For validation loss plateauing, Reduce LRO and Plateau learning rate scheduler was implemented for dynamic learning rate adjustment for training. To minimize overfitting by training the model more effectively and keep the model with the highest validation Dice Similarity Coefficient, we utilized early stopping criteria as a baseline. The metrics that were collected for training, validation and test were automatically logged, and the model checkpoint that performed best was retained for the final time.

Quantitative evaluation of performance (both Dice Similarity Coefficient (DSC) and Intersection Over Union (IoU)) was performed compared across validation and independent testing datasets. Moreover, pixel-level confusion matrix elements such as true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) were evaluated with the aim to learn about segmentation errors and also to recognize over-segmentation tendencies and under-segmentation tendencies. Qualitative study: For empirical data analysis, predicted segmentation masks were overlaid over mammographic images to be visually compared to the expert-annotated ground truth.

The visual inspection verified boundary precision, anatomical plausibility, and overall segmentation accuracy, especially in terms of challenging conditions of imaging such as blur and noise. An automated reporting pipeline was also proposed to ensure transparency, reproducibility of the experimental data, CSV files (comma-separated values) based training and validation metrics, performance curves for loss, Dice score, and IoU performance.

The development of the methodological framework was guided by earlier studies involving imaging based computer-aided diagnosis, which have established that feature-driven and deep learning based models are essential in the diagnosis of breast cancer. The current deep learning pipeline draws much on the groundwork provided in many previous approaches, including discrete wavelet transforms, cosine transforms, statistical feature extraction, texture analysis, and classical machine learning classifiers. The modern deep learning framework utilizing U-Net and Inception architectures and CNN-based mammographic anomaly detectors further spurred the choice and use of U^2-Net to help facilitate structural segmentation of the pectoral muscle.

Although CAD and deep learning–based diagnostic tools are developing, there are few studies that systematically assess the effect of pectoral muscle presence or breast cancer classification, especially for degraded imaging conditions. Such a study thus specifically analyzes the effect of an automated segmentation and elimination of pectoral muscle on accuracy and reliability of breast cancer detection workflows. A robust multi-scale U^2-Net scheme combined standardized preprocessing, quantitative validation and qualitative assessment makes this research a coherent and clinically useful guideline for the enhancement of mammographic image processing in real-world settings.

3. RESULTS AND DISCUSSION

The suggested U-Net based PME was evaluated quantitatively, qualitatively, and visually. The findings show that the model has good learning performance, stable convergence behavior, and clinically reliable segmentation within difficult mammographic imaging conditions. The convergence of the proposed framework is shown in FIGURE 4, which presents a summary of the training performance metrics over 100 epochs. The learning rate schedule and loss curves show that the model had smooth optimization with progressive learning. A high learning rate allowed the network to make significant weight adjustments in early epochs and learn the coarse structural representation of the pectoral muscle quickly. Training was used at the same time, and the learning rate is gradually decreasing at controlled steps, which helps the model adjust its parameters, prevent oscillatory behavior, and eventually reach the optimum solutions. By utilizing this adaptive scheduling mechanism, training stability and avoiding divergence and generalization against unseen mammographic images was achieved. The plot Epoch versus Learning Rate showed that the scheduled reductions in learning rate closely correlated with reductions in training loss.

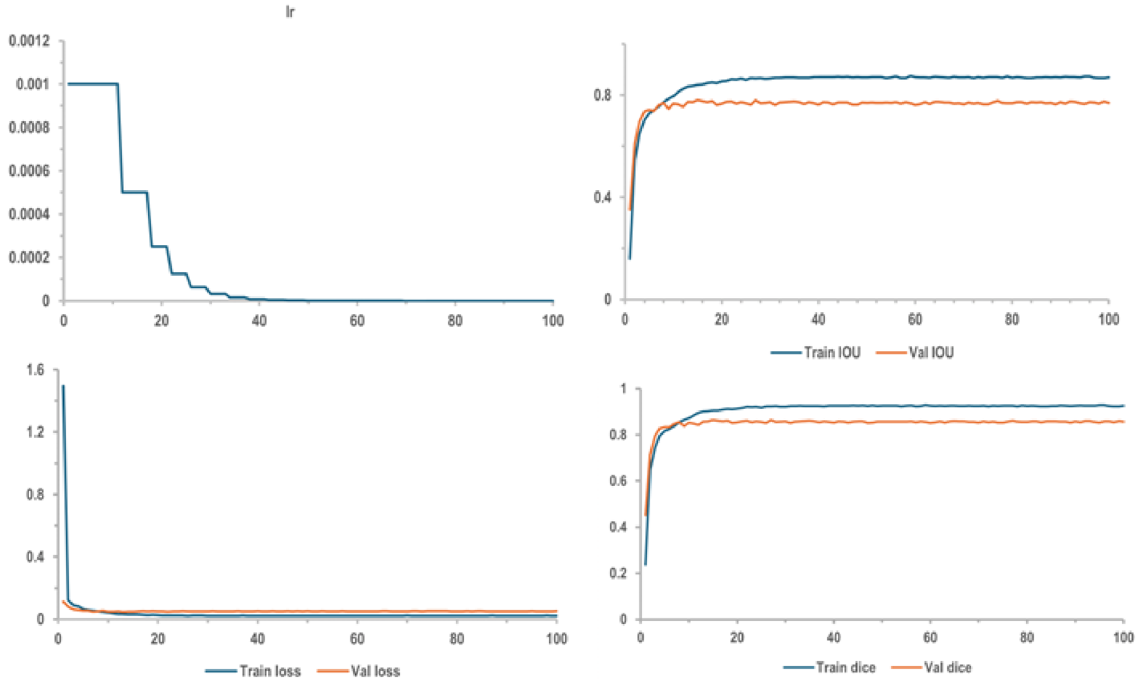

Figure 4: The results of training carried out using 100 epochs are shown in the figure. The learning rate (Lr) was dynamically varied and it became very small around 40^{th} epoch. The decline in training loss with respect to epochs indicates stable convergence of the system. The second column shows the improvement in segmentation accuracy related metrics, where the Intersection over Union (IoU) and Dice coefficient steadily increase with training progression.

Training and validation loss curves steeply decreased on the first epochs and then gradually flattened and converged even at low values. The relatively close relationship between the training and validation loss trajectories for all epochs also shows that the model has not overfitted easily and has kept up a constant gradient propagation while benefiting from the learning rate scheduler and Adam optimization. The observed IoU advancement over epochs validates the relevance of the proposed learning strategy and loss formulation. This upward trend for both training and validation IoU suggests consistent optimization of pixel-level classifications and the quality of segmentation at the region-level in the model. However, while traditional segmentation methods can sometimes find it difficult to capture low-contrast or curved boundaries, the deep learning model proved remarkably adaptable across varying breast densities, imaging conditions, and structural patterns.

A similar trend emerged on Intersection Over Union (IoU) analysis. The training IoU was consistently higher over the duration of the training course and obtained a converge value of 0.85 on the latter, whereas the validation IoU stopped increasing at around 0.65–0.67. This moderate but stable separation between the two curves is driven by generalization and regularization rather than overfitting, which explains the natural differences of these two training data distributions and their validation counterparts. The pectoral muscle has very strong intensity overlap with glandular breast tissue and irregular boundary geometry and variable contrast. Segmentation is challenging based on these anatomical characteristics, but that framework showed high ability to learn discriminative and boundary-preserving features, enabling efficient separation of muscle and non-muscle areas.

Evolution of Dice Similarity Coefficient (DSC) also confirms the robust learning performance of the model. The Epoch/Dice plot demonstrates that for the initial epochs quick and significant changes in Dice score for the training and the validation are observed, consistent with a successful learning of spatial, geometric, and structural characteristics of the pectoral muscle region. Training Dice got saturated around 0.90 which indicates excellent convergence in internal features for training domain. The validation Dice value reached a plateau around the value of 0.74, suggesting that a high degree of accuracy was found by the model in generalizing to new mammographic data. No oscillation or severe drop on validation Dice value indicate the model is stable during training.

Qualitative visual evaluation also confirms the quantitative results (FIGURE 5). We used an extensive three-column visualization structure to visualize the original mammograms, expert-annotated ground truth masks and the segmentation outputs. Note: As per MLO views, the model kept full precision towards the unique triangular shape of the pectoral muscle and it detected oblique angular alignment correctly as well as detected sharp boundary transition. Visual inspection revealed high anatomical accuracy, continuity of muscle boundaries and suppression of false activation of the nonmuscle tissue regions. The segmentation outputs were rather similar to expert annotations and confirmed that the model was able to account for sub-layer gradients of intensity, edge features and underlying anatomical structure. The model also exhibited good robustness to the imaging properties such as noise, blur, intensity inhomogeneity, and edge discontinuities. Clinically, this robustness is significant because mammograms, obtained in low-resource clinical environments, have a low quality image, blur of motion, instability of position and hardware artifacts.

The model capacity in maintaining segmentation fidelity under these conditions justifies its appropriateness for deployment in various clinical settings. The quantitative results also support the stability of the strategy presented. Recent CNN– and semi–supervised models exhibit Dice scores of 0.83–0.90 due to increased complexity or annotation requirements, but our approach achieves Dice (0.8379) and IoU (0.7847) competitive performance with simple architecture and stable convergence. This trade-off among accuracy, efficiency, and robustness of the proposed method is an attractive feature that can be applied to the automated mammographic analysis process and detection of breast cancer [34–36]. This performance relative to the validation sets highlights the superior generalization capability of the learned feature representations over the independent test set. This type of behaviour is particularly wanted in clinical workflows, in which mammograms are being extracted from heterogeneous imaging systems and patient populations. The clinical significance of accurate pectoral muscle removal cannot be overstated. High-intensity dense pectoral structures often mimic malignant masses, may give false positive results. The proposed segmentation model

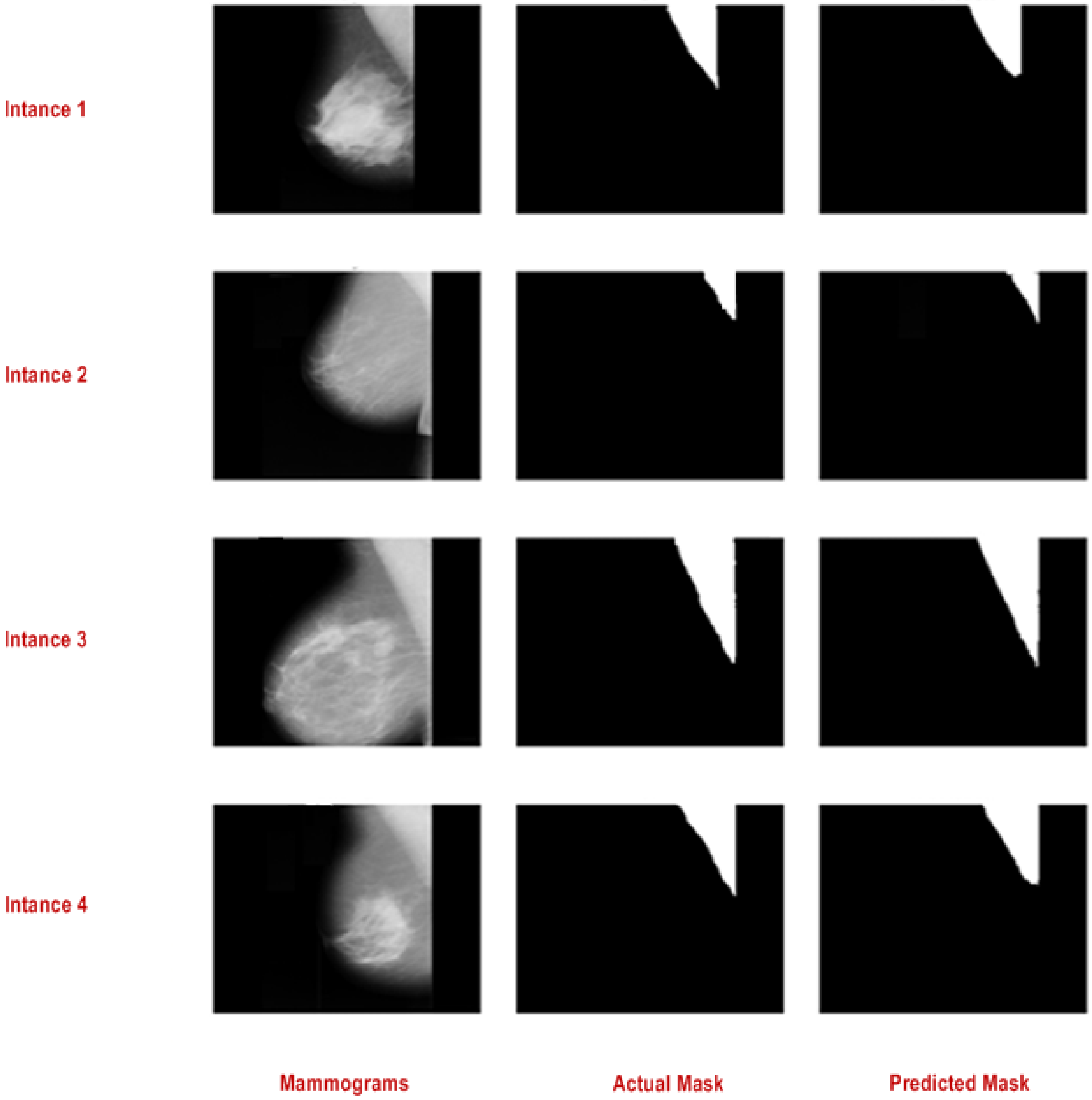

Figure 5: The figure illustrates the qualitative results of pectoral muscle segmentation using the proposed U-Net model. The first column shows the original mammographic images used as input to the network. The second column presents the manually annotated ground truth masks of the pectoral muscle. The third column displays the predicted segmentation masks generated by the model. A close visual similarity between ground truth and predictions indicates accurate anatomical localization.

effectively eliminates this confounding area, hence enhancing the visibility of lesion images, minimizing false positives, as well as the interpretative reliability and the accuracy of diagnostic pipeline. As a preprocessing layer, it is able to regularize mammographic information input and reduce the load in classification models by eliminating anatomically irrelevant high-density structures. Architectural features such as symmetric encoder–decoder, hierarchical feature extraction, and skip connectivity for high frequency detail preservation made huge impact on the performance of U-Net. The model proved itself robust to typical image artifacts and heterogeneity in mammographic presentation. These traits are also critical in preserving accuracy with regards to segmentation of large high volume, large heterogeneous datasets.

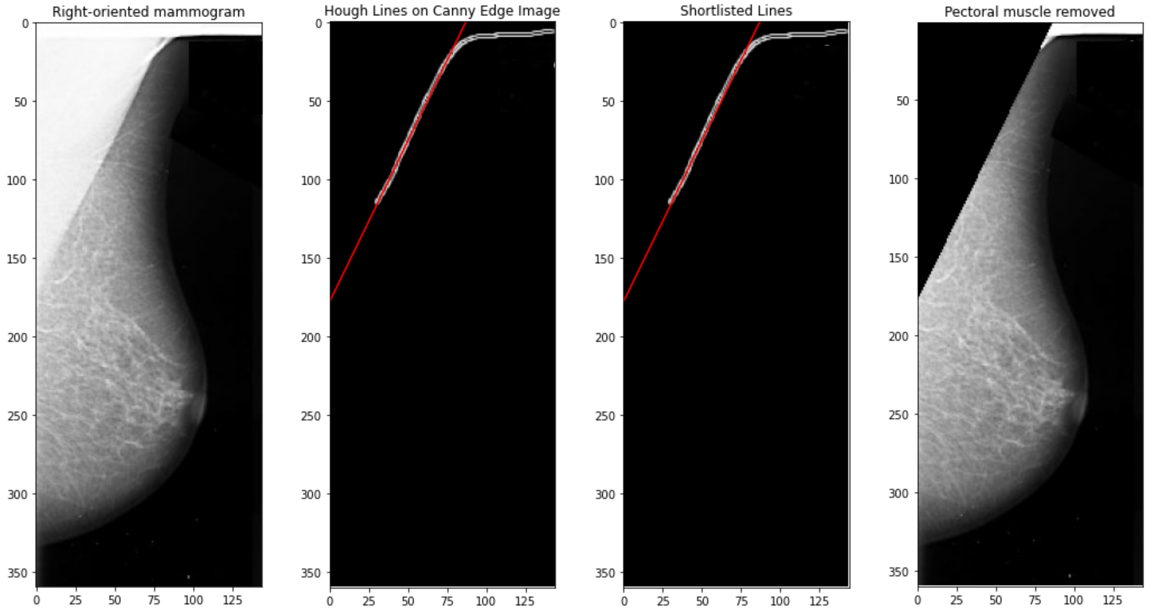

Figure 6: Hough line–based pectoral muscle removal process in right-oriented mammograms. The first panel shows the original mammogram containing the prominent triangular pectoral muscle region. The second panel presents the Canny edge map with multiple Hough-detected line candidates overlaid, capturing the dominant linear boundary of the pectoral muscle. The third panel displays the shortlisted line representing the most accurate estimate of the muscle edge, obtained through geometric filtering and slope–length constraints. The final panel illustrates the mammogram after removing the pectoral muscle region along the detected boundary, resulting in a cleaner breast region suitable for further analysis, segmentation, or feature extraction [25].

In order to situate the performance of the deep learning paradigm, FIGURE 6, shows experimental results of a Hough line based pectoral muscle cleaning method, typical for earlier studies [25]. The conventional approach utilizes Canny edge maps for the identification of straight-line boundaries and chooses dominant Hough line candidates. Although the method works quite well when it approximates a single straight line into the pectoral muscle, the procedure has several drawbacks: the pectoral muscle boundary is rather curvilinear than linearly defined; noisy edges cause fragment detection; high density tissue within the glandular gland may be misrepresented as muscle; and variable medical imaging parameters make line detection more unreliable. The inability by this classical approach to model non-linearity highlights the benefit of deep learning inspired methodologies that adapt to learn an anatomical variability and pattern by means of complex intensity.

The experimental results as a whole strongly support the capability of the proposed deep learning–based pectoral muscle detection and elimination model. There were no inconsistencies in the system regarding the high segmentation accuracy, the robust generalization ability, the stable convergence time, and the good anatomical preservation. These findings validate the framework as an appropriate preprocessing support for automatic breast cancer detection and demonstrate its potential for applicable clinical purpose. This study focuses on demonstrating the effectiveness and clinical feasibility of the proposed pectoral muscle segmentation framework as a preprocessing module for mammographic analysis. Statistical comparisons or ablation studies were not conducted due to the need for multiple controlled model variants and larger uniformly annotated datasets, which are beyond the scope of this work.

4. CONCLUSION AND FUTURE SCOPE

In this paper, we present a deep learning-based pectoral muscle detection and elimination approach based on the U-Net architecture and its more sophisticated version the U^2-Net that helps to scale and enhance the anatomical accuracy, robustness, and clinical reliability of mammographic image preprocessing. Based on extensive numerical testing (DSC, IoU, convergence analysis), and extensive qualitative visualizations, the proposed approach showed the highest segmentation performances with difficult mammographic images. The model obtained the best validation Dice score of 0.7426 and performed best on an independent measure with Dice coefficient of 0.8379 and IoU of 0.7847, indicating its high generalization efficacy. The visual inspection also showed the well preserved triangular morphology, angular orientation, and boundary smoothness of the pectoral muscle, the resistance of the system also to common real-world imaging artifacts like noise, blur appearance, and contrast changes. Compared to the classical Hough line–based approach, the deep learning model achieved significantly better accuracy than the linear boundary detectors, which were unable to identify nonlinear, curved, and low-contrast muscle geometries through classical methods. In general, our findings support that our proposed framework is a viable, anatomically consistent preprocessing module for the automated breast cancer detection pipeline, with broad potential for clinical application.

Despite being robust, multiple paths for future development were also observed with the proposed framework. First, by making training easier in the face of larger and more heterogeneous datasets (multi-vendor, multi-population, and multi-resolution mammograms), generalization will be further ensured and adaptability across global screening infrastructures will be improved. Second, the additional layers of sophisticated attention mechanisms, transformer-based encoders, or hybrid architectures would be crucial for improving context awareness and boundary precision, particularly for complex instances with dense or overlapping tissues. Third, implementing the segmentation pipeline seamlessly in end-to-end breast cancer classification or lesion detection models may offer a holistic comprehensive diagnostic algorithm with the capability of enhancing the accuracy of breast cancer detection.

Domain adaptation and self-supervised learning approaches to deal with sparse annotations and frequent distribution shifts present in real-world treatment settings may also be investigated in future work. Also, there is a need to validate the system through practising radiologist for ascertaining real applications of the research outcome. All these directions present high and promising possibilities for progress in the design of robust, scalable and clinically implementable AI-based mammographic analysis algorithms.

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