Breast Nodule Classification: Single-modality Feature Mining and Multi-modality Information Fusion

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Abstract. Breast nodules are a significant early imaging manifestation of different breast diseases, especially malignant breast tumors. Accurate detection of them is important for the early diagnosis and intervention of these conditions. Presently, automatic detection techniques for breast nodules are classified according to the number of data types used in training into methods relying on single - modality data and those using multi-modality data. This paper gives an overview of the current status of single - modality and multi - modality methods in order to find safer and more efficient paths for the development of automatic breast nodule detection techniques. The analysis shows that methods based on single - modality data should focus on improving feature extraction, which the model does best. On the other hand, approaches using multi-modality data can make use of research from single - modality data to improve both the quality and quantity of models and fused data.

Keywords: Breast Nodule Classification; Single-modality; Multi-modality.

1 Introduction

One of the most frequent breast problems in women is breast nodules, which may be either benign or malignant and some nodules are closely related to breast cancer [1]. The last few years have seen breast cancer emerge as a significant disease that has posed a severe threat to the health of women across the globe and its prevention and control situation has been deteriorating. Breast cancer has since 2020 become the most commonly diagnosed cancer globally, with more than 2.26 million new cases and about 685,000 deaths in that year alone, representing about 11 percent of all new cancer cases worldwide and being the number one cause of death among women due to cancer [2]. At the same time, according to the World Healthy Organization, there are variations in incidence and mortality rates of breast cancer between countries because of their levels of development [3]. High Human Development Index (HDI) countries record much lower mortality rates following diagnosis than low HDI countries. One important approach to decreasing the incidence rates is improving breast health screening technologies [3].

Breast ultrasound is one of the most common clinical screening procedures that is currently used in the initial screening of breast diseases because it has the benefits of being fast, inexpensive

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and does not involve radiation [1, 4]. It is sensitive to abnormalities like breast nodules and is especially well suited to dense breast tissue, which makes it particularly applicable to young women [1, 4]. Moreover, mammography is the best modality in screening microcalcification-type lesions in the breast [1, 4]. Combined X-ray and ultrasound scans can be performed on women aged over 40 years old to avoid calcific breast cancer, which is very common [1, 4]. As medical imaging data volumes continue to grow, Computer-Aided Diagnosis (CAD) technology has made substantial progress in identifying and categorizing breast diseases. Nevertheless, the current approaches have some weaknesses in terms of the modeling capacity of fine-grained features using single-modality data techniques, as well as in the compatibility and generalization performance of data fusion using multi-modality data techniques, which requires further investigation and enhancement [5].

To investigate safer and more convenient paths of the evolution of breast nodule detection and classification techniques, this paper surveyed the research on breast nodule classification strategies that use deep learning algorithms on single-modality data or multi-modality data. According to the research, single-modality studies must be aimed at investigating the compatibility between the model and the extracted features and ways of enhancing accuracy. Conversely, studies founded on multi-modality ought to concentrate on assessing the effectiveness of information fusion in testing and how it can be used to obtain better results. The analysis provided in this study may be used as a source of further studies concerning automated breast nodule detection technology.

2 Basic information

A breast nodule is a focal mass of abnormal tissue that has relatively distinct margins with the surrounding glandular tissue on imaging or physical examination. It usually develops in close connection to endocrine regulatory imbalance, especially the relative rise in estrogen and lack of progesterone, which can result in an irregular growth of breast tissue and therefore the formation of nodular masses [1]. Some of the common causes are hormonal imbalance, erratic lifestyle, suppression of emotions, and family history [1]. Breast nodules in clinical practice are often graded according to their imaging features, which are usually evaluated through a classification system that grades them between levels 1 and 6 in terms of risk of benignity or malignancy. Nodules at level 1-3 are predominantly benign or tend to be benign lesions, whereas nodules at level 4 and above show a very high probability of being malignant, with some already showing suspicious or definite malignant characteristics [1]. Pathologically, benign breast nodules consist mainly of soft-textured hyperplastic nodules of the breast, fibroadenomas of the breast with well defined borders and good mobility, and fluid filled breast cysts, among others; whereas malignant nodules consist mainly of types such as ductal carcinoma in situ (DCIS) and lobular carcinoma in situ (LCIS) [1].

3 Breast Nodule Classification Based on Single-modality Data

Classification of breast nodules on the basis of single-modality data is a research that uses only one type of data, which is easy and effective to process. But since the information is limited, it is hard to fully represent the nature of the nodules.

Ferreira et al. performed a comparative analysis of six advanced networks to solve the problem of the absence of publicly available standards and evaluation comparisons in convolutional neural network-assisted diagnosis of breast ultrasound nodule classification. This research provided a basis for testing the classification of breast lesions. It compared six models, GoogLeNet, InceptionV3, ResNet, DenseNet, MobileNetV2, and EfficientNet, using various data variants of the same dataset, which assessed the effects of data variants on the experiments as well as the performance and benefits among the models on several metrics. According to the experimental results, lesion input data with thin background boundaries are the most effective ones that help the model reach optimal performance, where EfficientNet has achieved the highest results of 97.65% accuracy and an AUC of 96.30% [5].

Xue et al. proposed a CNN with GGB, named GG-net, to address issues in breast ultrasound image lesion segmentation such as inconsistent lesion region intensities, speckle artifacts, and blurred boundaries. This method processes information in an end-to-end manner by first using a CNN to generate feature maps at multiple spatial resolutions. The receptive field of the features is then enhanced through ASPP, while the BD module in the shallow CNN layers facilitates the learning of numerous breast lesion boundary maps, resulting in improved boundary segmentation outcomes. The experiment demonstrated the superiority and effectiveness of the method on two related datasets, improving the segmentation of lesions in breast ultrasound images [6].

M Latha et al. solved the problem of decreased accuracy in CNN detection due to class imbalance and texture differences between some breast tumor types by introducing a technique that would improve the performance of the EfficientNet-B7 model using data augmentation methods. The method involves increasing the data set first, then classifying it with EfficientNet-B7, having higher robustness, and finally combining Grad-CAM to improve the predictive capabilities of the model. This technique has recorded outcomes in the classification of breast images that were way beyond those of modern CNN-based models, reaching an exceptionally high level of 99.14 percent accuracy, which increased the credibility of diagnosis assisted by models [7].

4 Breast Nodule Classification Based on Multi-modality Data

The multi-modality data-based Breast Nodule Classification is different from the single-modality data-based classification in that it combines various sources of information, which allows a more thorough assessment and provides more accurate results. It however, has challenges in the complexity of processing information and the difficulty of acquiring heterogeneous modality data that are well-matched.

Alom et al. suggested a deep neural breast cancer detection (DNBCD) model to solve the common problems of insufficient accuracy and interpretability in automated breast lesion detection using deep learning algorithms [8]. The model is based on DenseNet121, integrating various CNN layers including Dropout layers, and multiple preprocessing techniques like image normalization [8]. Grad - CAM is used by it to provide interpretability for predictions, so as to create a highly explainable AI framework that works with both histopathological images and breast ultrasound images [8]. This method showed its superiority and efficiency on the B-400x and BUSI data sets, achieving a classification accuracy of 93.97% on B-400x and 89.87% on BUSI, showing more potential and value for development than contemporary approaches [8].

Cruz-Ramos et al. suggested a system of breast cancer diagnosis that could be simultaneously adapted to mammography and ultrasound images, which solves the problem of deep learning feature dependency that is inclined to ignore medical knowledge and poor generalizability of handcrafted features [9]. The system uses CNN architecture in conjunction with conventional approaches to extract deep learning as well as handcrafted features [9]. It subsequently combines and optimizes these features by concatenation, genetic algorithms (GA), mutual information (MI), and others, allowing the identification and categorization of any two data sets of this kind [9]. The system performed well on mini-DDSM and BUSI datasets where it had an accuracy of 97.6% and precision of 98%, which is highly competitive and has potential applications [9].

Liu et al. suggested the FAMF-Net model to resolve problems caused by asynchronous image acquisition, poor interpretability, and class imbalance in the multi - modality fusion method of B-mode ultrasound and shear wave elastography (SWE) [10]. The model combines RAA, MAF, and RDO. It completes feature alignment and fusion using translation and cross - attention mechanisms [10]. It then dynamically optimizes the loss function weights to solve class imbalance and designs ablation experiments to show the modules' effectiveness [10]. This method showed its effectiveness and accuracy on a private multi - modality breast dataset from the Huazhong University of Science and Technology Union Shenzhen Hospital Ultrasound Department and the US3M dataset from Kaggle [10]. It performed well under extreme data imbalance conditions, getting an accuracy of 95.890.87% and a sensitivity of 81.825.75%, among other good metrics [10].

5 Limitations and Future Prospects

The single-modality data-based models have faster detection rates and cheaper training costs, with high feature extraction abilities that are specific to certain data types [5, 6]. Nevertheless, because of the shortcomings of single-source data, these models tend to reach optimal performance only in cases where lesions possess a specific property, which makes it hard to adapt them to a broad range of medical lesion images [5]. Though multi-modality data based models are more comprehensive than those based on single-modality data in terms of detection, they are less accurate because of ineffective fusion between different data types and imbalance of data categories [8, 9]. Moreover, this leads to a lower cost-effectiveness of training due to the challenge of collecting data sets [8, 9]. In future studies, the model approaches using single-modality data need to be aimed at investigating the compatibility of the models and data types, filtering the appropriate models according to the features of each dataset, and improving the ability to extract features out of every kind of data [5]. To decrease the imbalances between the data types, the model approaches relying on multi-modality data should focus on gathering, integrating, and training on a wider variety of imaging data [8, 9]. Moreover, the use and configuration of models must be modified depending on the results of single-modality studies to enhance the quality of the integrated data as well as the efficiency of extracting features out of the combined data [8, 9].

6 Conclusion

Currently, breast nodule detection has become a subject of high interest to most women and automatic auxiliary detection systems of breast nodules have gained more attention. The paper examines Breast Nodule Classification techniques on the basis of Single-modality data and Multi-modality data and compares the benefits and drawbacks of Single-modality and Multi-modality methods. It is analyzed that single-modality data-based detection can only be performed optimally in the case of certain types of data or specific lesion presentation, whereas multi-modality data-based detection has issues related to high difficulty of data fusion, imbalanced quantities of data, and unstable training results, which makes it hard to achieve high accuracy. The research concludes that single-modality data approaches may target the flexibility between experimental models and data types, and multi-modality data approaches may target the balance between data categories, and both may integrate with experiments based on single-modality data to increase the amount and quality of integrated data and model configurations.

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