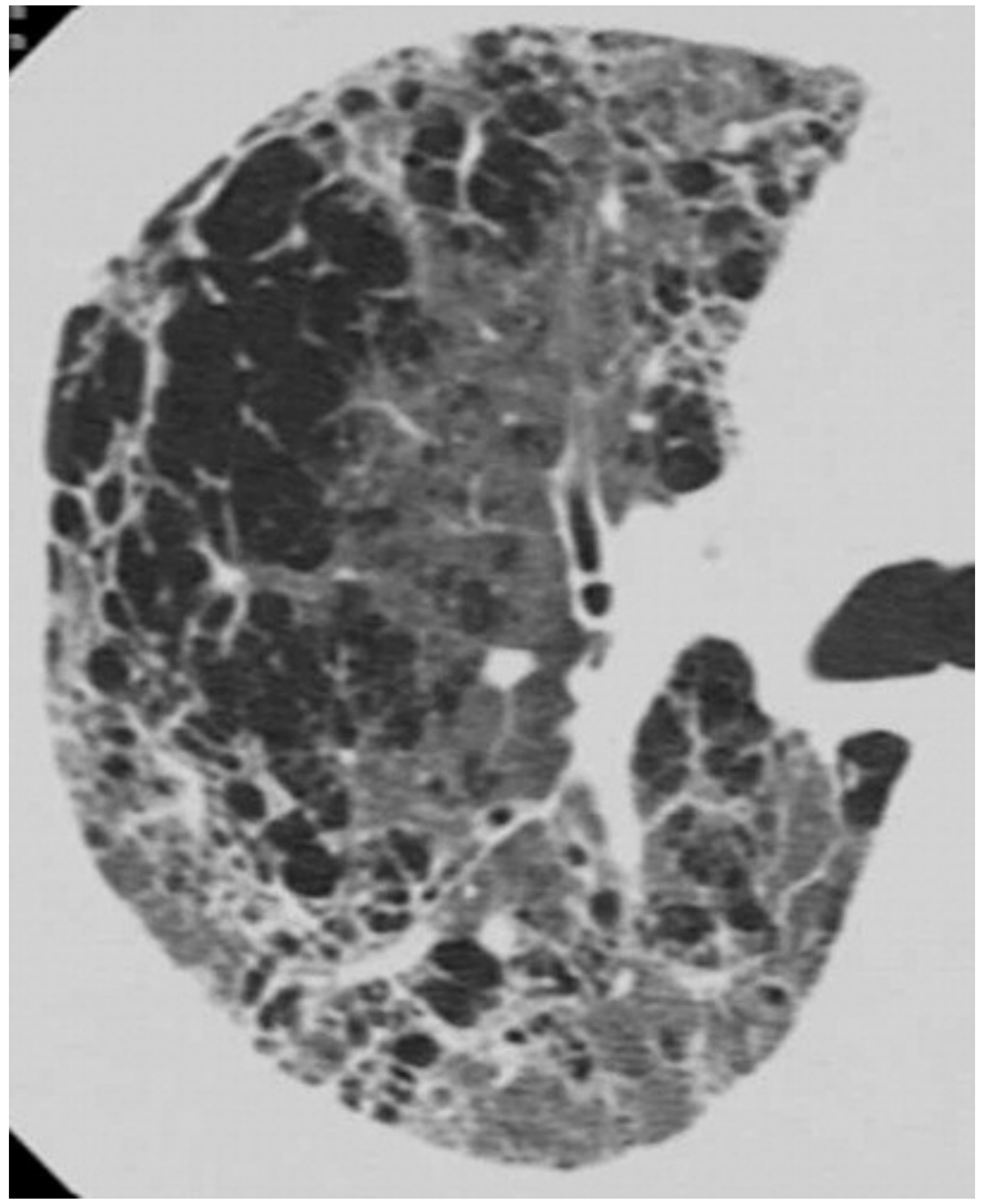
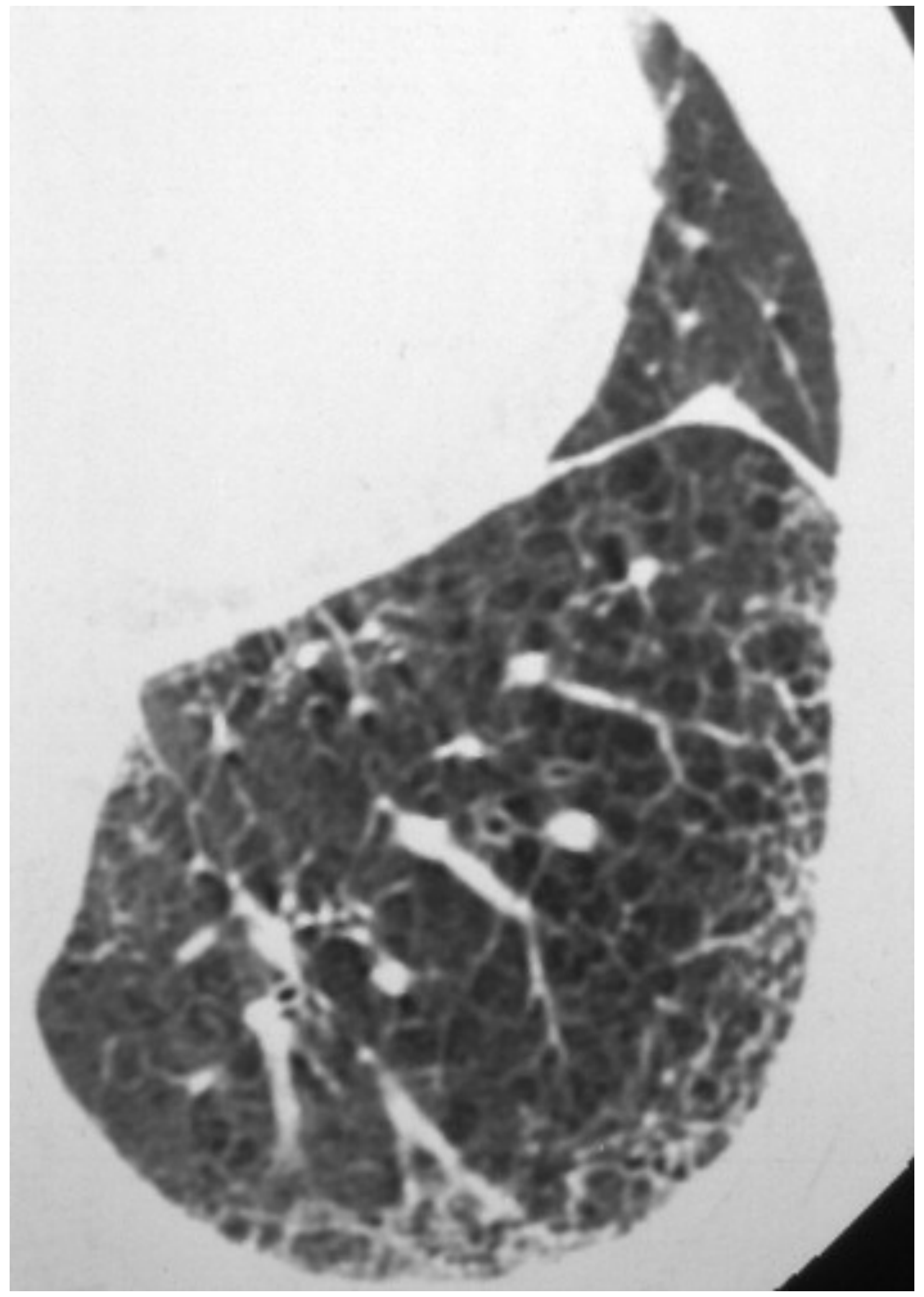
Deep convolutional neural networks to diagnose Idiopathic Pulmonary Fibrosis and Nonspecific Interstitial Pneumonia



Transverse CT slice in IPF patient [1]



Transverse CT slice in NSIP patient [1]

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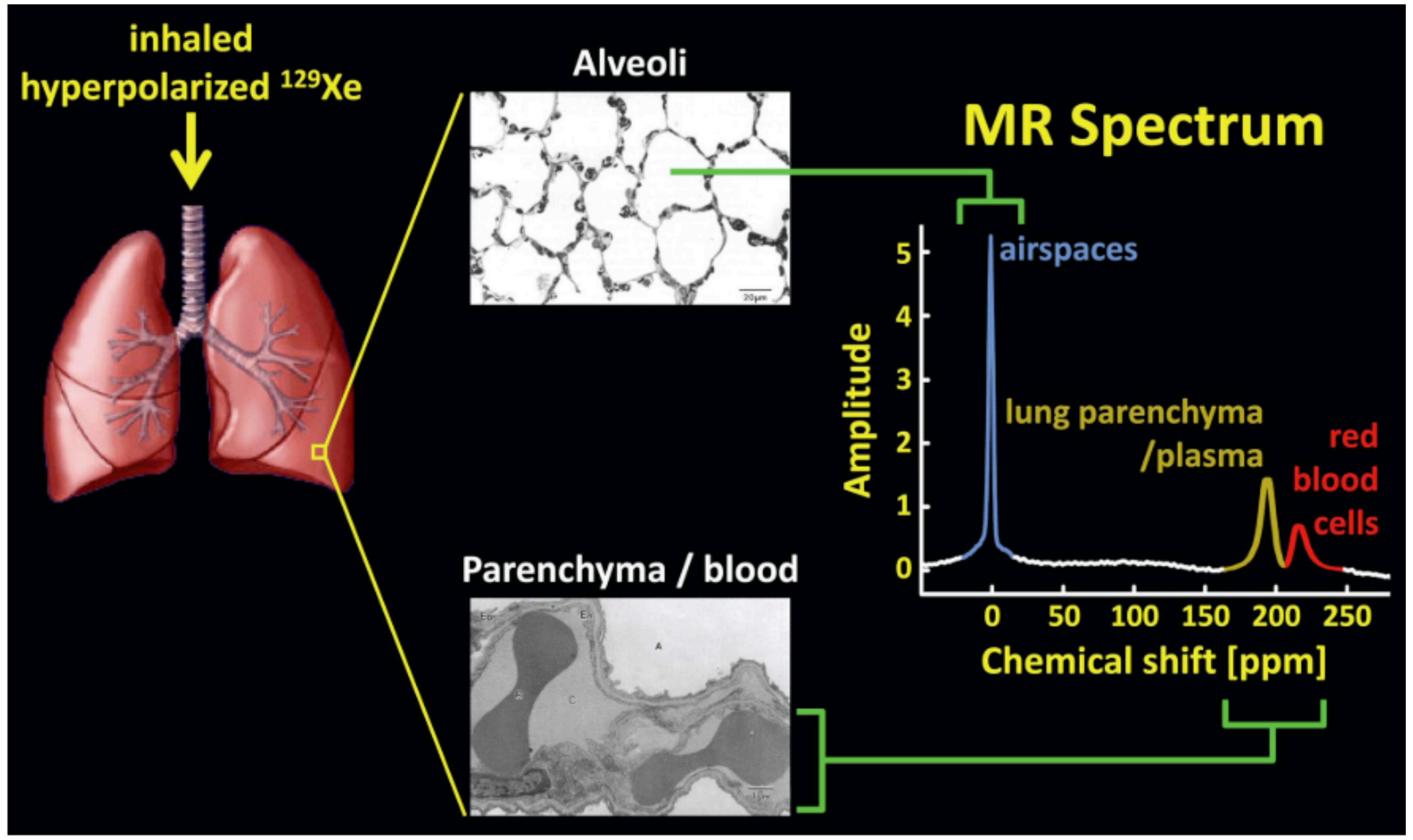
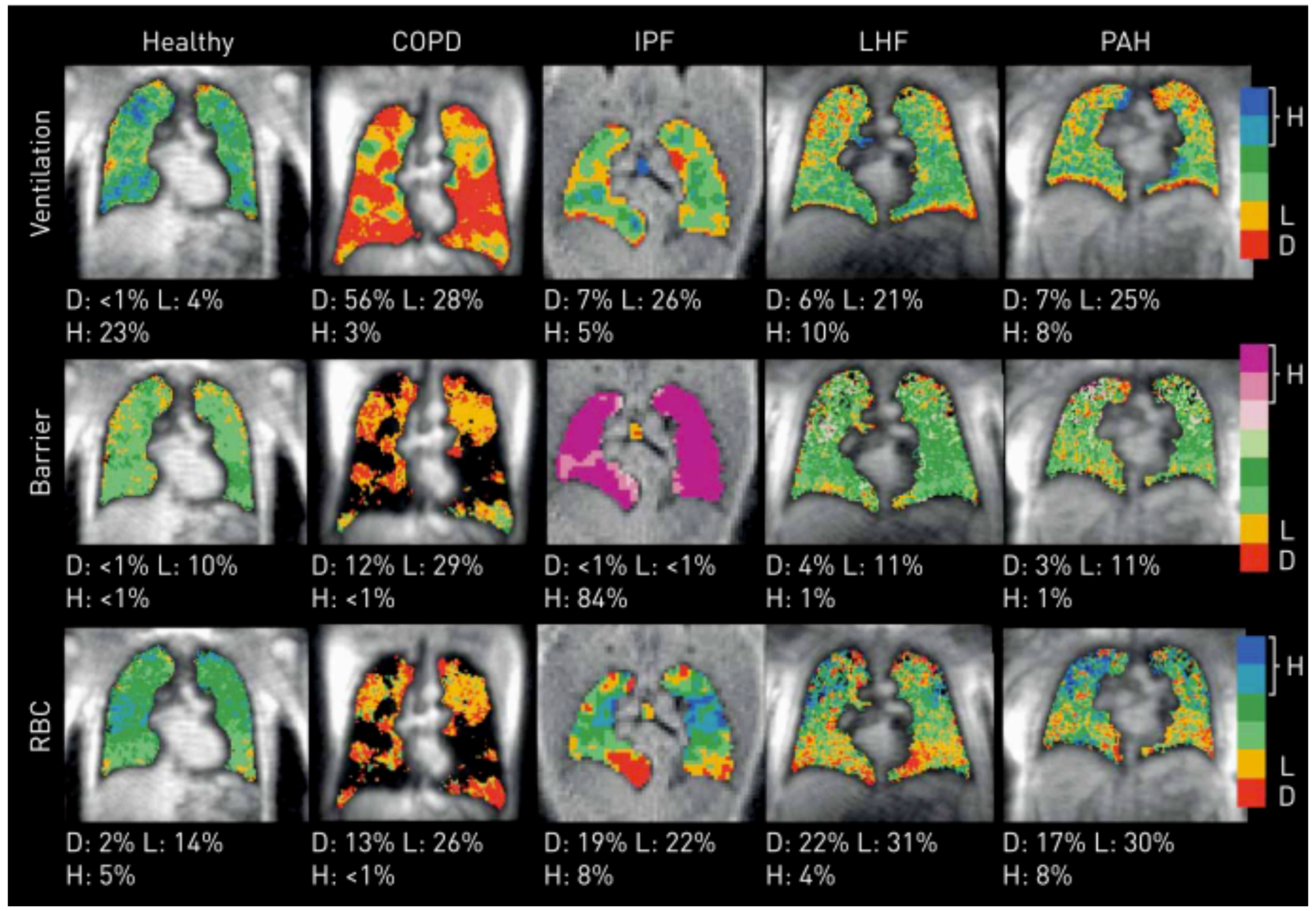
129Xe Hyperpolarized gas transfer imaging has ability to diagnose pulmonary disease progression



129Xe in the lung present in the airspaces and also lung parenchyma + blood [2]

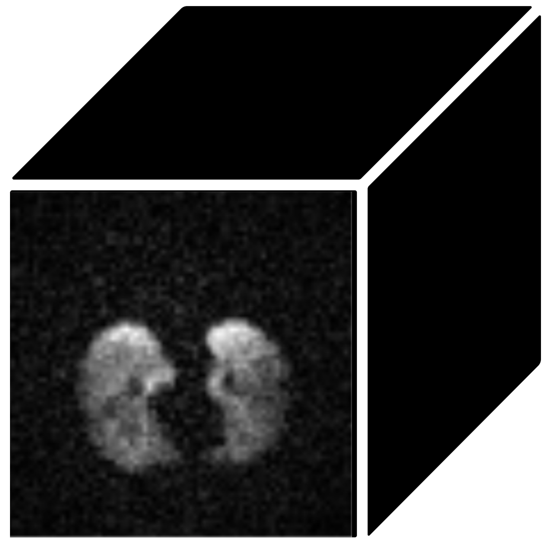


Ventilation, barrier uptake, and RBC transfer maps of subjects from various disease cohorts [3]

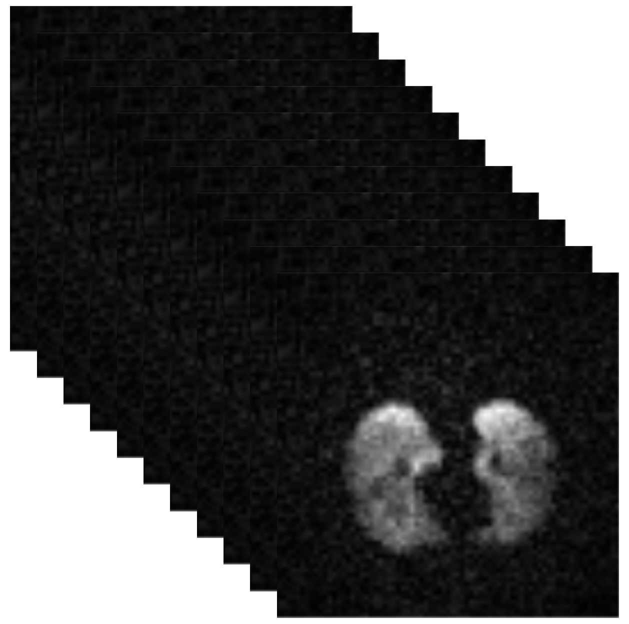
Image preprocessing pipeline

Select 10 slices in the middle

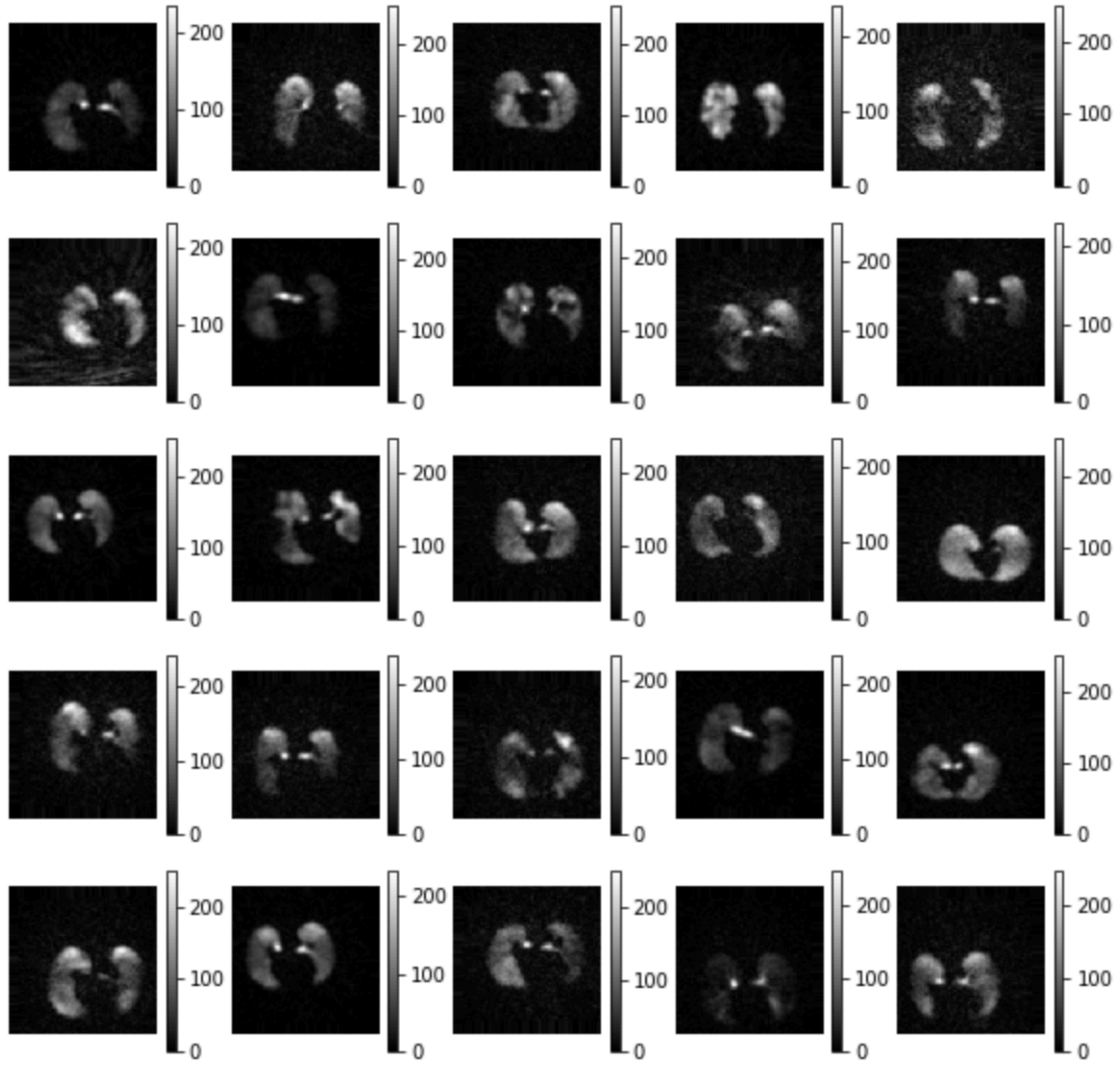
Image augmentation



128x128x128 labeled image

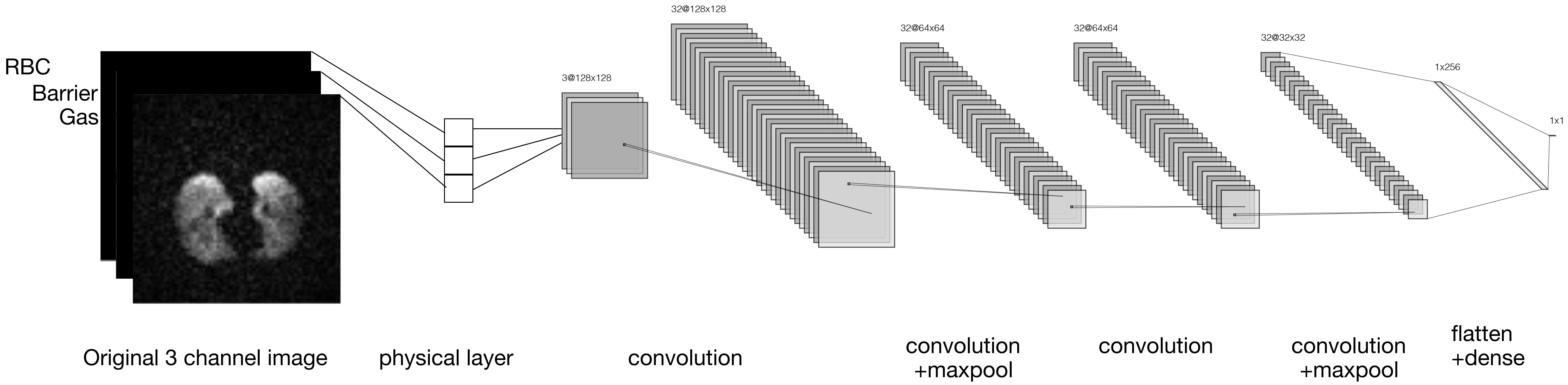


10 128x128 images



Example of images with
1) horizontal shift
2) vertical shift
3) sheer
4) brightness change

Physical layer can determine optimize the weighted image channels for classification

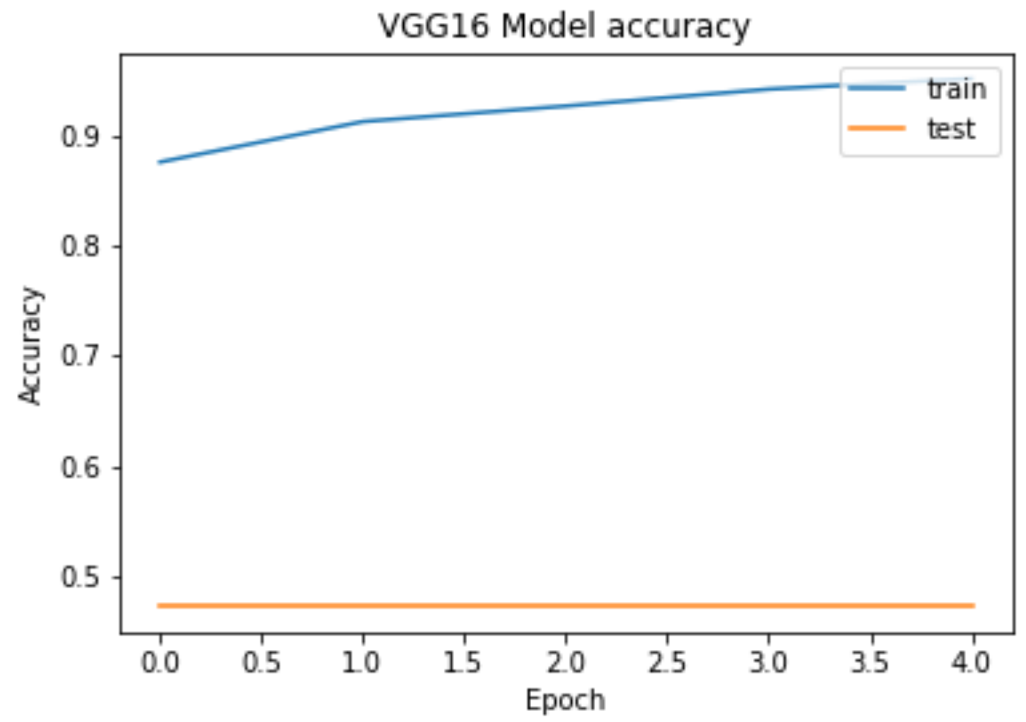


- 91 patients: 55 IPF and 36 NSIP, total of 910 2D slices
- number of epochs is 5
- Augmented training/test set ~3000/300 slices
- Adam optimizer with default learning rate

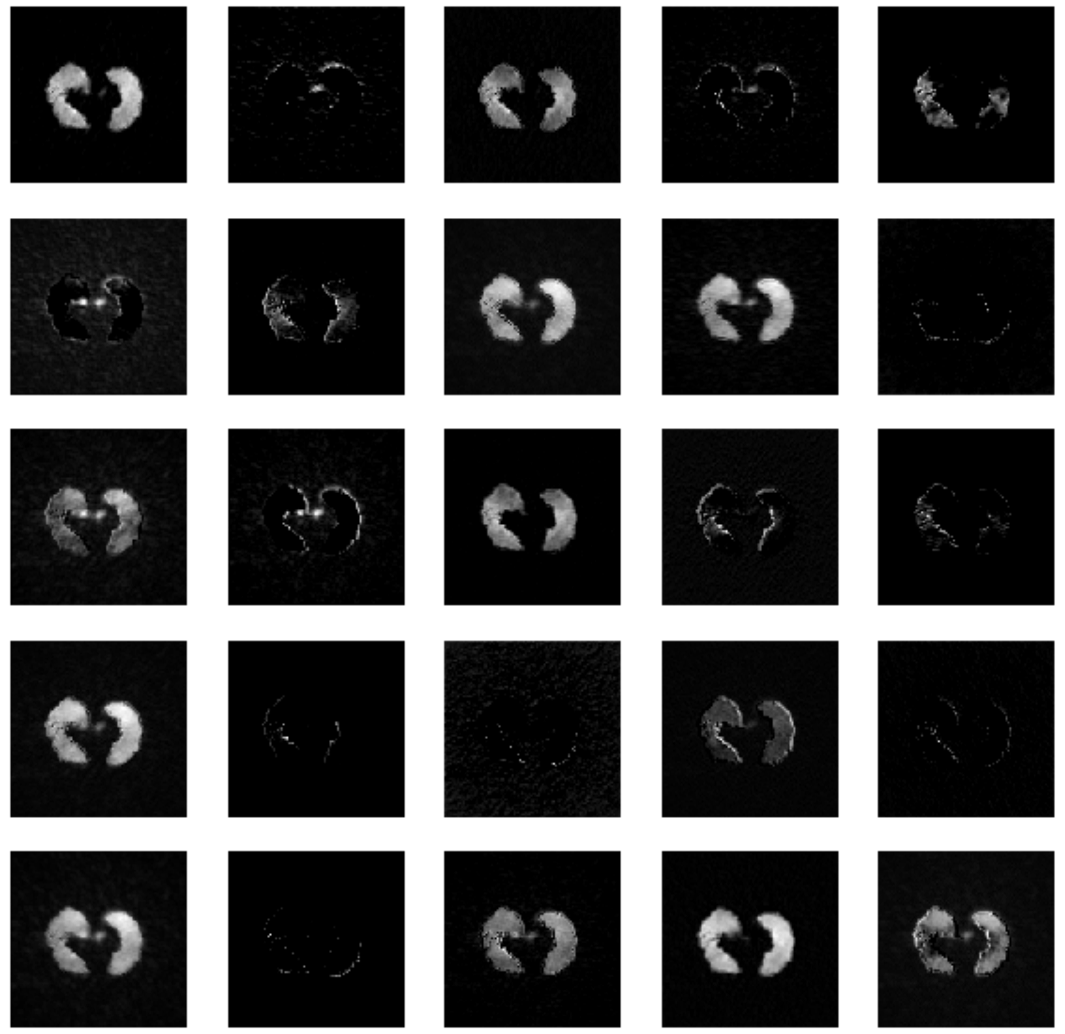
Assessing performance results

Model	Training accuracy / loss	Validation accuracy / loss	Test accuracy / lost
Custom CNN+No Physical Layer (NPL)	0.99 / 0.02	0.86 / 0.55	0.48 / 35
Custom CNN + Physical Layer	0.998 / 0.01	0.86 / 0.52	0.42 / 130
Custom CNN + NPL + Augmented training data	0.97 / 0.11	0.47 / 0.75	0.98 / 0.05
Transfer learning with VGG16 + NPL + Augmented training data	0.95 / 0.14	0.47 / 0.73	0.96 / 0.12

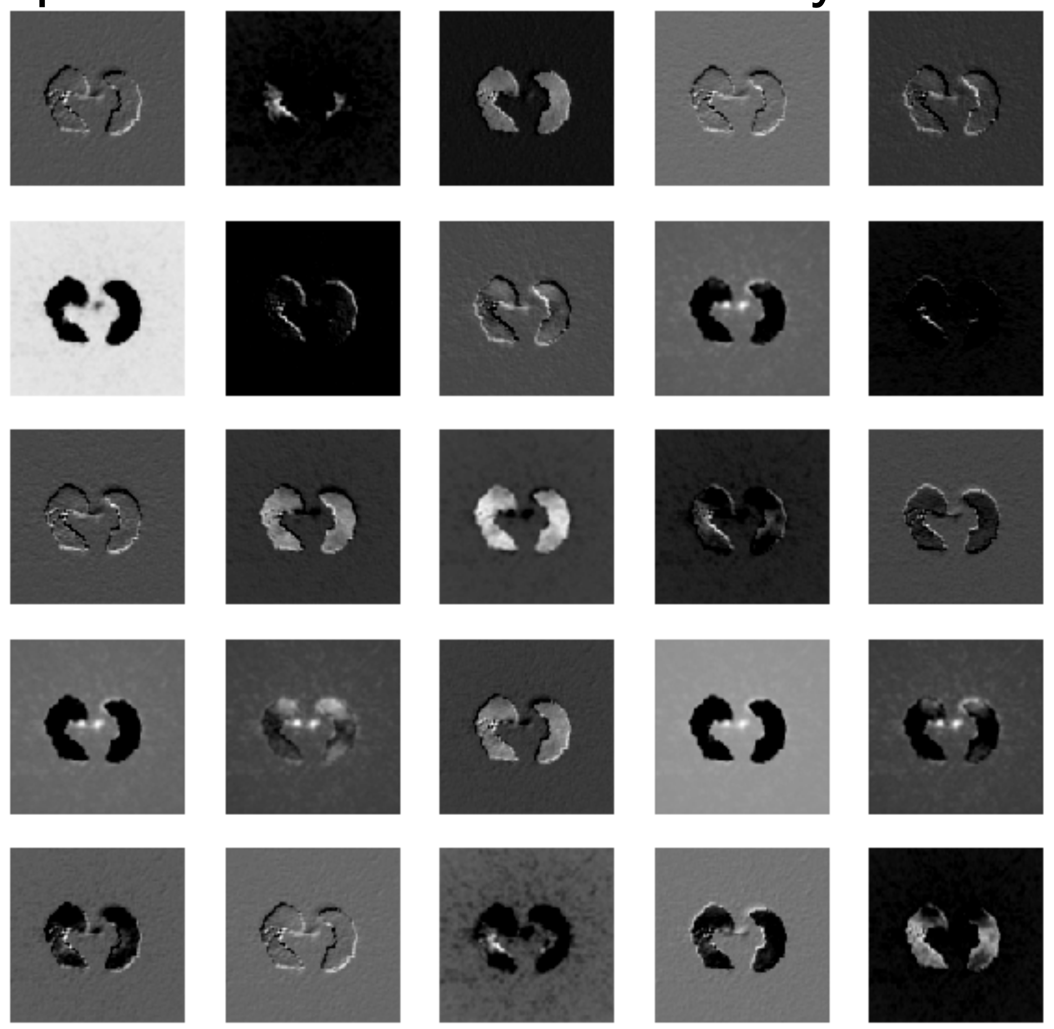
*Validation was used with un-augmented data
Test was used with augmented data



Output of first convolutional layer in custom model



Output of first convolutional layer in VGG16



Preliminary results obviate the need for future work

Dealing with the challenge of small radiological dataset

1. Use transfer learning and unfreeze the weights of VGG16 to train on the rest of HP gas imaging dataset
2. Augment more images and include elastic deformation to deal with the issue of **overfitting the lung volume shape**
3. Use *k-fold cross validation* sampling strategy [4]

Improving the dataset and the model

1. Explore multiple instance learning with time distributed layers to group slices from the same 3D image together
2. Explore 3D CNN's
3. Improve on how image dataset is prepared

Understanding the meaning of our features

1. Generate a *Class Activation Map* to assess important regions in the image for prediction [5]

References

- [1] Akira, M. *et al.* Usual interstitial pneumonia and nonspecific interstitial pneumonia with and without concurrent emphysema: Thin-section CT findings. *Radiology* **251**, 271–279 (2009).
- [2] Mugler, J. P. & Altes, T. A. Hyperpolarized 129Xe MRI of the human lung. *J. Magn. Reson. Imaging* **37**, 313–331 (2013).
- [3] Wang, Z. *et al.* Diverse cardiopulmonary diseases are associated with distinct xenon magnetic resonance imaging signatures. doi:10.1183/13993003.00831-2019
- [4] Montagnon, E. *et al.* Deep learning workflow in radiology: a primer. *Insights Imaging* **11**, (2020).
- [5] Selvaraju, R.R., Cogswell, M., Das, A. *et al.* Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. *Int J Comput Vis* **128,** 336–359 (2020). https://doi.org/10.1007/s11263-019-01228-7