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A Deep Learning Based Method For COVID-19 Classification Using Chest CT Images

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Abstract—**At the beginning of 2020, coronavirus disease 2019(COVID-19) infection spread in Wuhan, China and all over the world. Until April, it had affected millions of people. The computed tomography (CT) imaging is confirmed as one of the assessment method for COVID-19 patients. However distinguish the COVID-19 from those CT images is extremely challenging as it is very time-consuming, and lack of the experienced radiologists. So deep learning based approaches are proposed to triage the COVID-19 images from the normal or other pneumonia images. Here, we proposed a novel global average pooling (GAP) method for the deep neural network to improve the performance of the COVID-19 classification. The novel GAP method is using lung mask region as weighting factor for GAP, which reduce the influence of background region and highlight the classification features of interesting tissue region. The result of our method achieved the triage of COVID-19 with sensitivity 96.4% and specificity 93.3% on the independence validation dataset with 2062 CT scans.**

Keywords-component; DNN; CNN; Unet; COVID-19; GAP; mask weighted GAP; classification

I. INTRODUCTION

At the beginning of 2020, coronavirus disease 2019(COVID-19) infection spread in China, and all over the world. it is urgent to find an effective and accurate method to triage the COVID-19 patients from millions or billions people. Computed tomography (CT) imaging is a critical tool in the initial screening of COVID-19 pneumonia. However the chest CT images usually is consist of about hundred slices, it is very time consuming for the radiologists visually check whether they are COVID-19 images. Many classification and segmentation algorithms were developed to assist radiologists in COVID-19 identification and severity qualification[1, 2]. Md. Zabirul Islam [3] proposed a deep learning based system that combines the CNN and long short-term memory (LSTM) networks to automatically detect COVID-19 from X-ray images. In the proposed system, CNN is used for feature extraction and LSTM is used to classify COVID-19 based on those features. And it can help doctors to diagnose and treat COVID-19 patients easily. Zhang Li [4], developed a fully automated AI system to quantitatively assess the disease severity and disease progression of COVID-19 using thick-section chest CT images. Le Qin [5], developed a predictive model and scoring system to enhance the diagnostic efficiency for COVID-19, and CT features and scores were evaluated at the lung segment level according to the lesions' position, attenuation, and form. In most of these methods, the severity and disease progression of COVID-19 patients were being assessed, but there were few studies on the classification of COVID-19 versus non-COVID-19. Reference [3] also proposed a method for the early detection of COVID-19 patients, but this method was studied on X-ray images. Compared to X-ray images, CT images are more accurate and authoritative in the diagnosis of COVID-19 patients. Therefore, this study aimed to propose a mask-weighted GAP based deep learning method to triage the COVID-19 patients from chest CT images. We developed one software system to triage the CT scans, and proposed one novel mask weighted GAP method to improve the accuracy of COVID-19 triage.

The following sections introduce the details. Section II describe the dataset information and concrete algorithm for lung segmentation and COVID-19 classification. Section III describe both the quantitative and qualitative experiment results for segmentation and classification. The conclusion and future work is described in last section.

II. MATERIAL AND METHODS

A. Dataset

This study includes 6004 patients, with 10556 CT scans. The concrete dataset information is shown in Table.1. All the COVID-19 data were confirmed as positive by RT-PCR and were acquired from Dec, 2019 to April, 2020. For each patient, one or multiple CT exams were acquired at several time points during the course of the disease. All the data are provided with DICOM series, and all the data tag information are available. We defined the data exclusion criteria which do not use in our training and validation data, a. the contrast scan and b. slice thickness more than 3mm. After the exclusion, there are remaining 9862 CT scans. These remaining CT scans are split into 7800 training data and 2062 validation data. Training data is used for the model training, and validation data is only for validation of the model performance. The dataset comparison information of training and validation from scan point of view is illustrated in Figure 1.

TABLE I. DATASET INFORMATION

	Non-pneumonia	**CAP**	**COVID-19**
Patient count	1807	1803	2394
Scan count	2506	2633	5417

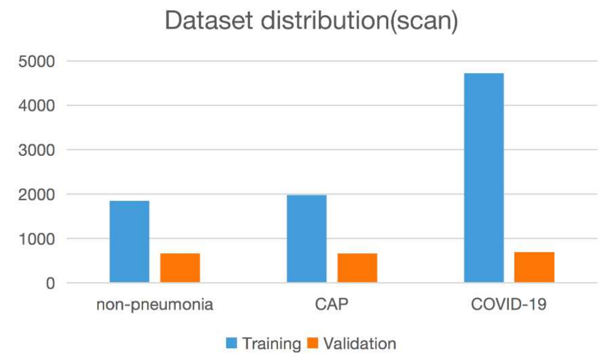

Figure 1. The distribution of raining and validation dataset from scan point of view.

B. *Algorithm Workflow*

COVID-19 triage is a little different problem from common classification problems[6-8], due to the COVID-19 related suspects are all in the lung region area. So these clinical information is much more useful for our triage problem, the entire image is not needed, only the lung region area classification is enough. The whole work flow chart of the COVID-19 triage algorithm is illustrated as in Figure 2. After input the DICOM series and related labels, there are three major steps to do. Firstly, do resampling the CT volume to isotropic volume. Secondly, do segmentation of the lung region. Thirdly, according to the lung region mask and CT image use deep neural network to do COVID-19 classification. The three steps will be introduced in the following sub-sections C, D and E. Sub-section F is the proposed novel mask weighted GAP method for classification. Both the training image and the testing image are processed by the same three steps.

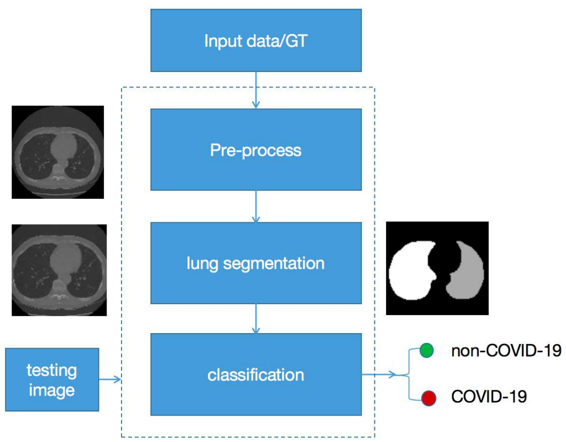

Figure 2. Workflow chart of the whole COVID-19 triage algorithm

C. *CT image preprocessing*

The preprocessing step is majorly to do image resampling to obtain the isotropic volume, which the pixel spacing between x, y and z direction are the same. To avoid the large memory usage, the isotropic CT volume is also downscaled to the size 128x128x128. This preprocessing will convert the data with different CT scanning parameters to the same condition, and it will be suitable for the next step lung segmentation and COVID classification.

D. *Lung segmentation*

The lung segmentation is based on the convolutional neural network(CNN) method using unet model[9-10]. The model network is described in Figure 3. There are two paths in the network. The left path is to encode the image features and the right path is to decode the features and localize the target tissue. The left contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3x3 convolutions,each followed by a rectified linear unit (ReLU) and a 2x2x2 max pooling operation with stride 2 for down-sampling.Every step in the expansive path consists of an up-sampling of the feature map followed by a 2x2x2 convolution that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. Here the input of our 3D unet model is the output of pre-processing step in sub-section C, which is the re-sampled iso-tropic volume with size 128x128x128. The output of 3D unet model is the segmentation mask of lung region. The training data for lung segmentation are open dataset named LUNA16[11],which could be accessed in LUNA16 website. LUNA16 have 888 lung volume data,with a slice thickness greater than 2.5 mm.

however here for segmentation, 300 volume data are selected for training and 30 volume data for validation. Considering the application scenario, roughly lung segmentation is enough for COVID-19 classification, so suitable size 128 is selected for training to reduce both the GPU memory limitation and the training time.

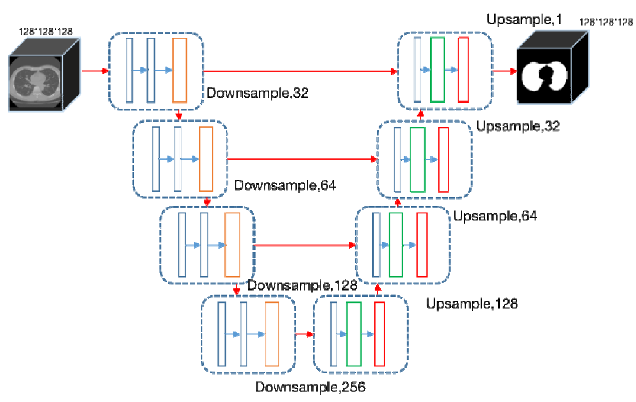

Figure 3. Unet network for the lung region segmentation.

E. *COVID-19 classification*

Residual Networks(ResNets)[12-15] achieved the state-of-the-art performance award at the ILSVRC 2015 for classification, localization, detection, COCO detection as well as segmentation tasks. COVID-19 classification method is based on the ResNet50, which is illustrated in the Figure 4. There are 49 convolution layers in the network and the residual connection to enhance the features in the deep layers.

The conventional residual network is using for one image classification. However our inputs are one serial of images, there are two ways to use these three dimension CT images. one is using 3D convolution, and modify the original ResNet to 3D ResNet, and the other is to use 2D convolution for the serial of images, and combine several 2D output features. Here we adopted the second method, considering the sparse information of COVID suspect and the large memory usage of 3D convolution. The ResNet model of one image will output the feature with size [2048x7x7] before fully connection layer. That means the original input image with 224x224, after ResNet, will obtain the output features with size[7x7]. One common way to handle the 7x7 block to obtain one value for classification, is global average pooling, which will introduce in next subsection.

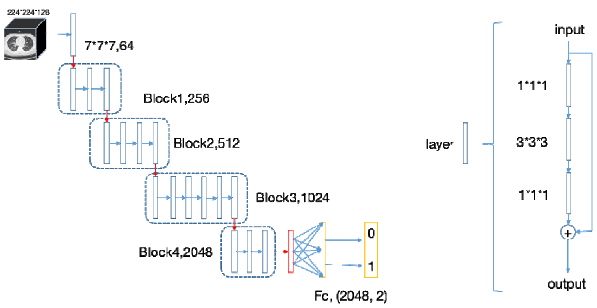

Figure 4. Resnet50 for COVID-19 triage based on CT images. The matrix is indicated the volume size, the last number is the channel number.

F. *Mask weighted GAP*

Conventional convolutional neural networks perform convolution operation in the lower layers of the network, and concatenation of the last convolution layer's feature map to the fully connected layer followed by a softmax logistic regression layer for classification[16]. This structure bridges the convolutional structure with traditional neural network classifiers. It treats the convolutional layers as feature extractors, and the resulting feature is classified in a traditional way. However the fully connected layers have much more parameters, global average pooling(GAP) layers are proposed in[17]. General global average pooling is to calculate the mean value of the entire feature image. The difference between fully connected layers and GAP layers is as illustrated in Figure 5. Fully connection layer maps all the pixels as the input for classifier, GAP maps entire image as one pixel as input for classifier. So the number of parameters and model complexity are reduced a lot.

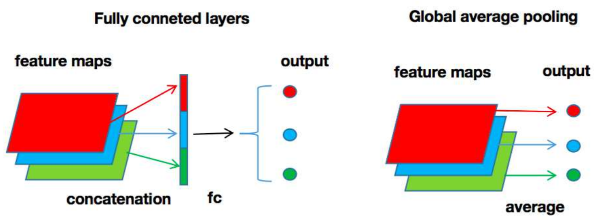

Figure 5. Comparison between fully connection and GAP

In medical image, the pixel is related to the concrete clinical structure, so the average pooling with the different weight factor according to the different tissue will be useful to reduce the inference of background noise. Here we use the segmented lung region mask to reduce the non-lung region inference for the COVID classification. As introduced in lung segmentation and the pre-processing of classification, we proposed the mask weighted GAP, as illustrated in Figure.6. Due to all the COVID-19 effected suspect region will be in the lung region, so we will only consider the feature map in the lung region area. When do global average pooling operation, only calculate the lung region in 7X7 block from last convolution layer in ResNet. Just as the right sub-figure shown, most features out of lung region are black, and features in lung region are significant. So lung mask weighted GAP could improve the sensitivity of suspect features contribution.

The mask weighted GAP calculation is illustrated in (1), $I_{feature}$ is the output feature image from last convolution layer of resnet50, $I_{smoothedmask}$ is the lung mask region, which is downscaled to 7X7 and followed by guassian smoothing, at last normalized summation of all the pixel value to 1. Conventional GAP is to obtain the average value of $I_{feature}$, however the weighted GAP is to combine the different weight from $I_{smoothedmask}$ and $I_{feature}$ to obtain the final value of $I_{featureweightedGAP}$.

$$I_{featureweightedGAP} = \sum_{i=0}^{i=7}\sum_{j=0}^{j=7} I_{smoothedmask(i,j)} \times I_{feature(i,j)} \qquad (1)$$

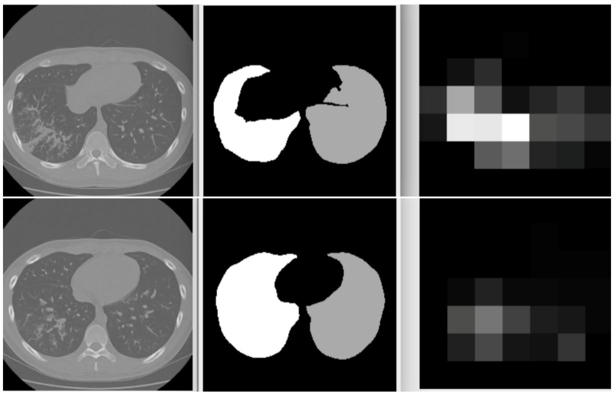

Figure 6. Mask weighted GAP with two different slices with and without suspect. The left is original image, middle is the lung region mask, right is the feature map after last convolution layer. The mask region include most of the highlighted feature map area, and non-lung region are most no signification feature area.

III. Experiments and Results

The lung region segmentation and the COVID-19 classification results are revealed in the following sub-sections. All the experiments are implemented by pytorch framework, and running in one DGX-station with 4xV100 GPUs.

A. Lung region segmentation

The lung region mask is generated by CNN network. The input is original CT data, output is the binary mask data which the non-lung region's pixel value is 0, and right lung region's pixel value is 1 and right lung region's pixel value is 2. Figure 7. illustrated the different image slices and related mask. Due to the lung segmentation is for COVID-19 classification, The lung segmentation do not need very accurate. Our segmentation result is validated using dice coefficient which is achieved about 96.5% on 30 independence CT scans.

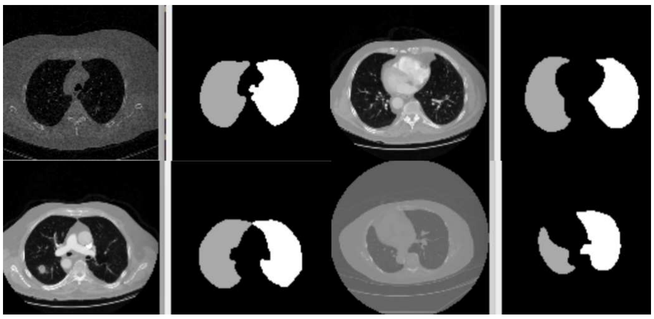

Figure 7. CT images and related mask. First and Third column are original CT image, second and last column are the corresponding segmentation results. Pixel in background is black, in right lung is gray, and in left lung is white.

B. COVID-19 classification

The classification algorithm is validated by the metric of sensitivity and specificity. The model is validated on 2062 CT scans. Figure 8. is the classification confusion matrix of two experiments, and the sensitivity of our proposed method is 96.4%, and specificity is 93.3%

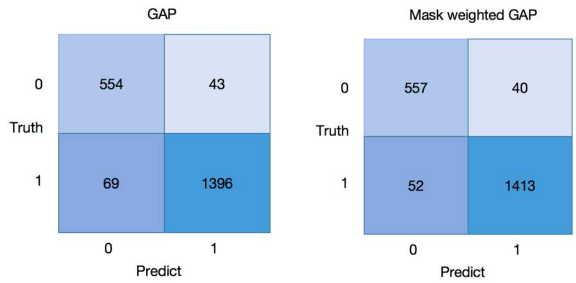

Figure 8. The confusion matrix of the two experiment results of resnet50 with GAP and with mask weighted GAP. 1 represents COVID-19 pneumonia, and 0 represents other pneumonia or normal. Truth means the ground truth confirmed by doctor, predict means the model inference result.

Table II illustrated the quantification metrics comparison between common GAP and mask weighted GAP. From the table, we could see that the mask weighted GAP will be much useful for medical image classification for the suspect in special clinical organ.

TABLE II. The classification comparison between resnet50 with and without our mask weighted GAP

Model(resnet50)	**Accuracy**	**sensitivity**	**specificity**	**F1 score**
GAP	94.6%	95.3%	92.8%	96.1%
weighted GAP	95.5%	96.4%	93.3%	96.8%

C. Visualization check of COVID-19 triage

To confirm the triage result of COVID-19, Grad-CAM[18] is adopted to fusion the key region for classification decision on the original image. A good visualization method is to use heavy color to highlight the suspect region, while light color to indicate the normal region. The color region is the most important region to decide whether the current image is COVID-19 image, red color means the high probability, green and blue are next priority. If the CT image is normal,the fusion image will be no significantly region colored. From Figure 9., we could see that the COVID-19 suspect region are highlighted by the red color, however the normal CT image region without significant color. This fusion color map help us to confirm the import CNN feature regions to distinguish COVID-19 suspects.

IV. Conclusion and Future Work

A novel lung mask weighted GAP for COVID-19 classification is proposed. As shown in the experiment result, the lung mask weighted GAP has achieved better performance. On all metrics the lung mask weighted GAP has about one percent improvement. This may be because lung mask weighted GAP method makes the model be attention to the lung region which contain the COVID-19 suspect, reduce the influence of background region and highlight the classification features of interesting tissue region. Future work will be focus on the attention of spatial and channel to enhance the key slice or filters weight for the classification. And also the localization and severity level estimation of COVID-19 suspects will be researched in next work.

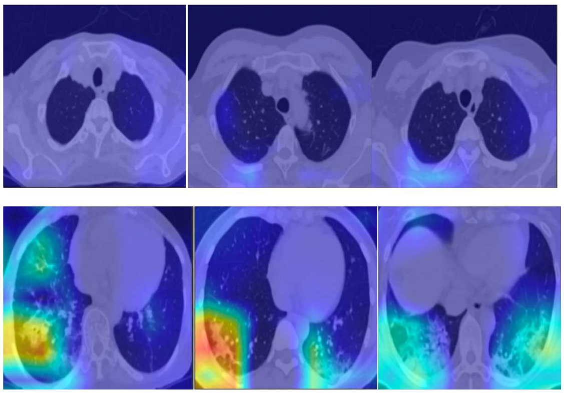

Figure 9. Fusion images with Grad-CAM, which indicate the import region for classification. First row are normal cases, second row are COVID-19 cases. RGB color indicate the high risk for suspects, light color indicate the normal region.

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REFERENCES

[1] Lin Li, etc., "Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT," Radiology,2020

[2] Fei Shan, etc., "Lung Infection Quantification of COVID-19 in CT Images with Deep Learning," Computer vision and pattern recognition, 2020

[3] Md. Zabirul Islam, Md. Milon Islam, Amanullah Asraf (2020) A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. Inform Med Unlocked 20:100412

[4] Zhang Li, Zheng Zhong, Yang Li et al (2020) From community-acquired pneumonia to COVID-19: a deep learning‑based method for quantitative analysis of COVID-19 on thick-section CT scans. European Radiology 30:6828-6837

[5] Le Qin, Yanzhao Yang, Qiqi Cao et al (2020) A predictive model and scoring system combining clinical and CT characteristics for the diagnosis of COVID-19. European Radiology 30:6797-6807

[6] Justin Ker, Satya P. Singh, etc.,"Image Thresholding Improves 3-Dimensional Convolutional Neural Network Diagnosis of Different Acute Brain Hemorrhages on Computed Tomography Scans," Sensors,2019,pp.2167

[7] Justin Ker, L. P. Wang, etc., "Deep Learning Applications in Medical Image Analysis," IEEE Access,2018,pp.9375-9389

[8] Satya P. Singh, Lipo P. Wang, Sukrit Gupta, Haveesh Goli, Parasuraman Padmanabhan, and Balazs Gulyas, "3D Deep Learning on Medical Images: A Review", Sensors, vol.20, 5097, 2020. doi:10.3390/s20185097

[9] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," Medical Image Computing and Computer-Assisted Intervention,2015,pp.234-241

[10] Özgün Çiçek, Ahmed Abdulkadir,etc., "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation," MICCAI,2016

[11] Armato SG, McLennan G, Bidaut L, etc., "The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): a completed reference database of lung nodules on CT scans," Med Phys, 2011, pp.915-931.

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, "Deep Residual Learning for Image Recognition," Computer vision and pattern recognition, 2016

[13] Fei Wang, Mengqing Jiang,etc., "Residual Attention Network for Image Classification," Computer vision and pattern recognition, 2017

[14] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," NIPS, 2012.

[15] Saining Xie, Ross Girshick,etc., "Aggregated Residual Transformations for Deep Neural Networks," Computer vision and pattern recognition, 2017

[16] Jie Hu, Li Shen, Samuel Albanie, Gang Sun, Enhua Wu., "Squeeze-and-Excitation Networks," Computer vision and pattern recognition, 2018

[17] Min Lin, etc., "Network in Network," In Proceedings of the IEEE International Conference on Learning Representations, 2014.

[18] Ramprasaath R. Selvaraju, Michael Cogswell, etc., "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization,"