

ADAM: Aneurysm Detection And segMentation Challenge

Unil – CHUV Team

Tommaso Di Noto ^a, MSc; Marie Guillaume ^a, MD; Sebastien Tourbier ^a, PhD; Yasser Alemán-Gómez ^{a,b}, PhD; Guillaume Saliou ^a, MD; Meritxell Bach Cuadra ^{a,c,d}, PhD; Patric Hagmann ^a, PhD; Jonas Richiardi ^a, PhD

a. Department of Radiology, Centre Hospitalier Universitaire Vaudois (CHUV) and University of Lausanne (UNIL)

b. Department of Psychiatry, Centre Hospitalier Universitaire Vaudois (CHUV) and University of Lausanne (UNIL)

c. Medical Image Analysis Laboratory (MIAL), Centre d'Imagerie BioMédicale (CIBM), Centre Hospitalier Universitaire Vaudois (CHUV) and University of Lausanne (UNIL)

d. Signal Processing Laboratory (LTS 5), Ecole Polytechnique Fédérale de Lausanne (EPFL)

Background

- Diagnosis of unruptured aneurysms is a critically important clinical task. It occurs to 1% to 3% of the population and accounts for more than 80% of nontraumatic subarachnoid hemorrhages¹.
- Not only a CNN-like model capable of automatically detect brain aneurysms could improve clinicians' performances², but it could also help mitigate the steadily increasing workload of radiologists in the next decades, speeding up the diagnosis process.

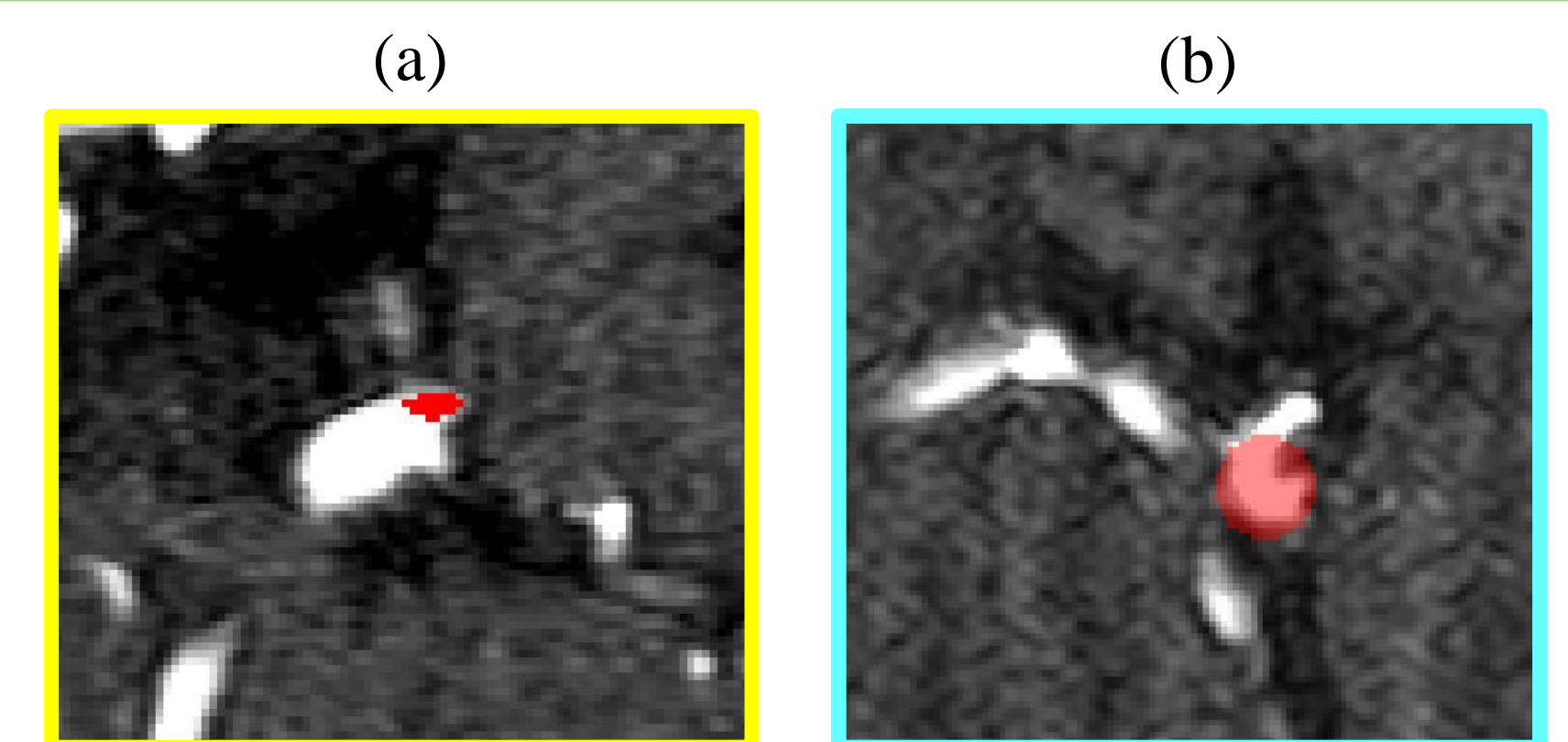
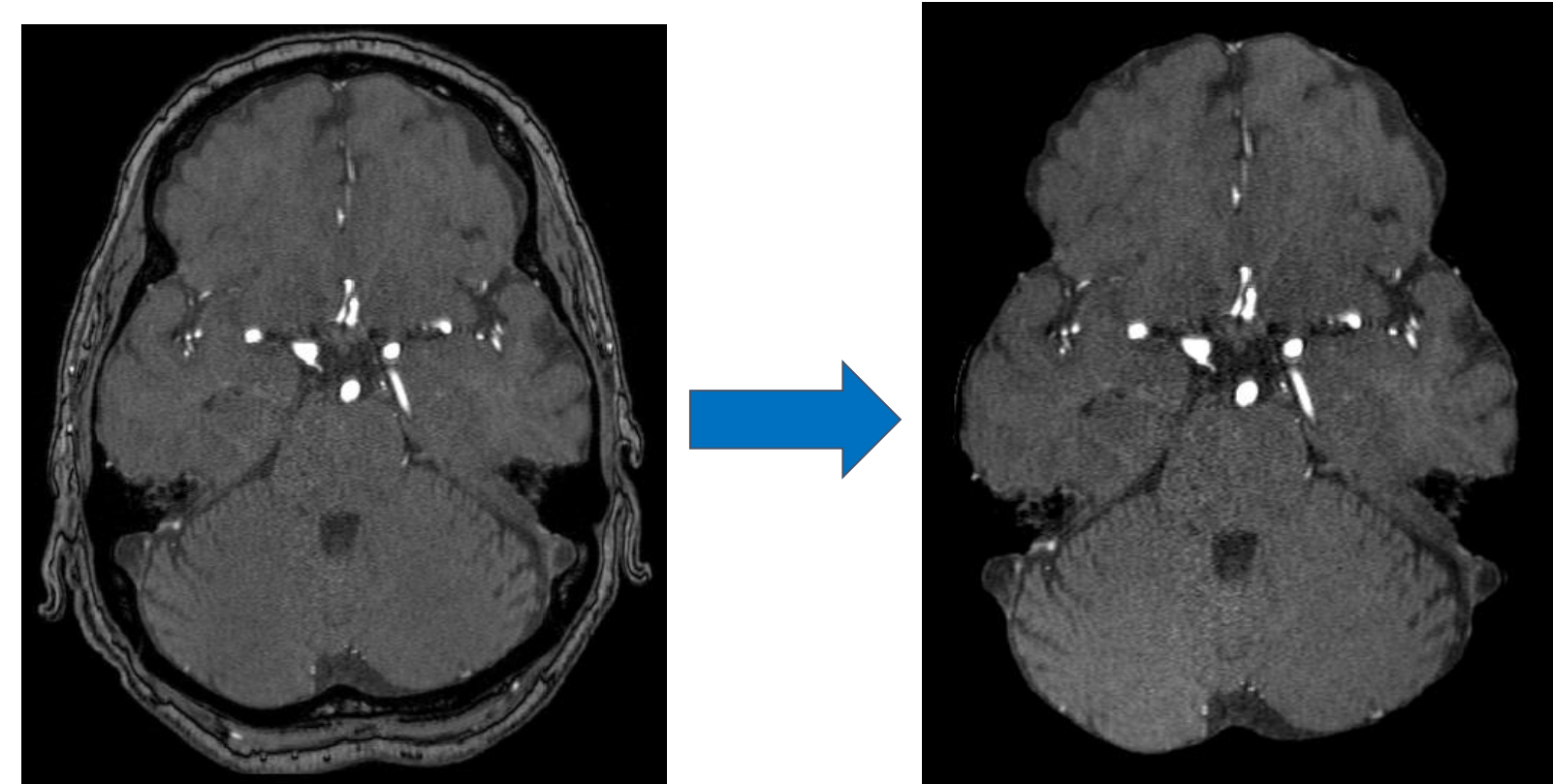
Materials & Methods

Dataset

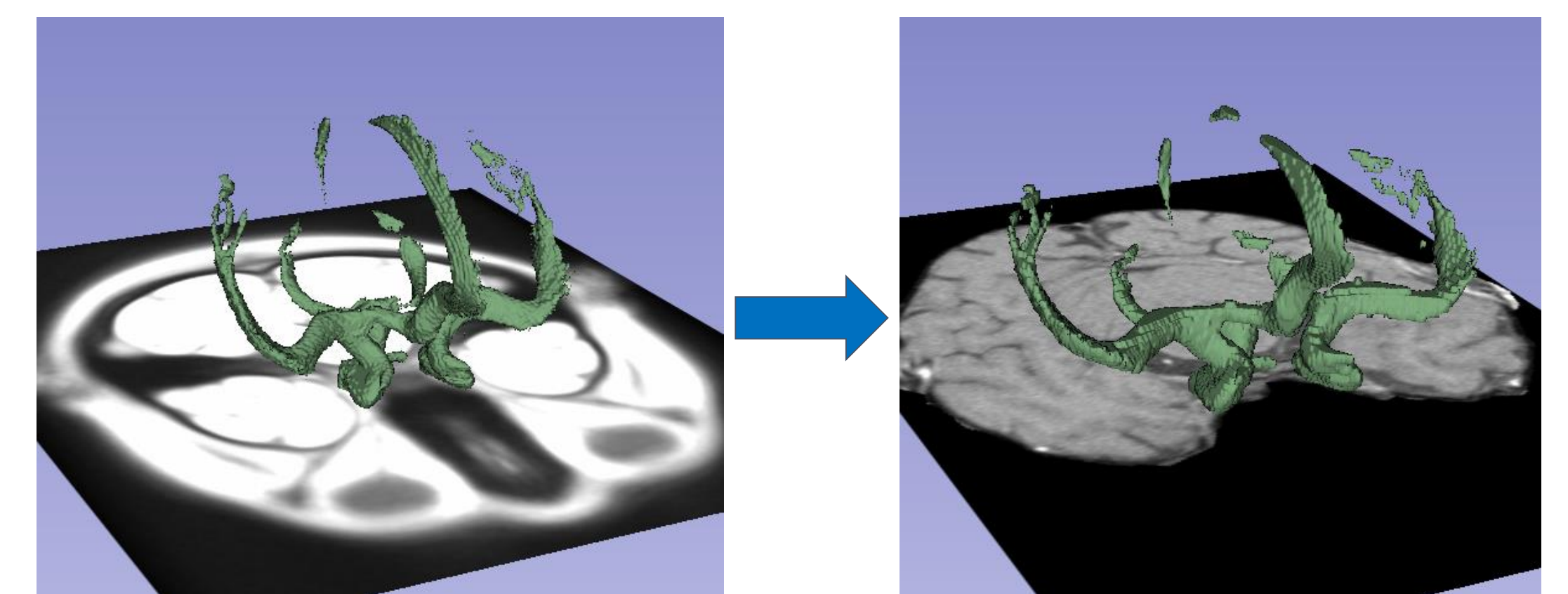
- ❑ **ADAM**: 113 subjects (93 patients, 20 controls); 125 aneurysms
- ❑ **CHUV**: 214 subjects (83 patients, 131 controls); 111 aneurysms

Pre-processing

- ❑ FSL Brain extraction³
- ❑ Registration of probabilistic vessel atlas⁴ from MNI to TOF space with ANTs⁵



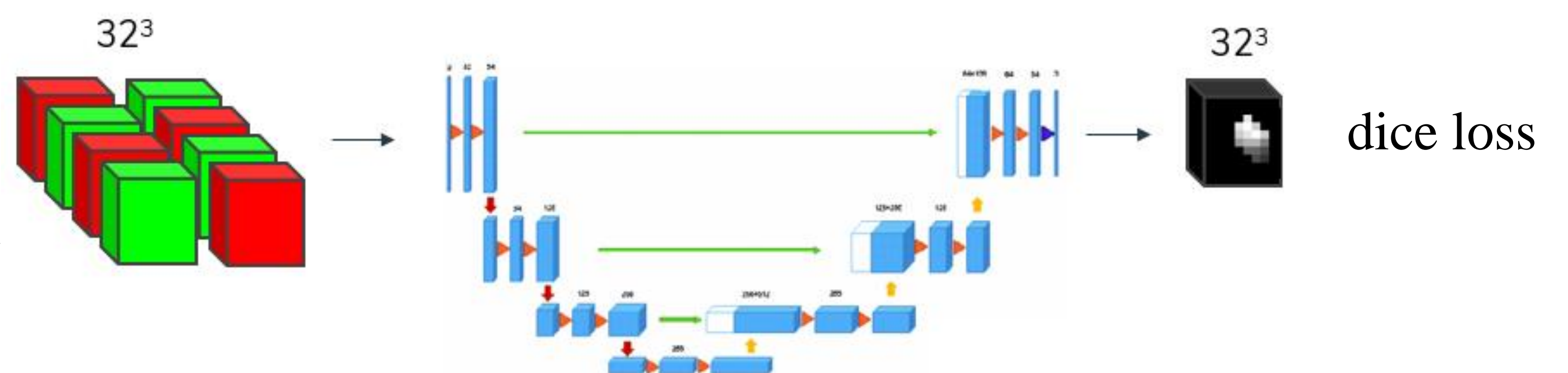
Axial slice of two manual masks. (a) «voxel-wise» mask of the ADAM dataset; (b) «weak» mask of our CHUV dataset. Weak labels correspond to spheres enclosing the aneurysms.



- **Train dataset creation:** for every subject, we extract 30 **negative** (i.e. without aneurysms) **patches**: 24 in correspondence with landmark points where aneurysms are recurrent and 6 in correspondence with other vessels. Moreover, for patients with aneurysms, we extract 5 **positive** (i.e. with aneurysm) **patches** with random shifts around the lesion. All patches have shape 32^3 .

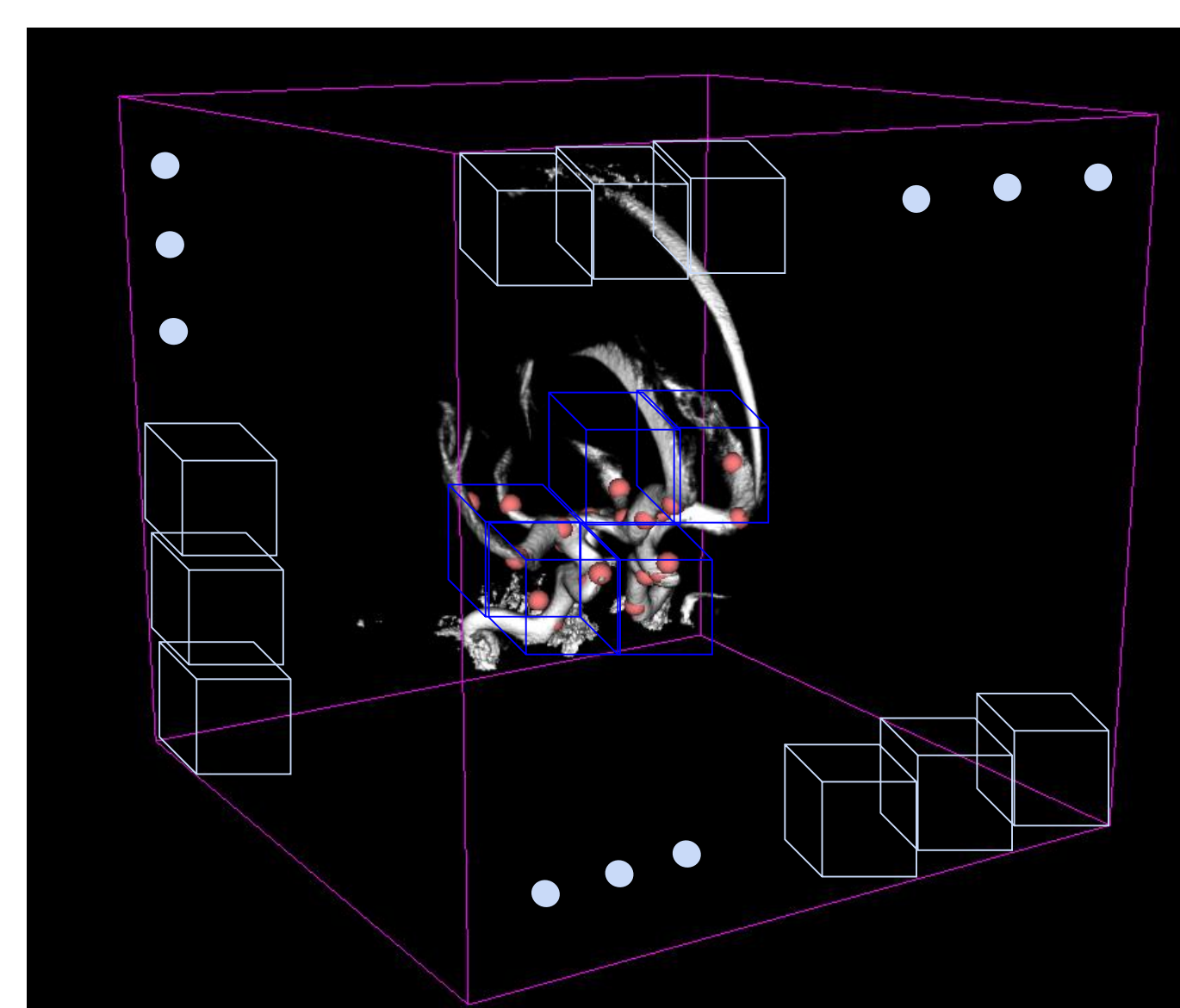
Patch-wise training 3D-Unet:

the model is trained to distinguish background voxels from aneurysm voxels through the Adam optimizer, with adaptive learning rate and 500 epochs.



Patient-wise inference:

at test time, every subject is scanned with a sliding-window approach. **White** patches in the figure are discarded because unlikely to contain aneurysms.



Instead, we retain the **anatomically-plausible patches**. These are then fed to the trained U-Net which outputs a prediction and thresholds it. If after the threshold there are still some non-zero voxels, the biggest connected component is considered a candidate aneurysm and its center of mass is used to compute the voxel coordinates of the aneurysm center.

FP reduction:

1. Max 4 FP per patient (most probable)
2. Merge predictions of adjacent patches

Detection Results

Team: unil_chuv	Task 1 Rank: 0.4	Task 1 Place: 9 th
(lower rank is better)		
Task 1	False Positives	Sensitivity
Average	1.45	0.2
Rank	0.06	0.73

References:

1. Jaja et al., (2013), *Neurocritical Care*
2. Park et al., (2019), *JAMA Network, Health Infor.*
3. Smith, (2002), *Human Brain Mapping*
4. Mouches et al., (2019), *Scientific data*
5. Avants et al., (2011), *Neuroimage*



Tommaso Di Noto

Email: Tommaso.Di-Noto@chuv.ch