

# A Learning Framework for Predicting CT-based PRM Biomarker from MRI Sequences in COPD

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## Objectives

- **CT and MRI provide quantitative indices** for regional structural and functional assessment of **chronic obstructive lung disease (COPD)**:  
Quantitative CT to detect emphysema and functional small airways disease (fSAD)  
Functional MRI to detect perfusion [1]
- Machine learning techniques can predict quantitative indices from alternative imaging modalities, with **the aim to reduce scanning time, radiation dose and/or costs in the clinical setting** [2,3]:  
mostly focus on lung ventilation, as lung perfusion indices suffer from signal-to-noise ratio, non-linearity of the contrast agent, and image artifacts  
utilize source images from a single modality or a single MR sequence
- Main contributions of our study:  
\* a deep learning-based model to **predict conventionally CT-based Parametric response mapping (PRM) lung voxel classifications** from **MRI solely**  
\* leverages complementary information from multi-sequence structural-functional MRI  
\* adaptive input in the scenario of missing sequences

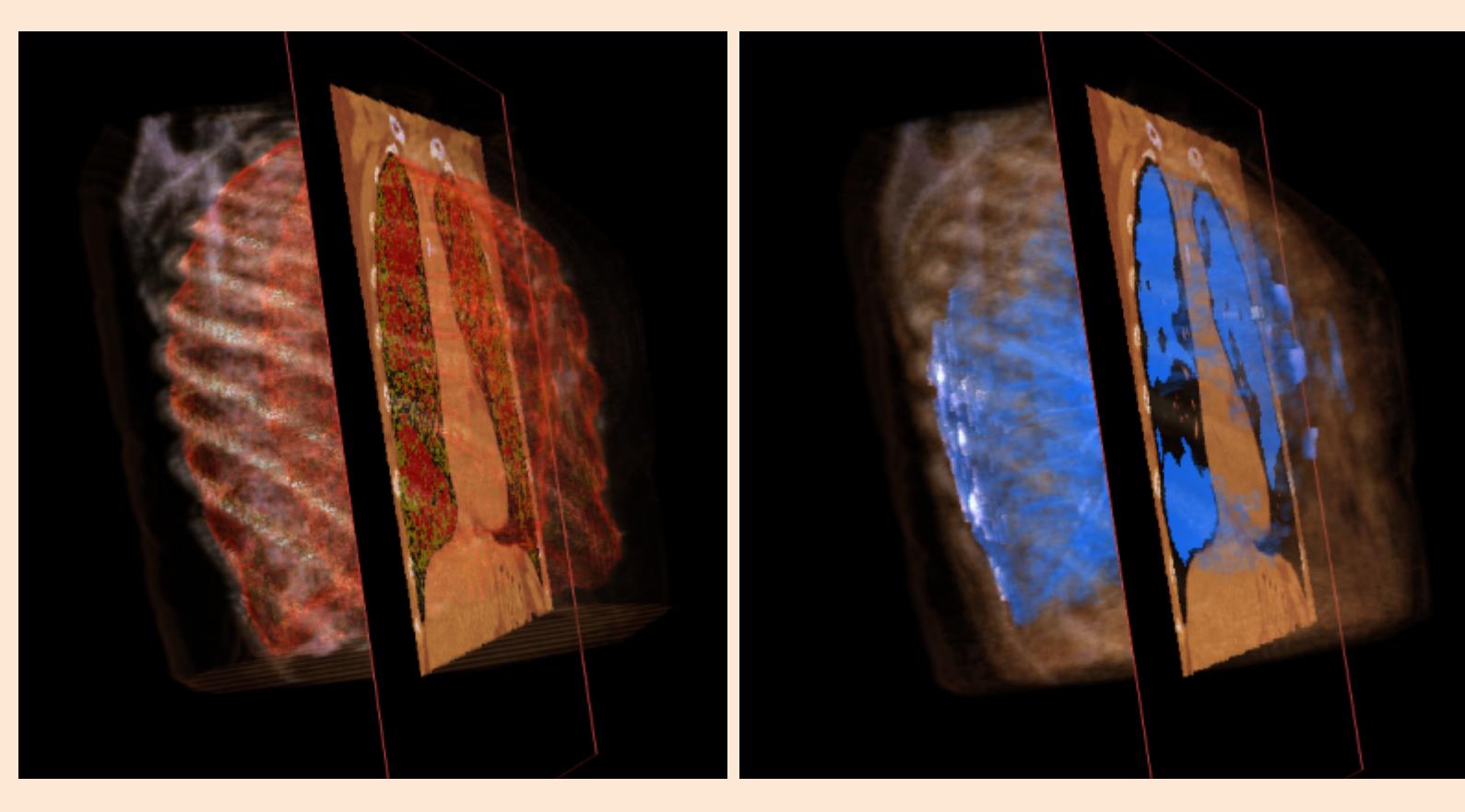
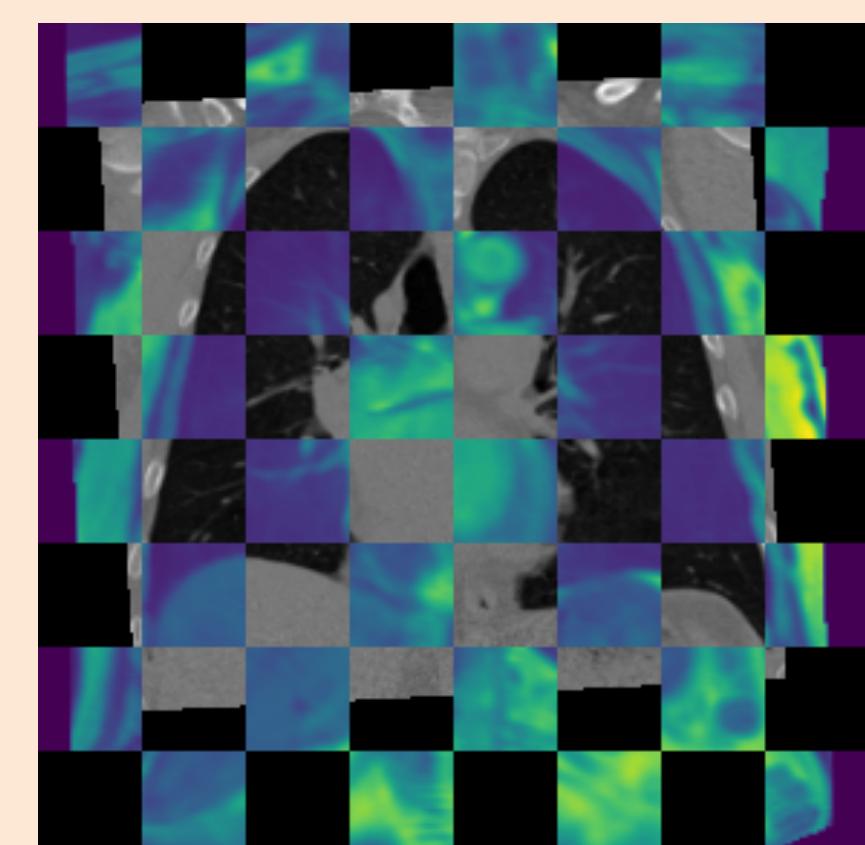


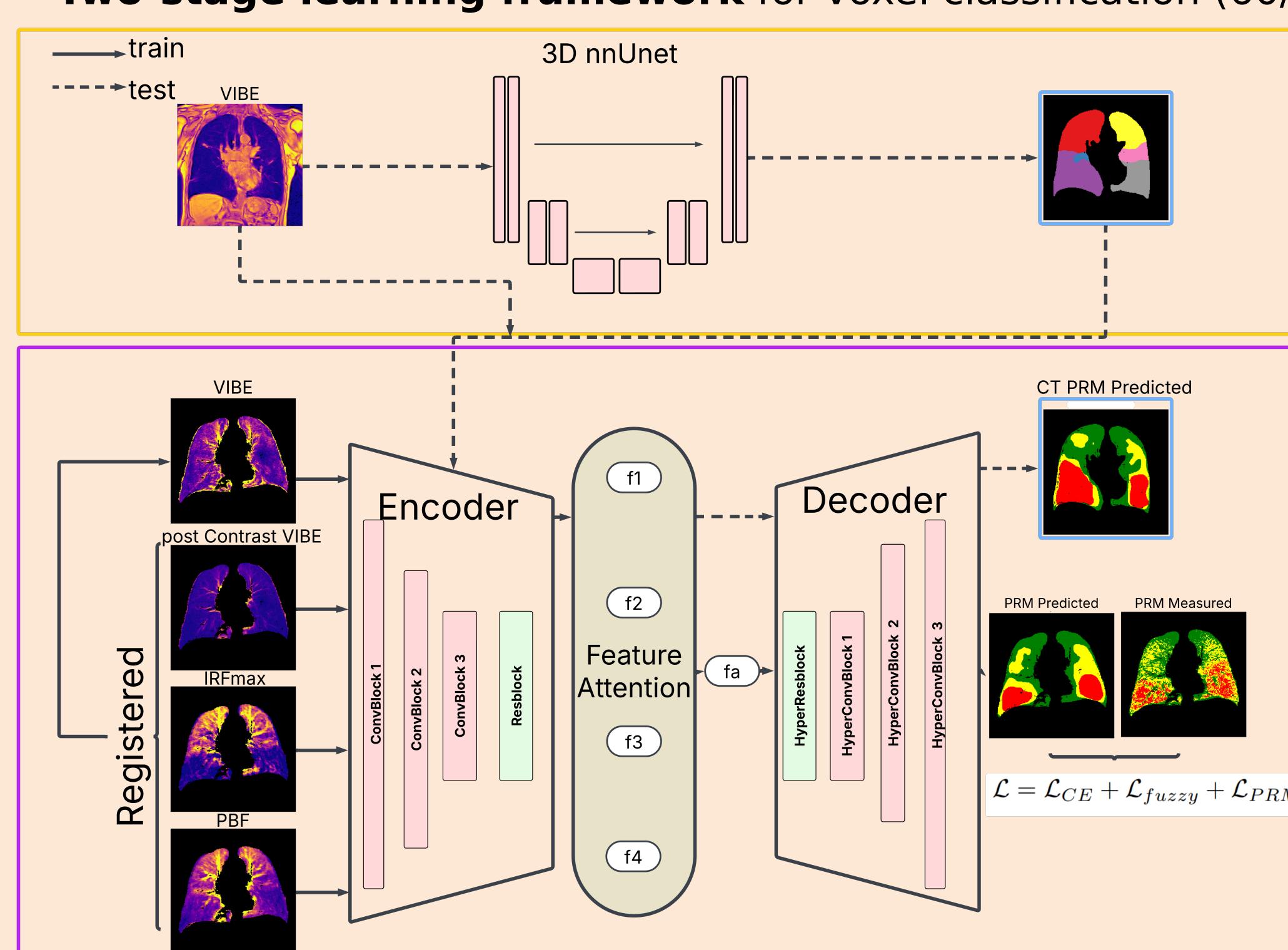
Illustration of **co-registered quantitative measurements** from CT and from DCE-MRI



Colored patches: DCE-MRI  
Gray scale patches: CT

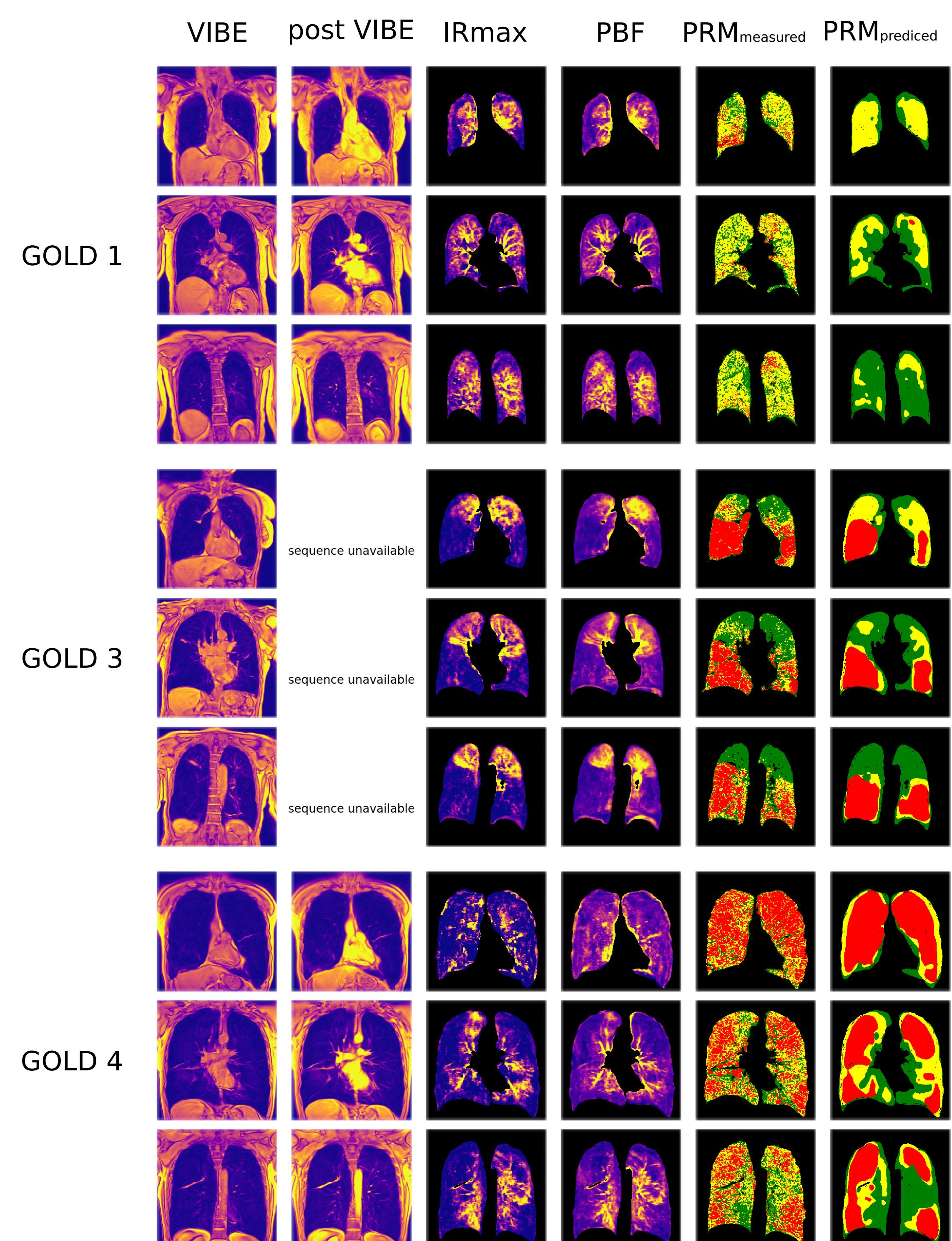
## Materials and Methods

- **104 subjects** from the “**COSYCONET**” cohort (Germany-wide large multi-center imaging trials in COPD).
- **same-day** non-enhanced **paired inspiratory-expiratory low-dose CT and morpho-functional MRI** incl. 4D contrast enhanced perfusion MRI.
- **Lung segmentation** and **quantification**  
CT : YACTA [4]  
Structural and functional MRI: in-house pipeline in MATLAB
- **Iterative deformable registration**  
Advanced Normalization Tools (ANTs)  
CT → structural MRI ← functional 4D perfusion MRI, post contrast MRI
- **Two-stage learning framework** for voxel classification (60/14/30 for train/validation/test)

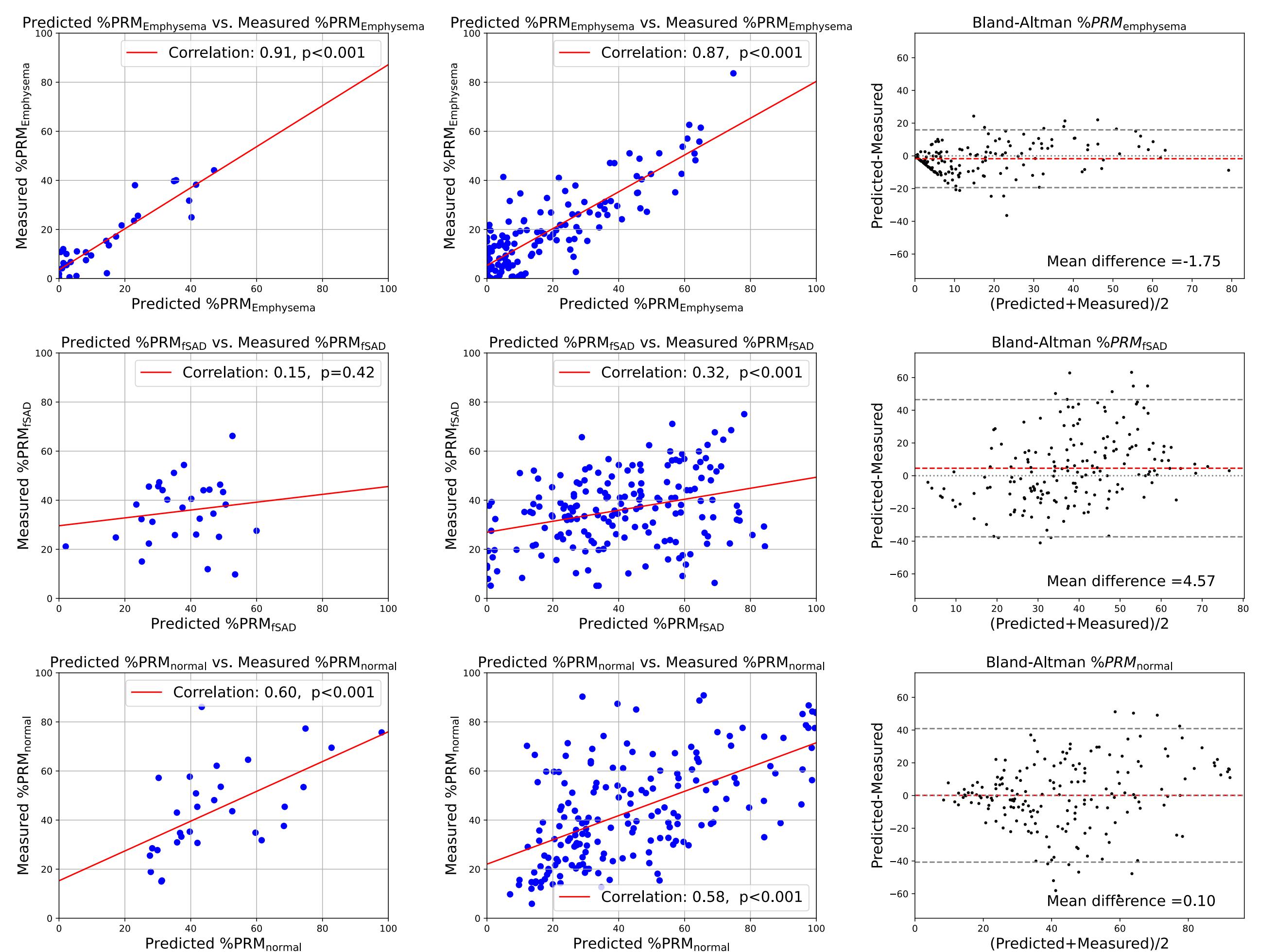


Overview of the framework:  
**Upper part:** nnUnet trained to segment lung lobes on structural MRI.  
**Lower part:** encoder-decoder-based image translation model [5] which predicts CT-driven PRM maps from structural and quantitative functional MRI.

## Results



Representative results from the unseen test set. T1-weighted structural VIBE, maximum contrast enhancement (IRMax) and Pulmonary blood flow (PBF) images are shown in relative intensity, PRM mpas were color coded as such: red represents PRM<sub>emphysema</sub>, yellow represents PRM<sub>fSAD</sub>, and green represents PRM<sub>normal</sub>.



Comparison between predicted %PRM<sub>Emphysema</sub>, %PRM<sub>fSAD</sub>, and %PRM<sub>normal</sub> against the measured values on CT. left: Pearson's correlation coefficient at patient level, middle: Pearson's correlation coefficient at lobe level, right: corresponding Bland-Altman plot at lobe level.

Model with Input Images	DICE <sub>emph</sub>	DICE <sub>abnormal</sub>	r% <sub>emph</sub>	r% <sub>fSAD</sub>	r% <sub>normal</sub>
All 4	<b>0.45 ± 0.22</b>	0.69 ± 0.18	<b>0.91*</b>	0.14	<b>0.60*</b>
VIBE, IRmax, PBF	0.43 ± 0.22	<b>0.70 ± 0.15</b>	<b>0.88*</b>	0.23	<b>0.62*</b>
post VIBE, IRmax, PBF	<b>0.44 ± 0.20</b>	<b>0.72 ± 0.15</b>	0.86*	0.13	0.46*
VIBE, post VIBE, IRmax	0.21 ± 0.20	0.50 ± 0.15	0.41*	0.28	0.13
VIBE, post VIBE, PBF	0.11 ± 0.07	0.33 ± 0.14	-0.16	0.13	-0.15
VIBE, IRmax	0.34 ± 0.20	0.49 ± 0.24	<b>0.89*</b>	<b>0.33*</b>	<b>0.70*</b>
IRFmax, PBF	<b>0.44 ± 0.20</b>	<b>0.72 ± 0.15</b>	0.85*	-0.14	0.44*
qMR					
QDP (derived from IRmax) [1]	—	—	0.61*	-0.18*	-0.6*
mean PBF	—	—	-0.08	-0.20	0.22

Model performance with different input image perturbations, in comparison with established qMR.  
\*represents p < 0.05

## Conclusion

- We proposed a deep learning-based framework that predicts CT-based regional abnormalities from multi-sequence structural functional MRI.
- effectively identifies emphysema, achieving strong correlation ( $r=0.91$  at patient level and  $r=0.87$  at lung lobe level).
- defining small airway obstruction regions remains challenging, only weak correlation was achieved.
- highlights the contribution of functional measurements, especially IRmax and PBF from DCE-MRI.