Intracranial aneurysm detection using deep learning

Presentation D1

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Overview

1. Context
2. Previous work
3. Recent works
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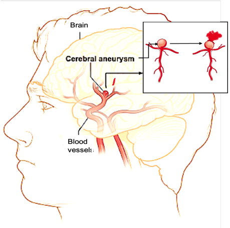
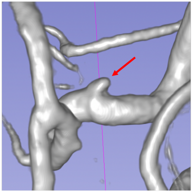
Introduction

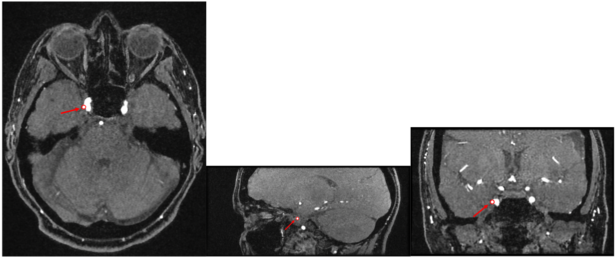
Intracranial aneurysm

- 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

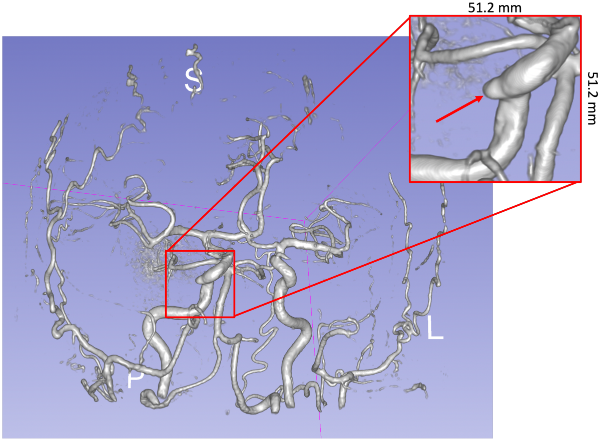


Figure: MRA[1] volume rendering (Aneurysm $= 10^{-6}$ global volume)

[1]Magnetic Resonance Angiography

Introduction

Challenges

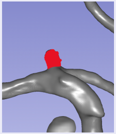
- **Data scarcity**
  - Small and private data sets (patient privacy).
  - 1-2 aneurysms per patient.
- **Data annotation**
  - Labeling medical imaging is difficult and requires experts.
  - Time consuming.
- **Class imbalance**
  - Aneurysms are small structures in MRA data ($\approx$10/1m voxels).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

Previous work

Data annotation

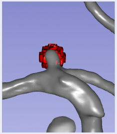
Voxel-wise annotation

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



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.



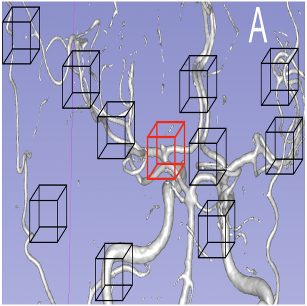
Previous work

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.



Previous work

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).

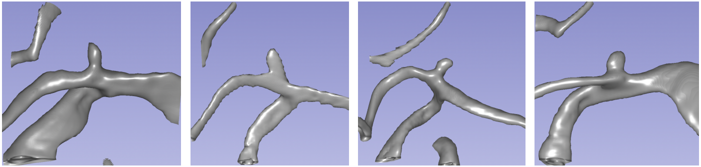
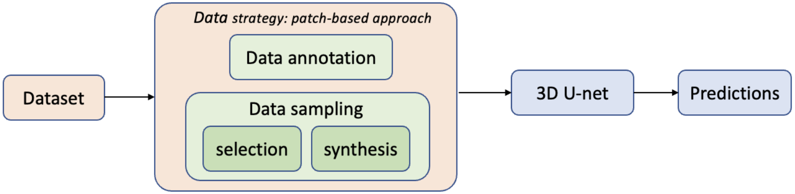


Figure: Generation of divers aneurysm shapes

Previous work

Main idea: 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.



Previous work

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: 0.80@0.40, 0.72@0.13 (AUC[2]=85.24%).

[2] Area Under Curve

Recent works

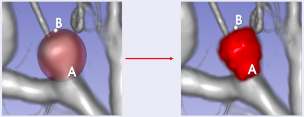
Dataset

Data Quantity: 111 → 471 patients

- CHRU Nancy: +21 patients
- CHUV Lausanne[3] 2021: +269 (/350) patients
- ADAM Challenge[4] 2020: +70 (/113) patients

Improved annotation

- Refined annotations: Otsu thresholding



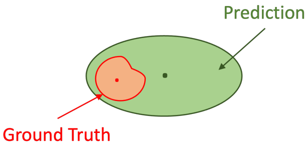
[3] Weak labels and anatomical knowledge: making deep learning practical for intracranial aneurysm detection in TOF-MRA, 2021

[4] https://adam.isi.uu.nl

Recent works

Evaluation - Metrics

- **Dice metric**
  - Adapted for segmentation tasks.
- **ADAM challenge**
  - Positive detection: if the candidate location coordinate is within the radius distance of the ground truth centre of mass location of the aneurysm.
- **Object detection tasks (computer vision papers)**
  - The Average Precision (AP) value for recall values.
  - Based on Intersection over Union (IoU).



Deep Supervised U-Net

- Small aneurysm signals are missed during the down-sampling operations.
- Forcing the decoder blocks outputs to yield a meaningful segmentation map according to the target image.

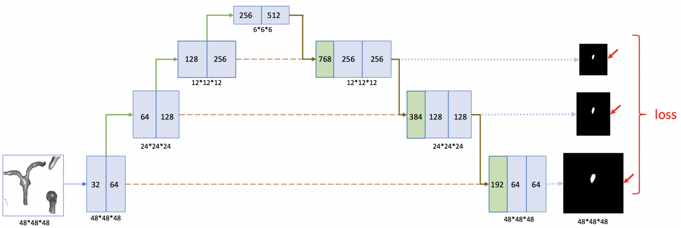


Figure: Deep Supervised U-Net (loss $= \sum_{i=1}^{3} loss_i$)

Self-Attention mechanism U-Net

- Focus and place more "Attention" on the relevant parts of the high-level feature maps.

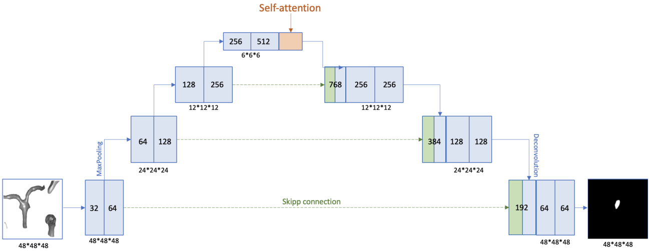
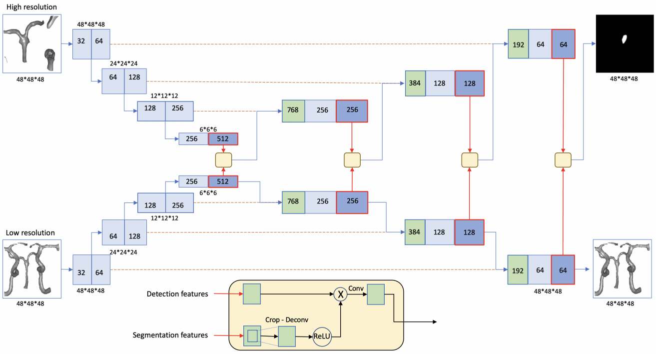


Figure: Self-attention U-Net

Dual U-Net with Attention mechanism

- Integrate information about the surface of the vessels surrounding the aneurysms.



Recent works

Results

- Network architecture: small impact on performance → Keep U-Net architecture.
- Equivalent results with nnU-Net[5]: AP = 80.24%.
- Less memory consumption & training time (20h vs 7days for nnU-Net).

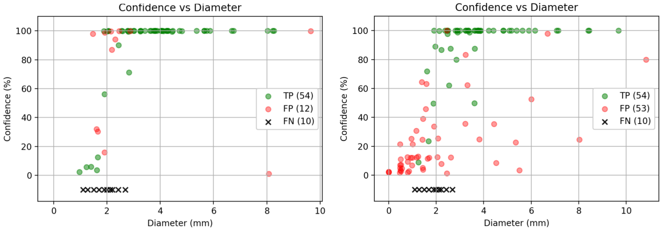


Figure: Performance of our method U-Net (left) vs nnU-Net (right)

[5]nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation, Nature Methods, 1-9

Conclusion

- Approach that focuses only on data and achieves competitive results compared to state-of-the-art methods.
- Models explainability.
- Regression problems:
  - Predict bounding spheres with confidence score (e.g. YOLO).
  - Predict the associated main axis of each detected aneurysm.

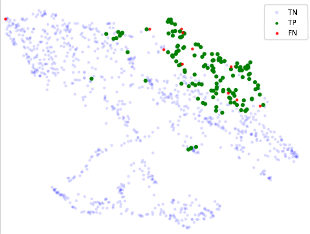


Figure: Visualization of Patch Embeddings using UMAP[6]

[6] Uniform Manifold Approximation and Projection for Dimension Reduction, 2020