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BI-RADS-NET-V2 A COMPOSITE MULTI-TASK NEURAL NETWORK FOR COMPUTER-AIDED DIAGNOSIS OF BREAST CANCER IN ULTRASOUND IMAGES WITH SEMANTIC AND QUANTITATIVE EXPLANATIONS

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ABSTRACT: Breast cancer is one of the most prevalent cancers in women nowadays, and medical intervention at an early stage of cancer can significantly improve the prognosis of patients. Breast ultrasound (BUS) is a widely used tool for the early screening of breast cancer in primary care hospitals but it relies heavily on the ability and experience of physicians. To validate our framework, experiments were conducted on a BUS image dataset with BI-RADS annotations from senior and junior radiologists. The results indicated that our proposed framework could improve the inference performance of junior radiologists. Our framework can be applied to all medical-imaging-assisted diagnosis scenarios with diagnostic specifications and has a wide range of application scenarios. Therefore, our proposed knowledge tensor can effectively help reduce the misclassification of BI-RADS characteristics by senior radiologists and, thus, improve the diagnostic performance of breast-ultrasound-assisted diagnosis.

Keywords: knowledge tensor; BI-RADS; generalization inference

I.INTRODUCTION

The incidence of breast cancer is already at the top of the list among women. According to the International Agency for Research on Cancer (IARC), the age-standardized incidence of breast cancer reached 5.2% in 2020 and will continue to grow. Comparatively, breast cancer has a high early-cure rate among all cancers [1]. According to the American Cancer Society (ACS), the five-year relative survival rate of patients with early-stage breast tumors is about 99% after treatment. Once breast cancer progresses to the distant stage, however, the five-year relative survival rate of patients drops to 30% [2], and the pain caused by the lesion itself and medical interventions can have serious negative effects on the patient's body and mind. Therefore, early detection and treatment of breast cancer are essential to improve the survival rate and quality of life of patients and help to increase the life expectancy of women.

In breast cancer screening, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US) are common medical imaging tools [3]. Among them, CT and MRI have high imaging resolution. Still, they are costly and complicated to operate, and the former has radiation, so they are more often used in the diagnosis of middle- and late-stage breast cancer. In contrast, US is low-cost, radiation-free, simple-to-operate, and has a higher diagnostic accuracy for breast ultrasound (BUS) imaging, so BUS is widely used in the screening and initial diagnosis of breast tumors in the early stages [4]. In addition, BUS imaging is also commonly used in postoperative follow-up to follow up on the results of breast tumor surgery [5]. Since BUS images are obtained as reconstructed images from ultrasound signals, radiologists need to interpret the image features based on their knowledge and experience in the field to obtain medical imaging reports of the lesion and give diagnostic opinions. However, the same problems that exist in other US imaging-assisted diagnostics exist in BUS-

assisted diagnostics, i.e., the imaging quality of the US image has a decisive impact on the performance of the assisted diagnosis and is highly dependent on the practice experience and scanning technique of the physician operating the ultrasound probe [6]. In other words, a senior radiologist performing a BUS scan is likely to obtain higher-quality images and arrive at a more accurate medical diagnosis than a junior radiologist.

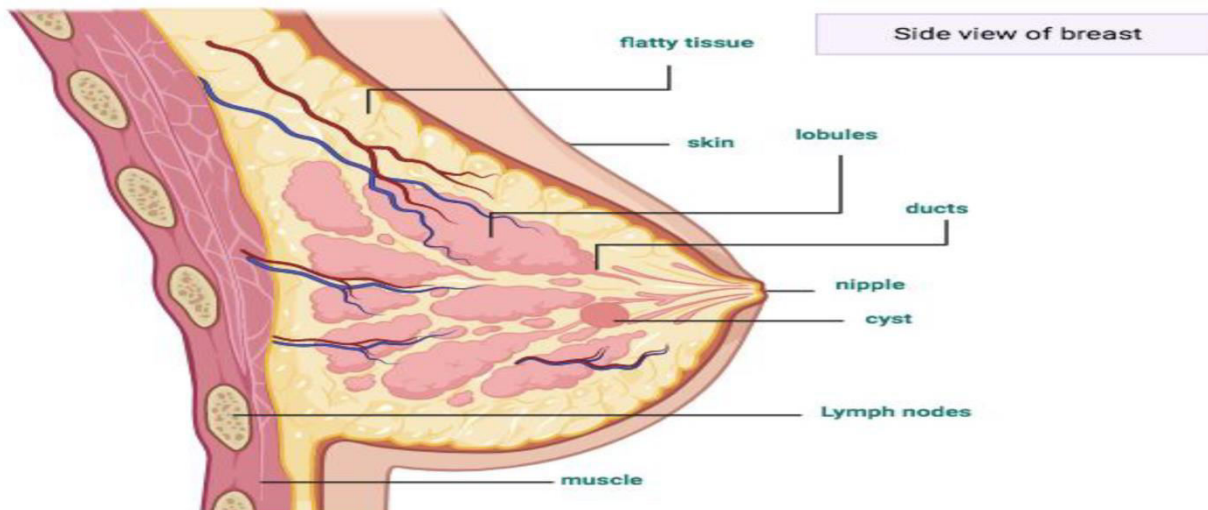


Fig 1: Breast Cancer Imaging

In the field of medicine, to address the influence of subjective factors such as experience and, thus, reduce misdiagnosis and underdiagnosis, doctors try their best to summarize their experiences and form diagnostic protocols to help young doctors improve their abilities as soon as possible. The Breast Imaging Reporting and Data System (BI-RADS) [7], published by the American College of Radiology (ACR), has become one of the main standards for the diagnosis of BUS, and the BI-RADS uses different scores to describe the presentation and significance of a particular feature of a BUS image, thus creating a scoring system that allows the imaging physician to make a comprehensive judgment of the different features of BUS and give a more accurate and objective diagnosis. BI-RADS takes full account of medical experience and knowledge and has strong interpretability, but identifying BI-RADS characteristics is still not an easy task. In addition, the operator's technique, imaging quality, and lesion characteristics on ultrasound also have a non-negligible impact on the auxiliary diagnosis of BUS images [8,9].

II.RELATED WORK

The advent of computer-aided diagnosis (CAD) has greatly eased the workload of radiologists and improved diagnostic performance [10,11]. With the rise of artificial intelligence in recent years, CAD has also introduced deep models to further improve the performance of BUS-assisted diagnosis. However, deep models currently still have certain limitations, such as the need for a large number of high-quality datasets to train models with good performance, poor resistance to noise interference, and end-to-end characteristics that make them uninterpretable. Combining CAD with BI-RADS is a viable approach. Usually, we need high-quality annotation to train high-performance BI-RADS characteristic recognition models. However, obtaining high-quality annotations is usually a difficult task. One possible approach is to train a high-performance BI-RADS characteristic recognition model from existing deep models, but this still requires a significant initial investment in annotating. Moreover, even with valuable medical semantic characteristic data, using them for assisted diagnosis is a difficult problem. Due to the problems of fewer dimensions and fewer data, traditional machine learning models, such as k-nearest neighbors (KNNs) and support vector machine (SVM), as well as deep learning models, are usually unable to effectively mine the information contained in them and are instead very prone to overfitting.

The training samples for KNN are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists of storing only the feature vectors and class labels of the training samples. In the classification phase, k is a predefined constant, and the classification of an unlabeled vector is achieved by assigning the most frequent label of the k training samples closest to that query point. Generally, the classification accuracy of KNN can be significantly improved if the distance metric is learned with specialized algorithms, such as large marginal nearest neighbor or neighborhood component analysis. One drawback of the basic “majority voting” classification method occurs when the distribution of classes is skewed. That is, examples of a more frequent class tend to dominate the prediction of new examples because they are common among the k nearest neighbors due to their large number. The idea of SVM, on the other hand, is to map the data into a high-dimensional space and separate the data by constructing a hyperplane in the high-dimensional space to achieve efficient classification. Usually, the computation in the high-dimensional space is very large, while SVM uses kernel functions to cleverly avoid directly computing the high-dimensional space tensor to achieve nonlinear classification. This allows the algorithm to fit the maximum interval hyperplane in the transformed feature space. The transformation can be nonlinear, while the transformation space is high-dimensional; although the classifier is a hyperplane in the transformed feature space, it can be nonlinear in the original input space. It is worth noting that the higher-dimensional feature space increases the generalization error of the support vector machine, but the algorithm can still perform well given a sufficient number of samples. So, it is important to fully exploit the empirical knowledge of senior radiologists to improve the accuracy of BI-RADS-based diagnoses from junior radiologists.

In this paper, we develop a novel knowledge tensor-aided breast ultrasound image assistant inference framework. We first construct the knowledge graphs with BI-RADS characteristics annotated by senior and junior radiologists, respectively. Then, we map knowledge entities and relations to embedding spaces decomposition is employed to reconstruct knowledge entities and relations to tensors. At the same time, the diagnosis of target entities based on spatial distance could be inferred. Experiments show that the diagnostic performance of the knowledge tensor is significantly higher for senior radiologists than for junior radiologists. By correcting the model with knowledge tensor scores, the corrected knowledge tensor diagnostic performance of junior radiologists is significantly better than the original one. In conclusion, the framework proposed in this paper can significantly improve the performance of BI-RADS score breast tumor assistant diagnosis for junior radiologists, which is important for clinical practice and could improve the generalization performance of the framework.

III.METHODS

In order to leverage the experienced knowledge of senior radiologists, we design a tensor distance-based correction mechanism. For a certain BUS image, a senior radiologist may give a more accurate diagnosis report than a junior one. Therefore, we used the BI-RADS score from senior radiologists as the gold standard to compare the BI-RADS score from junior radiologists for the same BUS images. In the tensor space, we can use the core tensor of the knowledge training of the senior radiologists to correct the core tensor of the knowledge training of the junior radiologists. Hence, we fused the BI-RADS scores of senior and junior radiologists in the training set to introduce a correction bias for improving the performance of inference.

Since tensor-decomposition-based models are sensitive to the positive and negative balance of samples, we used random undersampling and oversampling to balance the positive and negative samples. Unlike traditional structured data or image data, the head tensor of the knowledge tensor is real-named, i.e., the head entity corresponds to a particular case image, and, thus, simple replication of the data in oversampling is not useful for tensor space optimization. In view of this, we simulate more samples in oversampling by generating a fictitious new head tensor as the head entity of the duplicate knowledge.

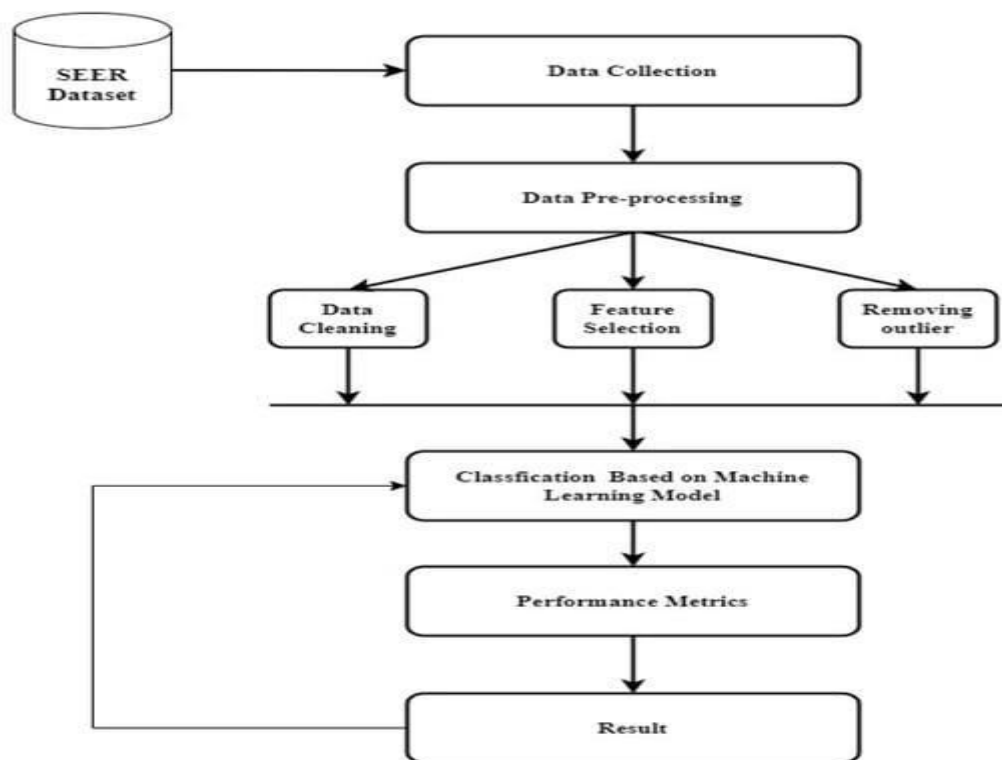


Fig 2: Work Flow

The experimental results corroborate the theory that BUS is highly dependent on radiologists' empirical knowledge. However, it takes a lot of time and financial resources to train a senior radiologist, and each senior radiologist develops from the experience of a junior radiologist. Therefore, we cannot expect to build a better and more standardized system of physician training to solve this problem for the time being. Young radiologists need to keep practicing in order to gain experience. Based on this, our proposed BI-RADS score correction mechanism based on knowledge tensor has a higher practical value. We can use the knowledge tensor decomposition to extract the experienced knowledge core of senior doctors and apply it to the clinical diagnosis of junior doctors so that the precious knowledge of senior radiologists is not limited to a single diagnosis but can be applied to other patient-treatment scenarios in a more generalized way.

IV.RESULT ANALYSIS

However, there are still some problems that need to be solved through further research in the follow-up. First, our proposed framework can only use the high-quality BI-RADS scores of senior physicians to correct the diagnoses of junior physicians, which has some generalizability but lacks greater interpretability, and the BI-RADS scores are already recognized by physicians as a high-quality diagnostic aid with clinical implications [35]. The use of a tensor decomposition model to extract the core tensor somewhat reduces the interpretability of the BI-RADS score itself. Therefore, it would be important to give an interpretable tensor constraint space that maintains the interpretability of medical features while tensorizing them into a generalized model with generalization capability. Second, our proposed framework is limited to correcting the scoring results of junior doctors and cannot help them to improve their diagnostic experience and ability. It would be of better clinical value to construct a differentiated assessment system to help junior physicians identify overlooked features or lack of experience. Finally, our study was limited to the ten most significant dimensional characteristics of the BI-RADS and did not cover all the dimensions of the BI-RADS scoring system. Being able to construct models that cover all dimensions of the scoring system would give our framework better performance and stronger generalization performance.

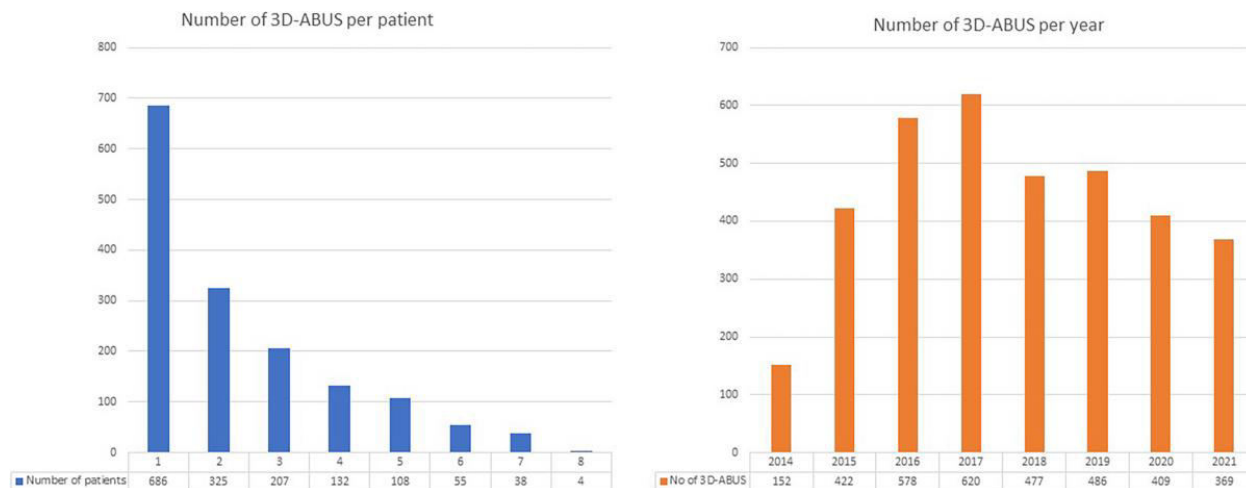


Fig 3: Diagnostic performance of 3D automated breast

The proportion of benign and malignant cases is relatively disparate. Therefore, we used random undersampling to keep the ratio of benign to malignant samples at 1:1. This was because the TuckER model is calculated and optimized based on tensor space distance and, thus, is sensitive to the equilibrium of positive and negative samples, so we balanced the proportion of positive and negative samples. Through undersampling, the number of both benign and malignant images is set at 746 from 826 cases in total. We then utilize five-fold cross-validation to prevent overfitting and, thus, go on to better evaluate the accuracy of the auxiliary diagnosis.

V. CONCLUSION

Considering that breast tumor screening using DM has some consequences and limitations because a higher number of unnecessary biopsies and ionizing radiation exposure endangers the patient's health [12], along with low specificity and high FP results, which imply higher, recall rates and higher FN results [191]. This is why US is used as the second choice for DM. Thus, US imaging is one of the most effective tools in breast cancer detection because it has been shown to achieve high accuracy in mass detection, classification [38], and diagnosis of abnormalities in dense breasts. For the abovementioned reasons, we have addressed using both kinds (DM and US) of images in this review, focusing on different ML and DL architectures applied in breast tumor processing, and offering a general overview of databases and CNNs, including their relation and efficacy in performing segmentation, feature extraction, selection, and classification tasks. Thus, according to the research shown in Table 1, the most utilized databases for DM images are MIAS and DDSM, and for US image classification, the public databases BUSI, DDBUI, and OASBUD are most used. The DM images contributed to 110 and 168 published conference papers for the DDSM and MIAS databases, respectively [5]. However, the databases report some limitations and advantages; for example, the MIAS database contains a limited number of images, strong noise, and low-resolution images. In contrast, the DDSM contains a big dataset.

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