

Aneurysm Pose Estimation with Deep Learning



Youssef Assis¹, Liang Liao^{1,2,3}, Fabien Pierre¹, René Anxionnat^{2,3}, Erwan Kerrien¹

¹ Université de Lorraine, CNRS, Inria, LORIA, F-54000 Nancy, France

² CHRU-Nancy, Department of Diagnostic and Therapeutic Interventional Neuroradiology, Nancy, France

³ Université de Lorraine, Inserm, IADI, F-54000 Nancy, France



Context & Contributions

Context

- Challenging clinical problem: unruptured brain aneurysm detection and assessment from TOF-MRA data.
- Need for automated and appropriate visualization of candidate aneurysms.

Contributions

- End-to-end CNN for pose estimation and object detection tasks.
- Efficient data sampling strategy.
- Evaluation metrics tailored to the problem.

Introduction

Brain aneurysms:

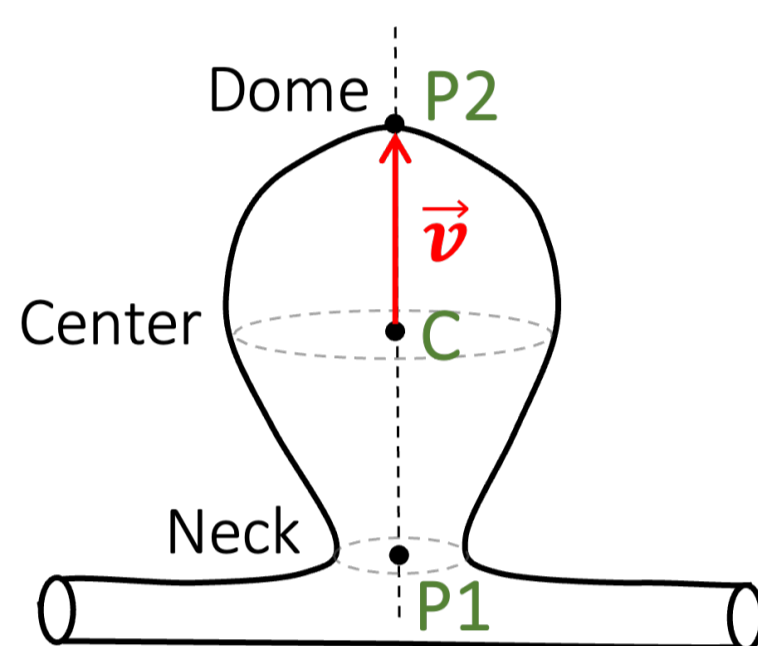
- Local dilatations of cerebral blood vessels.
- Mostly ball-shaped objects.

Objectives: Reformatted plane → Automated view

- Analyze connection to parent vessel.
- Similar to the DSA projection used for coiling.

Challenges:

- **Data scarcity:**
 - Small and private datasets.
 - 0 to 4 aneurysms per patient.
- **Class imbalance:** very small structures ($\approx 10/1M$ voxels).
- **Data annotation:** difficult and time-consuming.



Method

Datasets: 402 subjects

TOF-MRA	# Subjects	# Aneurysms	Mean size (mm)
In-house	132	206	3.97 ± 2.32
CHUV [1] (public)	270	164	3.74 ± 2.17

Data Strategy

- **Data annotation:**
 - Approximate and fast: 2 points (P1, P2) → Sphere.
- **Small patch-based approach:**
 - $96 \times 96 \times 96$ voxels ($38.4 \times 38.4 \times 38.4$ mm).
 - Non-intersecting patches → independent.
- **Data selection and synthesis:**
 - Negative patches (aneurysm-free): Selection
 - 40 patches per patient, randomly selected.
 - Mostly centered on blood vessels.
 - Positive patches (with aneurysm): Synthesis
 - 50 duplicates and deformation by random distortion.

Neural Network Architecture

- End-to-end 3D anchor-free CNN, inspired by 2D YOLO [2].
- **Pose Estimation:**
 - **Localization:** Center coordinates $C = (C_x, C_y, C_z) = (P1 + P2)/2$.
 - **Orientation:** Size and orientation $\vec{v} = (V_x, V_y, V_z) = (P2 - P1)/2$.
- **Object Detection:**
 - **Spheres:** center C , radius = $|\vec{v}|$.

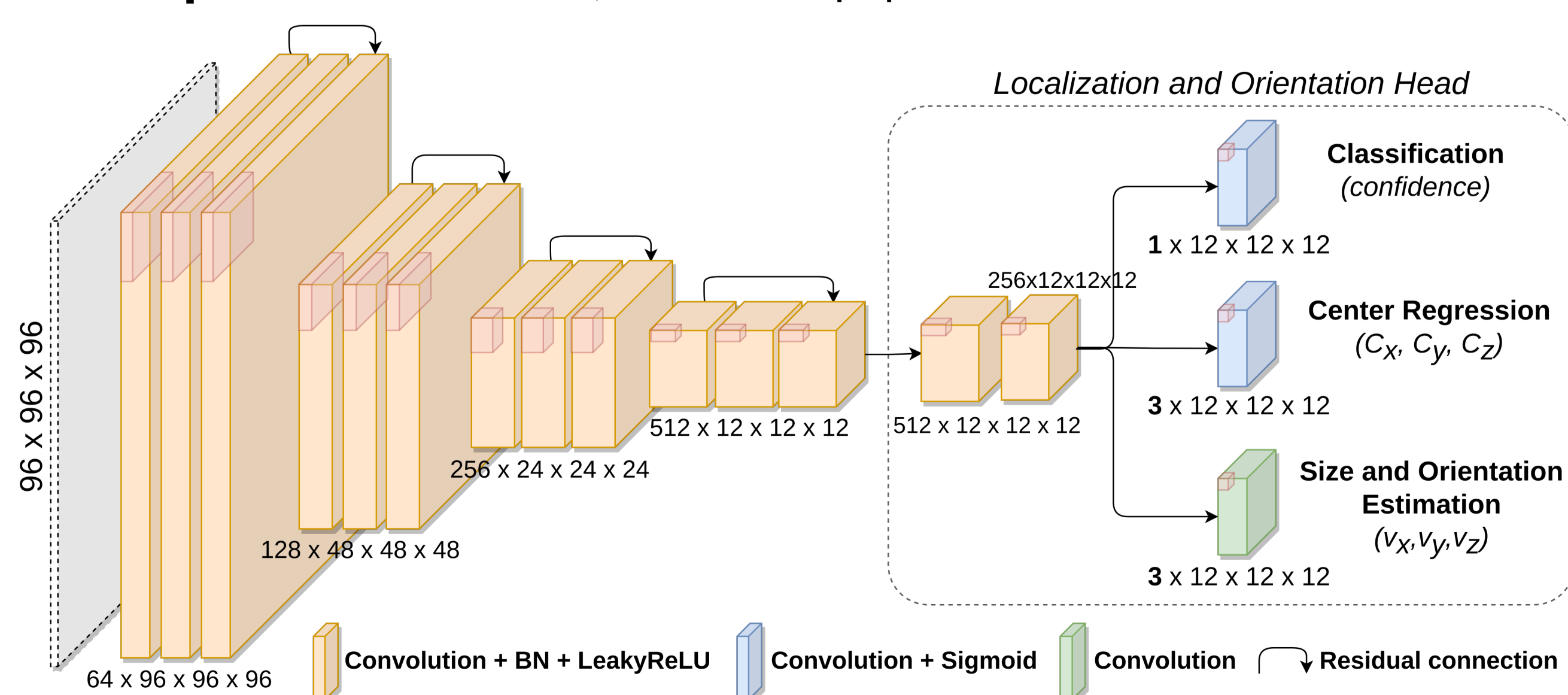


Figure 1: Our proposed aneurysm pose estimation architecture.

Experimental Study

Evaluation: 5-fold cross-validation

- Positive detection (TP):
 - Spheres (GT vs Prediction): IoU > 10%.

Pose Estimation: no SOTA to compare with

- **Datasets:** In-house and CHUV.
- **Localization:** Euclidian distance to GT center (mm)
- **Orientation:** Cosine similarity to GT orientation (acos)

	Localization (mm)		Orientation (°)	
	Median	Range	Median	Range
In-house	0.49	0.05 - 1.74	11.91	0.21 - 68.35
CHUV [1]	0.48	0.05 - 1.43	12.27	1.05 - 68.30

Object Detection: Spheres (C, radius)

- **Dataset:** CHUV [1].
- Compared with two fully automated SOTA baselines.

	Average Precision (%)	Sensitivity (%)	FP/case
nnDetection [3]	73.68 ± 6.38	84.76 ± 4.72	0.67 ± 0.12
nnUNet [4]	72.46 ± 4.74	71.95 ± 9.11	0.13 ± 0.06
Ours	76.60 ± 5.24	82.93 ± 5.92	0.44 ± 0.04

Qualitative Results

GT annotation (P1, P2) vs Predictions (Pred1, Pred2).
 $\text{Pred}\{1,2\} = C \pm \vec{v}$

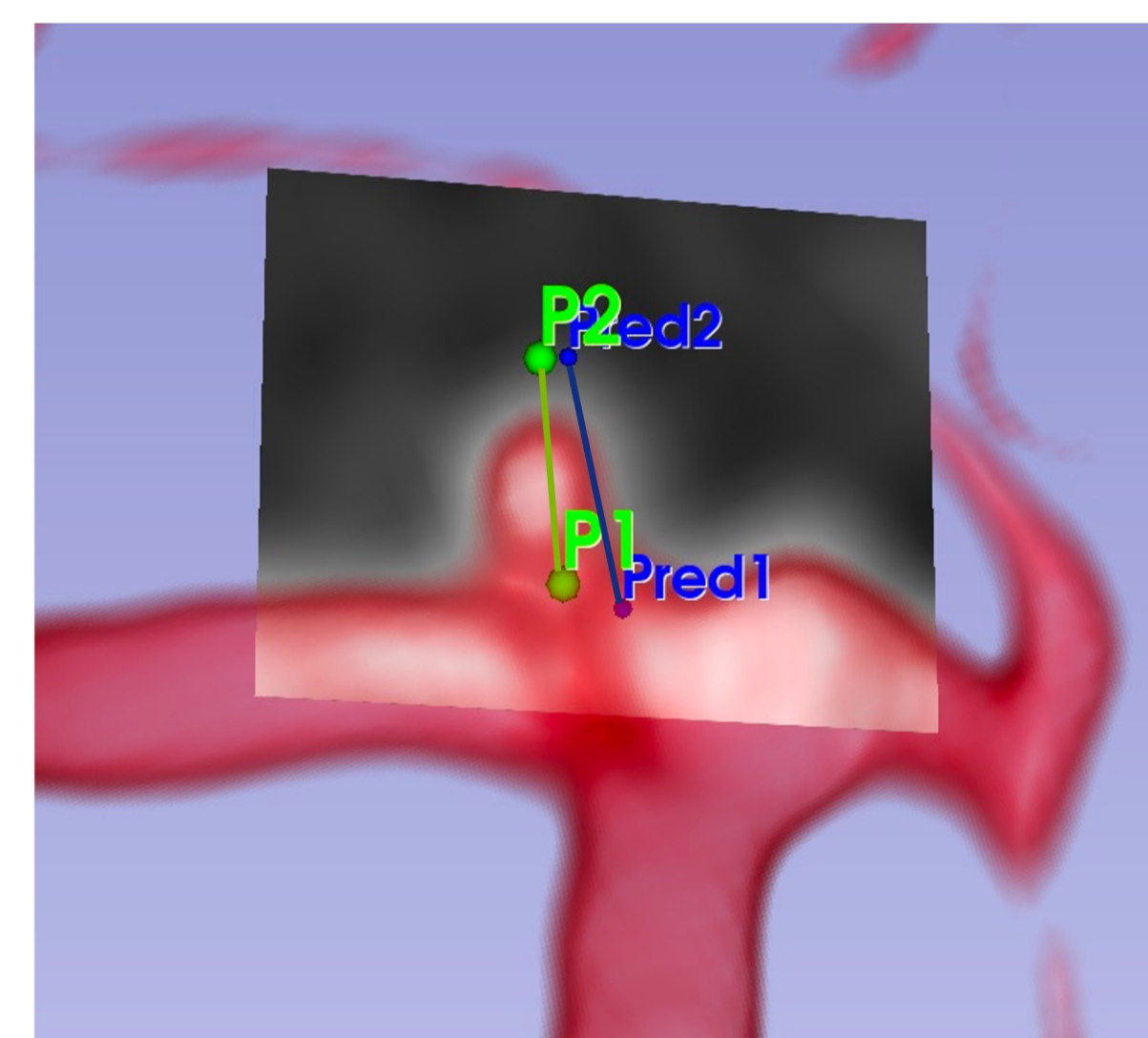


Figure 2: Detection of a very small 1.97 mm aneurysm (Error: 0.82 mm; 8.20°).

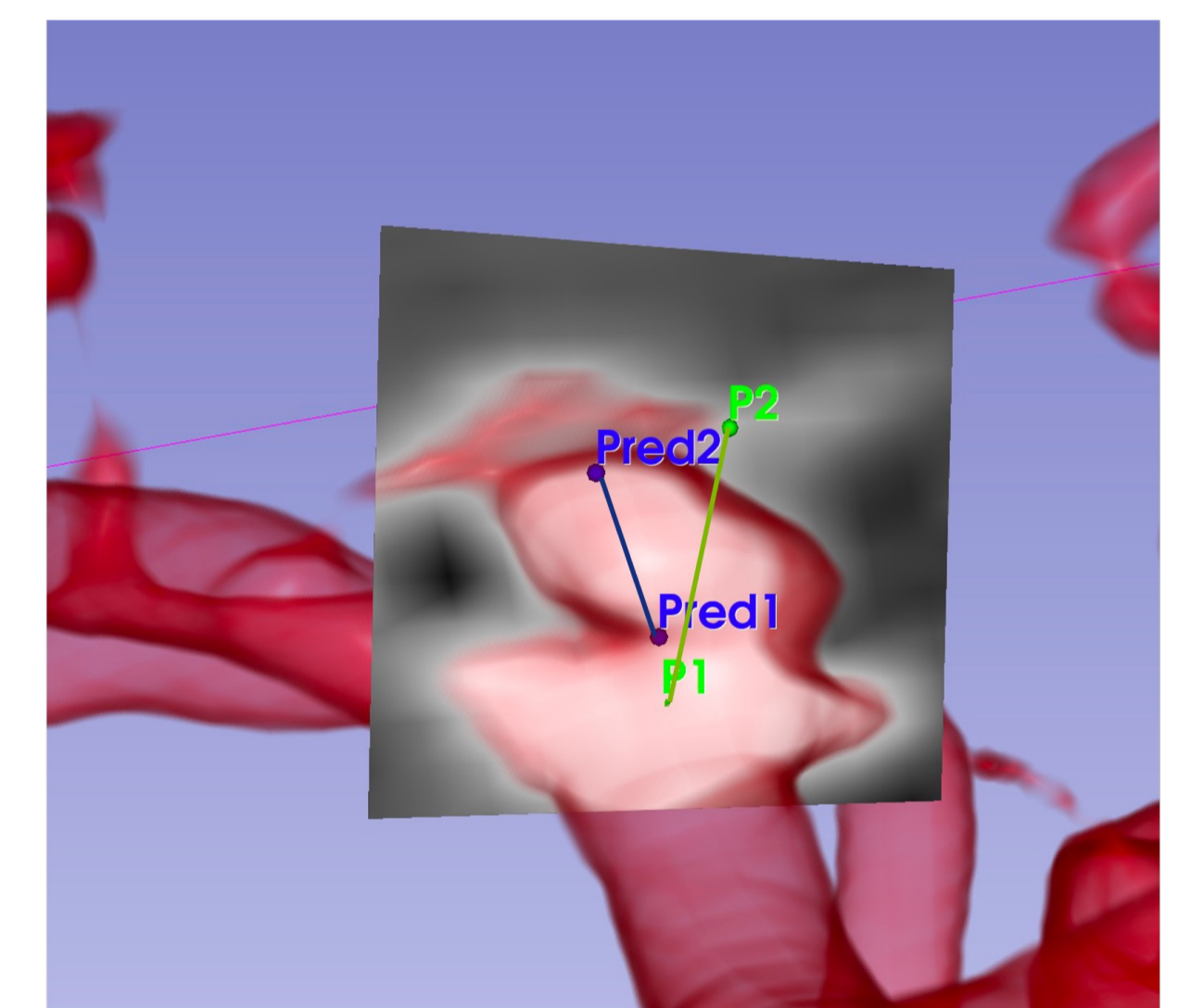


Figure 3: Large orientation error of 41.54° for a complex-shaped 3.52 mm aneurysm.

Conclusion & Perspectives

Conclusion

- The pose estimation architecture has shown promising results.
- Can also be applied to classical object detection tasks.
- Orientation errors are primarily due to annotation uncertainty for small and complex-shaped aneurysms.

Perspectives

- Develop a clinical definition for aneurysm orientation.
- Conduct evaluations in clinical settings.

Code and annotations are publicly available at:

<https://gitlab.inria.fr/yassis/DeepAnePose>.

References

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