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The Detection of Lungs Carcinoma Using MATLAB

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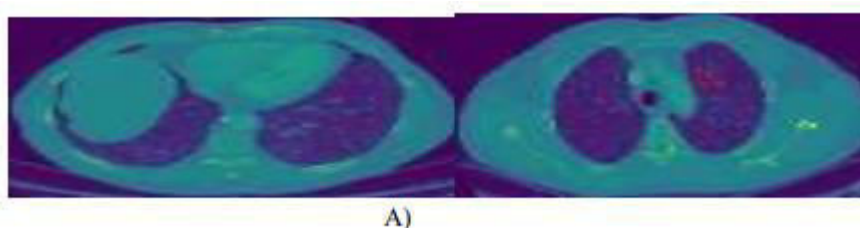
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ABSTRACT: Automatic lung cancer diagnosis from computer tomography (CT) images requires the detection of nodule location as well as nodule malignancy prediction. This paper proposes a joint lung nodule detection and classification network for simultaneous lung nodule detection, segmentation and classification subject to possible label uncertainty in the training set. It operates in an end-to-end manner and provides detection and classification of nodules simultaneously together with a segmentation of the detected nodules. Both the nodule detection and classification subnetworks of the proposed joint network adopt a 3-D encoder decoder architecture for better exploration of the 3-D data. Moreover, the classification subnetwork utilizes the features extracted from the detection subnetwork and multiscale nodule-specific features for boosting the classification performance. The former serves as valuable prior information for optimizing the more complicated 3D classification network directly to better distinguish suspicious nodules from other tissues compared with direct backpropagation from the decoder. Experimental results show that this co-training yields better performance on both tasks. The framework is validated on the LUNA16 and LIDCIDRI datasets and a pseudo-label approach is proposed for addressing the label uncertainty problem due to inconsistent annotations/labels. Experimental results show that the proposed nodule detector outperforms the state-of-the-art algorithms and yields comparable performance as state-of-the-art nodule classification algorithms when classification alone is considered. Since our joint detection/recognition approach can directly detect nodules and classify its malignancy instead of performing the tasks separately, our approach is more practical for automatic cancer and nodules detection.

I. INTRODUCTION

In nature, lung disease plays a major role in health issue. In any form of lung disease mainly the breathing gets affected, here are some common forms of lung diseases. Acute bronchitis, asthma, Chronic Obstructive Pulmonary Disease (COPD), Acute Respiratory Distress Syndrome (ARDS) and Lung cancer.

The undisciplined swelling of abnormal cells, which generally initiate in one or both lungs, mostly in the line of air channel. Those abnormal cells never grow to normal or healthy lung tissue, their rapid production cause tumors. If left untreated, this growth can spread beyond the lung by the process of metastasis into nearby tissue or other parts of the body. Tumors can either be benign or malignant. Lung cancer is also called carcinoma which is type of malignant. A malignant tumor consists of cancer cells which have the ability to spread beyond the original site.



A)



B)

II. OBJECTIVES

Medical imaging allows looking inside the body, without resorting to invasive methods. This technique plays an important role in early tumor (nodule) detection and treatment of cancer. It also guides the physician with information for efficient and effective diagnosis.

III. RELATED WORKS

A. NODULE DETECTION Nodule detection from CT images usually involves two steps: i) nodule candidate proposal and ii) false-positive reduction [30]. The goal of nodule detection is to identify potential nodule candidates from the remaining lung tissues, whereas the false positive reduction aims to suppress potential false positive due to interference from tissues such as blood vessels, etc. TABLE I summarizes some recent works on nodule detection and their performance⁷. Traditional detection methods usually rely on hand-craft features and classic image segmentation methods [31]. Recently, a more extensive dataset LIDC-IDRI is made publicly available. Hence, more sophisticated deep learning based methods can be applied and significantly better performance over traditional approaches in the larger dataset has been demonstrated [13, 32]. In Ding, et al. [33], a 2-D region proposal network, which is transferred from the general image detection framework [10], was proposed and an impressive sensitivity of 94.6% under 15 candidates per scan is achieved. Though a 2-D network generally has fewer parameters than a 3-D network,

5. This may reduce the overall classification rate.

6. This information can be used in say studying the relationship between the CT image features with genomic features in radiomics. it cannot fully utilize the 3-D shape information simultaneously. Therefore, more recent studies [9, 34, 35] tend to adopt 3-D CNN to solve the problem directly. For instance, Khosravan and Bagci [35] propose a 3-D densely connected region proposal network to acquire the region proposals. This densely connected network connects every two layers in the network, while the typical network only connects two successive layers. Therefore, it usually improves the overall performance over normal layer-by-layer connected network, while requiring much fewer parameters than many conventional 3-D networks. Besides the region proposal network, Pezeshk, et al. [8] proposed to segment the nodules from the CT scans directly. Similar pixelwise segmentation has been widely applied to biomedical-related applications, in which the 3-D U-net [36] and V-Net [37] are prevalent network architectures. While segmentation can provide more accurate information than detection only, it is also more involved as more detailed annotation will be required. Since LIDC-IDRI has released the pixel-wise segmentation label recently, training deep networks for nodule segmentation is now feasible, and it can potentially provide more information to the joint detection (segmentation) and classification of lung nodules.

7.

The false-positive reduction is another essential step after nodule detection to eliminate false positive candidates, and 3-D CNN is usually preferred [4, 8, 32, 33] because of their excellent performance. The network usually undertakes a classical classification task, i.e., classifying nodule with non nodule. Furthermore, there is no need to develop an independent network as features can be simply transferred from the detection stage for performing classification. In Qin, et al. [4], the feature from the nodule detection network is directly cropped. As the LUNA 16 competition provides an additional false-positive reduction (FPR) task which labels many possible false-positive nodules, better performance is achieved if a FPR network is trained to refine the detection result. Moreover, it is observed that even if the false positive samples in the detection task are collected without additional labels from FPR task, training their own FPR networks can also improve the result [25, 35].

B. NODULE CLASSIFICATION

Currently, nodule classification is performed either on the patient-level or nodule level. On the patient level, only the binary label for each patient is available regardless of the number of nodules of the patient. Liao, et al. [34] proposed

an end-to-end CADS and won the competition for patient-level lung cancer classification. The nodule-level evaluation is popular because it has an accurate label for each nodule and avoids the variance raising from the multiple instance problem. Indeed, the framework of both levels is quite similar, except for the training strategy.

IV. PROPOSED SYSTEM

We now present our joint nodule segmentation and recognition network (JNSC) and its construction, which consists of the following step: 1) data preprocessing and data augmentation (DPA), 2) multiscale voxel based feature extraction and nodule size estimation (MVFNSE), 3) 8 The choice of a size of "64×64×64" is to avoid possible memory limitation in GPUs, which is a commonly used method. Moreover, the performance degradation is found to be minimal. pseudo-label assignment for marginal samples (PSA), and 4) jointly-optimized nodule segmentation and classification (JNSC). In the DPA step, the training samples are generated from the CT scans data after standard processing procedure. Moreover, additional training samples are generated using data augmentation technique to improve the

V. BLOCK DIAGRAM



VI. EXPERIMENT RESULTS

A. NODULE DETECTION

We first evaluate the performance of the nodule detection performance of our JNSC and other state-of-the-art algorithms on the LUNA16 dataset. The standard ten-fold cross-validation of LUNA16 competition is adopted and the standard evaluation script is used to compute the Free response Receiver Operating Characteristic detection threshold to 0.4 and label the connected regions in the segmentation map based on their voxel connectivity [54]. Then, the region proposals can be extracted from the labelled map, and the center is calculated by the centre of mass of the proposed regions. Lastly, we use non-maximum suppression [56] on the proposed regions and exclude those with diameter less than 3 mm. Figure 5 shows five examples of our nodule detection results with a wide range of nodule diameters.

To visualize the 3-D segmentation result in a 2D figure, we present the cross sections of the nodules as well as the corresponding segmentation maps along the x - y , y - z and x - z planes. It can be seen from Figure 5 that the detected regions are relatively larger than the ground truth. Moreover, as shown in Figure 5 (b), our network can detect tiny nodules while distinguishing the small nodule from other body tissues like vessels. The resolution of CT scans in the z -axis is much lower than the resolution in the x and y -axis. For instance, the resolution in the x - and y -axis is usually 0.7 mm per pixel, but the resolution in the z -axis can vary from 1.25 to 3 mm per pixel. To ensure similar accuracy in the three dimensions, we employ interpolation to convert the resolution along the three dimensions to 1 mm per pixel. The result shows that our network can tolerate the problem of different resolutions and achieve similar performance on the three dimensions.



VII. CONCLUSION

A joint lung nodule detection and classification network for end-to-end lung nodule detection, segmentation and classification subject to possible label uncertainty in the training set has been presented. It operates in an end-to-end manner, which provides detection and classification of nodules simultaneously together with a segmentation of the detected nodules. A 3D encoder-decoder architecture is adopted for better exploration of the 3D nature of the data. The nodule classification subnetwork of the joint network utilizes the features from the encoder output of the detection subnetwork and the multiscale nodule-specific Features boosting the classification performance.

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