Applying Multiple Instance Learning for Breast Cancer Lesion Detection in Mammography Images

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Abstract: Breast cancer remains a major global health problem and early detection is essential to improve patient outcomes. Current computer-aided detection (CAD) systems for breast cancer are often based on fully supervised training, which requires careful manual annotation and accurate tumor segmentation. This paper presents a novel approach based on multiple instance and transfer learning techniques. Our method uses an adapted threshold segmentation technique to extract many small spots from mammography images. Instance features are then extracted using a pre-trained model and grouped into a unified representation. A classifier trained on these representations is used to classify the data. The proposed method eliminates the need for precise tumor segmentation while demonstrating high accuracy in breast cancer detection.

1 INTRODUCTION

According to recent American Cancer Society statistics, breast cancer will have the highest incidence and mortality rate of any cancer type in 2020 Siegel et al. (2023). The majority of breast cancers are detected by abnormalities in breast tissue. It can take years for an abnormality to develop into a malignant tumor. Early detection can thus play an important role in breast cancer prevention.

Currently, mammography is one of the most common methods of breast cancer screening. However, interpreting mammography results can be time-consuming and inconsistent across radiologists, even for the same patient. To address these limitations, a variety of computer-aided diagnostic (CAD) systems have been developed to detect abnormalities in mammogram images.

Breast cancer decision support systems typically include three major components: breast region segmentation, feature extraction, and abnormality classification. Potential lesions are identified during breast segmentation. For example, Khoulqi and Idrissi (2019) used a mathematical morphology-based segmentation algorithm to identify suspicious regions in mammographic images Khoulqi and Idrissi (2019). Gomez and his team used texture analysis to detect the contours of breast lesions Gomez-Flores and Ruiz-Ortega (2016). Reig and colleagues proposed another method for segmenting suspicious tissue in breast MRI images, which combines adaptive thresholding techniques Reig et al. (2020)

Hirra et al. (2021) proposed a deep learning-based method to improve lesion segmentation. Militello and his team also used a semi-automatic segmentation approach, integrating clinical information to improve tumor segmentation accuracy Militello et al. (2022). These new methods emphasize the growing importance of advanced segmentation approaches for improving lesion detection and characterization in breast cancer.

Shape, size, texture, edge features, vascularization, and kinetic features are distinguishing characteristics of malignant tumours in breast cancer feature extraction (Agner et al., 2011; Fusco et al., 2016). For example, Hirra et al. (2021) investigated the use of shape and texture features to characterize breast tumors, extracting these distinguishing characteristics using deep learning techniques. Similarly, sutton and colleagues used morphology-based features to distinguish breast tumor types, incorporating multiparametric MRI data to improve accuracy Sutton et al. (2015).

In a similar manner Moura and Guevara López (2013) used texture and edge features to character-

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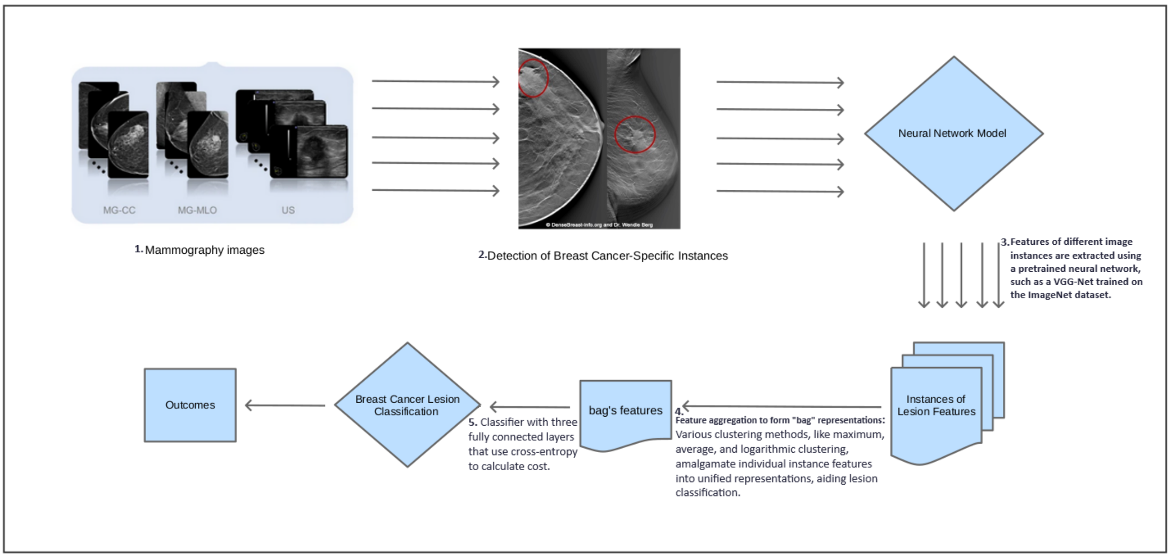

Figure 1: Proposed system for Lesion Detection and Classification in Breast Mammography Images.

ize breast tumors, employing geometric transformations to generate new discriminating features. Furthermore, Agner et al. (2011) used dynamic kinetic features extracted from dynamic imaging sequences to determine the malignancy of breast tumors. These approaches emphasize the importance of extracting specific features from breast tumors and using a variety of techniques to better differentiate malignant tumors.

The morphological, statistical, and textural features of tumors in mammographic images are extracted and classified using various classification algorithms. Most existing breast cancer decision support systems have three steps: identify tumor candidates in images, extract features from each tumor, and classify each breast tumor as negative or positive. These methods rely on fully supervised learning, which necessitates tedious manual annotation of object locations in a training set. Furthermore, there are no publicly accessible mammography datasets with annotated tumors.

Because tumors are small in comparison to the image size, and there are numerous artifacts in mammographic images, classification of the image set yields poor results. To address these limitations, we proposed a recent approaches, based on transfer learning to improve mammography image classification.

The rest of this article is organized as follows: Section II describes our method, while Section III presents experiments and results. Section IV is devoted to discussions and conclusions.

2 BREAST CANCER LESION DETECTION: MIL APPROACH AND LEARNING TRANSFER

This section presents the Multiple Instance Learning (MIL) formulation, defines learning transfer, and outlines the proposed system structure.

A) MIL.

MIL aims to learn $f : X \rightarrow Y$ using a training data set $D = (x_1, y_1), \ldots, (x_m, y_m)$, where $X_i = x_{i1}, \ldots, x_{im}$. X is referred to as a bag, while $X_{(j1,\ldots,m_i)}$ represents an instance. The number of instances in X_i is denoted by m_i, and $y_i \in Y = \{Y, N\}$. X_i is a positive bag, which means that $y_i = Y$ if there is a positive x_{ip}, whereas $p \in \{1, \ldots, m_i\}$ are unknown. The goal is to predict labels for unseen bags. In the case of breast cancer, this method could be used to learn how to identify and characterize lesion features from mammographic image datasets. These lesions could be referred to as "bags," and the features to be extracted would be the "instances" of these bags.

The basic idea behind MIL is to assign class labels globally, rather than individually to each instance. This implies that if a bag contains at least one positive instance (such as a region with a lesion), it is considered positive. When using MIL to classify breast cancer lesions, bags may represent complete mammographic images, while instances may represent regions of these images that could contain lesions. The features of these instances are then aggregated to create bag representations, and the bag is classified according to these aggregated representations.

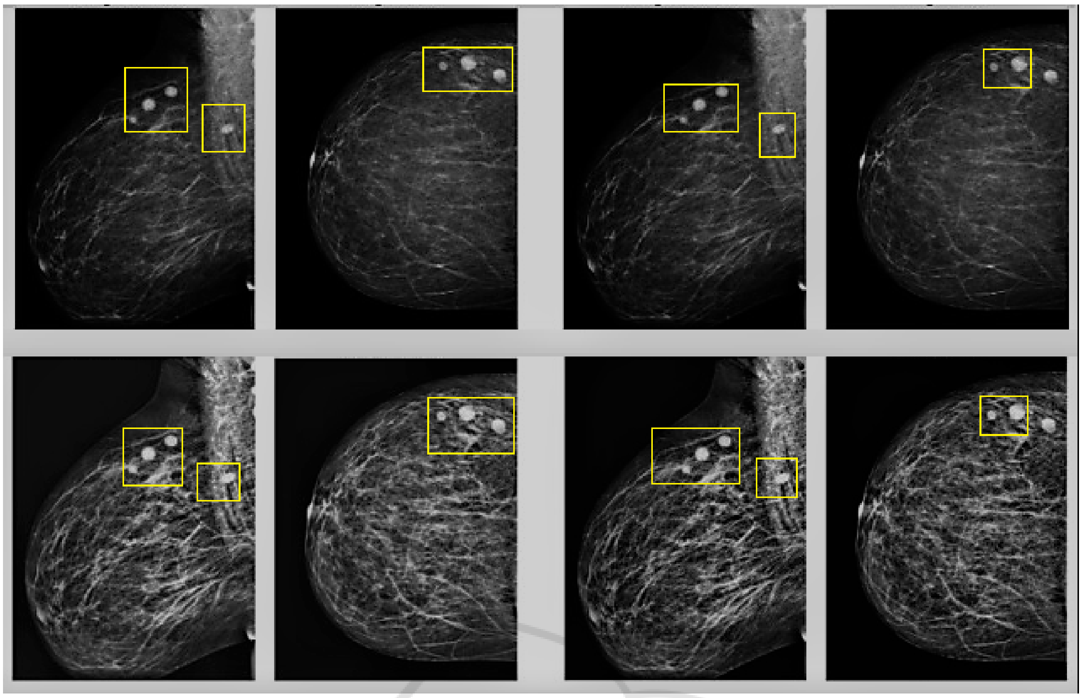

Figure 2: Breast region segmentation and instance identification.

B) Learning Transfer.
In recent years, deep convolutional neural networks (DCNNs) have quickly become the preferred methodology for medical image analysis. However, robust supervised training of a DCNN necessitates the use of a large number of annotated images Papandreou et al. (2015). Transfer learning entails using pre-trained networks to avoid the need for large datasets in deep network training Marcelino (2018); Baykal et al. (2020). In medicine, two learning transfer strategies have been used: the first uses a pre-trained network as a feature extractor, and the second refines a pre-trained network using training data. In the breast cancer context, transfer learning could be applied to pre-train neural networks on large datasets of general images, and then adapt these models to analyze mammographic images more specifically. This would make it possible to use and adjust features learned from big data to enhance the detection and identification of lesions in breast cancer images.

C) Proposed System for Lesion Detection and Classification.
Our proposed system, illustrated in Figure 1, outlines the learning structure. First, mammographic images are used for segmenting the breast region. The image is then split into a number of smaller regions. In our case, an image can be thought of as a bag, and the regions extracted from it as instances. We then use a pretrained network to learn these instance features, and a clustering layer to aggregate these instance scores into a score for the whole bag. Finally, we initialize the classification layer with random weights and set it up for mammography image classification.

This approach can be tailored to breast cancer by segmenting relevant areas of breast images, extracting features from regions of interest and using a pre-trained neural network to classify and identify relevant features of lesions or tumoral tissues.This would result in an efficient system for automatically analyzing mammographic images in order to detect and characterize abnormalities associated with breast cancer.

a) Breast Cancer Segmentation.
Firstly, threshold segmentation is employed to detect the breast area, followed by morphological processing to eliminate noise.

b) Instance Identification for Breast Cancer Lesion Localization.
The mammographic images are divided into several parts based on the segmentation results of the breast region. Each part is treated as a bag, with each area acting as an instance within the bag. Figure 2 illustrates the breast region segmentation and instance identification.

c) Feature Extraction for Lesion Detection.
To extract fixed features, we employ a VGG-Net that has already been trained on the ImageNet dataset. We

Table 1: Comparison of Breast Cancer Detection Algorithms.

Approaches	Accuracy	Precision	Recall	AUC
ResNet	0.8323	0.7750	0.8611	0.8323
VGG	0.7688	0.7648	0.8056	0.7758
Mean MILIL	0.8472	0.8049	**0.9277**	0.8333
Max MILTL	**0.9182**	**0.8260**	**0.9277**	**0.9277**
Log MILIL	0.8790	0.8039	0.8789	0.8867

commence by extracting features from each instance using the feature extractor, and then utilize a clustering layer to aggregate these instance features into a bag. The proposed system explores three clustering methods: maximum clustering, average clustering, and logarithmic clustering.

d) Classification of Cancer Lesions.

For classification, we construct a classifier with three fully connected layers that utilize cross-entropy to calculate cost. These steps are adapted to analyze mammographic breast cancer images specifically by identifying relevant regions, extracting significant features, and using a pre-trained network to classify and select relevant lesion or tumor tissue features.

3 EXPERIMENTS AND RESULTS IN BREAST CANCER DETECTION

A) Materials.

The mammography data used in this study consist of 78 cases from The Cancer Imaging Archive (TCIA), comprising 41 cases with lesions ranging in size from 5 to 9 mm and 37 cases with at least one lesion measuring 10 mm or larger. Each patient case includes two images, one in front and one in profile, totaling two positive images (with a lesion). We also randomly selected an equal number of negative images from cases where no lesion was found.

Although our data case is limited, it still has relevant features for our research on detecting breast cancer lesions. It's curcial to consider that our dataset may not be fully representative, and that the results of our study may be influenced by its specific composition. As researchers, we have taken numbres steps to minimize the potential biases associated with using this dataset. For example, we use a ten-point cross-validation method to assess classification results and reduce the risk of assessment bias. In addition, 10 iterations were carried out to thoroughly evaluate the statistical results of our study. All these steps allowed to improve the consistency of our results.

B) Experimental and Evaluation Setup.

In this section, we conducted two comparative experiments with the VGG-16 and ResNet50 pre-trained networks, respectively. These models are available through the TensorFlow model repository. We utilized a ten-fold cross-validation method to evaluate classification performance and mitigate evaluation bias. Our study's evaluation metrics include accuracy, precision, recall, and AUC. Additionally, we conducted 10 trials to assess the statistical results.

C) Results.

Table 1 indicates that the models we constructed outperform the existing VGG-16 and ResNet-50 pre-trained networks. Furthermore, MILTL with a maximum clustering layer outperforms the other two methods, with an accuracy of 0.9182 and an AUC of 0.9277. These findings demonstrate the efficacy of the developed methods, which were specifically tailored for the analysis of mammographic images for breast cancer. They emphasize the importance of using specialized methods to enhance classification performance in this context.

4 CONCLUSION

Multiple Instance Learning (MIL) provides an excellent framework for classifying mammography images. In this work, we propose a new approach for the automatic detection of breast lesions using mammography. The method includes breast region segmentation, instance identification, feature extraction, and classification. Because of the nature of the MIL method, breast region segmentation does not necessitate precise segmentation results, which undeniably simplifies and saves time for lesion detection. Our method allows for improved classification accuracy. In the future, we will focus on the probability relationship between the bag and the instances to ensure instance labeling, especially for positive instances.

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