Addition of Emphysema-CNN score improves upon prescreening risk calculated by LCRAT

# Introduction

According to the Global Initiative for Chronic Obstructive Lung Disease (GOLD), chronic obstructive pulmonary disease (COPD) is a disease characterized by persistent respiratory symptoms and airflow limitation caused by a mixture of small airways disease (bronchiolitis) and parenchymal destruction (emphysema)(1). COPD is projected to be the third leading cause of death by 2020 so improved methods for diagnosis are going to be critical in the coming years. Furthermore, the primary modality for diagnosis of emphysema is chest CT scan, so there is substantial potential for quantitative analysis of emphysema.

## Quantitative Analysis of Emphysema

The current state of the art method for performing quantitative analysis of emphysema is the Density Mask technique(2). Density Mask measures the percentage of voxels in the lung below a certain density threshold, and if this percentage is above a preset threshold then the patient is considered emphysematous. This technique has shown to be very effective when used consistenly on the same scanner where the threshold can be tailored to that scanner and reconstruction kernel; however, Density Mask suffers greatly when the CT scans are taken from a more diverse data set as in the case of the NLST(3). The CT scans from the NLST come from 33 sites across the US and 23 different scanner models reconstructed using 44 different reconstruction kernels(4). Therefore, it is paramount to develop quantitative methods that are much more robust in the face of ever-growing datasets.

In order to quantitatively analyze emphysema in a more robust manner, we use as our model a three dimensional convolutional neural network (3D CNN). Our 3D CNN utilizes multiple layers of convolutions to detect and weight features at all scales throughout the lung image. This does have the downside of requiring significantly more computational power, but most of this is required during training and not during deployment.

## Lung Cancer Risk Prediction

Cite Hilary’s Markov paper and give a basic explanation here

# Methods

The chest CT scans used in this study were taken from the all three years of the NLST from both the LSS branch and the ACRIN branch; 8416 patients were used for training, 480 for validation, and 2016 for testing. Each CT scan was labeled by radiologists at the site of the screening for lung CT abnormalities.

The scans were first converted to NifTI-1 format, then cropped to a bounding box around the lung using the Progressive Holistically-Nested Network (P-HNN) lung segmenter(5), normalized in three different lung windows of -1000, 200, -160, 240, and -1000, -775, and rescaled to a standard size of 128x128x128. These lung windows were chosen due to their use in the P-HNN segmenter(5). The resulting 3-channel image was then fed into a standard 3D convolutional neural network. The network consisted of five 4-layer blocks of 3x3x3 convolution, batch normalization, ReLU activation, and 3D max pooling; then a convolution group of 2x2x2 convolution, batch normalization, ReLU activation, and 50% dropout before a fully connected group of 1x1x1 convolution, 50% dropout, 1x1x1 convolution, 50% dropout, a flattening layer, and a dense layer with 2 class outputs. In order to compensate for the asymmetry of the labels (there were many more non-emphysematous cases than emphysematous cases), positive labels were weighted 3 times as much as negative labels in the training process.

Three neural networks were trained for this experiment. One for just T0 scans, another for T0 and T1 scans, and a final model for all T0, T1, and T2 scans. Each neural network was trained concurrently on 4 NVIDIA Titan X graphics cards using Python 2.7 and Keras bindings for Tensorflow(6). The majority of the time spent training the model was spent preprocessing the CT images into the format necessary for our model.

# Results

As a classifier, the network had moderate success. After 26 epochs of training, the T0 model had a classification AUC of 0.673; after 20 epochs of training, the T1 model had a classification AUC of 0.689; and after 24 epochs of training, the T2 model had a classification AUC of 0.684. The confusion matrices for each model are displayed below.

T0 model:

Negative Positive   
 Negative 1221 39 1260  
 Positive 657 99 756

T1 model:

Negative Positive   
 Negative 1828 579 2407  
 Positive 797 844 1641

T2 model:

Negative Positive   
 Negative 2797 757 3554  
 Positive 1343 1167 2510

# Discussion

The results presented here show that 3D CNN-based approaches are a promising direction of research for computer-aided diagnosis of emphysema. As well as just diagnosing emphysema, neural networks could identify multiple CT-diagnosed diseases to identify risk factors for lung cancer, or even identify lung cancer risk directly.

# Conclusions

While not accurate enough to be used in a clinical environment, this shows that there is value in working directly with CT data instead of just in derived values. Furthermore, the neural network approach is significantly more robust than the density mask approach, even with a very basic network.

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