Localizing Pulmonary Lesions using Fuzzy Deep Learning

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***Abstract*—The usage of medical images is part of the clinical daily in several healthcare centers around the world. Particularly, Computer Tomography (CT) images are an important key in the early detection of suspicious lung lesions. The CT image exploration allows the detection of lung lesions before any invasive procedure (e.g. bronchoscopy, biopsy). The effective localization of lesions is performed using different image processing and computer vision techniques. Lately, the usage of deep learning models into medical imaging from detection to prediction shown that is a powerful tool for Computer-aided software. In this paper, we present an approach to localize pulmonary lung lesion using fuzzy deep learning. Our approach uses a simple convolutional neural network based using the LIDC-IDRI dataset. Each image is divided into patches associated a probability vector (fuzzy) according their belonging to anatomical structures on a CT. We showcase our approach as part of a full CAD system to exploration, planning, guiding and detection of pulmonary lesions.**

***Keywords*-CNN; nodule detection; fuzzy detection; deep learning; lung cancer**

I. Introduction

According to the statistics of the American Cancer Society [1], in 2019 in the U.S., there will be an estimated 1.762.450 new cancer cases and 606.880 cancer deaths. Lung and bronchus cancer for both sexes occupies the second more frequent with 228.150 new cases, with 62.53% of mortality. Lung cancer takes more lives annually in the U.S. than the next three most common cancers combined.

Only 19% of all people diagnosed with lung cancer will survive 5 years or more, but if it is caught before it spreads, the chance for 5-year survival improves dramatically. For instance, the relative survival rate compares people with the same type and stage of cancer to people in the overall population. Thus, the localized lung cancer, when there is no sign that the cancer has spread outside of the lung, has 60% of survival rate.

The early detection of any possible cancer lung lesion allows the application of a treatment to avoid the lesion gradual expansion. Lung lesions (commonly named as tumors), vary in size, locations and tissue type. Nowadays, the detection and diagnostic of lung cancer are based on CT (Computed Tomography) images which is more effective than plain chest X-ray [2]. These CT images open a possibility to use different software to support and enhance the physicians labour.

Software allows the manipulation of images extracted from a CT. Images could be presented in 2D, 3D and mixed ways to visualize them. The axial, sagittal and coronal called as anatomical planes of the body are a primordial way to present these data. Then, physicians explore a patient over the anatomical planes (or using a 3D views) to locate the possible lung lesions and to extract all key features the most as they can (e.g. exact location, dimensions, tissue type).

The patient image exploration is a process performed before a procedure such as a biopsy, and some cases to detect or classify a lung lesion as benign or malign. Computer-aided detection (CADe) or computer-aided diagnosis (CADx) are systems to assist physicians in the proper interpretation of patient images. Moreover, CADe allows computing values as nodules diameter/volume [3], path to follow from the trachea until a lesion [4], degree of the lesion [5], and more. The amount of data, the precision of a system and the effectiveness in operations rooms are part of an active field of research.

As part of the research in this field, the neural networks arise as a good solution to detection, localization and segmentation of lung lesion structures. Thus, considering that the high variability of lesions shape, size and texture, the classic low-level descriptors fail to capture discriminate features, we propose the usage of a convolutional neural network (CNN) for detection of nodules. In this paper, we present a simple architecture based on convolutional filters for localization of lung lesions in CTdata using belonging probability vectors (fuzzy approach).

This paper is organized as follows: Section II presents a few related works for this research. The full explanation of our approach, including the dataset used and the proposed architecture is presented in Section III. In the Section III details of the experimentation performed are presented. Finally, Section V shows the conclusions and future work on this investigation.

II. Related work

Part of the previous planning consist in the localization of possible pulmonary lesions, called as lung nodules, by physicians. Then, the early detection of these nodules from CT scan is key to improving lung cancer treatment but poses a significant challenge for radiologists due to the high throughput required of them. The detection is also challenging due to the various shape, size, density, and location of the nodules.Studies have adopted machine learning approaches such as segmentation, clustering, Artificial

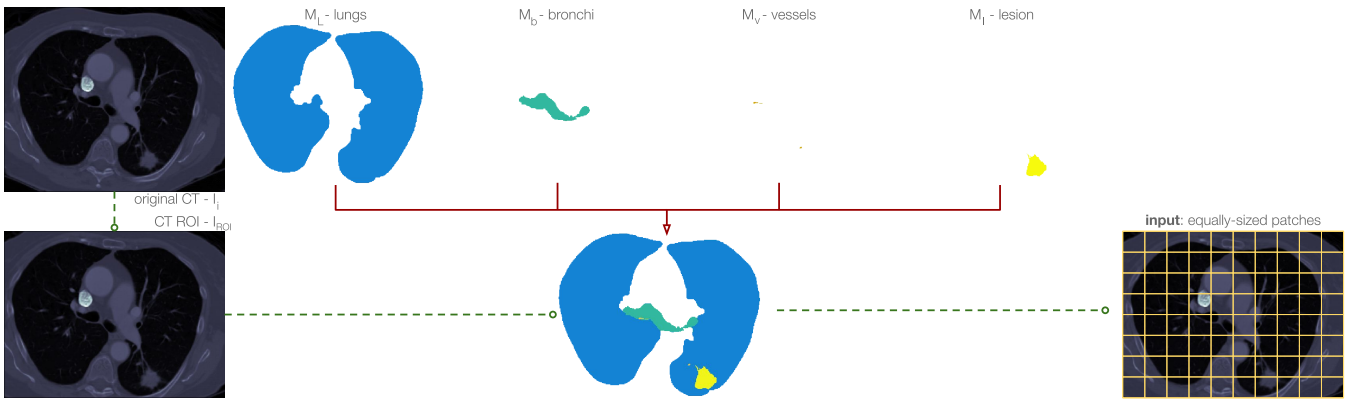

Figure 1. Representation of input for the CNN. Image I_i is aligned to $size$ frontier to I_{ROI}. Masks of lungs - M_L, bronchi - M_b, vessels - M_v and bronchi - M_b are used to compute belonging probability of each anatomical structure on each slice of a CT.

Neural Network and Supporter Vector Machines (SVM) to tackle this problem [6], [7], [8], [9], [10]. As shown in [11], these systems typically use a candidate selection step, which identifies all objects that resemble nodules, followed by a machine learning classifier which separates true nodules from false positives.

In [11] argues that these VBN systems typically use a candidate selection step, which identifies all objects that resemble nodules, followed by a machine learning classifier which separates true nodules from false positives. Indeed, several works are focused on deep convolutional neural network (DCNN)-based approaches for this task [12], [13], [14] also, working together with already existing computer-aided diagnosis systems [15].

As stated in [16], the importance of medical imaging analysis is on the extraction of effective and efficient information to improve the clinical diagnosis. Also, the authors presented a review of the current state-of-the-art in medical image analysis using deep convolutional networks. For instance, some work uses the fuzzy approach for inferences. A remarkable work is presented by Bonanno et al. [17] where they show an approach for rule based methodology into neural networks using fuzzy inference systems. Furthermore, Hosseini and Maryam [18] present a notable proposal to integrate the best features of fuzzy systems and neural networks using an adaptive neuro-fuzzy inference system. Those work represents a clear tendency on mixing different points of view to improve the clinical diagnosis.

III. Convolutional Neural Network

This section covers the explanation of our approach describing the input dataset used and the CNN approach for training and evaluation.

A. Dataset

As part of a deep learning approach, the network requires data to train the model. The selected data were obtained from the Lung Image Database Consortium image collection (LIDC-IDRI) [19] which consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions. This collection, initiated by the National Cancer Institute (NCI), contains 1018 CT cases (124 GB) with their associated XML files with results of a two-phase image annotation process performed by four experienced thoracic radiologists.

However, for this research, we transform the DICOM data to NIfTI file format to save content data (i.e. Hounsfield values). In our approach, the network training for the localization we only consider the data marked, in LIDC-IDRI, as *nodule* $>$ *or* $=$*3 mm* and *nodule* $<$*3 mm*.

B. CNN Architecture

The convolutional neural network (CNN) is a type of neural network mostly used to analyze images. Basically, CNN is a fully connected network (i.e. multilayer perceptron), where each neuron in one layer is connected to neurons in the next layer. This type of network is inspired into the biological process according with the connectivity pattern between neurons in the visual cortex.

Moreover, the convolutional operation involves the combination of input data (feature map) with a convolution kernel (filter) to compose a transformed feature map. The filters are modified based on learned parameters to obtain the most useful information for a specific task. Common tasks for CNNs include: image recognition, image classification, video labelling, text analysis, speech recognition, natural language processing, text classification, virtual assistants, self-driving cars and more.

In this paper, the proposed input CNN consists of a set of 2D images corresponding to non-overlapping patches of each slice of a patient. The squared patches have a dimension of $size \times size$ over the CT data. An image patch joining with a probability vector is the ground truth of the network. The probability vector is composed for the pixel's proportion to belong to an anatomical structure. The anatomical structures

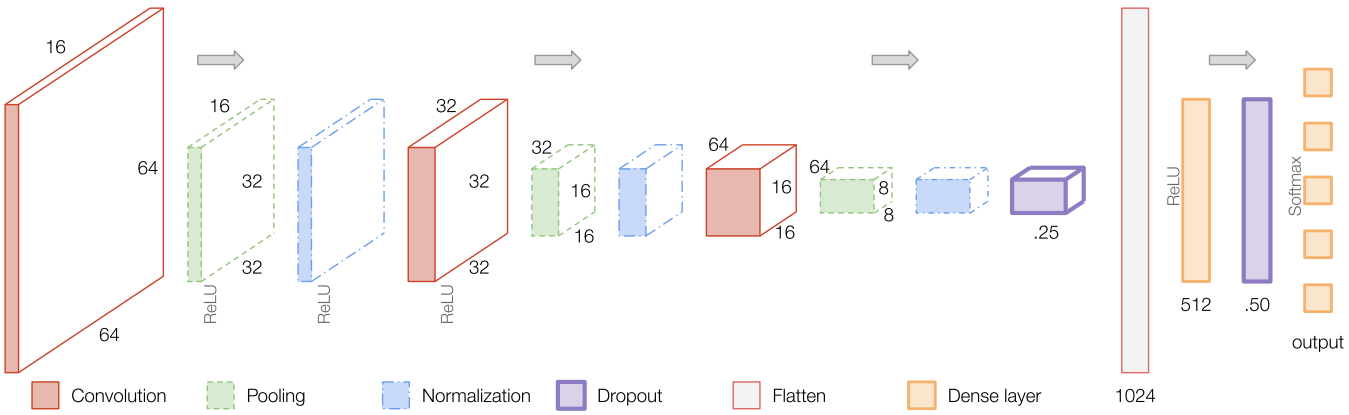

Figure 2. Proposed convolutional network architecture for lung lesion detection.

considered are: background, lungs, bronchi, vessels and lesions.

The defined anatomical structures are separated from other employing volumetric mask. The volumetric masks are created using our own segmentation algorithms. The background is defined as each value different to lungs, bronchi, vessels and lesions, therefore there is no mask for the background. The mask for lungs M_L, the mask for bronchi M_b, the mask for vessels M_v, and the mask for lesion M_l together composing a full mask to label pixel. Those labelled pixels allowed counting them to compute the probability belonging vector on each anatomical structures.

The probability vector specifies a five-vector for each anatomical structure. To compute it, an input image I is divided into equally sized patches of size $size \times size$, and for a patch each pixel is count according which anatomical structure it belongs. Thus, for counting the division (i.e. patches) are achieved over masks images. For instance, Figure 1 shows an image I_i representing the i-th slice of a patient CT. The masks M_L, M_b, M_v and M_l are computed for I_i.

It is importance to notice that no scaling was applied to the CT data. Then, not all time the width and height of image are aligned with $size$. For the aligning, we created a ROI (I_{ROI} shown in Figure 1) to the original CT, and patch computation is performed over the ROI data.

Figure 3 shows a colored representation of I_{ROI} divided into equally sized patches. For instance, the red square represents the belonging probability vector $[0.03, 0.61, 0.31, 0.05, 0.0]$ and green square represents the vector $[0.0, 0.59, 0.0, 0.0, 0.41]$, values for [background, lungs, bronchi, vessels, lesion] respectively.

Different CNN architectures and parameters were tested. We selected a simple and effective configuration taking patches of 64×64 pixels from CT data. The architecture is shown in Figure 2. The convolutional-pooling-normalization layers are composed three times executed in that order, before reducing into 1024 neurons to create an output dense layer with five output.

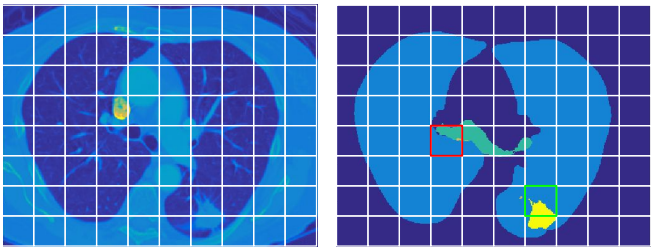

Figure 3. Equally sized patched for colored (Left) CT slice and (Right) masks with 2 marked regions in red and green.

The five-output dense layer uses the *softmax* activation function. We define this architecture to allow change parameters on each layer to suit the appropriate configuration to locate lesions. Also, using the same patch-based dataset, we are focused on other tasks as the classification between medium/small nodules or more than five classes (considering more anatomical structures).

For training and evaluation, the data division was 70/30 from the total dataset in Nifti format. Notice that data should be normalized before enter into proposed CNN architecture.

IV. Experimentation

Aforementioned, the CNN was trained using the data from LIDC-IDRI extracted from [20]. However, our network will be used on patient's data from the Bellvitge Hospital [21] where there are different acquisition devices, image configurations and parameters. With the current architecture using the parameters presented in Figure 2, we obtained an accuracy of 81% on average for training/evaluation.

Then, we evaluated a total of 796 patients, where 557 were used for training and 239 for evaluation. Each patient contains between 2000 to 6500 patches; the lungs occupies the 32-38% of the total, the bronchi occupies the 0.8-3.2%, the vessels the 0.08-0.16% and lesions only the 0.02-0.07%. Also, considering all slices for a patient, the lesions are in

the 2-5% of the total number of slices (for a total number of slices between 100-150 approximately). To balance the input about the lesions to detect, we created sliding windows over the lesions to increase those values.

For obtaining statistical values, we computed the TP (true positive), FP (false positive), TN (true negative) and FN (false negative). The evaluation (i.e. network prediction) obtains a five-vector, where we focus on the last position (lesion value). In this way:

- TP is increased when both lesion prediction and ground truth are positive (presence of a lesion)
- FP is increased when lesion prediction is positive and ground truth is zero (absence of a lesion)
- TN is increased when both lesion prediction and ground truth are zero (absence of a lesion)
- FN is increased when lesion prediction is zero and ground truth is positive (presence of a lesion)

The probabilities allow us to combine with other techniques to determine the best-suited place in a CT where anatomical structures are present.

V. Conclusion and Future Work

In this paper we presented a network architecture for localization of peripheral pulmonary lesions using CT images. The network output contains fuzzy values according to a belonging probabilities value of anatomical structures segmented into CT data. This detection is part of BronchoX [22] to offer an interactive easy-to-use system to improve the diagnosis and exploration of peripheral patient nodules. This could be used in the bronchoscopy planning stage and during an intervention into the operating room.

The CNN architecture offers a flexible way to change the parameters to explore the layers for obtaining the best combination to locate different structures. When the number of filters are increasing as much as deep layer, the obtained features allow discriminated structures. The five-output belonging probability vector is a useful tool to analyze the effectiveness of the network.

The low proportion of lesion pixels present on each CT represent an unbalancing situation between lesions vs. other structures. To avoid this, adding the lesions with different patch sizes or using sliding-window might be a solution. However, this approach could be unfair for a general classification when the same network is used to different structures (e.g. vessels). For the future, we propose different loss functions in terms of probability as L2-norm or categorical cross-entropy.

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