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Pulmonary Embolus Detection with Dual-Energy CT Data Augmentation

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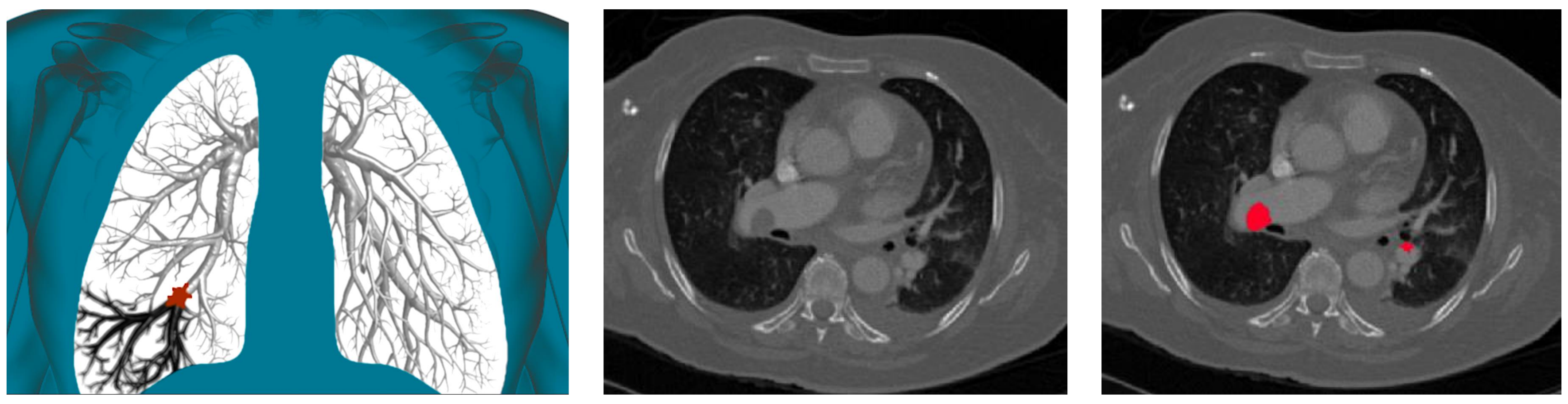
TUHH UNIKLINIK KÖLN PHILIPS

I INTRODUCTION

Background

- A pulmonary embolus (PE) is a blood clot in the pulmonary arteries, obstructing the blood flow, resulting into dead space and poor oxygenation of organs [1,2]
- The standard method for detecting PEs is a CT scan, which must be acquired according specific protocols to achieve contrast in the arteries [1,2,3]
- Emboli become visible by contrast occlusions within CT scan [1,2,3]



Motivation

- Early detection decreases lethality rate from 30% to 2% [4]

Problems

- Deviations from PE protocol affect contrast in CT scan and visibility of emboli [5]
- Detection algorithms are limited on CT scans acquired regarding PE protocols and cannot handle contrast variations [5]
- Data sets covering all variations are difficult to generate, especially due to the problematic annotation on low-contrast images [5]

Objective: Implementation of a deep-learning based automatic detection of pulmonary emboli. Thereby, the generalization capacity regarding different data sets and contrasts is analyzed and improved.

II DATA SETS

Public and Single-Energy CT (SECT) data sets

- **FUMPE: F**erdowsi **U**niversity of **M**ashhad's **P**ulmonary **E**mbolism [1]
- **CADPE: C**omputer **A**ided **D**etection for **P**ulmonary **E**mbolism [2]

In-house and Dual-Energy CT (DECT) data set

- **UKKPE: U**niklinik **K**öln **P**ulmonary **E**mbolism

data set	year	N	$\frac{N_{PE}}{N}$	$\frac{N_{Proxi}}{N}$ [%]	$\frac{N_{Peri}}{N}$ [%]	$V_{\min}$ / V_μ / $V_{\max}$ [cm^3]
UKKPE	2021	114	4.84	24	76	$4.5 \cdot 10^{-3}$ / 1.44 / 65.24
FUMPE	2018	35	3.14	61	39	$0.5 \cdot 10^{-3}$/ 4.24 / 46.27
CADPE	2013/19	91	3.48	37	63	$3.4 \cdot 10^{-3}$ / 4.40 / 63.65

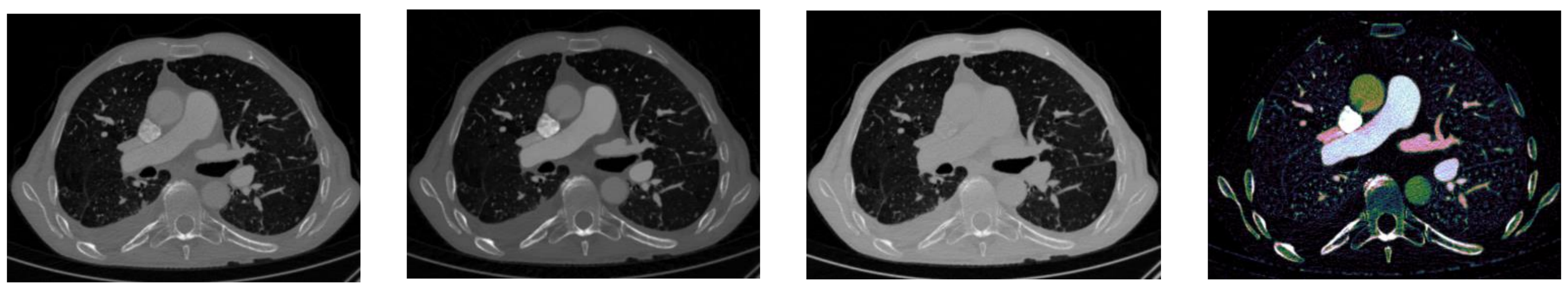
Overview of the data sets, while N is the number of scans, N_{PE} the number of emboli, $N_{Peri/Proxi}$ the number of peripheral/proximal emboli and V the volume of emboli

Single-Energy CT (SECT)

- Image were collected with one spectrum, resulting in conventional scans [6]

Dual-Energy CT (DECT)

- Simultaneously collection of low and high energy data [6]
- Enables computation of different image representations [6]
- Take advantage of energy dependency for material differentiation [6]
- Monoenergetic images simulates how the image would look like, if the data is measured with a monochromatic X-ray beam at that energy [6]
- Low/high monoE images has a high/low contrast [6]



Conventional MonoE50 MonoE150 Iodine Map

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[1] Masoudi, Mojtaba, et al. "A new dataset of computed-tomography angiography images for computer-aided detection of pulmonary embolism." *Scientific data* 5.1 (2018): 1-9.
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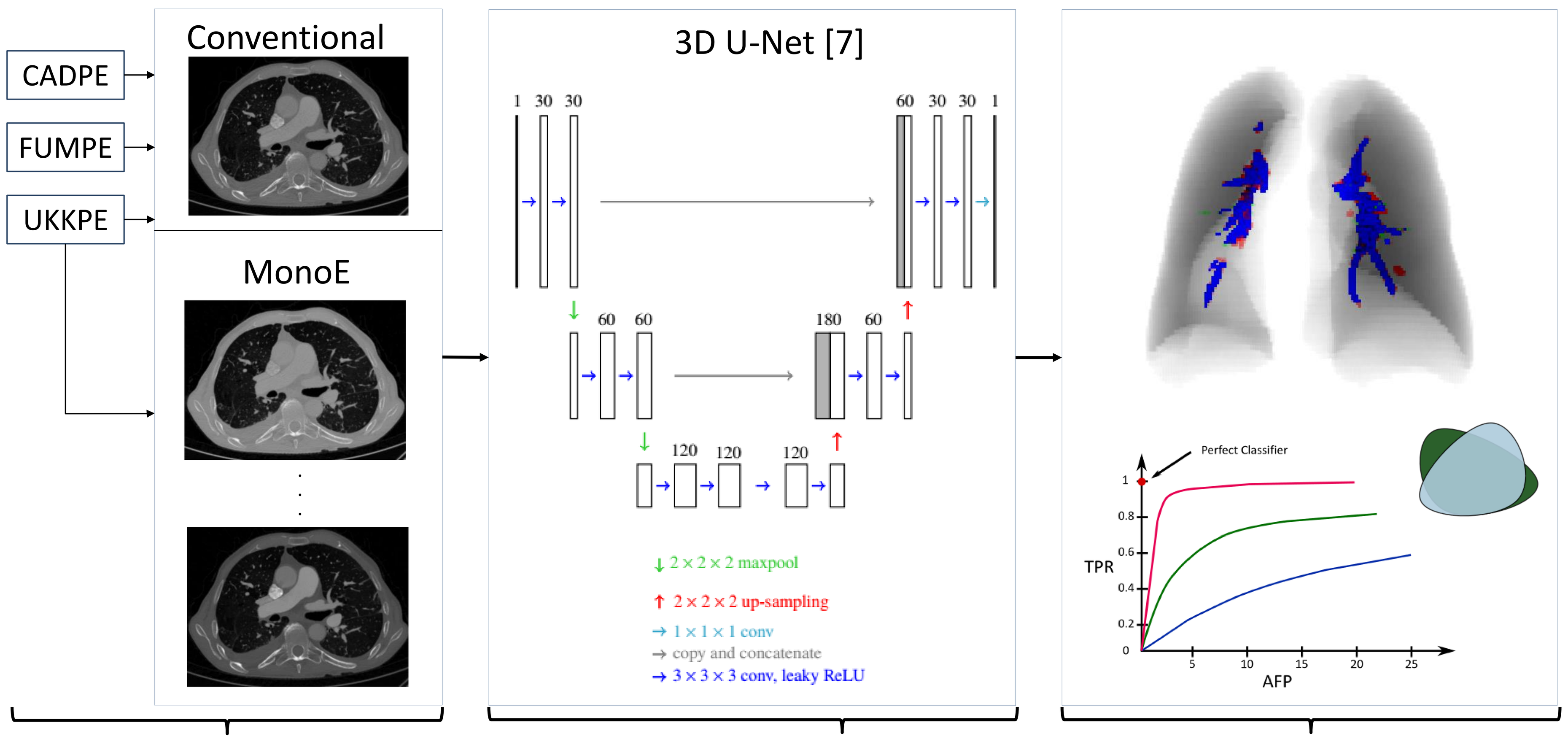
[3] Henzler, Thomas, et al. "CT imaging of acute pulmonary embolism." *Journal of cardiovascular computed tomography* 5.1 (2011): 3-11.
[4] Lin, Yi, et al. "Automated pulmonary embolism detection from CTPA images using an end-to-end convolutional neural network." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2019.
[5] Lartaud, Pierre-Jean, et al. "Spectral CT based training dataset generation and augmentation for conventional CT vascular segmentation." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2019.
[6] Forghani, Reza, et al. "Dual-energy computed tomography: physical principles, approaches to scanning, usage, and implementation: part 1." *Neuroimaging Clinics* 27.3 (2017): 371-384.
[7] Ronneberger, Olaf, et al. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

III METHODS & EVALUATION



Input

- 100% conventional images of each data set
- 50% conventional + 50% monoE images (UKKPE)
- MonoE images are generated using random energy level $E \in [E_{\min}, E_{\max}]$

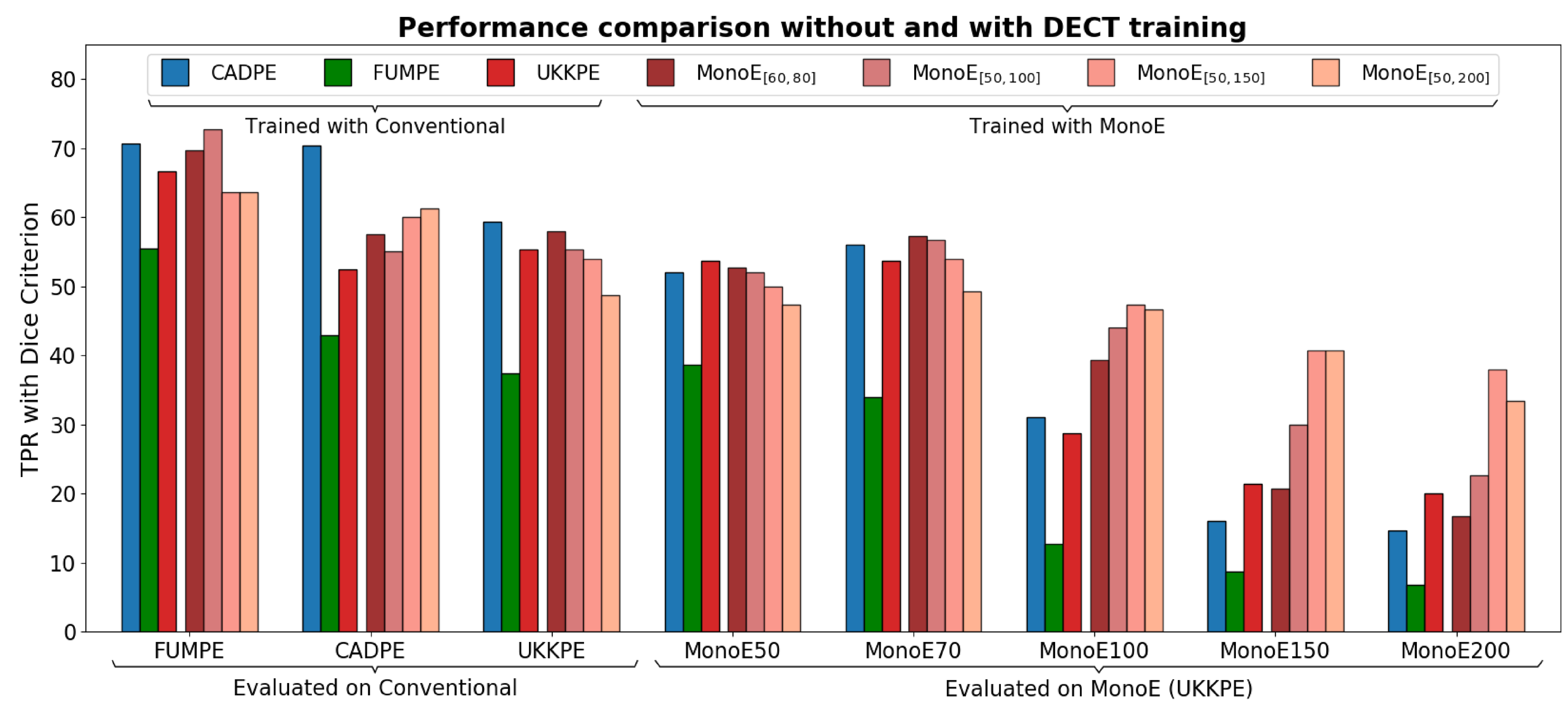
Training

- 3 conventionally trained networks
- 4 networks trained with DECT augmentation using different energy intervals

Evaluation

- Consider sensitivity at an average false positive rate of 5
- Hit, if Dice score of prediction and embolus is at least 20%

IV RESULTS



Evaluation of the seven networks on conventional test images from FUMPE, CADPE, UKKPE and on monoE test images of fixed energies of UKKPE

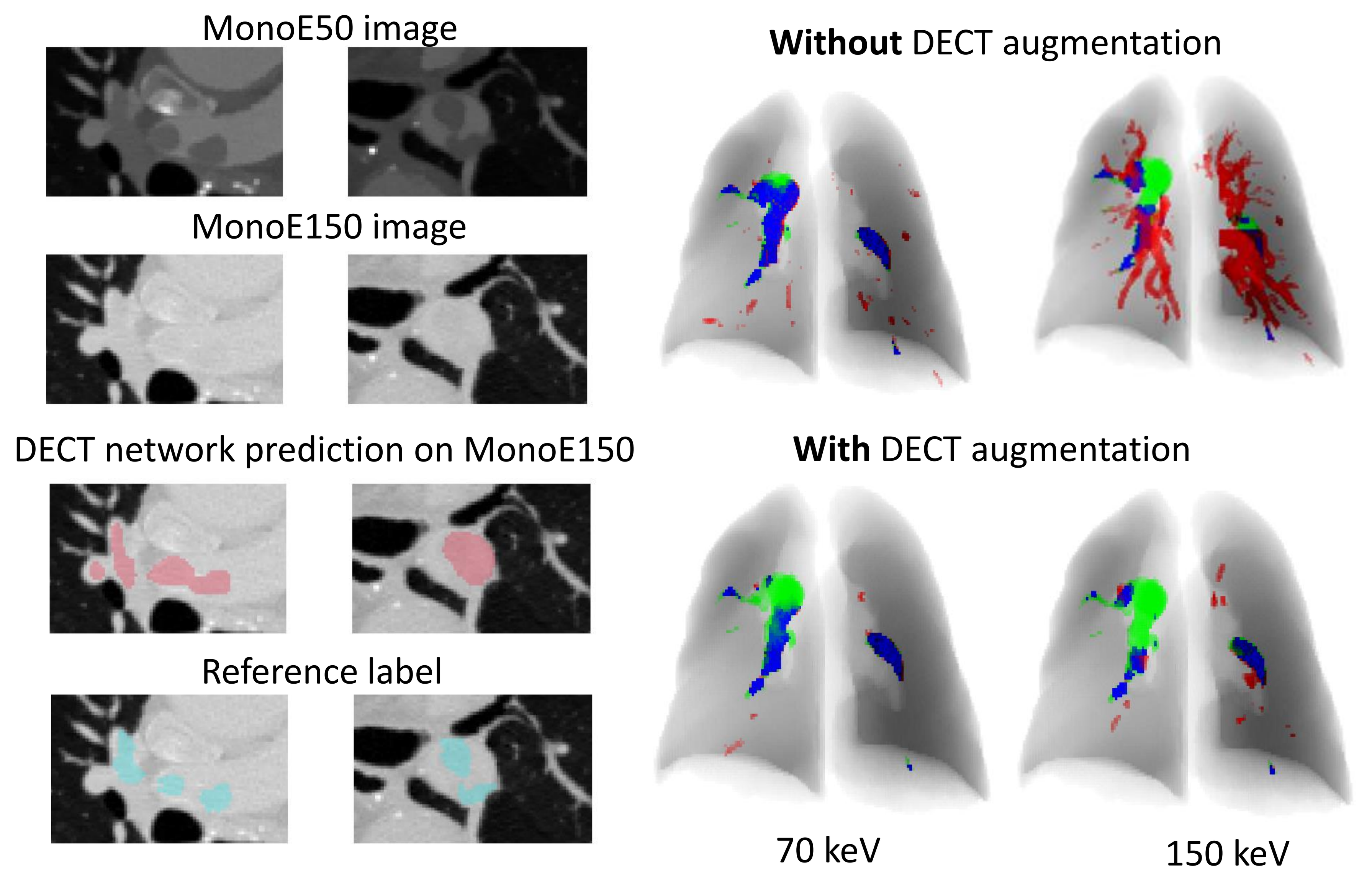
Conventional trained networks

- Cannot handle contrast variations of monoE test images
- Generalizability depends on used training data set

DECT augmentation

- increases performance on monoE test images
- improve the performance on conventional test images

Network trained with DECT augmentation still detects emboli on monoE150 images, while networks trained without DECT augmentation tends to segment the complete vessel tree.



Results: Conventionally trained networks cannot handle contrast variations. Training with DECT augmentation leads to more contrast-independent networks and can increase the performance on conventional images.