

# Intracranial Aneurysm Pose Estimation with Deep Learning

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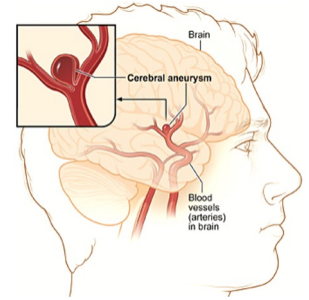
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# Introduction

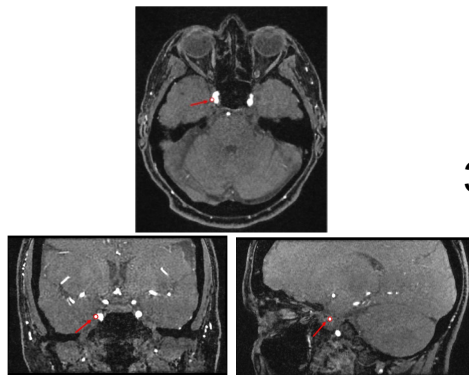
## Challenging clinical problem:

- Intracranial aneurysms:
  - Abnormal focal dilation of cerebral blood vessels.
  - Very small structures (1-30mm), mostly ball-shaped.
- Detection and evaluation from TOF-MRA data:
  - Navigating through different 2D cut planes: manual and time-consuming task.



## Objective: Automated detection and appropriate visualization

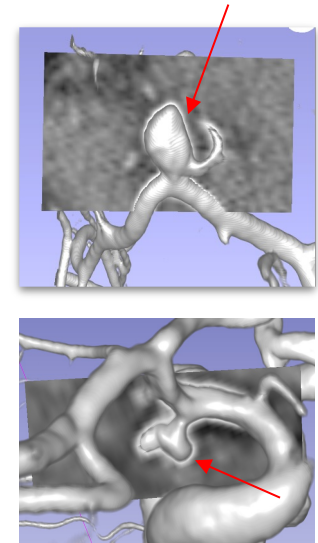
- Reformatted Plane for better understanding.
- Analyse connection to parent vessel.



3D TOF-MRA  
Image

Pose Estimation

Aneurysm Localization  
+  
Orientation Estimation



DSA: Digital Subtraction Angiography.



# Introduction

## Challenges:

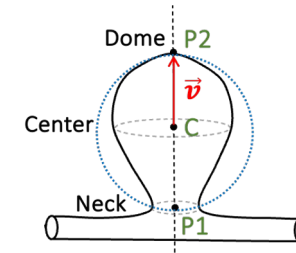
- **Data Scarcity:**
  - Limited and private datasets.
- **Class Imbalance:**
  - Aneurysms are rare (0 to 4/patient)
  - Small structures in MRA data ( $\approx 10/1M$  voxels).
- **Data Annotation:**
  - Difficult and time-consuming expert labelling.
  - How to label aneurysm orientation?

# Our proposed method

## Efficient Data Strategy

### 1. Data annotation:

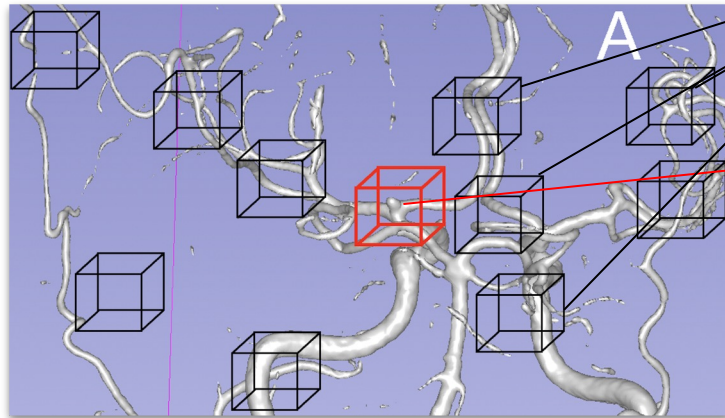
- Simple and fast annotation: Sphere defined by two points (P1, P2).
- Approximately 4 times faster than the voxel-wise annotation [2].



### 2. Small non-intersecting patches:

- Small patches of 96x96x96 voxels (38.4x38.4x38.4 mm): larger training samples.
- Non-Intersecting patches: Reliable background modeling.

### 3. Data sampling and generation:



TOF-MRA image with one aneurysm.



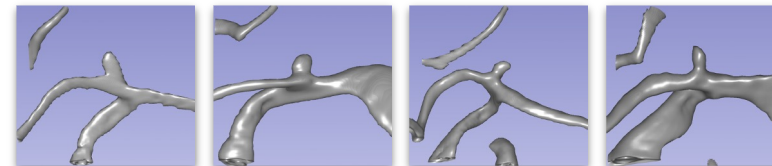
#### Negative patches: aneurysm-free

- Selecting 40 candidate patches per patient.
- Mostly centered on blood vessels.



#### Positive patches: with aneurysm

- Centered on aneurysms, duplicated 50 times.
- Apply random deformable distortion for varied shapes.

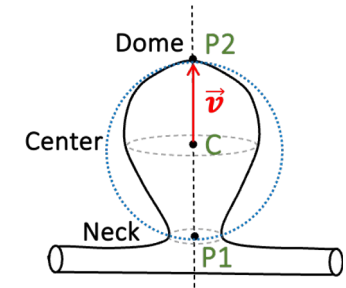


Some instances generated for the aneurysm.

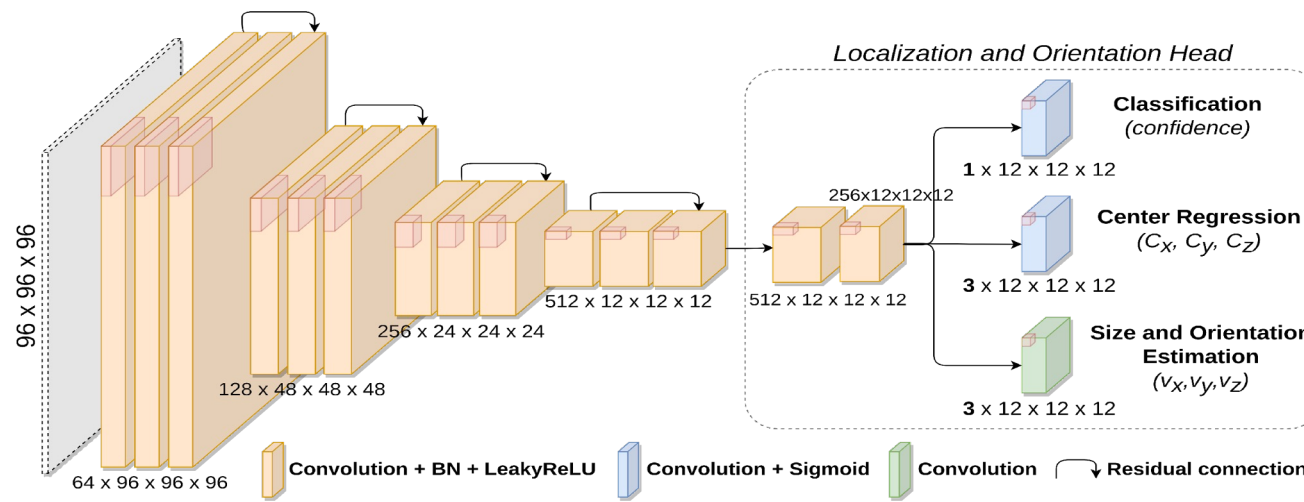
# Our proposed method

## Deep learning architecture

- **End-to-end 3D CNN:** Inspired by the 2D YOLO [3].
- Adapted for both pose estimation and object detection tasks:
  - **For Pose Estimation:**
    - **Localization:** Center coordinates  $C = (C_x, C_y, C_z) = (P_1 + P_2)/2$ .
    - **Orientation:** Size and Orientation  $\vec{v} = (V_x, V_y, V_z) = P_2 - C$ .
  - **For Object Detection:**
    - **Spheres:** Center  $C$  and radius  $|\vec{v}|$ .



Patches of  $96 \times 96 \times 96$  voxels  
 =  $(12 \times 12 \times 12 =)$  1728 cells  
 of  $8 \times 8 \times 8$  voxels each



*Our proposed pose estimation and object detection architecture.*

High class imbalance  
 Positive (P) and Negative (N)

**Loss function**

$$= \text{BCE}(P) + 0.5 \times \#P \times \text{BCE}(N) + 5 \times \text{MSE}(C_x, C_y, C_z, V_x, V_y, V_z) + 5 \times (1 - \text{Cosine similarity}(\vec{v}))$$

[3] Redmon et al. Yolov3: An incremental improvement, arxiv preprint, 2018.



# Our proposed method

## Implementation details

- **Training:**
  - 200 epochs.
  - Learning rate =  $10^{-2}$ .
  - Batch size = 32.
  - Balanced batch sampling: Random selection  
Batch = 4 negative patches + 28 positive patches
- **Inference:**
  - Split into 96x96x96 patches with an isotropic voxel resolution of 0.4mm.
  - Overlapping patches: 16 voxels.
  - Non maximum suppression (Spheres, IoU = 10%).

BCE: Binary Cross Entropy.

MSE: Mean Squared Error.

# Evaluation study

## 5-Fold cross validation

- **Datasets:** 402 subjects

TOF-MRA	# Subjects	# Aneurysms	Mean size (mm)
<i>In-house</i>	132	206	$3.97 \pm 2.32$
<i>CHUV [2] (public)</i>	270	164	$3.74 \pm 2.17$

- **Aneurysm Pose Estimation:** No existing SOTA to compare with.

	Center Localization (mm)		Orientation (°)	
	Median	Range	Median	Range
<i>In-house</i>	0.49	0.05 - 1.74	11.91	0.21 - 68.35
<i>CHUV [2]</i>	0.48	0.05 - 1.43	12.27	1.05 - 68.30

- **Aneurysm detection:** Spheres (IoU > 10%).

Dataset: CHUV [2]	Average Precision (%)	Sensitivity (%)	FP/case
<i>nnDetection [4]</i>	$73.68 \pm 6.38$	$84.76 \pm 4.72$	$0.67 \pm 0.12$
<i>nnUNet [5]</i>	$72.46 \pm 4.74$	$71.95 \pm 9.11$	$0.13 \pm 0.06$
<i>Ours</i>	$76.60 \pm 5.24$	$82.93 \pm 5.92$	$0.44 \pm 0.04$

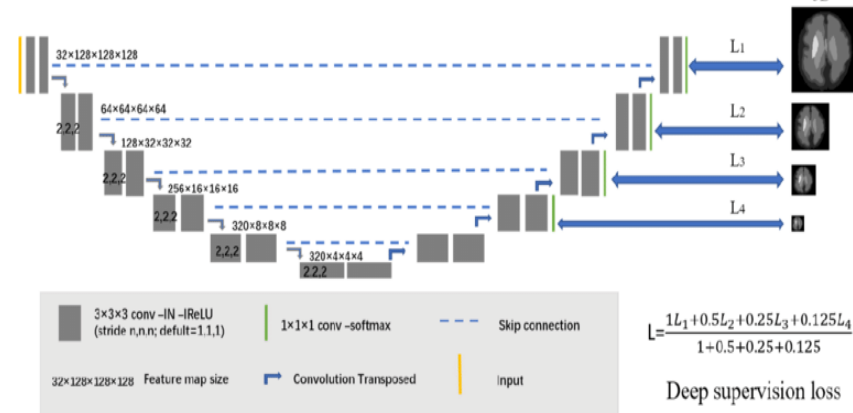
[4] Baumgartner et al. nnDetection: a self-configuring method for medical object detection. MICCAI, 2021

[5] Isensee et al. nnu-net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 2021.

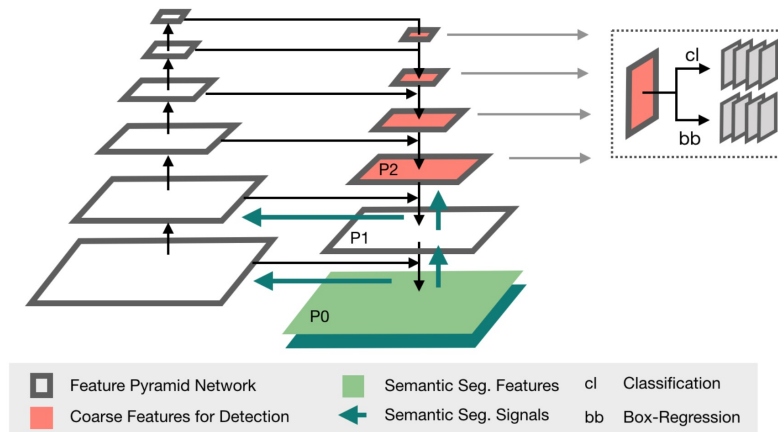
# Evaluation study

## nnUNet and nnDetection : Fully automated methods

- **Image Segmentation:** nnUNet [4]
  - Based on UNet architecture.
  - Patch size: 224 x 256 x 56 voxels.
  - Loss function: CE + BCE.
  - Deep supervision.



- **Object Detection:** nnDetection [5]
  - Based on RetinaUNet [6] architecture.
  - Patch size: 256 x 256 x 56 voxels.
  - Detection Loss : BCE + Generalized IoU.
  - Segmentation Loss: Dice + BCE.



[4] Baumgartner et al. nnDetection: a self-configuring method for medical object detection. MICCAI, 2021

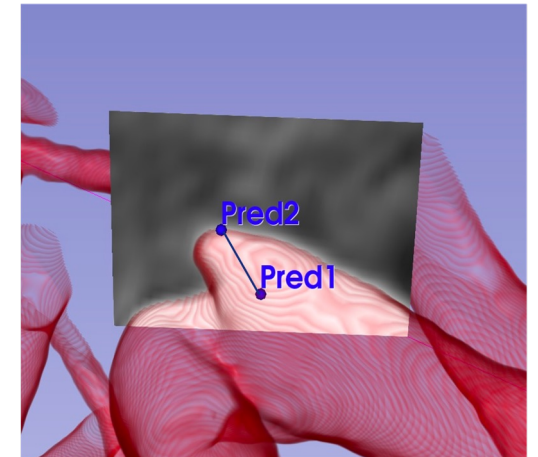
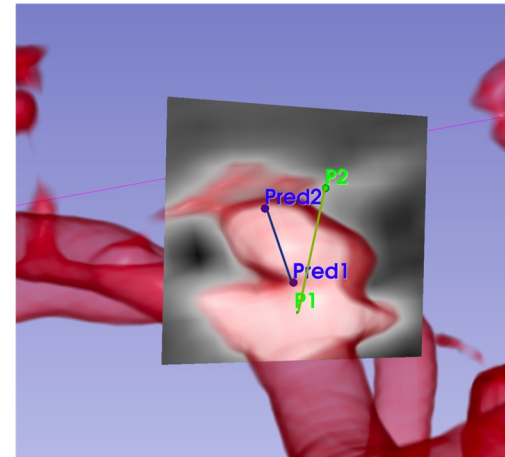
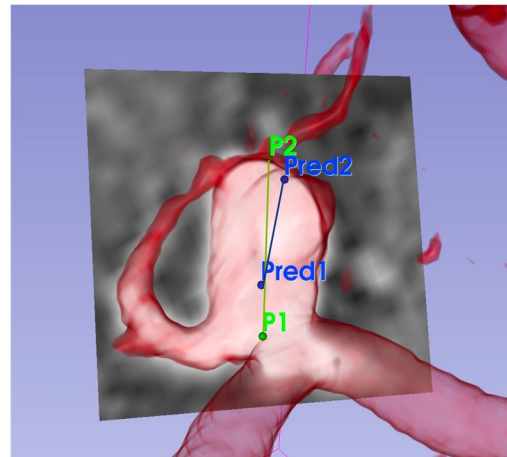
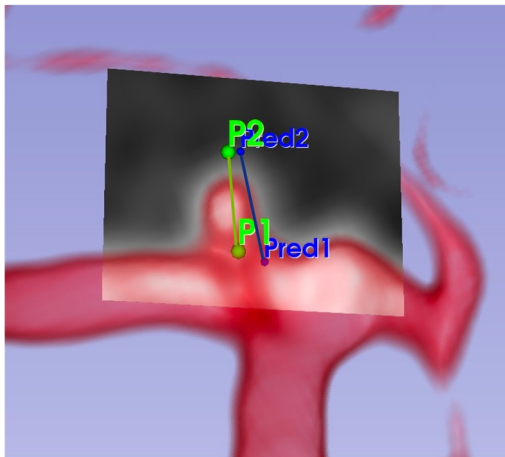
[5] Isensee et al. nnu-net: a self-configuring method for deep learning-based biomedical image segmentation. Nature methods, 2021.

[6] Jaeger, Paul F Retina U-Net: Embarrassingly simple exploitation of segmentation supervision for medical object detection, Machine Learning for Health Workshop, 2020.



# Qualitative results

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



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

(2) Spherical-shaped 7.69mm aneurysm (Error: 0.72mm , 10.62°).

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

(4) Detection of unlabeled aneurysm of 3.50mm (expert sensitivity <100%).

# Conclusion

- **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>.