Improving the performance in AI-driven analysis of hyperpolarized-gas MR images

INSIGNEO Institute for *in silico* Medicine

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Background

Hyperpolarized gases, typically ^{129}Xe or ^{3}He, are used as a visualisation agent to accurately portray the distribution of gas within a patient's lungs and airways. Coupled with MRI, hyperpolarized gases can produce a 3 dimensional image of the lung where brighter voxels tend to represent the presence of the gas and darker spots in the lung represent areas where the gas hasn't travelled, these usually are areas of low ventilation or defects[1]. Patients are made to inhale the harmless hyperpolarized gas for a short period of a few seconds and then are placed under an MRI scan. Hyperpolarized gases are used to enhance MRI signal and have the potential to provide early detection of pulmonary diseases. Figure 1 shows an example of ^{129}Xe ventilation image.

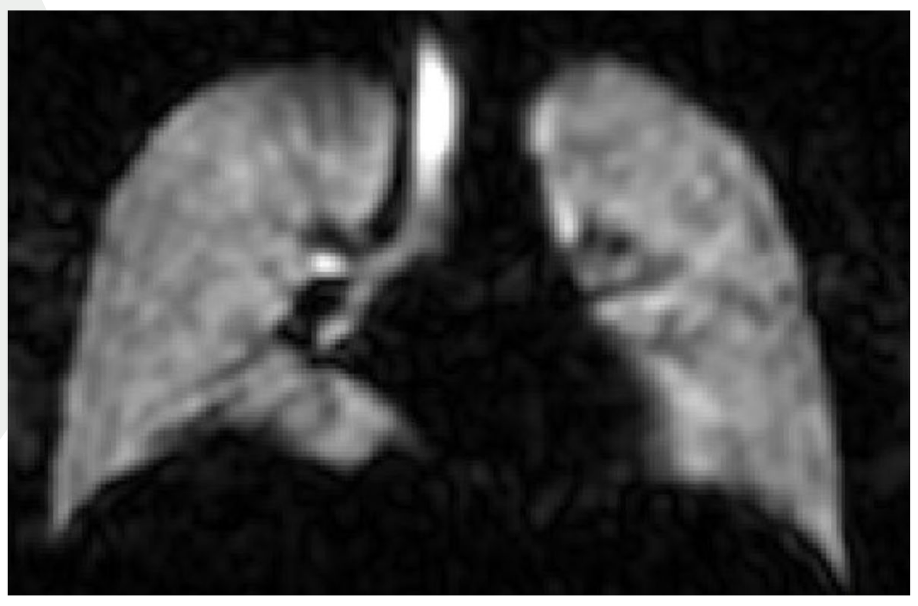

Figure 1 - Ventilation (^{129}Xe MRI)

Aims

The aim of this project is to increase the performance of estimating the lung cavity using Deep Learning. Given a dataset containing ventilation images, anatomical images and segmented images(Figure 3), our task was to create a convolutional neural network that would be able to segment input images, the ventilation image mapped on top of the anatomical image (Figure 2), into background, lung cavity, airways, Artifacts and partial volume voxels. There were three key areas we identified that could help improve the performance: Manual Editing, hyperparameter optimisation and data augmentation.

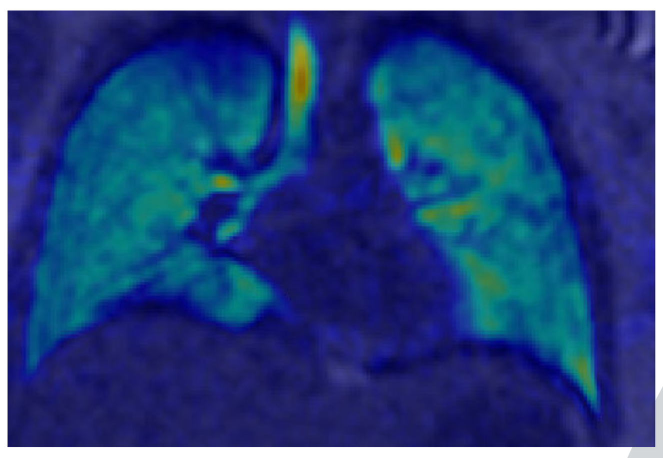

Figure 2 - Overlayed Anatomical and ventilation (^{1}H MRI + ^{129}Xe MRI)

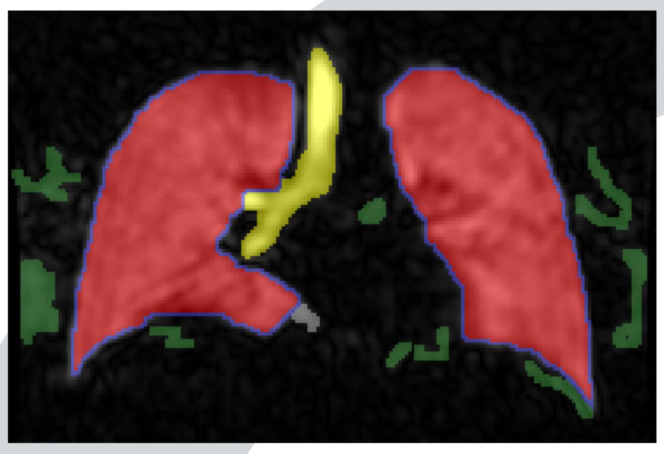

Figure 3 - Expert Segmentation

Fig 3 Description

- Red - Lung Cavity
- Yellow - Airways
- Green - Artifacts
- Grey - Partial volume voxels

Methods

We carried out this project in several stages

Stage 1 - Data pre-processing
In order for the network to be able to function accordingly, the data provided needed to be in a specific structure and format. We created several Python scripts that would process our original data by mapping previous labels into new labels in our segmented image, then separate the images into different folders (Anatomical, Ventilation and Segmented) and finally convert the format from MetaImage Medical Format (.mha) to Nifti (.nii.gz) format so that it could be handled in our deep learning script without any errors.

Stage 2 - Initial Network Creation
We wanted to create a network that would provide us with baseline results so we could see if our changes made a difference to the performance of the lung cavity estimation. To do this we used a PyTorch based framework called Monai. We used a Unet structure with 2 input channels (ventilation and anatomical images) and 5 output channels (1 for each label), these parameters were unique and essential to our problem and would not be changed. The network also had 5 layers (16,32,64,128,256) and a kernel size of (5,5,3), we also used DiceLoss as our loss function. These parameters we intended to change to see if it would result in a performance increase. We then ran training on this model with the unlabelled data.

Stage 3 - Manual Editing of segmented images
In this stage we identified images that were the best candidates for manual editing by writing a python script that would comb through the segmented images and rank these images based on the average amount of unlabelled signal.
During the editing process we labelled large Artifacts that were previously unlabelled and corrected any errors with the labelling. We created a new dataset with the manually edited images and referred to this new dataset as the labelled images/data.

Stage 4 - Data Augmentation
We made a new Deep Learning script that was the same as the initial one but with added transforms to the data. We used transforms provided by monai such as RandRotate and Rand3DElasticd to make the data more diverse which in theory would prevent the network from overfitting on the training data and help the network come up with a general solution that would perform well on unseen data.

Results

We created an evaluation script that would use our testing dataset and provide us with the median Dice score of each label (lung cavity, airways, Artifacts,partial volume voxels) for a specific model. This would essentially tell us how good a model was at predicting each label. We trained three networks. One was a plain network that used the original dataset and had no transforms applied, this would give us a baseline result for comparison. The next network (labelled) used the dataset containing manually edited images and the last network (Transforms) used data augmentation.

	Plain	Labelled	Transforms
Lung Cavity	0.93	0.94	0.91
Airways	0.72	0.69	0.68
Artifacts	0	0.1	0
Partial volume voxels	0	0	0

Figure 4- Median dice score per label

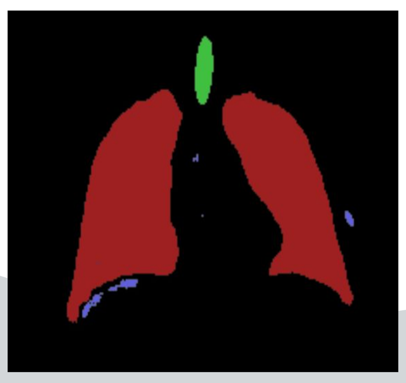

Figure 5 - Example prediction by network

Fig 5 Description

- Red - Lung Cavity
- Green - Airways
- Blue - Artifacts

Conclusions

Looking at the table of results (Figure 4), the model that was trained using the dataset consisting of manually annotated images produced the best results where there was an increase in the accuracy of estimation for both the lung cavity and Artifacts. The model that was trained using transformed data scored worse for the estimation accuracy of the lung cavity and airways. Based on the results it is implied that using manually edited data increases the networks performance, this is most likely because the network is given more information about the data so its predictions would be more accurate. Also imprecisions in the dataset were corrected during the manual editing stage which could have also helped the network to produce more accurate predictions.

Refrences

[1]Hyperpolarised gas imaging, https://www.sheffield.ac.uk/polaris/hyperpolarised-gas-imaging

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