A Comprehensive Two-Step Methodology for Automated Segmentation of Architectural Distortion in Mammograms

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***Abstract*— Breast cancer is one of the most prevalent forms of cancer worldwide and a leading cause of mortality among women. Early detection of breast cancer is crucial for effective treatment. Architectural distortion (AD) is an early sign of breast cancer, characterized by a subtle contraction of breast tissue that often goes unnoticed. Traditional methods of detection heavily rely on the expertise of radiologists, making the process more difficult. To address this, we propose a deep learning approach to automate precise and efficient AD segmentation. Our approach involves a two-step process. In the first step, we utilize a Mask R-CNN Detectron2 model to perform AD segmentation across the entire set of mammography images. This initial segmentation provides a baseline for identifying AD regions. The ResNet-18 patch model is incorporated into the Mask R-CNN model's segmentation pipeline in the second stage. The purpose of this combination is to improve AD area localization and precision. By combining the strengths of both models, we achieve improved accuracy in AD segmentation. The evaluation of our fully automated method yielded remarkable outcomes on a diverse test set consisting of private datasets, including the Baheya dataset and the NCI dataset, as well as the publicly available Digital Database for Screening Mammography (DDSM). The results showed a Segmentation Accuracy of 0.852, Classification Accuracy of 0.915, and Mean Average Precision (mAP) of 0.894. These findings demonstrate potential to enhance the efficiency and accuracy of AD detection and segmentation in mammogram images, contributing to early diagnosis and treatment planning for patients at risk of breast cancer.**

Keywords—Breast Cancer, Mammogram images, Segmentation, Deep learning, Architectural Distortion, Mask R-CNN, ResNet-18.

I. INTRODUCTION

Architectural Distortion (AD) is a concerning finding in mammography that indicates abnormal regions [1]. It is characterized by the shrinkage and deformation of breast tissue, making it difficult to detect [2]. AD refers to abnormal tissue patterns and disrupted anatomical structures in mammograms that deviate from the expected architectural arrangement. Its subtle, uneven, and tiny characteristics pose challenges for evaluation [3]. However, computer algorithms can automatically detect abnormal AD regions in mammograms, providing a useful tool for early detection and assisting radiologists and physicians in diagnosing breast cancer.

Mammography screening remains the primary and most efficient technique for diagnosing breast cancer in women [4], and among the abnormal spots detected on mammograms, AD ranks as the third most common suspicious symptom [5]. AD may be the first sign of cancer, appearing up to two years before other findings [6]. Its subtle appearance and overlap with normal breast tissue make detection and accurate segmentation difficult. Despite the importance of identifying AD, it remains a challenging task due to its delicate appearance, resemblance to normal breast tissue, and factors like breast tissue density, small size, and variable asymmetry [5]. Nevertheless, detecting AD is crucial as it can serve as an early indicator of underlying malignancies, guiding clinicians in making informed decisions about further diagnostic tests and treatment strategies.

Deep learning-based image segmentation methods, such as the Mask R-CNN Detectron2 model proposed by He et al. [7] and the ResNet-18 patch model introduced by He et al. [8], were selected over other deep neural network (DNN) models for their specific advantages. Mask R-CNN combines object detection and segmentation, reducing complexity and computational needs. Its Region Proposal Network (RPN) accurately localizes objects, crucial for precise AD segmentation. The model provides pixel-level segmentation masks for detailed boundary delineation. This approach is excellent for capturing intricate details in AD segmentation and for identifying objects even in cluttered backgrounds.

The ResNet-18 patch model was chosen for its efficiency and feature extraction capabilities. Its shallow architecture balances speed and performance for quick predictions. Focused on localized image regions, the patch-based approach is advantageous for AD segmentation. ResNet-18's success in image classification tasks makes it suitable for medical image analysis. When combined with Mask R-CNN, ResNet-18 refines segmentations by closely analyzing patches, enhancing both precision and accuracy in AD segmentation.

Several previous studies have explored different methods for AD detection. Nemoto et al. [9] introduced a novel