Intracranial Aneurysm Detection using Spherical Representations

Youssef Assis[1], Liang Liao[1,2,3], Fabien Pierre[1], René Anxionnat[2,3], Erwan Kerrien[1]

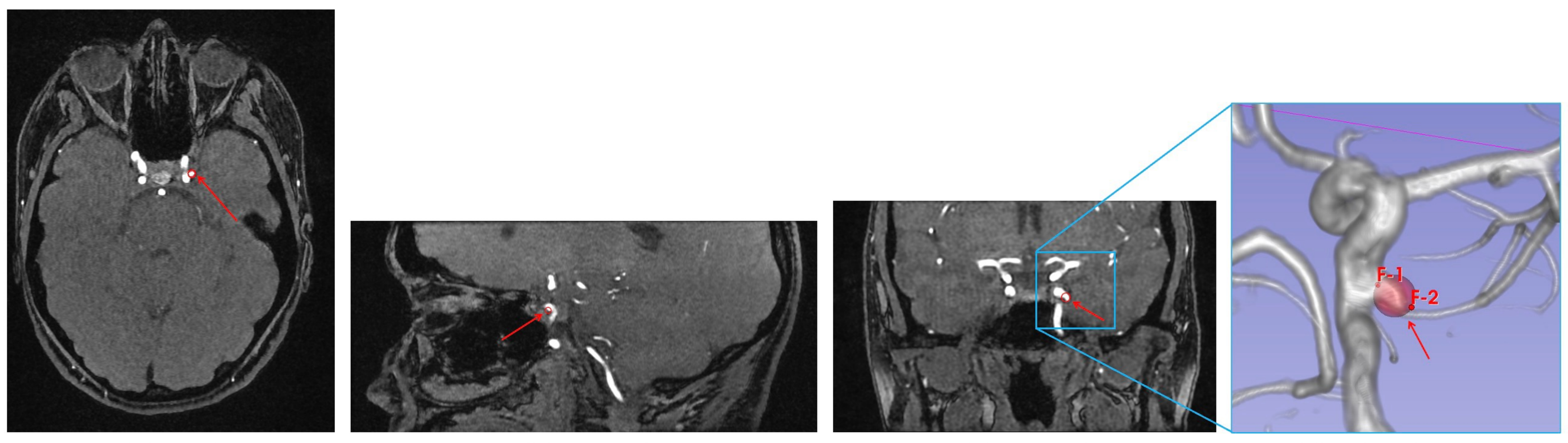
[1] University of Lorraine, CNRS, INRIA, LORIA, F-54000 Nancy, France
[2] Department of Diagnostic and Therapeutic Neuroradiology, University of Lorraine, Nancy, France
[3] IADI, INSERM U1254, University of Lorraine, Nancy, France

Context & Contributions

- **Context**: Detection of unruptured Intracranial aneurysms is a difficult problem.
- **Goal**: - Automate aneurysm detection.
  - Assist radiologists in their clinical routine.
- **Contributions**: - Efficient data sampling strategy.
  - 3D adaptation of the YOLO [4] architecture.
  - More adapted evaluation metrics.

Introduction

- **Intracranial aneurysms**: local dilatations of cerebral blood vessels (Figure 1, red arrows).
- Extremely difficult detection problem:
  - **Data scarcity:** - Small and private datasets.
    - 0 to 5 aneurysms per patient.
  - **Class imbalance**: very small structures (≈10/1M voxels).
  - **Data annotation**: difficult and time-consuming.



(a) Axial (b) Sagittal (c) Coronal (d) Sub-volume 3D

Figure 1: MRA (a,b,c) cut planes; (d) VR view (aneurysm size 3.80mm)

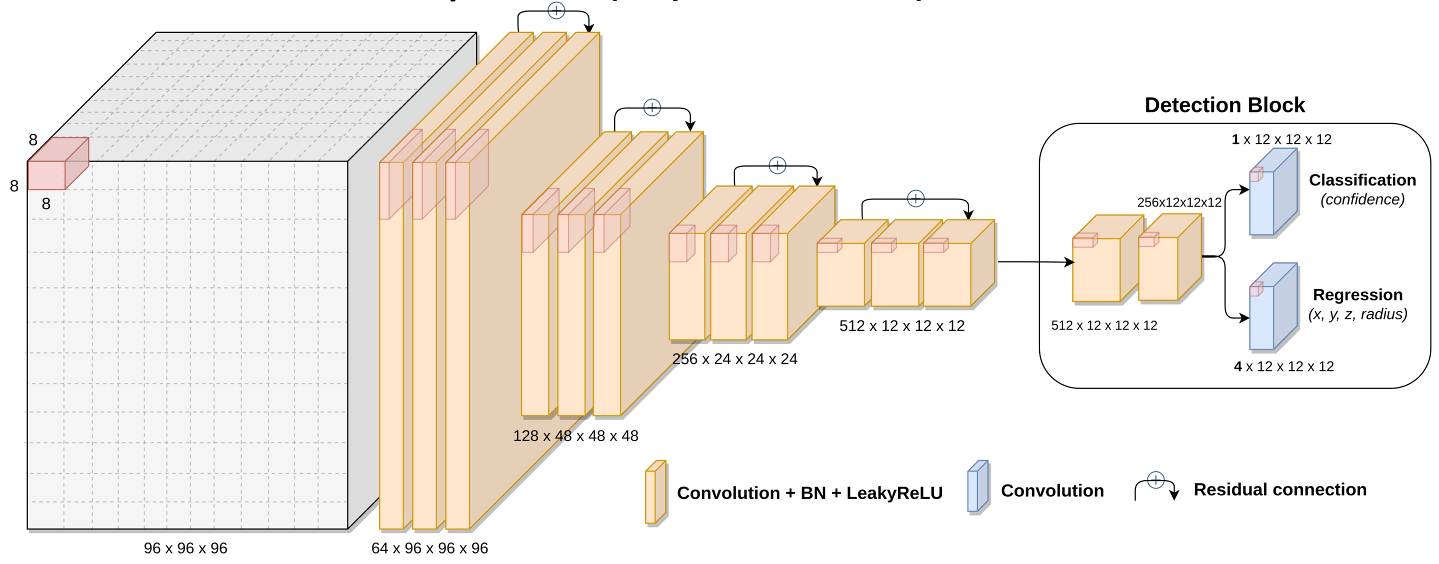
Method

1. **Datasets:** TOF-MRA images

	# Subjects	# Aneurysms	Mean size
CHRU Nancy	132	206	3.97mm
CHUV Lausanne [1]	270	164	3.74mm

2. **Data Sampling Strategy:**
   - **a) Data annotation:**
     - Approximate and fast: 2 points → Sphere (Figure 1).
   - **b) Small patch-based approach:**
     - 96 x 96 x 96 voxels.
     - Non-intersecting → independent patches.
   - **c) Data selection and synthesis:**
     - Negative patches (without aneurysm): Selection
       40 patches per patient; Mostly centered on blood vessels.
     - Positive patches (with aneurysm): Synthesis
       50 duplicates and deformation by random distortion.

3. **Deep Neural Network Architecture:**
   - 3D anchor-free adaptation of the YOLO [4] architecture.
   - Detection → Sphere (*x, y, z, radius*) + confidence score.



4. **Evaluation:**
   - Based on Intersection-over-Union metric (TP = IoU > 10%).
   - Average Precision (AP), Sensitivity, False positives per case.

Experimental Study

1. **Preliminary study: CHRU Nancy**
   - **Ablation study confirms our data sampling strategy:**
     - Data selection and synthesis.
     - Spherical representation >> Box representation.
     - Anchor-free >> Anchor-based.
   - Results (5-Fold cross validation):
     - Average Precision: 81.22%.
     - Sensitivity: 81.55% associated with 0.57 FP/case.

2. **Validation with public dataset: CHUV Lausanne [1]**
   - 5-Fold cross validation.
   - Very competitive results.
   - Reduced training and inference time.

	Average Precision (%)	Sensitivity (%)	FP/case	Training Time
nnDetection [2]	73.68	84.76	0.67	29 hours
nnUnet [3]	72.46	71.95	0.13	5 days
Ours	75.80	84.76	0.57	24 hours

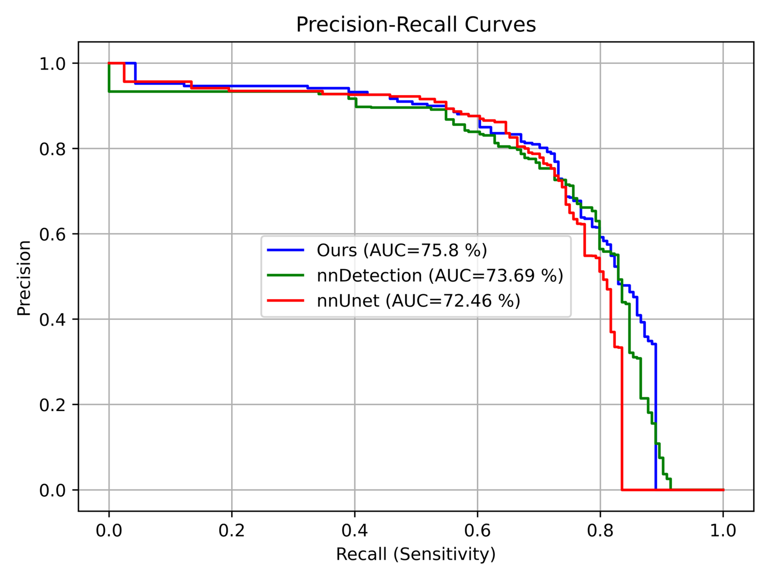


Figure 3: Precision-Sensitivity curves

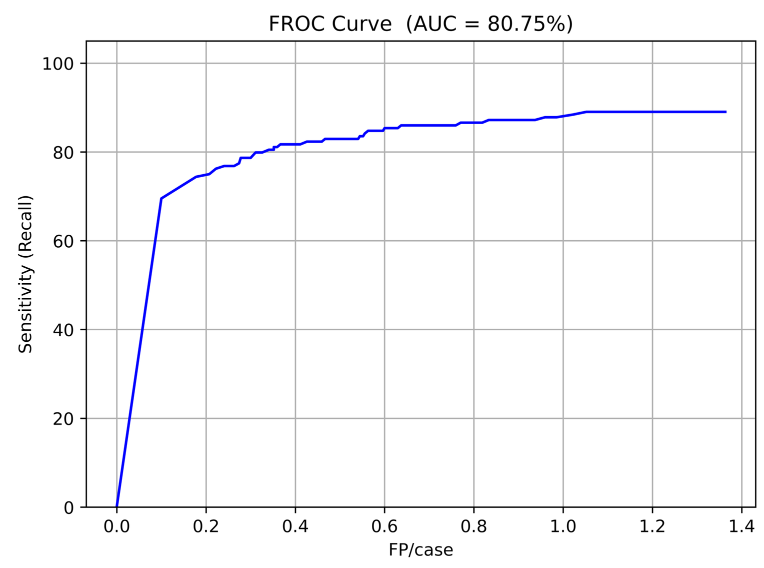


Figure 4: FROC curve of our method

Visual Results

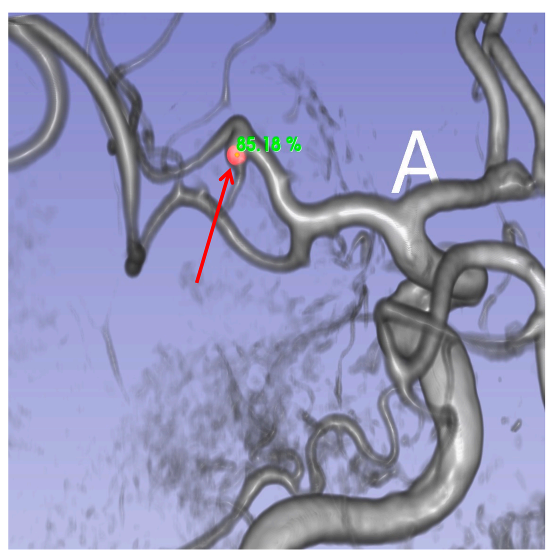


Figure 5: Branching of small arteries can be mistaken for an aneurysm (false positive)

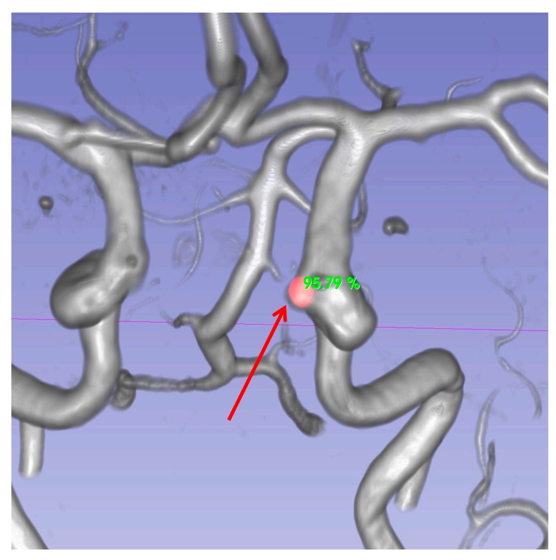


Figure 6: A detected aneurysm that was overlooked during the annotation phase (Expert sensitivity < 100%)

Conclusion & Perspectives

- Combination of an efficient data sampling strategy with a 3D YOLO architecture for aneurysm detection.
- Can be easily adapted for small object detection problems.
- **Perspectives:** combine and improve the performance with recent training techniques from 2D object detection.

References

[1] Di Noto et al. Towards automated brain aneurysm detection in TOF-MRA: open data, weak labels, and anatomical knowledge, Neuroinformatics, 2022.
[2] Baumgartner et al. nnDetection: a self-configuring method for medical object detection. MICCAI, 2021.
[3] Isensee et al. nnu-net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 2021.
[4] Redmon et al. Yolov3: An incremental improvement, arxiv preprint, 2018.