I-VESSEG:
A framework to accelerate cerebrovascular image analysis

I-VESSEG - un cadre méthodologique pour accélérer l'analyse d'images cérébrovasculaires

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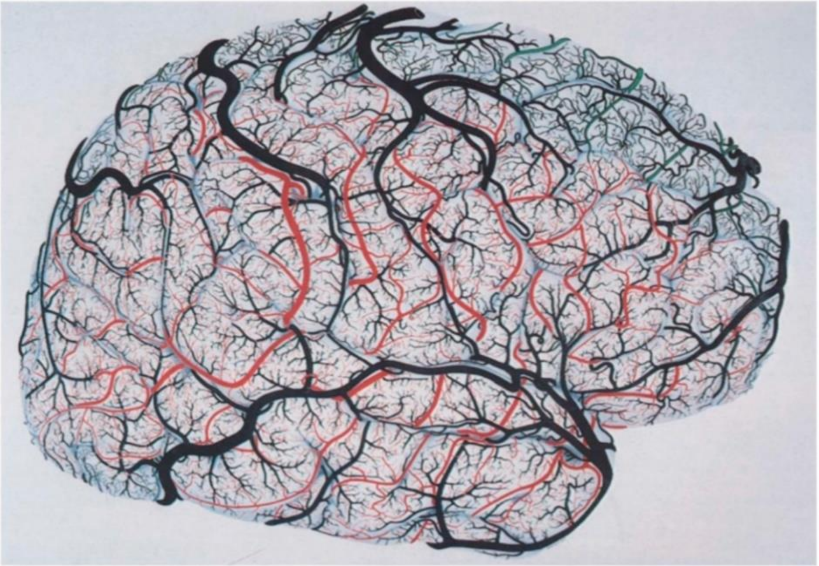
June 15th 2023
Atelier R-Vessel-X

CONTEXT & MOTIVATION

The Cerebrovascular Tree



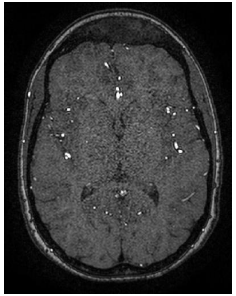
[Uludağ & Blinder, NeuroImage 2018]

The **cerebrovascular system** is a **complex network** of arteries and veins supplying the brain cells with nutrients and oxygen.

Given its high complexity, **in-depth understanding** of its **anatomy** and **function** is a **challenging task** [Ramos et al., Forkert et al.].

[Helthuis et al, Anat Rec.2019]

Ex-Vivo Analysis



In-Vivo Analysis

RL. Ramos et al. J Undergrad Neurosci Educ. 6(2) 2008; N. Forkert et al. Methods of Info in Med 52(6) (2013)

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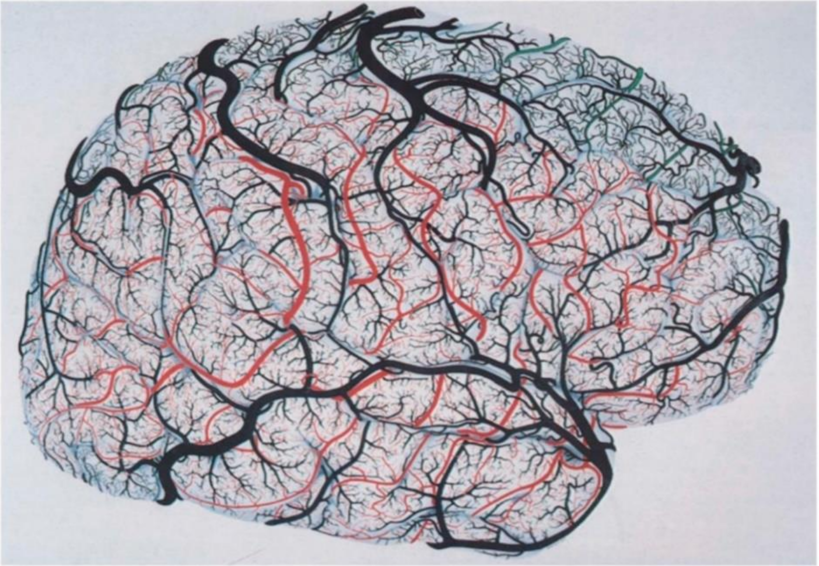
The Cerebrovascular Tree



[Uludağ & Blinder, NeuroImage 2018]

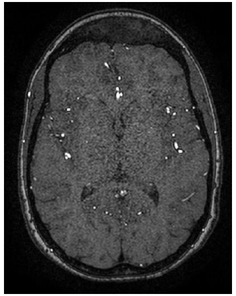
The **cerebrovascular system** is a **complex network** of arteries and veins supplying the brain cells with nutrients and oxygen.

Given its high complexity, **in-depth understanding** of its **anatomy** and **function** is a **challenging task** [Ramos et al., Forkert et al.].

[Helthuis et al., ...19]

Not Scalable

Ex-Vivo Analysis



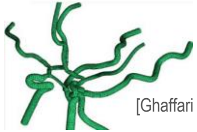
In-Vivo Analysis

RL. Ramos et al. J Undergrad Neurosci Educ. 6(2) 2008; N. Forkert et al. Methods of Info in Med 52(6) (2013)

Analysis Pipeline

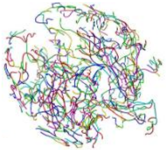
Segmentation → Modelling → Simulation (CFD) → Visualization

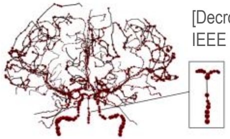
[Livne et al. Front Neurosci 2019; Hilbert et al. Front in AI 2020; Ni et al CIBM 2020; Tetteh et al. 2020; Mou et al, MedIA 2021; Dang et al 2021]



[Ghaffari et al. ESC 2015]

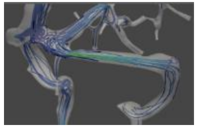
[Moriconi et al. IEEE TMI 2018]

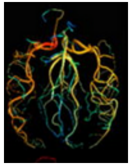




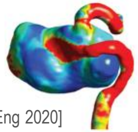
[Decroocq et al. IEEE EMBS 2022]

[Miraucourt et al. ISBMS 2014]

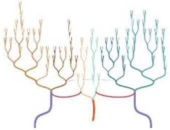




[Ghaffari et al. CIMB 2017]

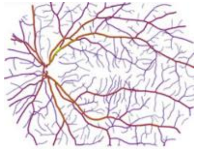


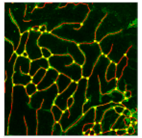
[Rayz et al. Ann Rev Biom Eng 2020]



[Pandey et al. IEEE TVCG. 2019]

[Bumgarner & Nelson, CRM 2023]

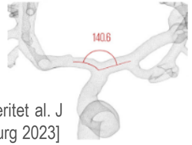




[Montoya-Zegarra et al. J Ang 2018]

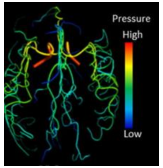
No successful end-to-end pipeline

Analysis Pipeline



[Boucheritet al. J Neur Surg 2023]

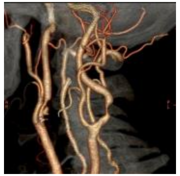
Geometric & intensity patterns



[Ghaffari et al. CIMB 2017]

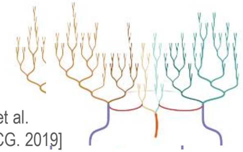
Blood flow

Segmentation → Modelling → Simulation (CFD) → Visualization



From Radiopaedia [1]

Occlusions



[Pandey et al. IEEE TVCG. 2019]

Visual assessment

Common to all stages there is image segmentation

(an open problem)

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[1] https://radiopaedia.org/articles/carotid-artery-stenosis

EURECOM

I-VESSEG Framework

Our hypothesis:

To reach a **better understanding of the cerebrovascular tree** architecture and function we need to **solve** current **methodological challenges** that **limit** its **quantification and characterization in a reliable, reproducible and efficient way**

Our goal:

To develop **learning-based tools** that **ease the analysis** of the cerebrovascular tree in a **seamless way**

Where to start?

Segmentation → Modelling → Simulation (CFD) → Visualization

[Livne et al. Front Neurosci 2019; Hilbert et al. Front in AI 2020; Ni et al CIBM 2020; Tetteh et al. 2020; Mou et al, MedIA 2021; Dang et al 2021]

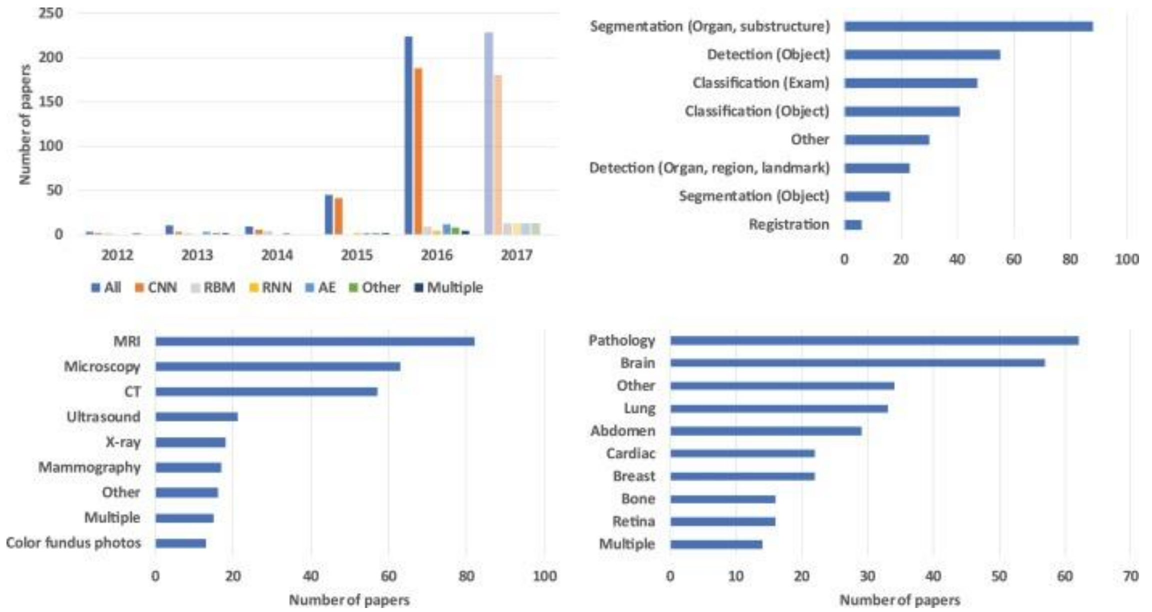
- **Critical to all the stages** of the analysis pipeline
- Remains an **open problem**
- Learning-based methods have **not reached maximal performance** yet

2020 25th International Conference on Pattern Recognition (ICPR)
Milan, Italy, Jan 10-15, 2021

Vesselness Filters: A Survey with Benchmarks Applied to Liver Imaging

Jonas Lamy*, Odyssée Merveille†, Bertrand Kerautret*, Nicolas Passat§, and Antoine Vacavant‡
* Université Lyon 2, LIRIS (UMR 5205), Lyon, France

An Overview of Deep Learning for Medical Image Analysis



Source: Litjens et al, MedIA 2017

Word count:

Term	Count
Artery/Arteries	4
➢ Carotid	2
Vessel	15
➢ Carotid	2
Carotid	6
Brain	**62**

Data Availability

IMAGENET 1 281 167

biobank uk 48 000

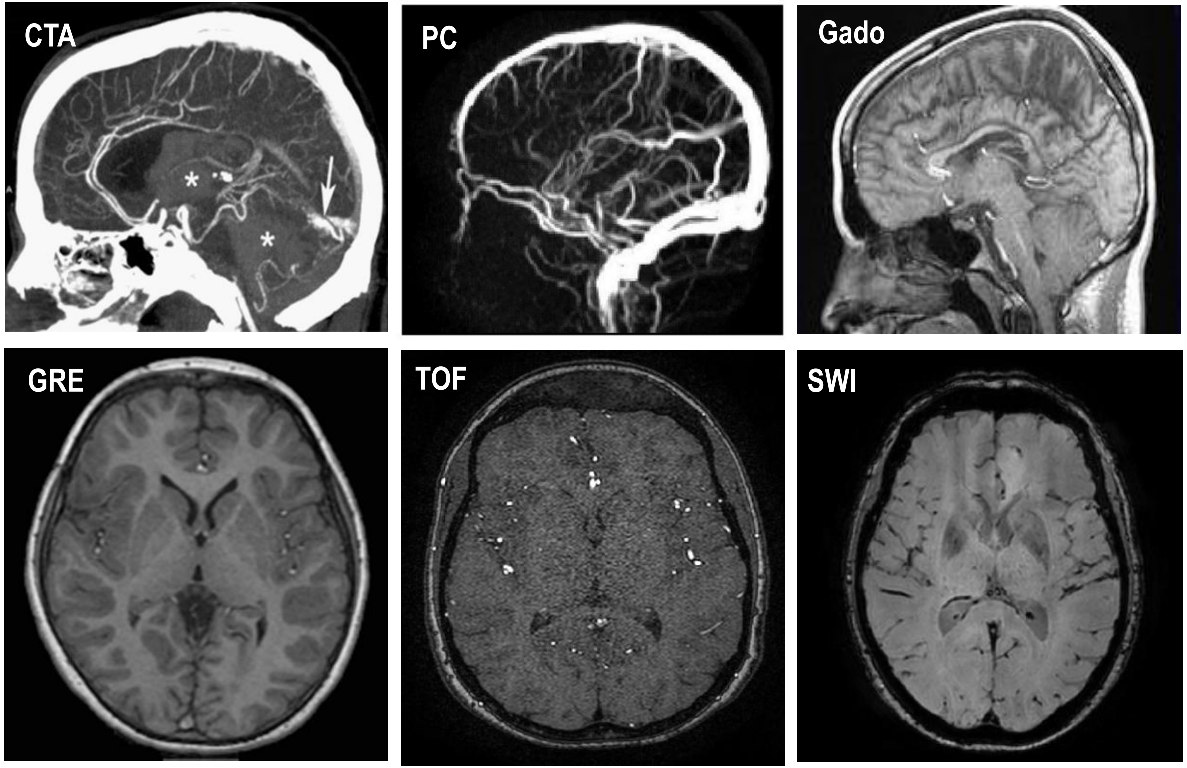
vs.

Study	Image Modality	Database Size	Public Images	Public Labels
Livne et al.	TOF	66	N	N
Hilbert et al	TOF	264	N	N
Ni et al.	CT	20	N	N
Tetteh et al.	SYNTH/mCT/TOF	136/20[1]/40	Y[2]/N/N	Y/N/N
Taher et al.	TOF	270	N	N
Mou et al.	SYNTH/TOF	136/50	Y[2]/Y[3]	Y/N
Dang et al.	SYNTH/TOF/SWI	136/150/30	Y[2]/N/N	Y/N/N

TOF: time-of-flight, CT: computed tomography, SYNTH: synthetic, mCT: micro computed tomography, SWI: susceptibility-weighted images

M. Livne et al. Frontiers in Neuroscience (2019); A. Hilbert et al. Frontiers in AI (2020); J. Ni et al., Comput. Biol. Med. (2020); G. Tetteh et al. Frontiers in Neuroscience (2020); F. Taher et al. IEEE Access (2020); L. Mou et al. MedIA (2021); V. Dang et al. MedIA (2022)

Multiple Image Modalities = Multiple Methods



No single technique can be used across modalities

Traditional methods

- Ad-hoc tuning

ML/DL techniques

- Re-training
- Re-labelling

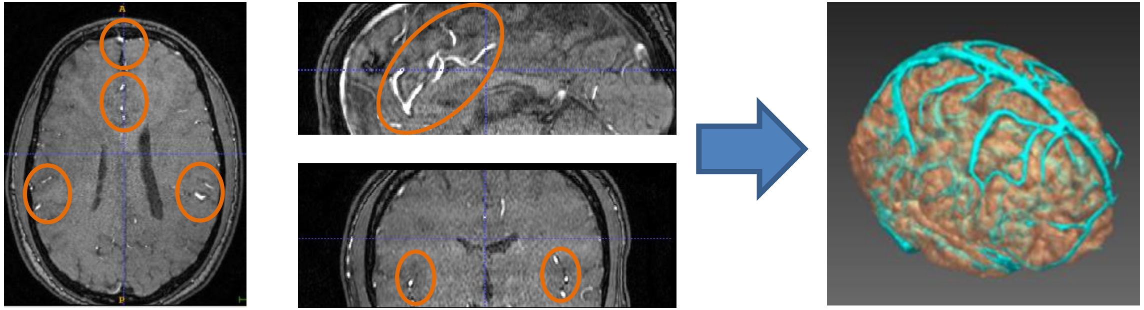
In this talk

- Accelerate Image Annotation
- Reduce Number of Required Annotations
- Generalization

ACCELERATE IMAGE ANNOTATION

State-of-Things: 3D Brain Vessel Segmentation

Brain Vasculature: Anatomical planes & 3D segmentation



Challenges: Complex tree-like structures and small objects

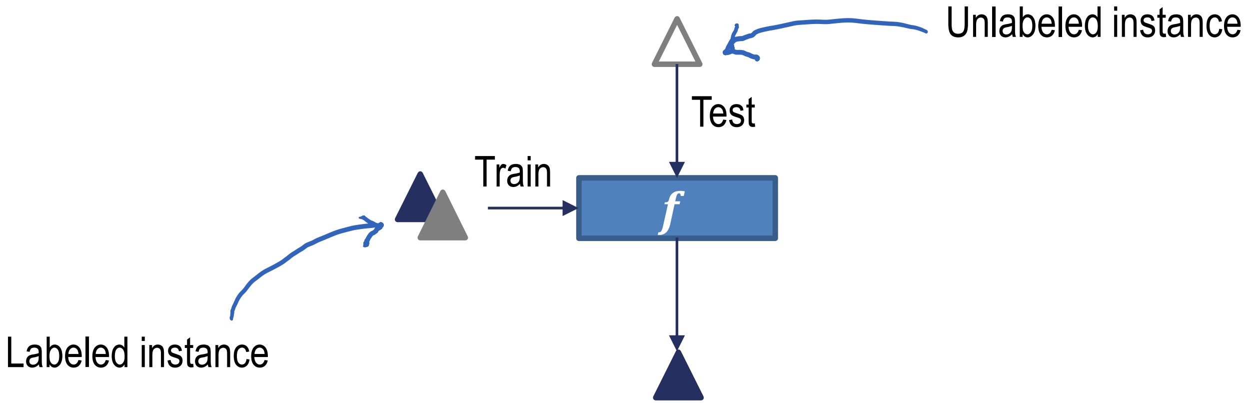
State of the art

- ML/DL methods not as established
- Pixel-wise annotation is prone to errors and expensive
- Most weak labels for segmentation assume blob-like objects
- Ad-hoc filters prone to errors

Multi-instance learning:
Relax constraints on granularity of the annotations

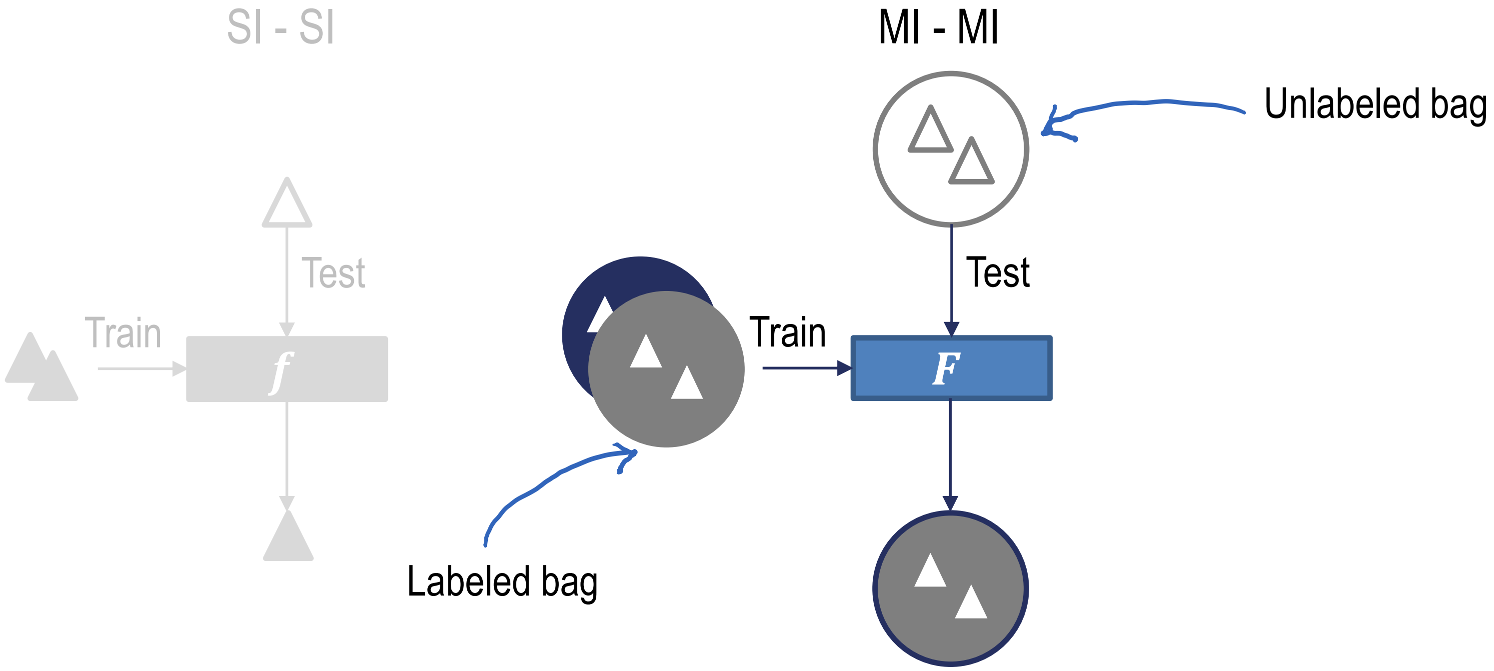
Multi-instance (MI) vs. Supervised Instance (SI) Learning

Supervised Instance (SI) – Supervised Instance (SI)



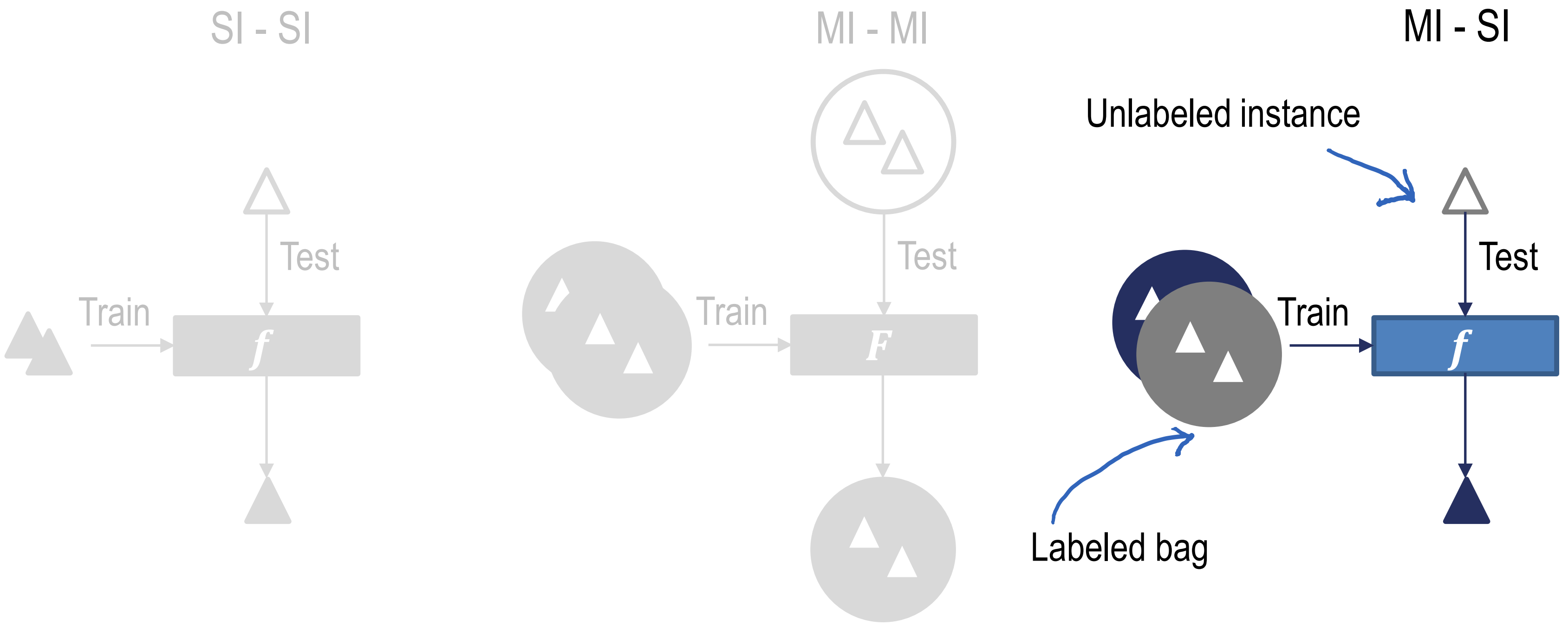
Train on instance, test on instance

Multi-instance (MI) vs. Supervised Instance (SI) Learning



Train on bag, test on bag

Multi-instance (MI) vs. Supervised Instance (SI) Learning

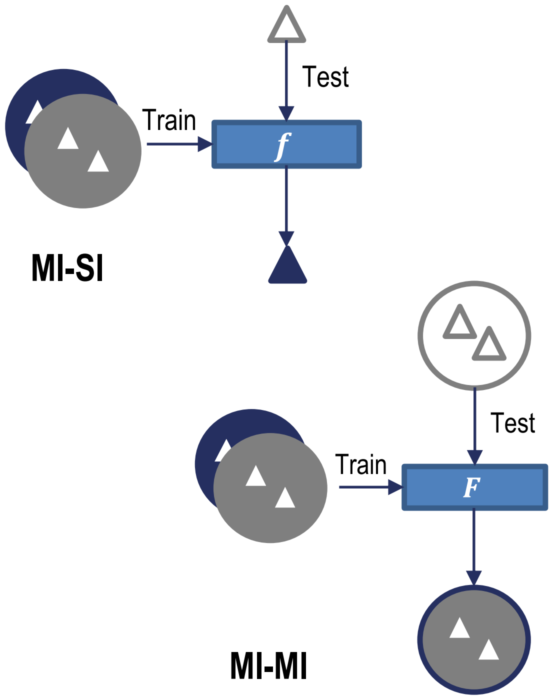


Train on bag, test on instance

Diagram adapted from V. Cheplygina, DMJ. Tax & M. Loog, Pattern Recognition (2014)

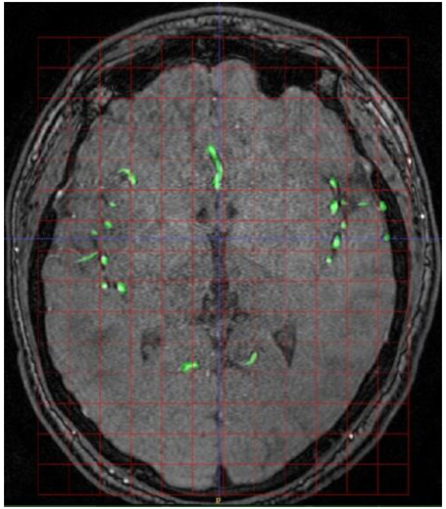
Vessel-Captcha: Efficient Vessel Annotation & Segmentation

In collaboration with: UCL, Inria & Universitat de Barcelona



1. **MI-SI:** EASE ANNOTATION VIA TRAIN ON BAGS, TEST ON INSTANCES
2. **MI-MI:** DATA AUGMENTATION & FILTERING VIA TRAIN ON BAGS, TEST ON BAGS

Vessel-Captcha: MI – SI to Ease Annotation

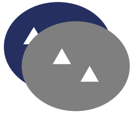


Vessel-CAPTCHA

Completely Automated Public Turing Test To Tell Computers and Humans Apart – CAPTCHA [von Ahn & Dabbish, 2004]

1. **MI-SI:** EASE ANNOTATION VIA TRAIN ON BAGS, TEST ON INSTANCES

△ - Image Pixel



- 2D Image Patch: $\widehat{\mathrm{X}}_k$

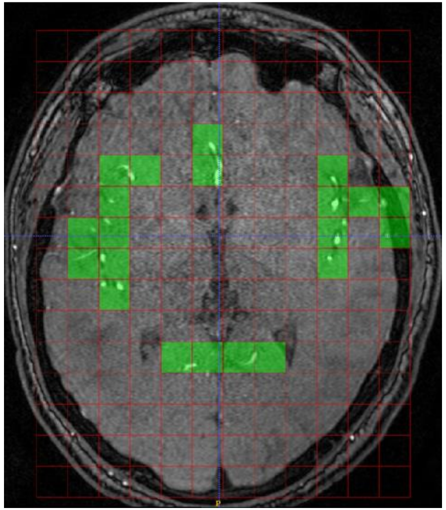
Annotation Rule:

$$\widehat{\mathrm{X}}_k : D_k \rightarrow \mathbb{R}$$

$$U_k : D_k \rightarrow \{0,1\}$$

$$f(U_k) = 1 \Leftrightarrow \exists (i,j) \in D_k \; s.t. \; U_k(i,j) = 1$$

MI-SI: Ease Annotation Via Train Bags, Test on Instances



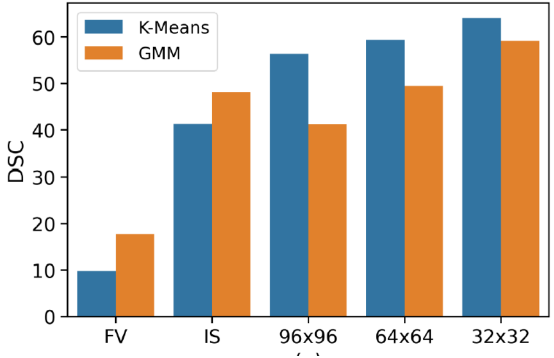
Vessel-CAPTCHA

Problem: How to go from the bag to the instance?

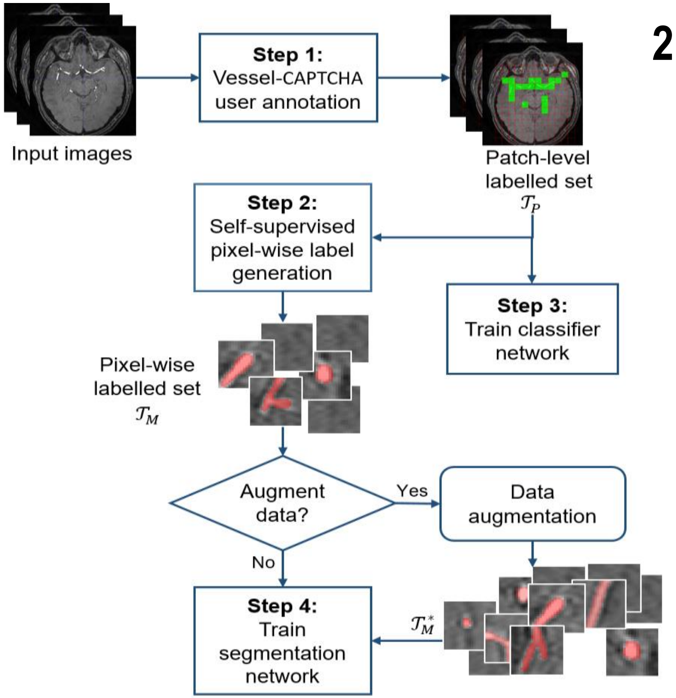
Trick for semantic segmentation: Generate weak instance-level labels

[Ahn & Kwak,2018; Hong et al. 2017; Luo et al. 2020; Schlegl et al. 2015]

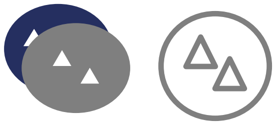
$$M_k(i,j) = \begin{cases} 0 & \text{if } f(U_k) = 0, \\ KM(\hat{X}_k(i,j)) & \text{otherwise,} \end{cases}$$



Vessel-Captcha: MI-MI for Data Augmentation & Filtering



2. **MI-MI:** DATA AUGMENTATION & FILTERING VIA TRAIN ON BAGS, TEST ON BAGS



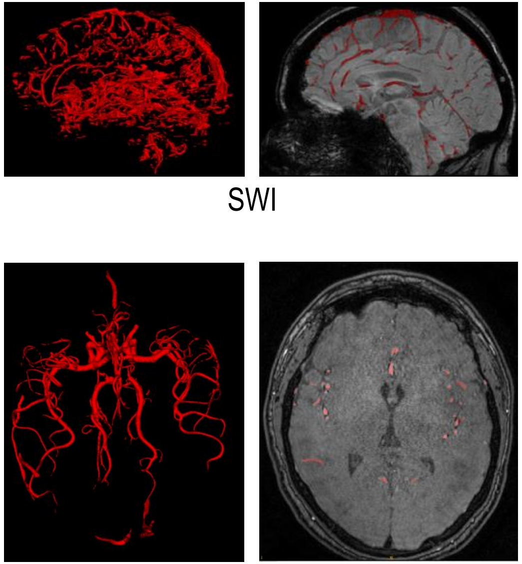
- 2D Image Patch: $\widehat{X}_k$

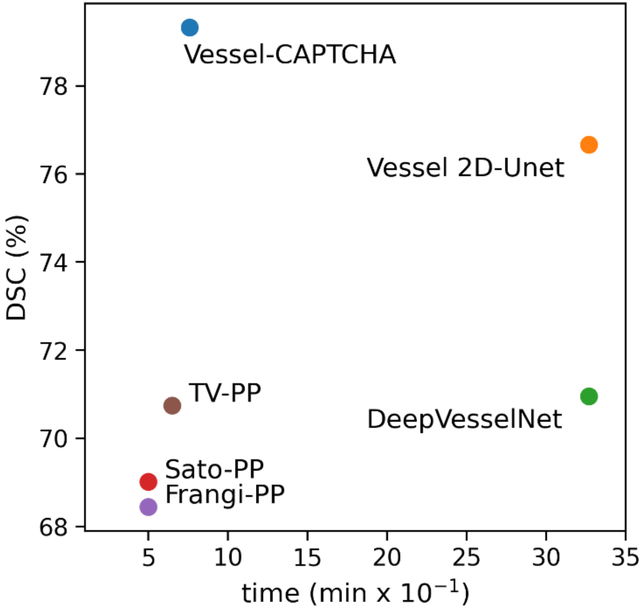
Classification Network acts as a second opinion

		VGG-16	ResNet	2D-UnetCl	2D-PnetCl
TOF	Precision	92.48±1.54	93.66±1.48	94.82±0.48	**94.91±1.04**
	Recall	87.39±4.60	93.27±1.73	94.04±0.65	**94.94±1.09**
	F-score	88.68±3.81	93.34±1.62	94.27±0.54	**94.71±1.23**
SWI	Precision	82.34±1.15	80.14±1.13	82.44±1.18	**82.97±1.55**
	Recall	77.45±4.17	**79.39±3.35**	74.35±5.35	79.30±4.07
	F-score	78.76±3.39	79.17±2.31	76.42±4.63	**80.31±3.31**

V. Dang, F. Galati, R. Cortese, G. Di Giacomo, V. Marconetto, P. Mathur, K. Lekadir, M. Lorenzi, F. Prados-Carrasco, MA. Zuluaga
MedIA 75 102263 (2022)

Vessel-Captcha: Performance Analysis





<u>Conclusion:</u> Multi-instance learning allows to reduce annotation burden of neurovascular images by 77% without degrading performance

V. Dang, F. Galati, R. Cortese, G. Di Giacomo, V. Marconetto, P. Mathur, K. Lekadir, M. Lorenzi, F. Prados-Carrasco, MA. Zuluaga
MedIA 75 102263 (2022)

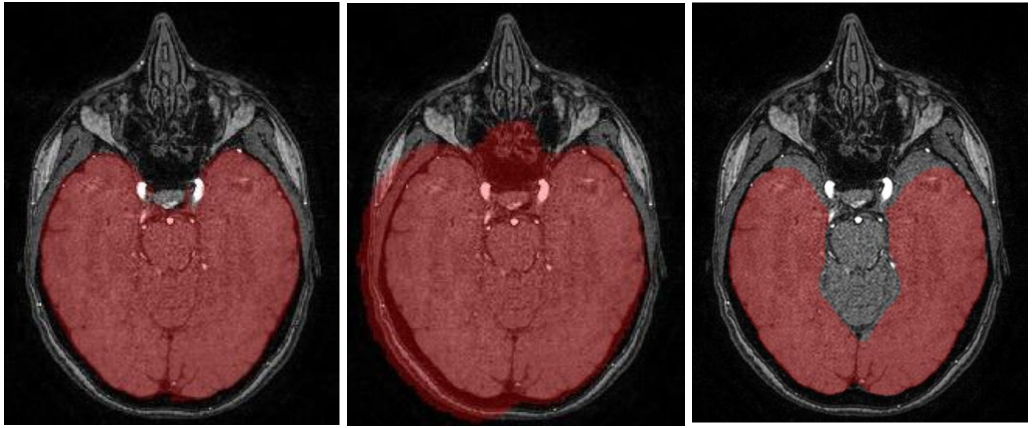
REDUCE REQUIRED ANNOTATIONS

State-of-Things - Continued

Brain Mask Segmentation as a Requirement

State-of-the-art 3D brain vessel segmentation requires a **brain mask**

- **Training:** Removes non-brain signal
- **Testing:** Limits inference space



State-of-the-art brain segmentation methods fail on neurovascular image modalities

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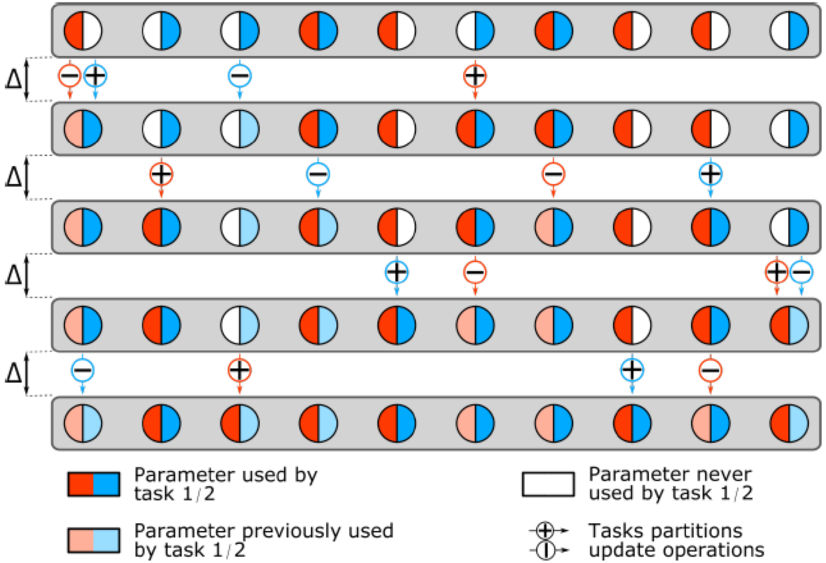
Background: Multi Task Learning (MTL)



Typical setup consists of a **shared deep network** with **task-specific** prediction **heads**

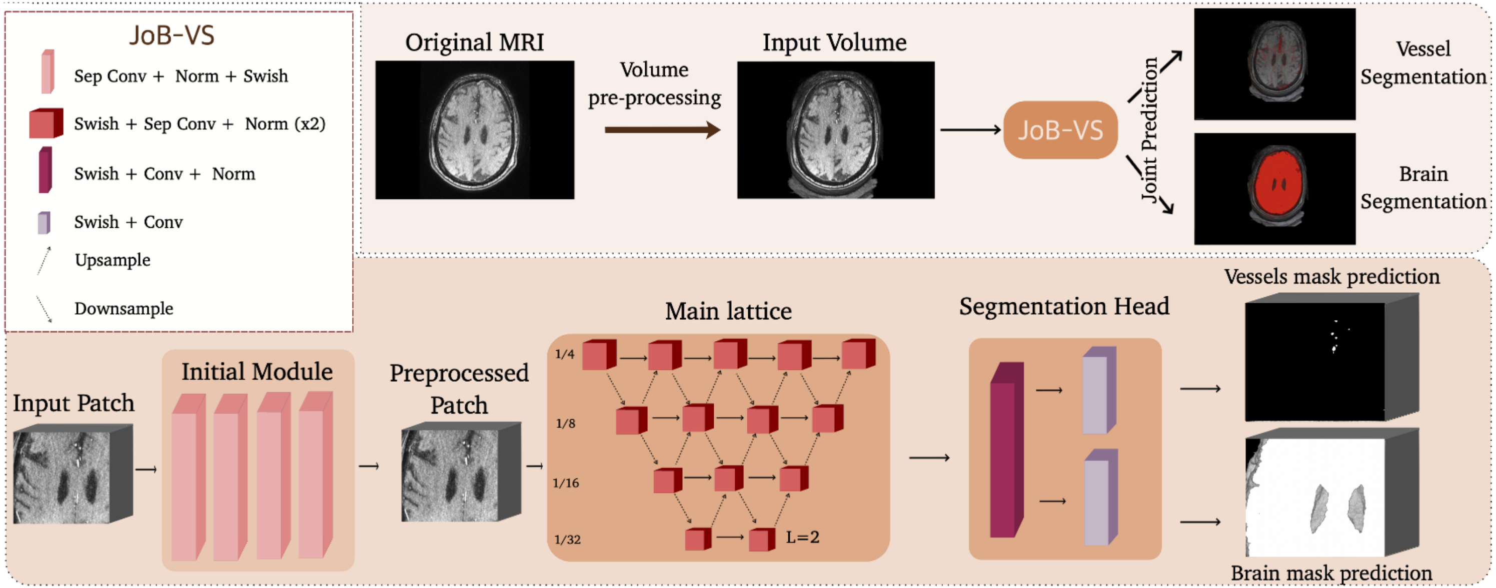
Idea: Use MTL to simultaneously segment the vessels and the brain

- **Pro:** No brain masks at inference
- **Con:** Brain masks for training

Challenge: Brain and vessels are objects with very **different sizes**

JoB-VS: A Joint Brain-Vessel Segmentation Framework

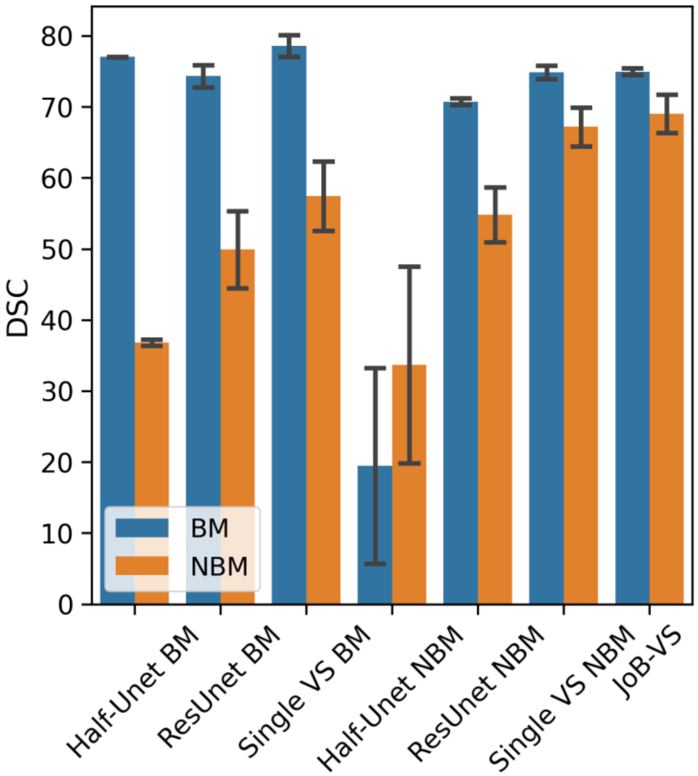
In collaboration with:



- Builds upon the RObust Generic medical image segmentation framework (ROG)[1].
- **Triangular-shaped lattice** to preserve the advantages of **multi-scale processing**.
- **Dual segmentation head** for simultaneous brain and vessel segmentation.

N. Valderrama, I. Pitsiorlas, L. Vargas, P. Arbelaez, MA. Zuluaga. In: ISBI 2023; [1] L Daza, JC Pérez, P Arbeláez. In: MICCAI 2021

JoB-VS: Performance Analysis



Model	Brain DSC (%)	Vessel mAP (%)
Single-task	96.29±0.08	66.67±7.61
JoB-VS	95.73±0.74	70.03±4.31

Quality of the mask plays a crucial role

Left: Benchmarks use ground truth mask

Top: Single task model uses automatic mask

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N. Valderrama, I. Pitsiorlas, L. Vargas, P. Arbelaez, MA. Zuluaga. In: IEEE ISBI 2023

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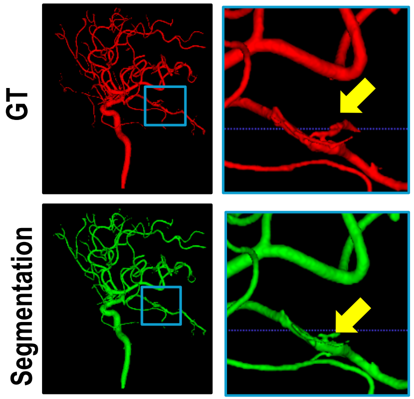
Job-VS: Generalization Capabilities

SHINY-ICARUS

Task: Segmenting a vascular tree that branches from the Internal Carotid Artery (ICA) with an aneurysm.

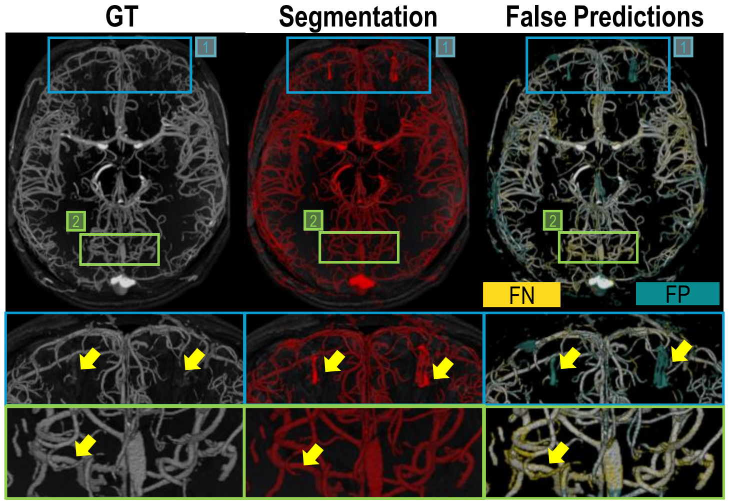
JoB-VS achieved an average dice score of **92.3** and a clDice of **90.9** in the test set.



SMILE-UHURA

Task: segmentation of small vessels from 7T MRA images.

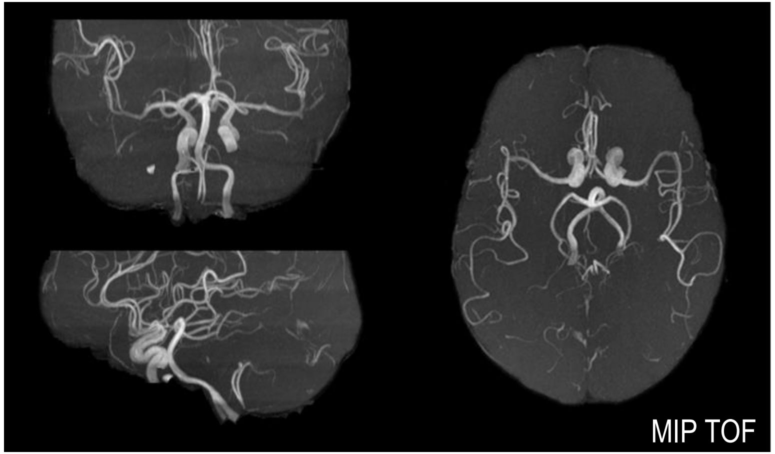
JoB-VS achieved an average dice score of **79.2** and a clDice of **79.4** in the validation set.

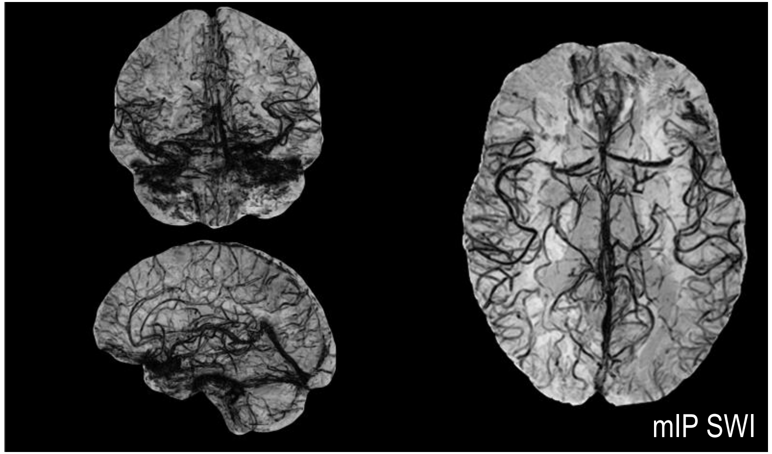


N. Valderrama, I. Pitsiorlas, L. Vargas, P. Arbelaez, MA. Zuluaga. In: IEEE ISBI 2023

GENERALIZATION

A Quick Recap





Two **generalizable architectures** that can **segment** vessels from **different** image **modalities**

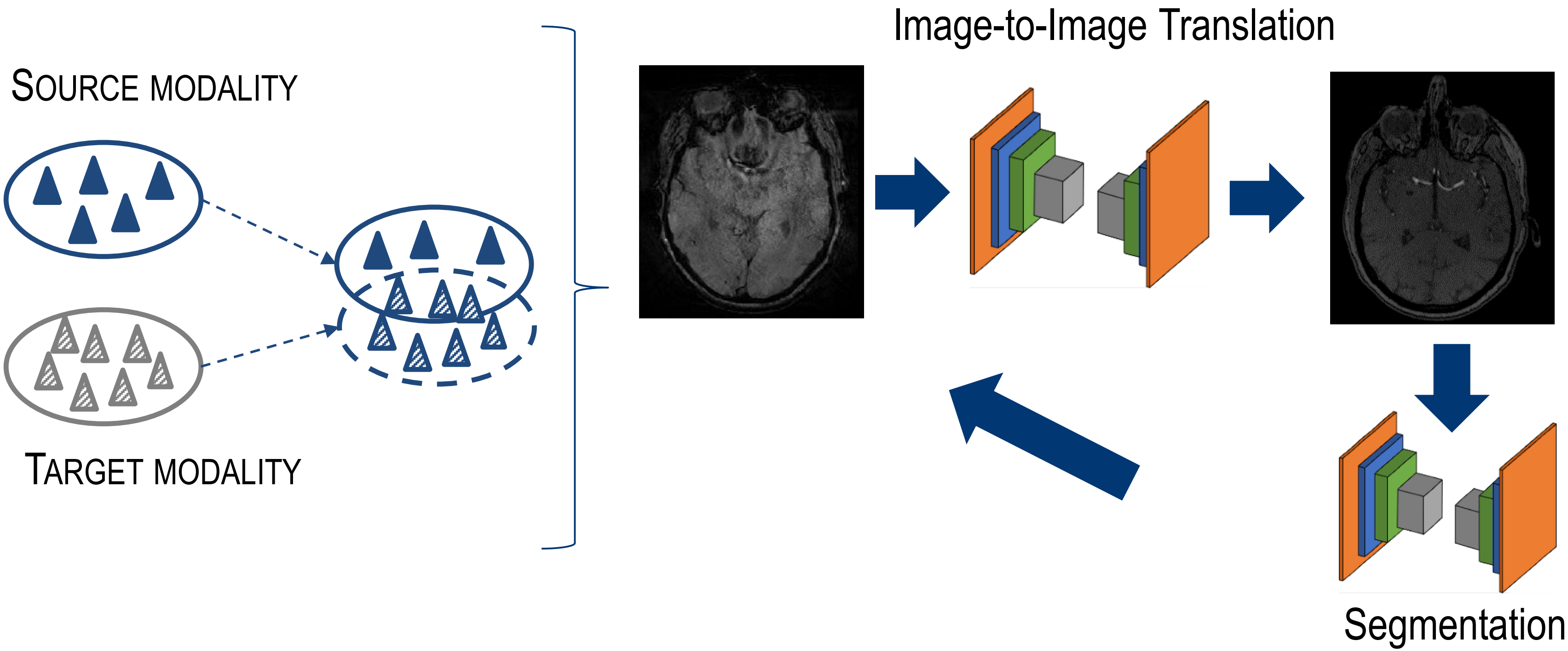
Each modality **requires separate training**: no single model can cope with multiple modalities

Same underlying **information** (vessels), but **easier** to identify **in some** image **modalities**

Can we learn to segment from the easier task and use this knowledge in the difficult one?

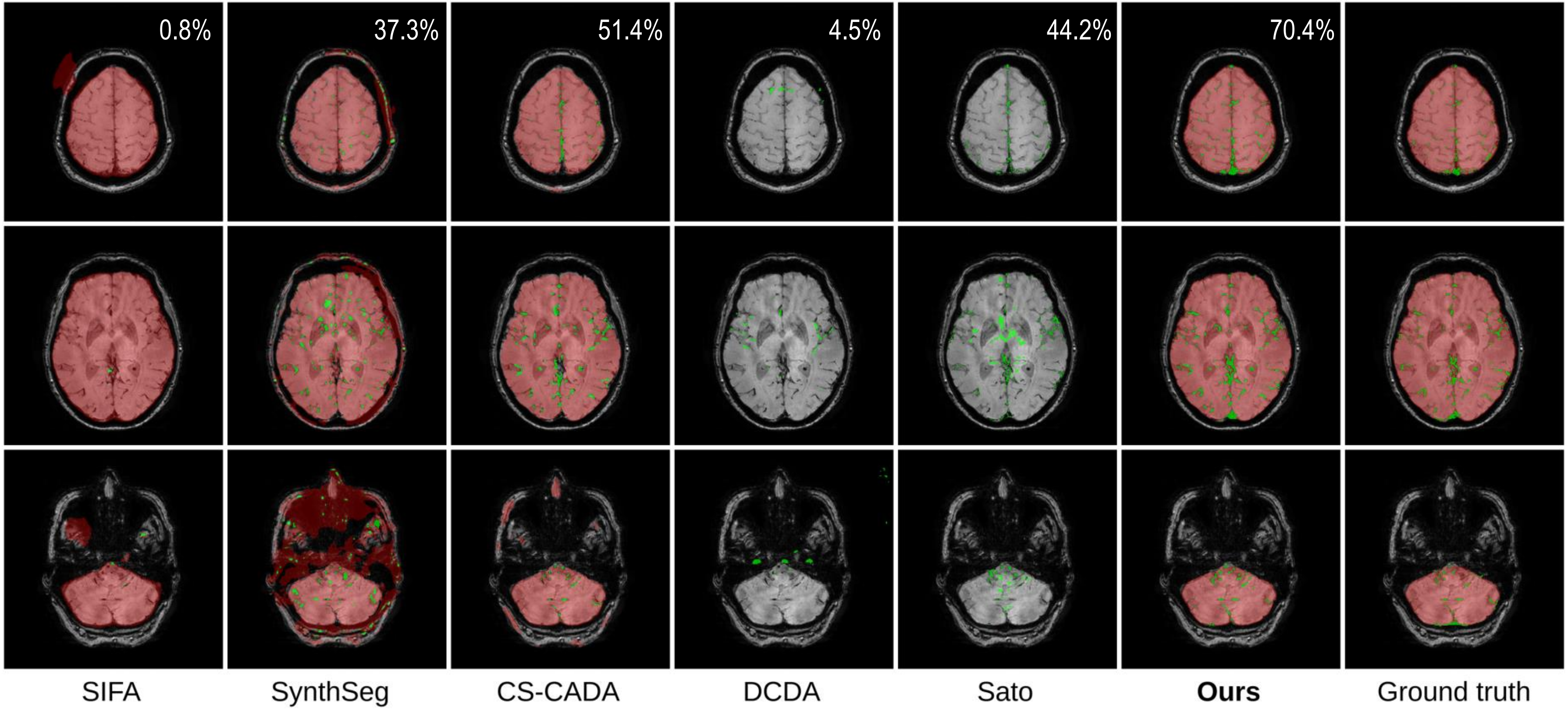
Domain Adaptation for Vessel Segmentation

In collaboration with: Aramis Lab, CHU Nice, UCL and U. Siena



F. Galati, D. Falcetta, R. Cortese, B. Casolla, F. Prados, N. Burgos, MA. Zuluaga (Under review)

A2V: Performance Analysis



F. Galati, D. Falcetta, R. Cortese, B. Casolla, F. Prados, N. Burgos, MA. Zuluaga (Under review)

FINAL REMARKS

Summary: Dice Across Models

Model	Training	Inference			
		TOF	SWI	TOF 7T	DRA
Vessel-CAPTCHA	TOF	79.32 ± 3.02			
	SWI		Good		
JoB -VS	TOF	74.98 ± 0.58			
	TOF 7T			79.2*	
	DRA				92.3*
A2V	TOF	79.3 ± 4.4	70.4 ± 2.4		

*Estimated by challenge organizers

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Summary

Gaining a better understanding of the cerebrovascular tree architecture is currently challenged **by technical and methodological bottlenecks** that limit its analysis

Strategies to overcome this limitations include: **efficient use of data, minimization of user interaction and better generalization**

However, there are still several aspects that need to be solved: **access to larger sets of data, heterogeneity, robustness, quality control**, **reliable evaluation** and an **unified framework**

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ANR-22-FAI1-0003-02

3iA Côte d'Azur
Interdisciplinary Institute for Artificial Intelligence

I-VESSEG: A framework to accelerate cerebrovascular image analysis

MERCI

https://github.com/i-vesseg/

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June 15th 2023
Atelier R-Vessel-X

KING'S College LONDON

EURECOM