IDENTIFICATION OF BRONCHOPULMONARY SEGMENT CONTAINING COVID ABRASIONS USING EG-CNN AND SEGNET

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Abstract

As the current COVID pandemic is a huge concern, more effective methods are required for treatment and analysis of this disease. If COVID analysis is aided by automated detection of the disease, this will reduce time and also speed up treatment. In this research, the particular bronchopulmonary segment containing COVID is detected to narrow and segregate the treatment area. Computer Tomographic Images are passed through EG-CNN which is modelled with Segnet to detect COVID-19 abrasions. The output of the two CNNs are gated to develop the final result with high accuracy.

Introduction

The outspread of a new type of pneumonia which is also known as corona virus or COVID-19 has become an international concern [1] causing million deaths around the world. The most efficient method in suppressing this disease is by early and speedy diagnosis. The process of COVID detection is automated and can be accelerated by separating the lung into smaller portions for detection. Bronchopulmonary segments [2,3] are portions of the lungs where each segment is independent of the other. Each separate bronchopulmonary segment is scanned separately for identification of COVID within the segment. The demarcation of bronchopulmonary segment in the output image aids doctors in identifying the segment requiring treatment. In this study, the proposed CNN consists of a dual learning structure. The first learning algorithm is incorporated with Segnet encoder decoder to identify COVID-19. The second learning scheme adopts a Region Proposal network [4] with shadow identification to identify bronchopulmonary segments in lungs. Once the segments are identified they are finally combined with the first learning algorithm's output to produce the final result. Loss incurred during detection is calculated and incorporated continuously into the CNN to produce more accurate results.

Working Model Description

Digital Imaging and Communications in Medicine (DICOM) images are initially preprocessed, arbitrarily resized and converted into bitmap images which are then passed into the EG-CNN [5]. The proposed model (EG-CNN) consists of two learning branches. Unlike the original algorithm which uses a generic CNN encoder/decoder, the first learning branch adopts the SegNet encoder/decoder to detect COVID-19. The output of detected edges is further enhanced. The output of the two layers are finally concatenated with each other to produce the final output. The gated edge layer uses a 3D Sobel filter [6] to enhance the detected bronchopulmonary segments.

SegNet Layer

The SegNet CNN [6, 7] layer consists of an encoder and a decoder which is succeeded by a pixelwise classified layer. The encoding architecture is similar to Vgg16 [8] and consists of 13 convolutional layers to classify the different textures of the CT image. The large image datasets are initialized, and weights are applied to train the images to classify various features. High resolution feature maps are obtained from the encoder by discarding fully connected layers during convolution, thereby reducing the number of parameters required during training. The output from the encoder is passed into the decoder with the same number of convolutional layers. The output from the decoder is finally passed through SoftMax classifier which classifies each pixel into an independent feature probability. The output with K feature classes obtained from the feature map are then classified as COVID-19 features or normal lung features by comparing it with ground truth trained images.

Gated Edge Layer with Region Proposal Network (RPN)

The edge boundary information that was capture during encoding is then passed into RPN [2,9] where it is converted into a feature map. The RPN is configured to understand the shadow of the various bronchopulmonary segments by using the Bimodal Histogram Splitting function [2,3,9]. In this function the mean of a possible bronchopulmonary segment shadow is considered as the threshold point. All identified mean values are summed up to form the threshold value and the process is repeated till a constant threshold is achieved for a set of mean points. All the calculated thresholds are joint to form a histogram, which could represent a possible bronchopulmonary segment. The segments containing the highest offsets for each classification is passed into the gated edge layer.

The output from the RPN is fed into the gated edge layer. This layer highlights all detected segment edges and connect the feature maps of COVID-19 with bronchopulmonary segments at different resolutions [10]. An attention map is obtained by combining the output from SegNet and RPN into the 3D convolutional layer with the help of ReLU which is defined by the equation.

$$(\sigma)\ \mathrm{Re}(n) = \max(0, n)$$

where, *n* depicts the number of pixels undergoing ReLU in the image.

The attention map denotes the number of bronchopulmonary edges detected from the CT image, which is equal to the number of resolutions that exist in the CNN architecture.

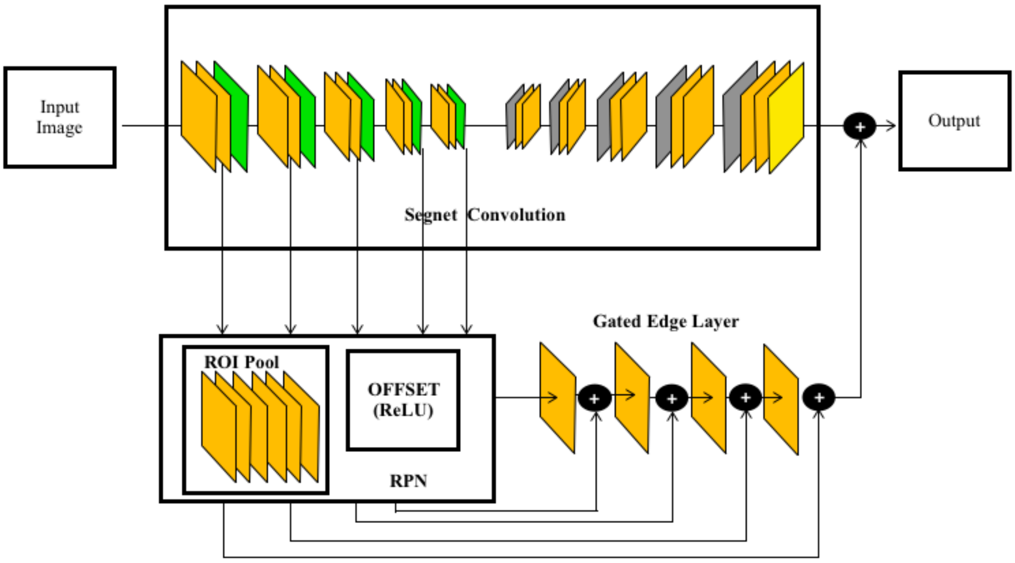

Fig. 1. EG-CNN with SegNet – Proposed Working Model

The entire working model is depicted in fig 1. The concatenation with each image resolution from RPN [2, 9] with the Gated Edge layer helps in reducing the image pixel loss that is incurred at each resolution stage. The output shows the concatenation of the first and second CNN results.

Loss Function

The total loss (L_{CNN})calculated for the entire working model is as follows:

$$\boldsymbol{L_{CNN} = L_s + L_c + L_B}$$

where

L_S depicts the semantic loss,

L_C depicts the consistency loss,

L_B depicts the edge loss.

All the loss is calculated during training so that larger losses can be adjusted. If the loss is small, it is ignored and if the loss is big, weights are adjusted and fed into the system to produce better output results.

Dataset Training and Output Results

The COVID dataset is obtained from Italian Society of Medical and Interventional Radiology [11]. The working model is implemented on an 8 GPU which experiences a weight decay of 0.0014. The ground truth for COVID-19 and bronchopulmonary segment detection is provided by local hospitals and authenticated by radiologists. The loss incurred during training is calculated using cross entropy [12, 13] function. During loss calculation, class loss and median loss are also calculated for each training set. This calculation helps to reset the weights in the encoder to reduce pixel loss. The average loss recorded from each training data set is approximately 0.0473.

The dataset containing about 387 COVID-19 CT images are used for testing. To identify accuracy of bronchopulmonary segmentation, the mean, standard deviation, median, sensitivity and specificity are calculated for each lung lobe. The output analysis percentage (%) is calculated from the dice similarity coefficient [14, 15] by comparing the output with ground truth and the coefficient of segmentation is approximately 95.7 percentage depicting the correlation of most outputs with the ground truth. The volume of error estimated for the detection of bronchopulmonary segments is close to 7.8%. The measure the accuracy of covid-19 detected inside each lung segment which depicts the percentage of infection is calculated using Hounsfield histogram [2, 16] unit and a graph is used to represent the infection for each segment. The graph calculates the output accuracy to be approximately equal to 1.0 thereby confirming the preciseness of COVID detection Each testing is carried out in 9.3 seconds depicting the speed of the proposed system.

Conclusion

The identification of bronchopulmonary segments aids the doctors in identifying which lobe of the lung requires treatment, as each lobe is independent of the other. Identifying the presence of COVID-19 within the defined bronchopulmonary segment reduces the area of detection, speeds up analysis and helps in faster treatment. This research proposes an accurate system to identify bronchopulmonary segments containing COVID-19 abrasions. The output obtained from the system is precise and can be used in hospitals for diagnosis purposes.

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