AIstroSight Vascular Segmentation of fUS Images using Deep Learning

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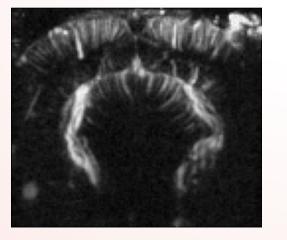


Contribution

- First deep learning application for fUS vascular segmentation
- Competitive segmentation performance compared to stateof-the-art
- Optimal performance with only 100 temporal frames from the fUS stack
- Strong generalization across varying brain states

Functional Ultrasound Imaging (fUS)

Captures changes in CBV related to neuronal activity

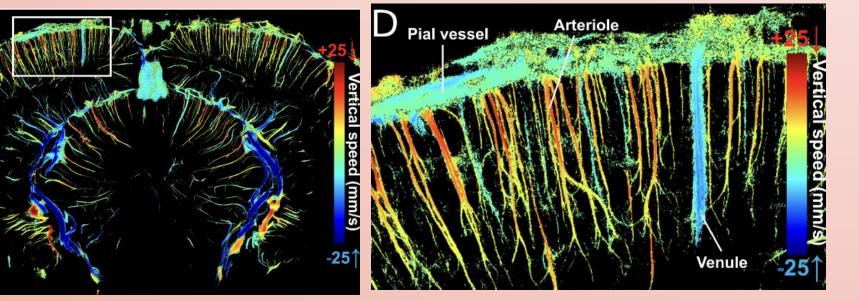


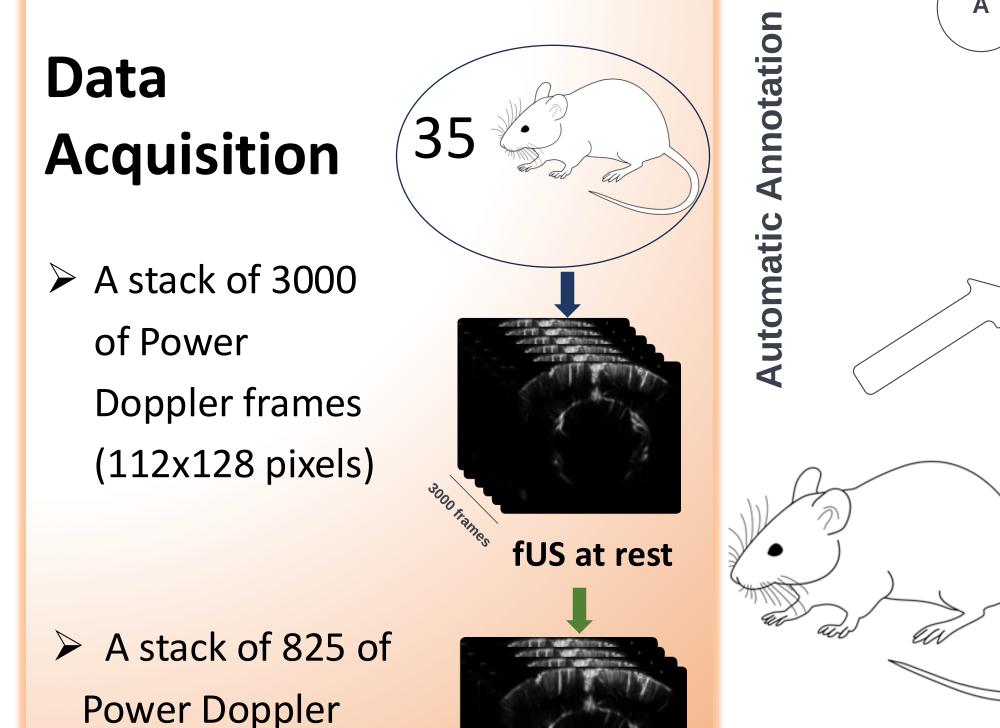
- Achieves high spatial and temporal resolution
- How to identify vascular compartments linked to neuronal activity?

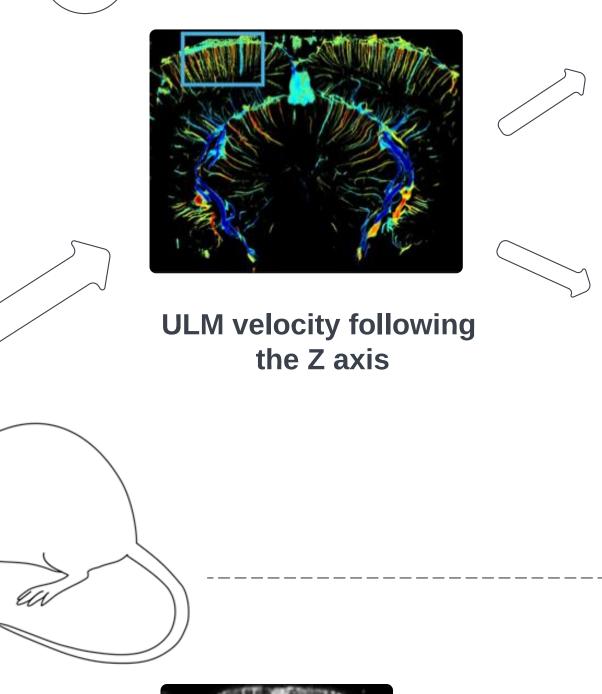
Ultrasound Localisation Microscopy (ULM)

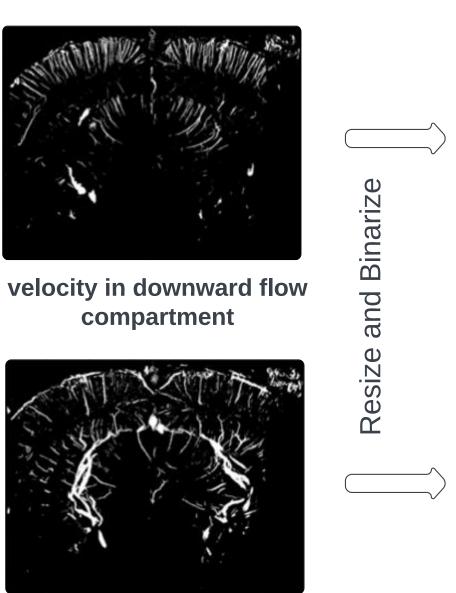
- Advanced imaging employing ultra-fast sampling to improve spatial **resolution** to few microns
- Requires the injection of contrast agents (Invasive)
- Improvement of fUS signals interpretation, supporting preclinical neurovascular research
- **Use it for Automatic** \geq

Annotation of fUS!









velocity in upward flow compartment



perdiction

diction

Artery (cortex) /

Downward

mask

fUS Segmentation

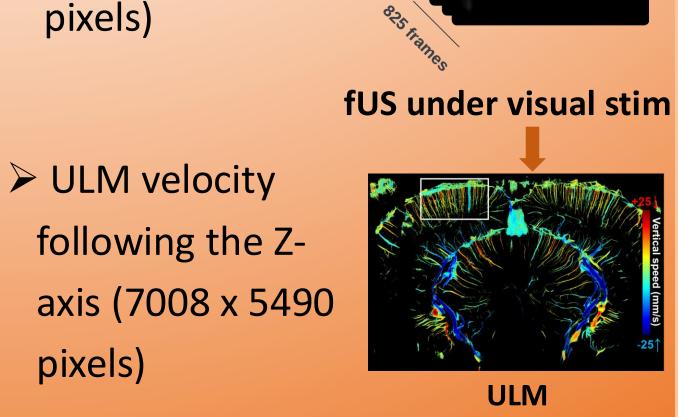
- Benchmarked 7 UNet models
 - UNet
 - RestNet
 - Unet++
- RestNet • UCTransNet

MultiresUNet

- Attention UNet
 TransUNet
- Used 4 loss functions

 $\mathcal{L}_{Dice \ CE} = \alpha \ \mathcal{L}_{CrossEntropy} + \beta \ \mathcal{L}_{Dice}$ $\mathcal{L}_{CF_V} = \alpha \mathcal{L}_{CrossEntropy} + \beta \mathcal{L}_{VesselDensity}$ $\mathcal{L}_{CF_B} = \alpha \, \mathcal{L}_{CrossEntropy} + \gamma \, \mathcal{L}_{FractalDim}$ $\mathcal{L}_{CF} = \alpha \mathcal{L}_{CrossEntropy} + \beta \mathcal{L}_{VesselDensity} + \gamma \mathcal{L}_{FractalDim}$

- $\succ \mathcal{L}_{VesselDensity}$ computes the **propotion** of **arteries** and **veins** in the image
- **L**_{FractalDim} includes an apriori about vessel shape complexity
- Trained all models with different losses (28 configurations)

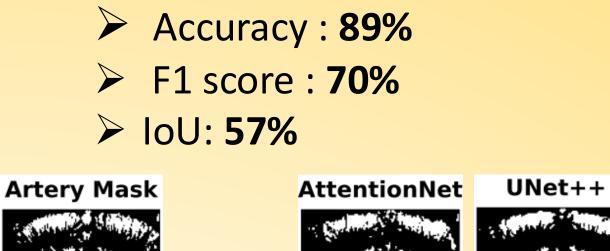


frames (112x128

Input Artery (cortex) / Output Downward prediction 3000 conv 3x3, ReL copy and crop max pool 2x2 **fUS frames** B Vein (cortex) / Upward

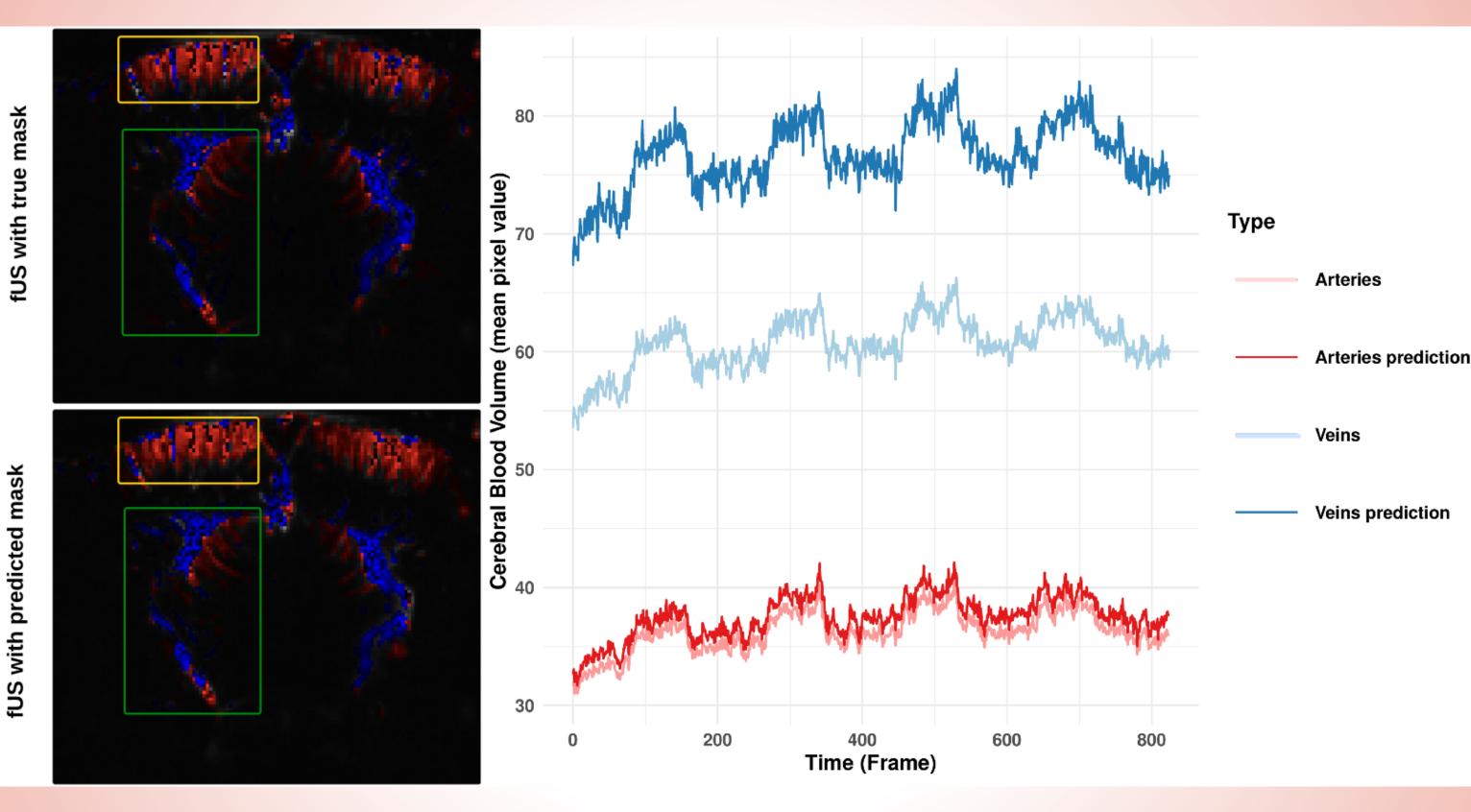
Best Performance

Achieved by **Attention UNet** \bullet and **Unet++** trained with a CF loss



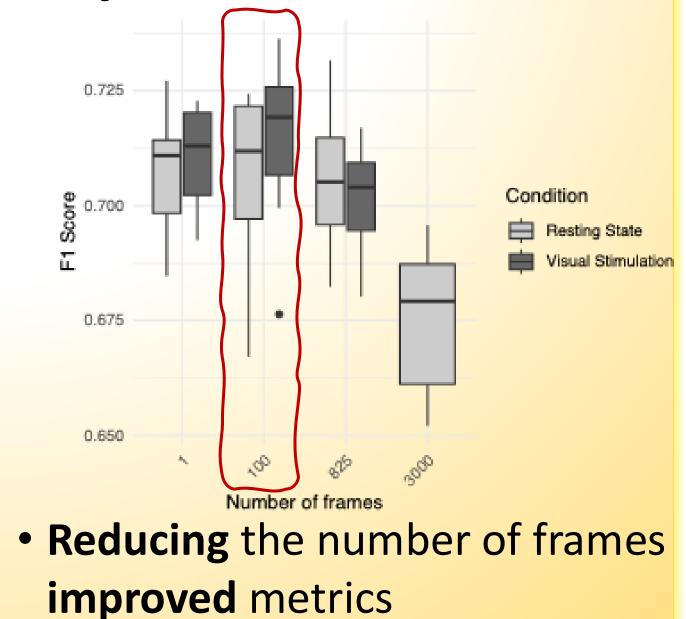
Visualizing vascular structures in fUS imaging

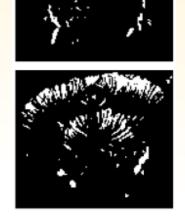
- **Overlaid masks** of arteries in red and veins in blue over a random fUS frame taken under visual stimulation
- **Extracted true and predicted CBV** evolution over time in the cortex region

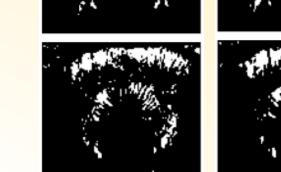


- Dataset = fUS stacks of 3000 frames at rest
- Metrics reported over a 7-fold cross validation

Impact of fUS Depth on performance





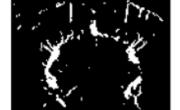


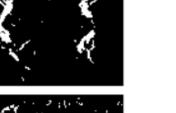
AttentionNet

Vein Mask



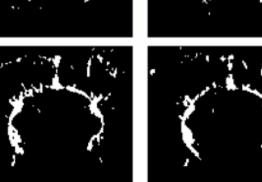
Prediction

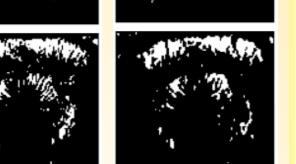












UNet++

Noticed the 4 patterns related to the response to visual stimulation

• Over all rats :

0.98 of correlation for arteries and 0.55 for veins in the cortical region > 0.87 of correlation for downward flow and 0.98 for upward flow in the lower regions

> Best performance with only **100** frames

Cross-Condition efficacy of fUS-models

Train on rest state and test on visually stimulated session Used different rats for each condition Reached an accuracy of 90% and **F1 score of 0.71%**





