- UNIVERSITÉ DE LORRAINE -

- LABORATOIRE LORRAIN DE RECHERCHE EN - INFORMATIQUE ET SES APPLICATIONS

- TANGRAM Team -

Intracranial aneurysms detection using deep learning

Presentation D1

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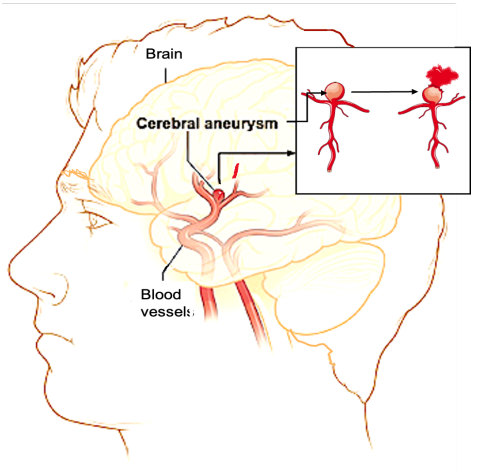
Overview

1. Context
2. Challenges
3. Previous works
4. Our contribution
5. Conclusion

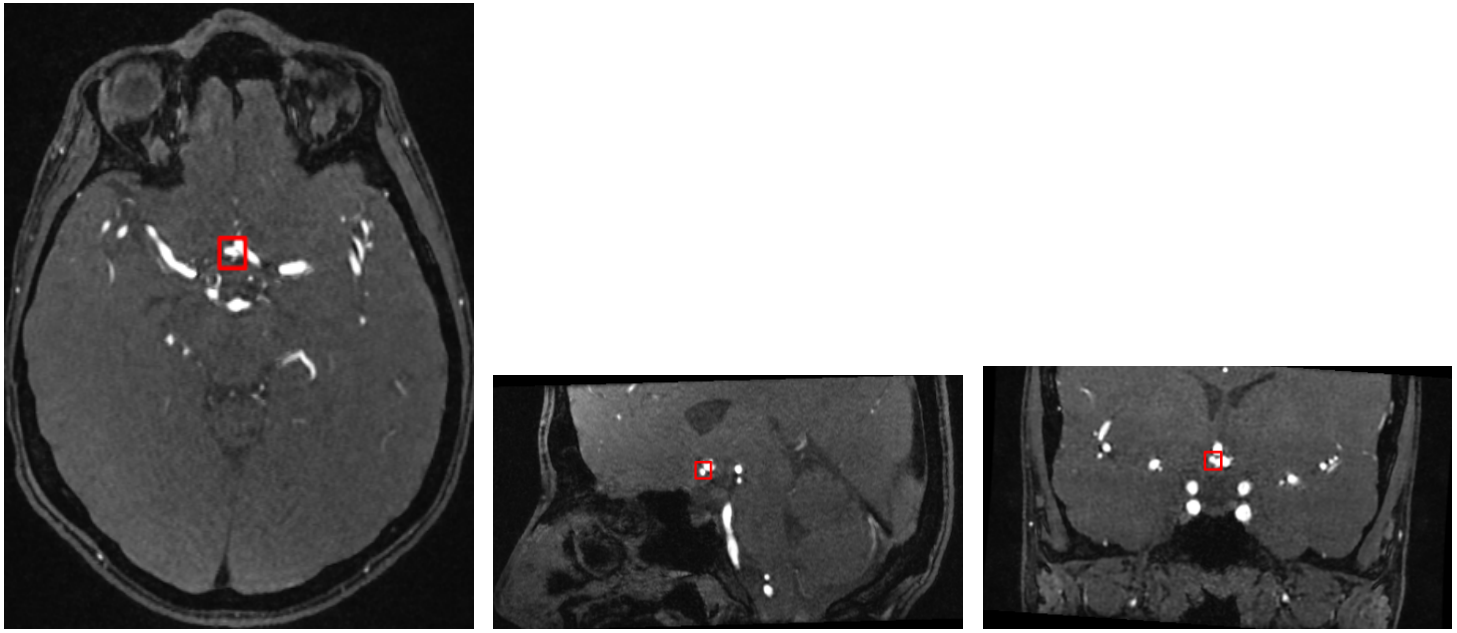
Introduction

Intracranial aneurysm

- An abnormal localized bulge at the blood vessel surface (1-30mm, avg 6mm).
- **Prevalence**: 3 to 7% of the general population.
- **Reason**: weakness in the wall of the blood vessel.
- **Risk**: rupture → hemorrhage → high morbidity/mortality.



Introduction



(a) Axial (b) Sagittal (c) Coronal

Figure: Slice axes

Introduction

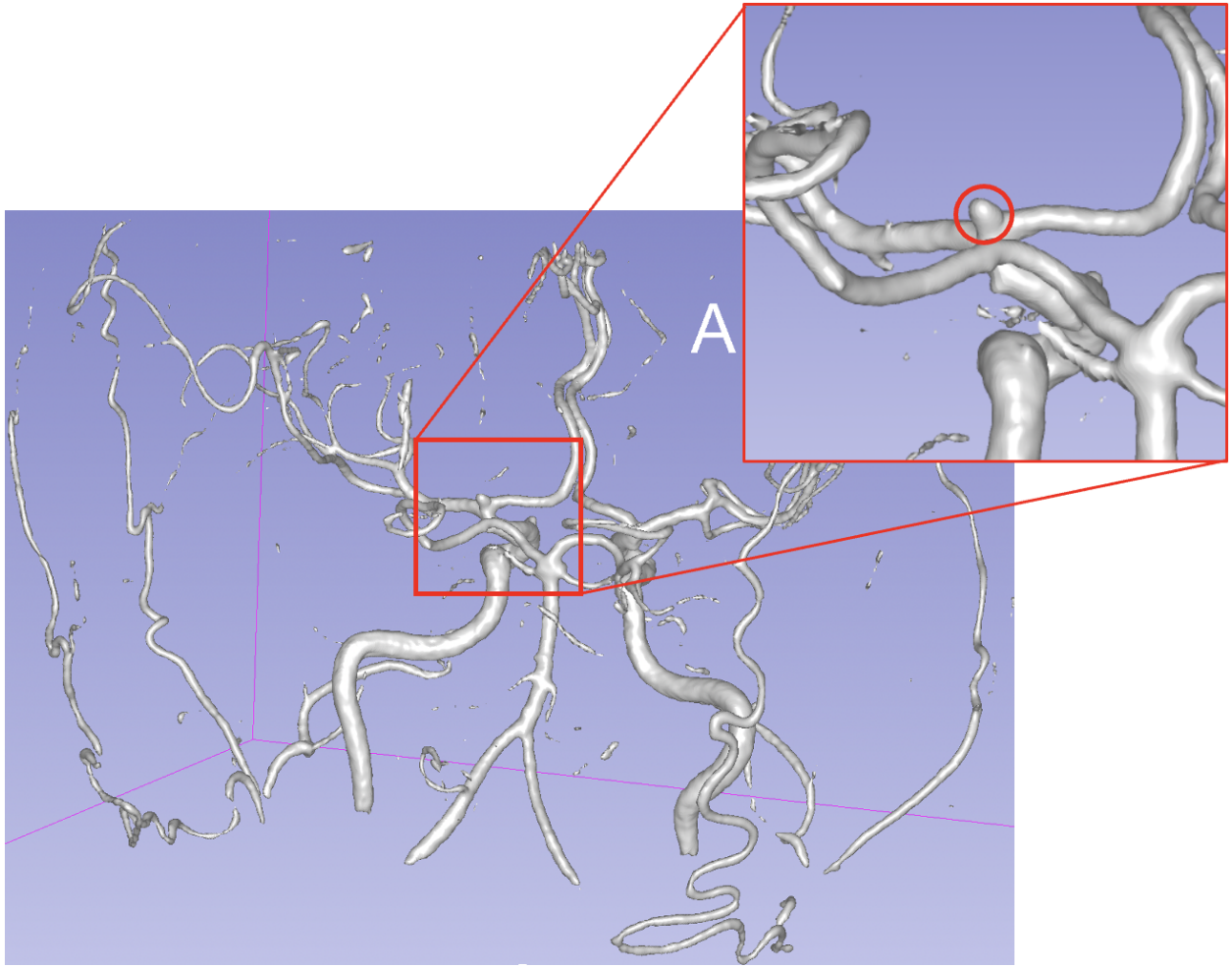


Figure: MRA[1] volume rendering

[1] Magnetic Resonance Angiography

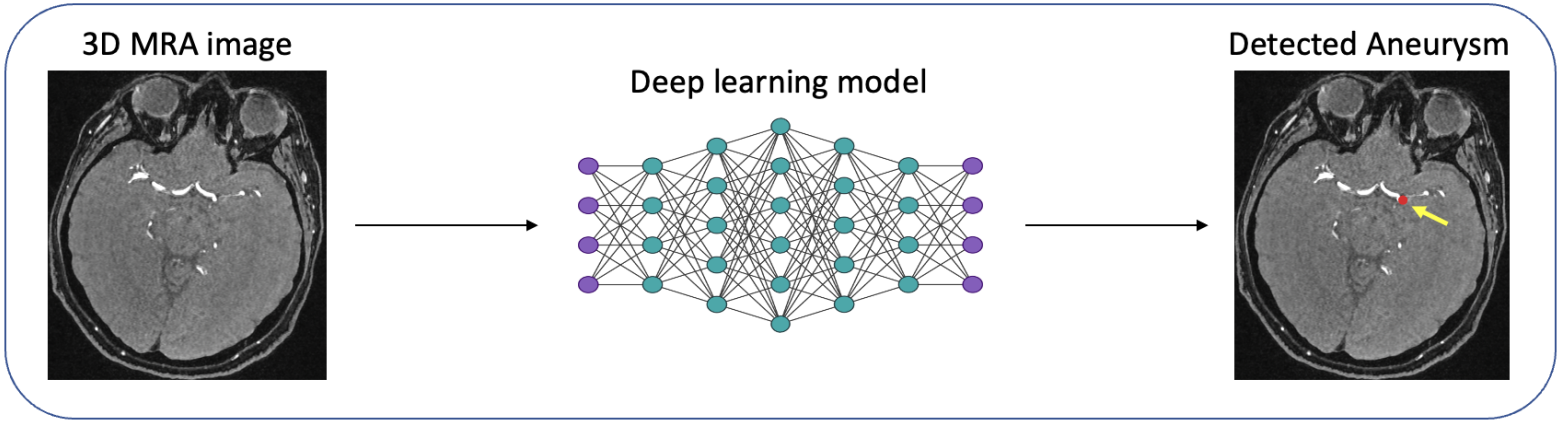
Challenges of learning from medical data

- **Data scarcity**
  - Small and private data sets.
  - 1-2 aneurysms per patient.
- **Data annotation**
  - Labeling medical imaging is difficult and requires experts.
  - Time consuming.
- **Class imbalance**
  - Aneurysms are small structures in MRA data ($\approx$10/1m voxels).
- More computational power to process 3D volumes.

Introduction

Objective

- Assist radiologists in their clinical routines.
- Provide an efficient deep learning-based tool for the detection of intracranial aneurysms from MRA images.
- Requires high sensitivity and low false positive rate.



Existing approaches

Geometry-based (pre-2017)

- Pre-require: vessel segmentation $\rightarrow$ surface.
- Objective: find abnormalities on vessel surface.

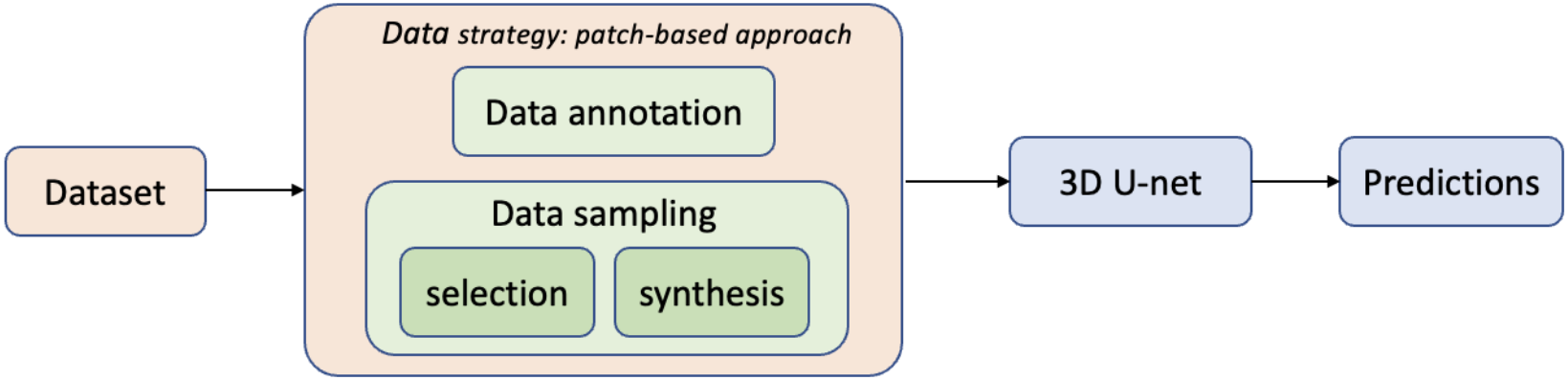
Deep learning-based (post-2017)

- **2D approach**
  - Transform 3D image into 2D images.
  - Process 2D images using CNN model (encoder, U-net. . .).
- **3D + Patch-based approach**
  - Split the entire image into 3D patches.
  - Process each patch using 3D CNN model (3D U-net variants).

Our contribution: An efficient data strategy for the detection of brain aneurysms from MRA with deep learning

Main idea of the article: focus on data

- Simpler (and faster) data annotation: larger database.
- Small patch approach: less memory consumption.
- Guided patch selection: manage scarcity.
- Positive patch synthesis: handle class imbalance.



Our contribution: Dataset

Description

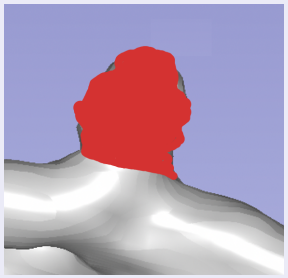
- 111 patients.
- Collected at CHU, Nancy between 2015 and 2020.
- Dimension: 512×512×254.
- Resolution: 0.4 mm voxel size.
- 1-5 aneurysms per patient.
- Total: 155 aneurysms.

	Min	**Max**	**Mean**
Size (mm)	1.23	19.63	3.86

Our contribution: Data annotation

Voxel-wise annotation

- Labeling each voxel of the aneurysm.
- Tedious and tainted with intra- and inter-rater variability.
- Hard and time consuming.



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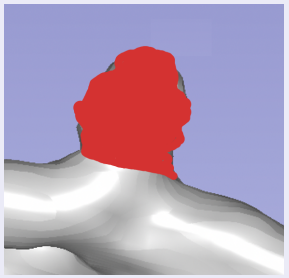
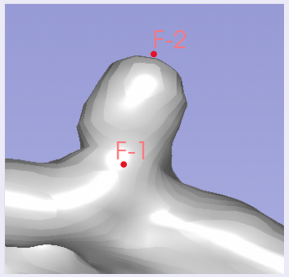


Our proposed annotation

- Approximate each aneurysm by a sphere defined by two points, the center of the neck and the dome.
- Rough but fast annotation.



Our contribution: Patch-based approach

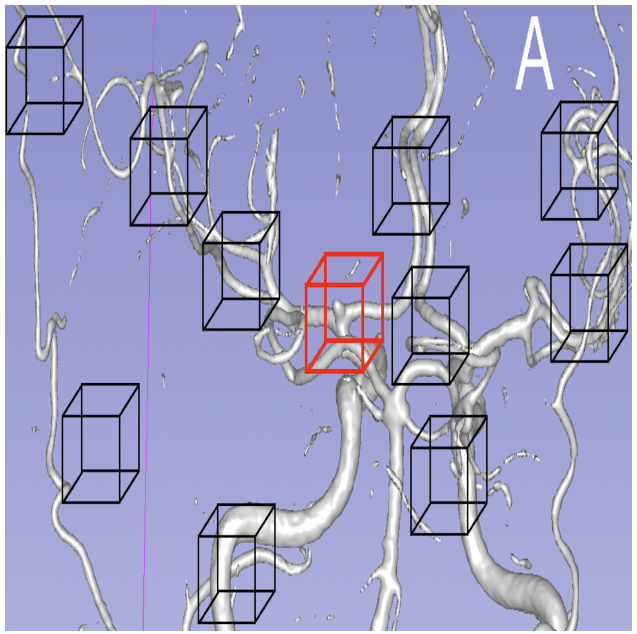
- Small patches: 48 x 48 x 48 voxels.
- Many non-overlapping patches: patch independence.
- Many aneurysm-free patches: reliable statistics on the background.
- Questions:
  1. Patch selection?
  2. Positive vs negative patch imbalance?

Our contribution: Data selection

How to select patches ?

Vessel signal is also scarce: risk of detecting vessels vs background

- **Positive patches**: centered on each aneurysm.
- **Negative patches**: centered half on blood vessels and half on parenchyma.

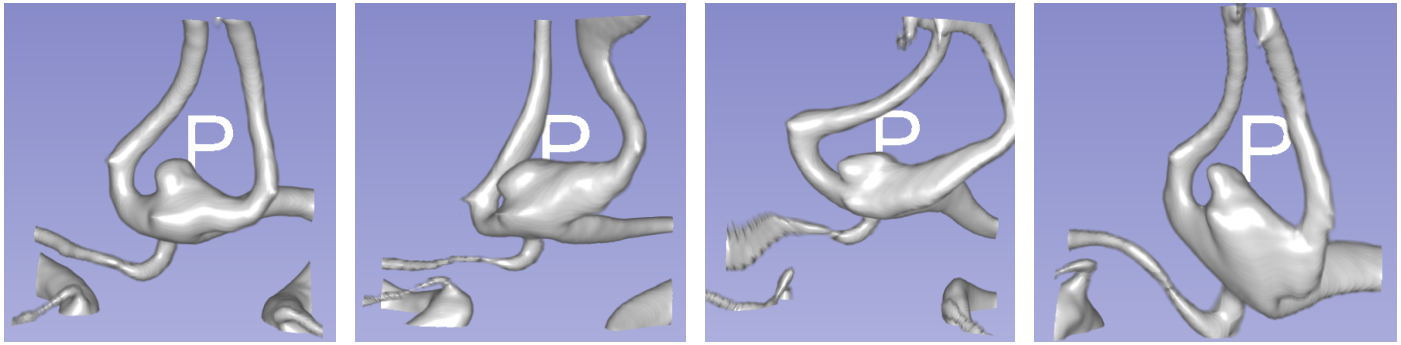


Our contribution: Data synthesis

Data synthesis

Class imbalance: few positive patches vs many negative patches.

- **Positive patches** are duplicated and deformed by a random distortion (3D cubic spline transform).



Our contribution: Deep learning model

Training network

- **Network**: vanilla 3D U-Net.
- **Input shape**: $48 \times 48 \times 48$.
- **Loss function**: Binary cross-entropy.
- **Hyper-parameters**: 100 epochs, Adam optimizer, fixed learning rate of 0.0001, 10 patches per batch.
- **Evaluation metrics**: Dice, Cohen's Kappa.
- **GPU**: GTX 1080Ti with TensorFlow and Keras (Grid'5000).

Experimental study

- Ablation study:
  - Training/Validation/Test: 78/22/11.
  - Model0: 200 negative patches, 50 duplicates and BCE.
  - Model1: Focal loss as loss function.
  - Model2: 5 duplicates for each positive patch and BCE.
  - Model3: 50 duplicates but with no random distortion applied.
  - Model4: 100 negative patches.
- 5-fold cross-validation.

Results

- Ablation study

	Validation set		*Testing set*	
Model	**Dice**	κ	**Sensitivity**	**FPs/case**
Model0	**0.339**	**0.665**	**0.970**	**0.454**
Model1	0.089	0.527	0.803	0.190
Model2	0.038	-1.21e-8	0	0
Model3	0.434	0.772	0.879	1.545
Model4	0.245	0.589	0.833	1.0

- 5-fold cross-validation
  - Sensitivity 0.82@0.61 FPs/case
  - ADAM top list: [abc] 0.68@0.40, [mibaumgartner] 0.67@0.13
  - FROC analysis (Model0): 0.80@0.40, 0.72@0.13 (AUC=85.24%)

Results

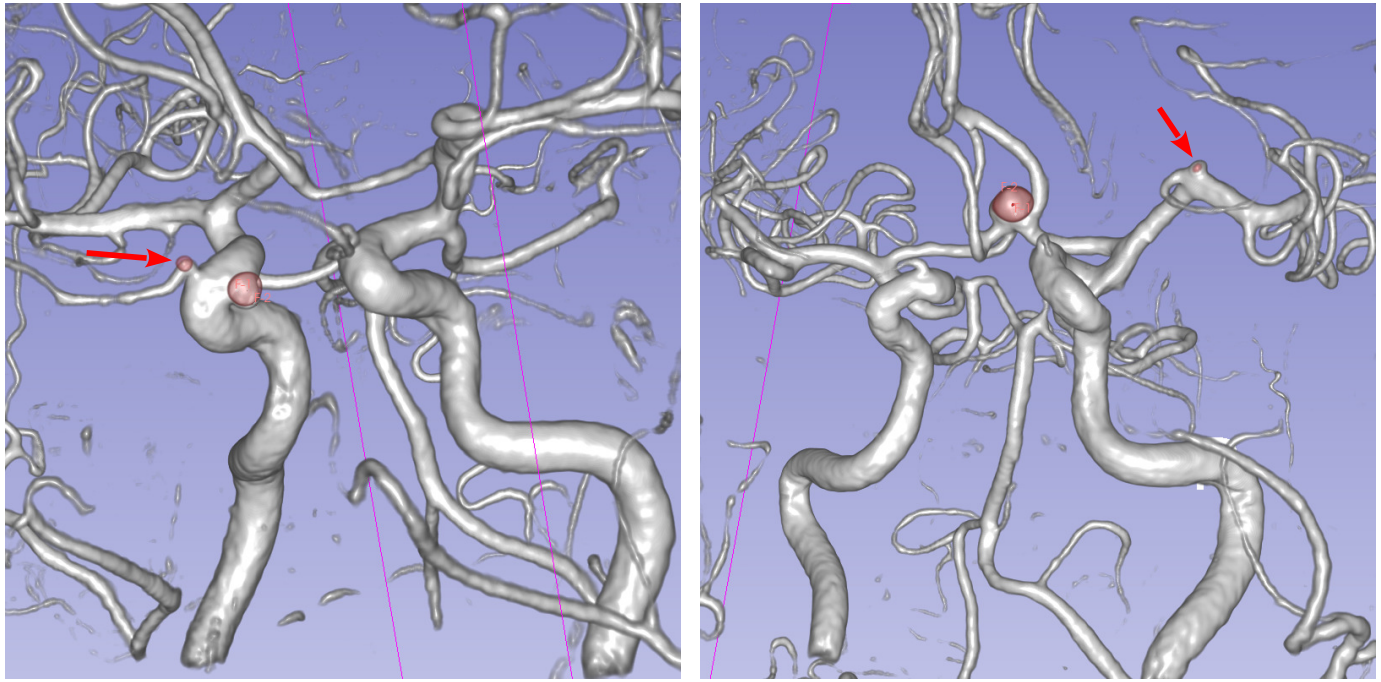


Figure: (left) FP at the branching of small artery. (right) Example of an overlooked aneurysm.

Conclusion

Conclusion

- Efficient data strategy to detect intracranial aneurysms from MRA images.
- State of the art sensitivity of 0.82 at 0.61 FPs/case.

Future works

- Combine this data strategy with more sophisticated architectures and loss functions.
- Investigates the κ score as a loss function, to leverage its capacity to assess the quality of a classifier despite class imbalance.