Research of Covid-19 with Different CT Scan Images

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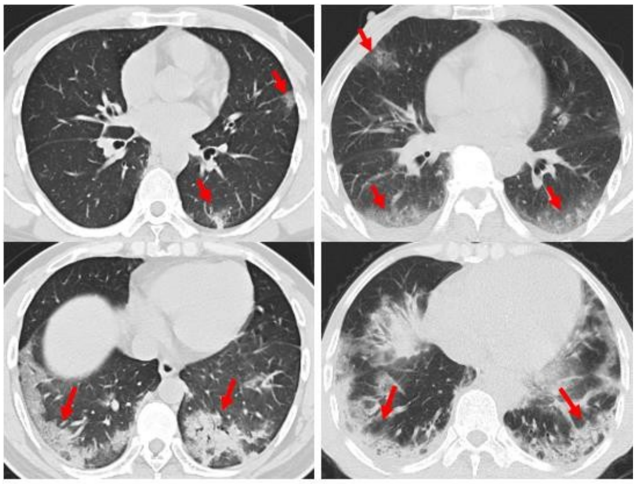
Abstract: We propose a conceptually simple framework for fast COVID-19 screening in 3D chest CT images. The framework can efficiently predict whether or not a CT scan contains pneumonia while simultaneously identifying pneumonia types between COVID-19 and Interstitial Lung Disease (ILD) caused by other viruses. In the proposed method, two 3D-ResNets are coupled together into a single model for the two above-mentioned tasks via a novel prior- attention strategy. We extend residual learning with the proposed prior-attention mechanism and design a new so- called prior-attention residual learning (PARL) block. The model can be easily built by stacking the PARL blocks and trained end-to-end using multi-task losses. More specifically, one 3D-ResNet branch is trained as a binary classifier using lung images with and without pneumonia so that it can highlight the lesion areas within the lungs. Simultaneously, inside the PARL blocks, prior-attention maps are generated from this branch and used to guide another branch to learn more discriminative representations for the pneumonia-type classification. Experimental results demonstrate that the proposed framework can significantly improve the performance of COVID-19 screening. Compared to other methods, it achieves a state-of-the-art result. Moreover, the proposed method can be easily extended to other similar clinical applications such as computer-aided detection and diagnosis of pulmonary nodules in CT images, glaucoma lesions in Retina fundus images, etc.

Keywords: COVID-19, pneumonia, residual learning, medical image classification, deep attention learning.

I. INTRODUCTION

The novel coronavirus (COVID-19) has rapidly spread to most countries worldwide. There have been 4,521,252 confirmed cases all around the world. when, compared to the real- time reverse-transcriptase polymerase chain reaction (RT-PCR), computed tomography (CT) is an effective tool for much faster screening of COVID-19. However, manual screening of COVID-19 from CT images is a time-consuming and labor- intensive task, since doctors must find the lesions from volumetric chest CT scans in a slice-by-slice manner Besides, as shown in Fig. 1, COVID-19 in CT images are similar to other types of viral pneumonia, which makes it hard to manually distinguish COVID-19.

However, developing such a system is a challenging task, because the lesions of pneumonia in CT images have wide variations in appearances, sizes, and locations in the lung regions, as shown in Fig. 1. It seems difficult to design suitable methods to handle the complicated characteristics of the pneumonia lesions using just the classical image processing techniques or conventional machine learning methods that rely on handcrafted descriptors.



(a) COVID-19 (b) ILD

Fig. 1 Lung Regions

In recent years, the development of deep convolutional neural networks (DCNNs) has led to a series of breakthroughs for image classification, object detection and semantic segmentation in the field of natural image processing. These breakthroughs also revealed that deeper models can achieve superior performance. Therefore, it is feasible that training very deep CNN-based models to achieve promising performance in COVID-19 screening. Nowadays, it is very easy to construct robust deep models with more than 100 layers using residual learning blocks. However, some challenges remain and should be addressed when applying the above-mentioned deep learning methods for the proposed COVID-19 screening task. First, it is very hard to collect sufficient samples together with accurately annotated labels to train very deep models in a short time, especially for object detection and segmentation models. Training of these models requires additional meticulous annotations that were manually labeled by experienced doctors. One example is that training most object detection models requires bounding boxes of desired targets, while training segmentation models requires lesion-aware masks. Labeling these annotations is also very time-consuming and impractical to doctors. Second, a volumetric CT scan has three dimensions. The computational cost and memory requirement both increase with 3D inputs. It is infeasible to train a very deep 3D CNN-based model due to the constraint of hardware resources. Third, a perplexing problem is the inter-class similarity and intra-class variation of pneumonia lesions, as demonstrated in Fig. 1. Finally, a lung image infected with pneumonia still contains a large part of non-lesion regions, which also have a wide and complicated variation of tissues. Obviously, the non-lesion regions have great negative impact on the performance. It is much more complicated than detecting objects of scenes in natural images. To address the above-mentioned issues, we propose a novel multi-task prior-attention residual learning strategy for one- stage lesion-aware COVID-19 screening in CT images.

(1) Similar to the residual learning, the proposed strategy is also based on modular designment. The prior-attention mechanism is incorporated into residual blocks. Thus, deep models can be easily built by stacking the PARL blocks and trained end-to-end.

(2) The afore-mentioned issues (i.e., insufficiency of training data, inter-class similarity, intra-class variation, and non-lesion regions of images) are the common challenges in the whole field of medical image processing. Among these issues, the "non-lesion regions" can aggravate the other issues and it is the main obstacle in improving performance, especially under scenarios where the non-lesion regions in medical images have complicated tissue variations.

II. SYSTEM MODEL

The proposed framework for the COVID-19 screening contains two main stages: (a) lobe segmentation using 3D-Unet as a pre-processing step and (b) pneumonia prediction using 3D-ResNets with prior-attention mechanism.

1.Lobe Segmentation

The human lungs are divided into five distinct anatomic compartments called **lobes**. The separating junctions between the **lobes** are called the lobar fissures. The left lung consists **of** the upper **and** lower **lobes**, which are separated by the left oblique or major fissure.

Lung segmentation in CT images is an important pre-requisite step for automatic pneumonia detection. The left and right human lungs are divided into a total number of five lobes (i.e., two lobes in the left lung and three in the right). Previous investigators used UNet or its variants to segment lung regions or lung lobes. Lobe segmentation is more complicated than lung segmentation. However, in clinical practice, lobe information can play a pivotal role as reference for doctors to locate pulmonary lesions and perform their quantitative analysis of the lesions. Hence, it is a basic function in most commercial CAD systems. In this study, we also directly segment lung regions into five lobes.

To achieve this task, we trained a 3D-UNet for lobe segmentation in volumetric CT scans. For a given scan, we first use thresholding and connected-component labeling algorithms to obtain a binary lung mask that indicates the coarse lung regions. Then, we crop a sub-image containing lung regions covered by convex hull of the lung mask, which removes noise outside the lungs, as well as reducing the cost of GPU memory. Finally, we apply the trained 3D-UNet model on the sub-image to obtain its lobe mask.

1.Pneumonia Prediction

After the lobe mask is obtained, we crop refined lung regions according to the lobe mask. The cropped image is then resized to 96 □ 96 □ 96 and fed into the 3D-ResNets for pneumonia prediction.

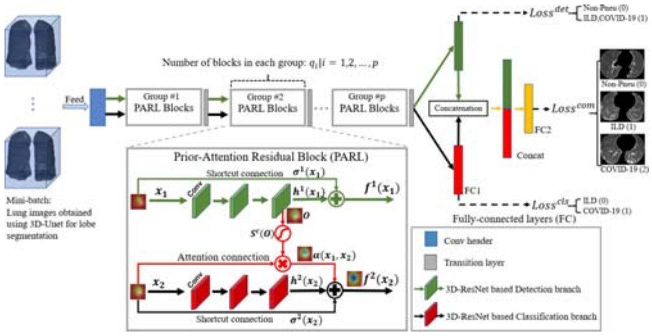


Fig. 2. The architecture of the proposed multi-task prior-attention residual learning strategy.

As shown in Fig. 2, two 3D-ResNet based sub-networks are designed for two tasks: pneumonia detection (as demonstrated with green cubes) and pneumonia-type classification (as demonstrated with red cubes). The detection sub-network is implemented as a binary classifier that can identify whether or not a given CT scan contains pneumonia, while the type- classification sub-network is implemented for binary classification of ILD and COVID-19. The two sub-networks are fused together using an extra fully-connected layer (as illustrated with the yellow rectangle in Fig. 2) for final three- category classification, i.e., Non-Pneu, ILD, and COVID-19. To enhance the COVID-19 screening, the convolutional layers of the two sub-networks are closely combined via a prior- attention mechanism. The inference procedure can be expressed as:

$\boldsymbol{P} = f(\boldsymbol{I}, \boldsymbol{W}_{det}, \boldsymbol{W}_{cls}|S(\boldsymbol{W}_{det}), \boldsymbol{W}_{fc})$ where $\boldsymbol{I}$ is the volumetric lung image that fed into the model f.

$\boldsymbol{W}_{det}$ and $\boldsymbol{W}_{cls}$ indicate the learned convolutional weights of the detection and the type-classification sub-network, respectively. $\boldsymbol{W}_{fc}$ denotes the learned weights of the fully- connected layers. $S(\cdot)$ denotes an attention function. The output

$\boldsymbol{P}$ is a softmax probability vector:

$\boldsymbol{P} = [p^{non}, p^{ild}, p^{cvd}]$,

where p^{non}, p^{ild}, and p^{cvd} are the probabilities corresponding to the three classification categories (i.e., Non-Pneu, ILD, and COVID-19), respectively.

Normally, the lung areas in a CT image contain a large part of non-lesion regions, where complicated variation of lung tissues exist, e.g., vessels and fibers. Obviously, these non- lesion regions have negative impact on the type-classification. To alleviate this issue, we generate soft lesion-aware maps using the convolutional feature maps of the detection sub- network who has remarkable lesion localization ability. The soft maps are then fed into the type-classification sub-network to make it pay attention to the lesion regions. Since the attention information is generated from another model, rather than the type-classification model itself, we call it "prior-attention".

III. PREVIOUS WORK

1.Semantic Segmentation

Semantic segmentation plays important role in the field of pattern recognition. Its main task is to identify all pixels that belong to objects of a specific class in an image. To this end, many DCNN-based segmentation methods have been proposed in literature. Some proposed a fully convolutional networks (FCN) for semantic segmentation in natural images. Convolutional operations are stacked layer-by- layer to extract hierarchical feature maps of an input image. The final layer of the feature maps is then used to generate a pixel- wise probability score map indicating which class the pixels belong to. Upon the FCN, several variants were developed for more precise segmentation.

Recently, DCNN models were also developed for medical image segmentation. In this study, a 3D U-Net was also trained for lobe segmentation as a pre-processing step of the COVID-19 detection.

1.Deep Attention Learning

The performance of a model is supposed to depend heavily on the model depth (i.e., the deeper, the better). To train robust models as deep as possible, many prior works have focused on either collecting large-scale datasets (e.g., the ImageNet database or developing powerful computational tricks, such as the dropout normalizations and "shortcut connections". Among these tricks, the dropout and normalizations can effectively suppress the over-fitting issue. However, the main obstacle in training deep models is the so- called degradation problem. The residual learning technique successfully addresses this issue using residual learning blocks with "shortcut connections". Although these tricks have demonstrated their validity in many applications, it is still a challenge to train very deep models in some specific scenarios (e.g., the field of medical image analysis) due to the complicated application tasks and the shortage of large-scale datasets.

Recently, some works have investigated that the attention mechanism is an effective technique that helps further improve the performance of DCNNs The network is constructed by a cascade of several attention modules. Each module contains a trainable encoder-decoder structure to learn soft attention masks, which are then multiplied to the convolutional feature maps to highlight important information.

Although all the above-mentioned attention mechanisms effectively improve the performance of deep learning models in large-scale natural image classification tasks, they still suffer from a main drawback for medical image classification. Generally, lesions in medical images have the issue of inter- class similarity, intra-class variation and complicated contextual information as discussed in Section I. These attention mechanisms (trained using only targeted lesion. In contrast, the proposed prior-attention mechanism can learn more effective soft-attention maps, since the training is driven by binary classification between lesion images and normal images without lesions. In contrast, the proposed prior-attention mechanism can learn more effective soft-attention maps, since the training is driven by binary classification between lesion images and normal images without lesions.

1.COVID-19 Screening

Some attempts have been made to develop CAD systems for COVID-19 screening in CT images. For example, trained a 2D convolutional neural network (CNN) for three-category classification of CT scans, i.e. COVID-19, community acquired pneumonia (CAP), and non-pneumonia. The network takes a series of CT slices as input and uses the 2D-ResNet50 as a backbone to extract CNN features from each slice of the CT series. The features are then combined using a max-pooling operation and the resulting map is fed to a fully connected layer to generate a probability score for each class. first used a 3D segmentation model, to segment lesion candidates from CT images. Then, the candidates were classified into COVID-19 or Influenza-A viral pneumonia using a 2D-

ResNet18 model.

Although these attempts have demonstrated their validity in COVID-19 screening, some drawbacks remain in clinical application. More specifically, there are many causes of pneumonia such as infections from various types of bacteria and viruses. classified pneumonia into either COVID- 19 and Influenza-A. This classification task is too simple for clinical application.

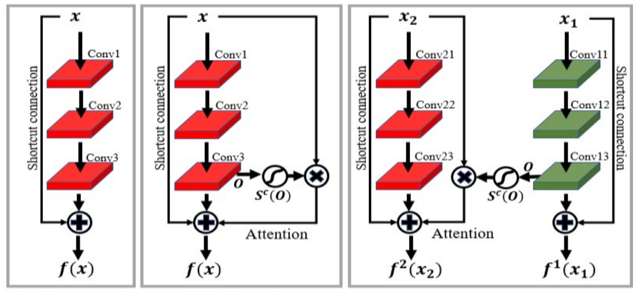
seems more significant in clinical application as their model can distinguish COVID-19 from CAP, rather than just Influenza-A. However, one of the main challenges in clinical practice is identifying COVID-19 from other viral pneumonia types. The CAP cases collected by contain a large number of non-viral pneumonia cases. Therefore, the ability to differentiate COVID-19 from other viral pneumonia types needs further verification. Besides, they trained a single 2D- CNN for classifying non-pneumonia (Non-Pneu), CAP, and COVID-19. This training strategy may fail to learn sufficient discriminative semantic representations for effectively differentiating pneumonia types due to two main reasons: (1) Models trained for multi-class categorization tasks may suffer from the inter-class interference issue. For instance, the Non-Pneu cases inevitably interfere with the training of classification between COVID-19 and other pneumonia types.

(2) A lung image infected with pneumonia still contains a large part of non-lesion regions as mentioned in Section I, which also prevents the improvement of classification performance.

In summary, our contributions can be concluded as: (1) our study focuses on developing techniques for classifying COVID- 19 from other types of viral pneumonia. (2) We directly use 3D CNNs to extract features from the whole 3D lung regions so that richer 3D spatial information can be learned. (3) We conduct experiments to demonstrate that the proposed method can achieve state-of-the-art performance. The main improvement of the proposed method relies on the application of prior-attention mechanism and multi-task training for learning more discriminative lesion-aware representation for the COVID-19 screening.

IV. PROPOSED METHODOLOGY

Network architecture of the 3D-UNet trained for lobe segmentation is shown in Fig. 3. The input image size is 128 □ 96 □ 128 (Z □ Y □ X) and the output size is 128 □ 96 □ 128 □ 6. The six channels of output map correspond to predicted probabilities of six categories, including non-lung regions, upper and inferior lobes of left lung, and upper, middle, and inferior lobes of right lung, respectively. As introduced in Section III-A, to remove most non-lung regions, each scan is pre-segmented using a coarse lung segmentation method. The resulting image has a wider side in the X direction than the Y direction. Hence, we set the anisotropic input size (i.e., 128 □ 96 □ 128) empirically in our implementation to keep the shape and the size of the image as much as possible.

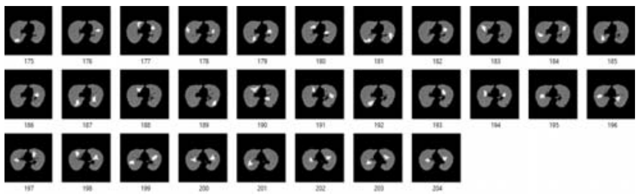


(a) Without-attention (b) Self-attention (c) Proposed prior-attention

During the training stage of 3D-Unet, a mini-batch size of 2 samples were fed into the model. In this study, we focused only on the pneumonia classification tasks, rather than the lobe segmentation task. More details of 3D-UNet and lobe.

Samples collected:

COVID 19:



ILD:

NORMAL:

V. SIMULATION/EXPERIMENTAL RESULTS

This phenomenon demonstrates that the multi-task learning strategy can suppress the inter-class interference issue by splitting the three-category classification task into two binary classification tasks, and thus the performance is improved.

TABLE 1. RESULT

VALIDATION ACCURACY	79.01
LEARNING RATE	0.01

VI. CONCLUSION

In this paper, we presented a novel multi-task prior-attention learning strategy to implement COVID-19 screening in volumetric chest CT images. Specifically, we integrated two ResNet-based branches into one model framework for end-to- end training by designing a prior-attention residual learning (PARL) block. Inside these blocks, hierarchical attention information from lesion region detection branch was transferred to COVID-19 classification branch for learning more discriminative representations. Compared to other methods with self-attention and without attention, our method located lesion regions more correctly so that the extra supervision information is more effective to enhance the performance of COVID-19 classification tasks. Experimental results demonstrated that our method surpassed other state-of-the-art COVID-19 screening methods. In the near future, more efforts will be devoted to exploring how to identify COVID-19 in the early stages and how this prior-attention mechanism can be applied in other medical image analysis problems.

VII. FUTURE SCOPES

OTHER than covid 19, CT scan images can also predict fungus such as black, white and yellow (Mucormycosis) Patients who have recovered from COVID 19 can undergo CT scan test so that at the early stage we can detect harmful upcoming viruses.

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