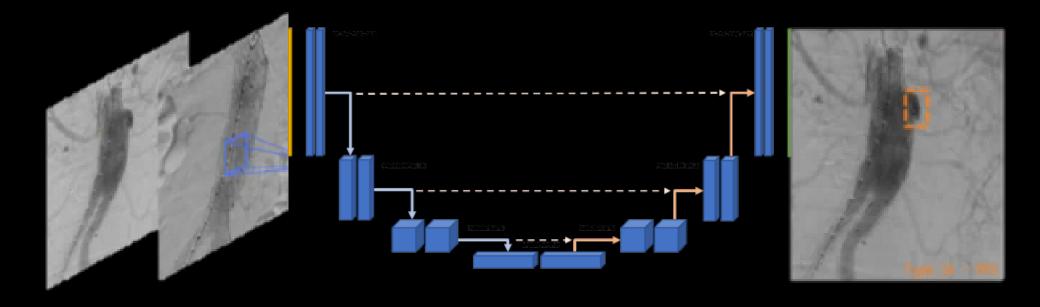


Artificial intelligence-based intraoperative endoleak visualization with completion digital subtraction angiography images during EVAR

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Disclosures

Speaker name:

Stefan Smorenburg

I have the following potential conflicts of interest to report:

- □ Consulting
- Employment in industry
- $\hfill\square$ Stockholder of a healthcare company
- \Box Owner of a healthcare company
- X Other(s)

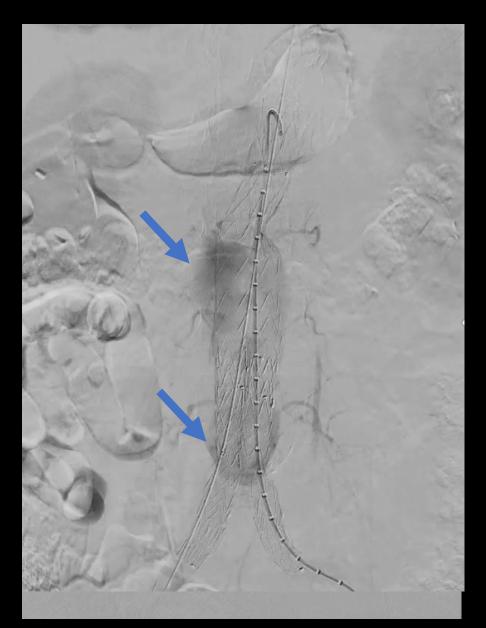
partly funded research by Philips

 \Box I do not have any potential conflict of interest

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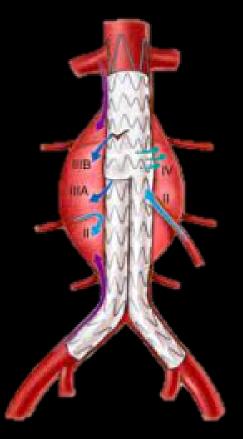
Completion angiography

- Performed at the end of every EVAR procedure
- Digital subtraction angiography (DSA)
- Inspection of:
 - Stent graft position
 - Patency of renal/visceral/iliac arteries
 - Endoleaks

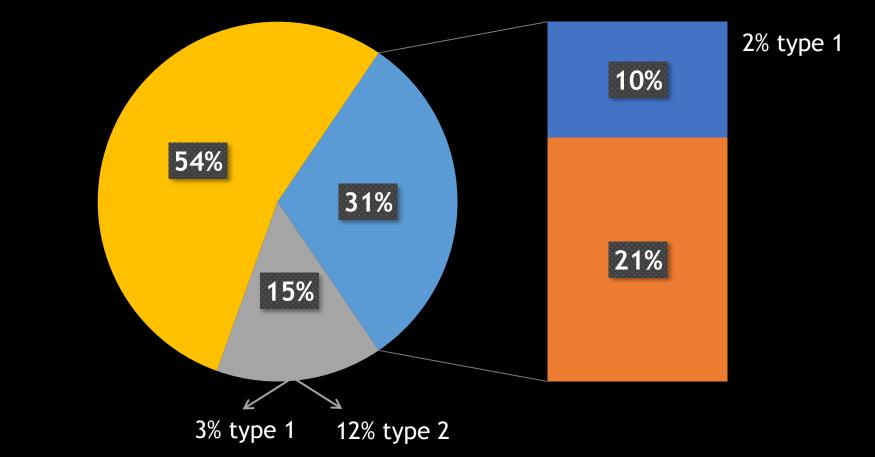


Intraoperative endoleaks

- Types 1 and 3 endoleaks can be treated within thesame procedure:
 - proximal/distal ballooning (1a/1b)
 - cuff extension (1a)
 - endoanchors (1a)
 - distal leg extension (1b)
 - relining (3)
- Current endoleak assessment is performed by 'visual inspection'
 - subjective
 - limited by human interpretation
 - physician experience







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Study aim

To perform **automatic analysis** of **completion angiography** imaging obtained during EVAR procedures with **artificial intelligence**-based **deep learning**

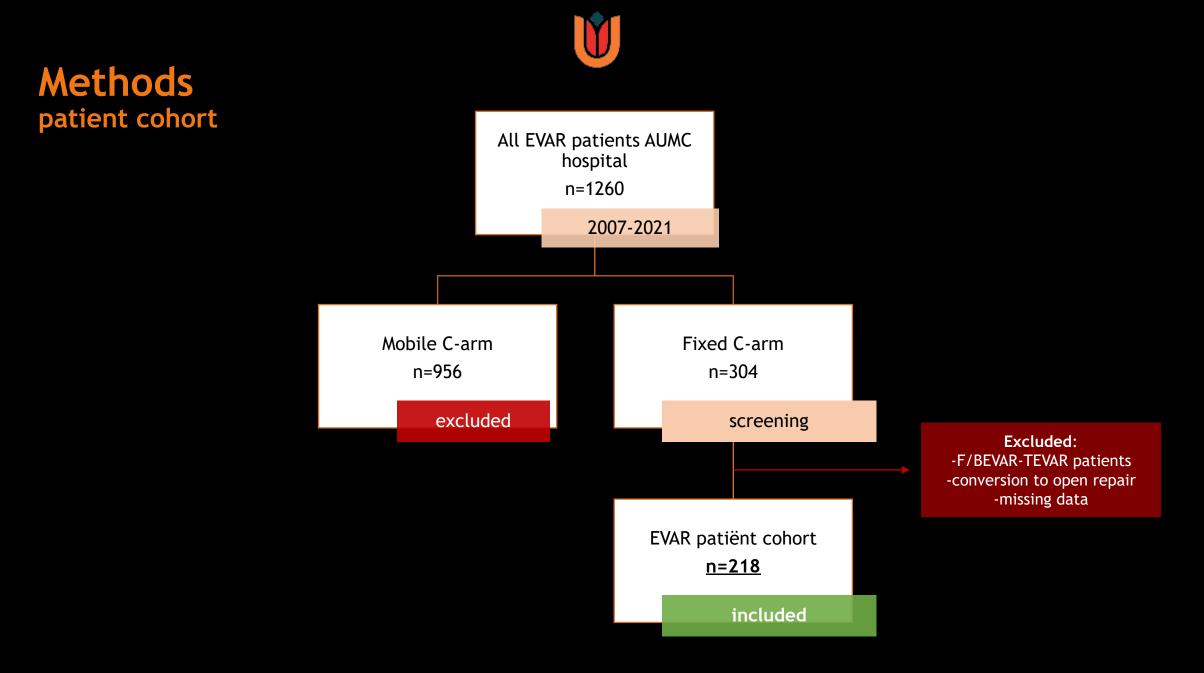
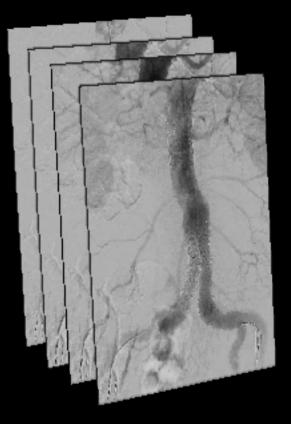
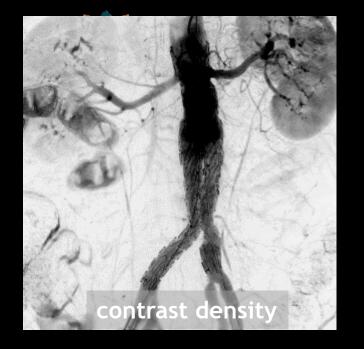
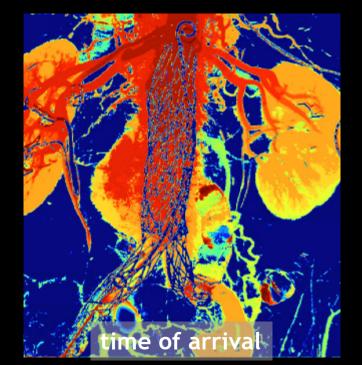


Image preprocessing perfusion parameters



DSA movie was converted











Manual labeling for model input

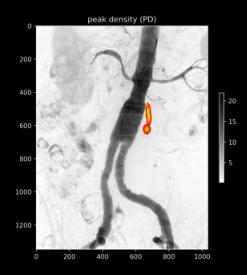
- 2 vascular surgeons
- 2 interventional radiologists
- 1 operating team
- Scored the completion angiographies on:
 - Endoleak yes/no
 - Type
 - Location

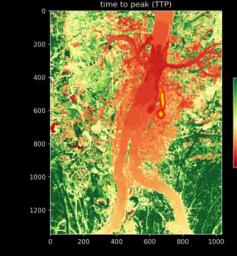


Deep learning model

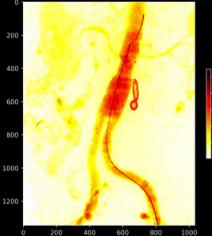


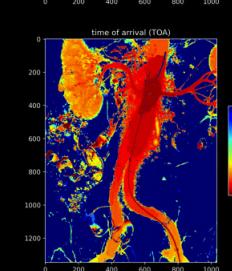
inputs:





area under the curve (AUC)



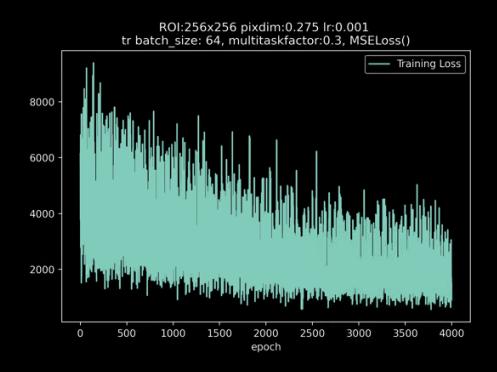


- U-Net architecture
- Data:
 - 220 completion angiograms
 - Half with endoleak
 - Split in train (70%), validation (10%) and test set (20%)

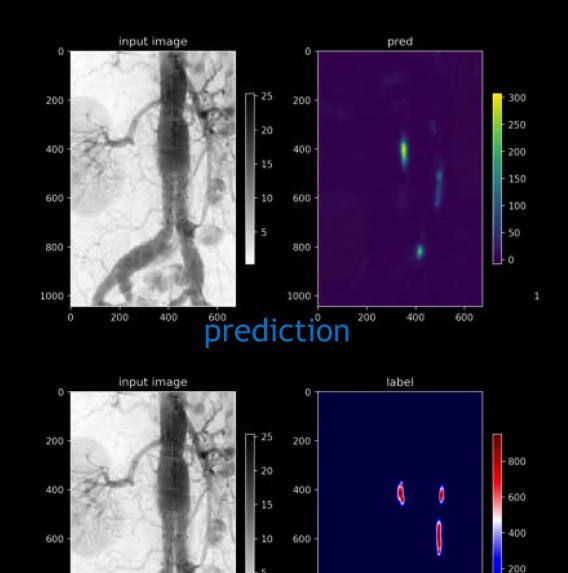
Training (154)	Val (22)	Test (44)
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- Data augmentation:
 - Vertical flipping
 - Z-axis rotation (15 degrees)
- MSE-loss, Adam optimizer
- Pytorch and Medical Open Network for AI (MONAI)

Results Deep learning model



Training loss declining

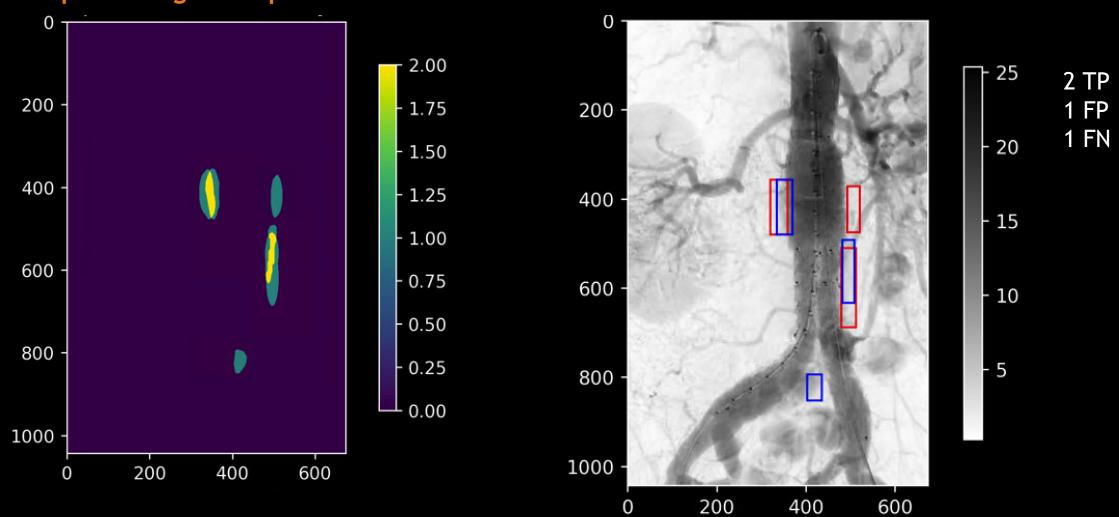


label "

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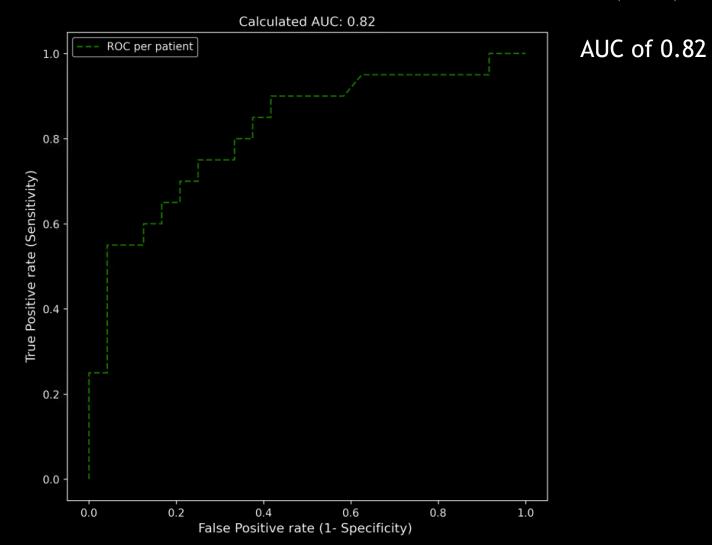


Results Deep learning intraoperative endoleak visualization



blue=prediction, red=label

Results Receiver operating curve (ROC) with area under the curve (AUC)





Conclusion

We developed a fully automated endoleak visualization method, based on the completion digital subtraction aniography during EVAR.

The extraction of detailed imaging knowledge, can aid in intraoperative clinical decision making.

Future development will focus on better endoleak classification.

Al-team at Amsterdam UMC

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Dieuwertje Alblas - mathematician Kaj Kappe - technical physician

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