# Fast Dynamic Perfusion and Angiography Reconstruction using an end-to-end 3D Convolutional Neural Network


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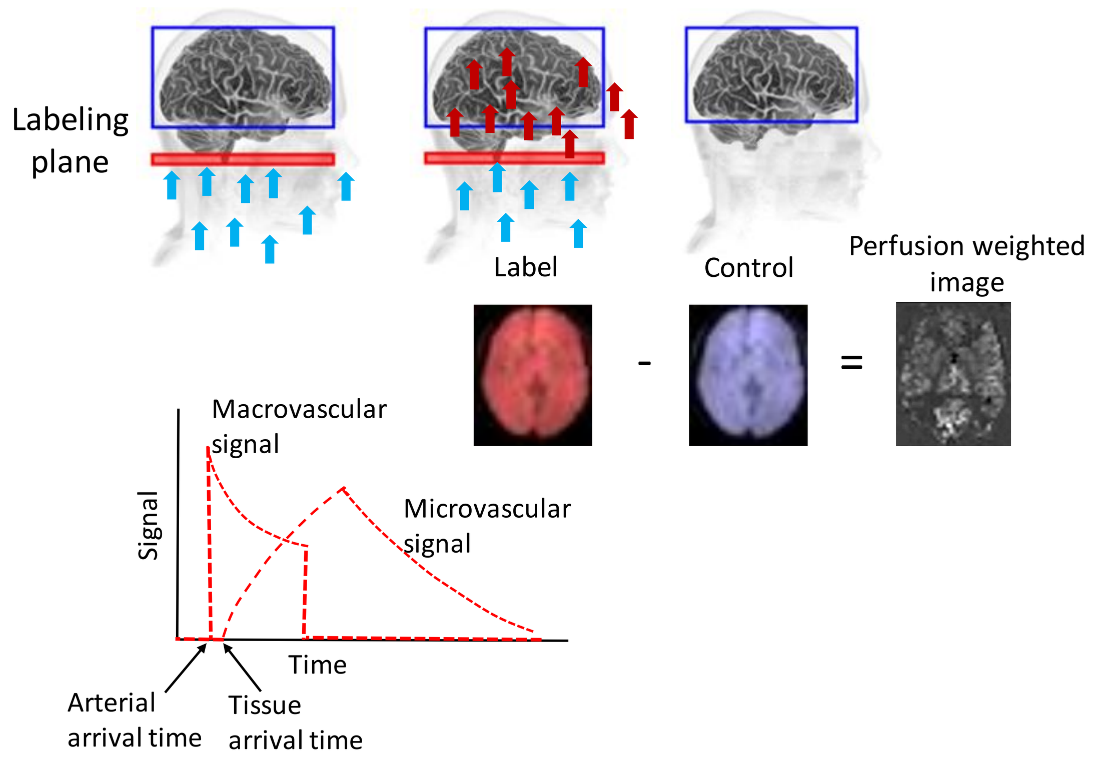
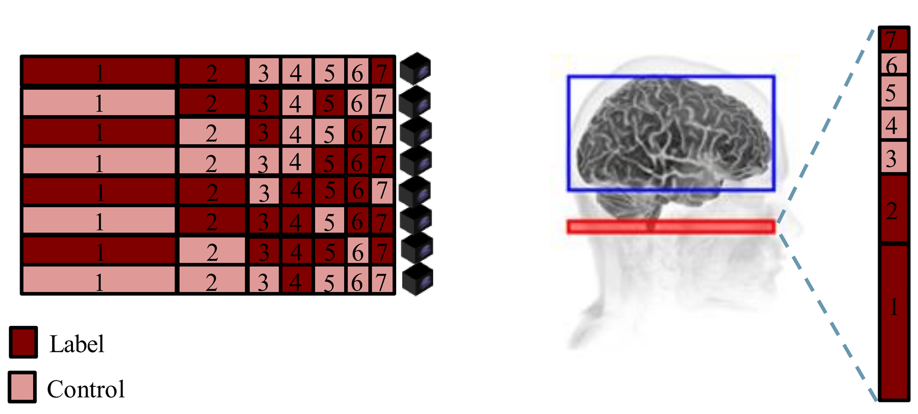
## ABSTRACT


- Arterial spin labeling (ASL) is a MRI technique which uses magnetically labeled blood water as an endogenous tracer for assessing cerebral blood flow (CBF)




Arterial spin labeling (ASL)

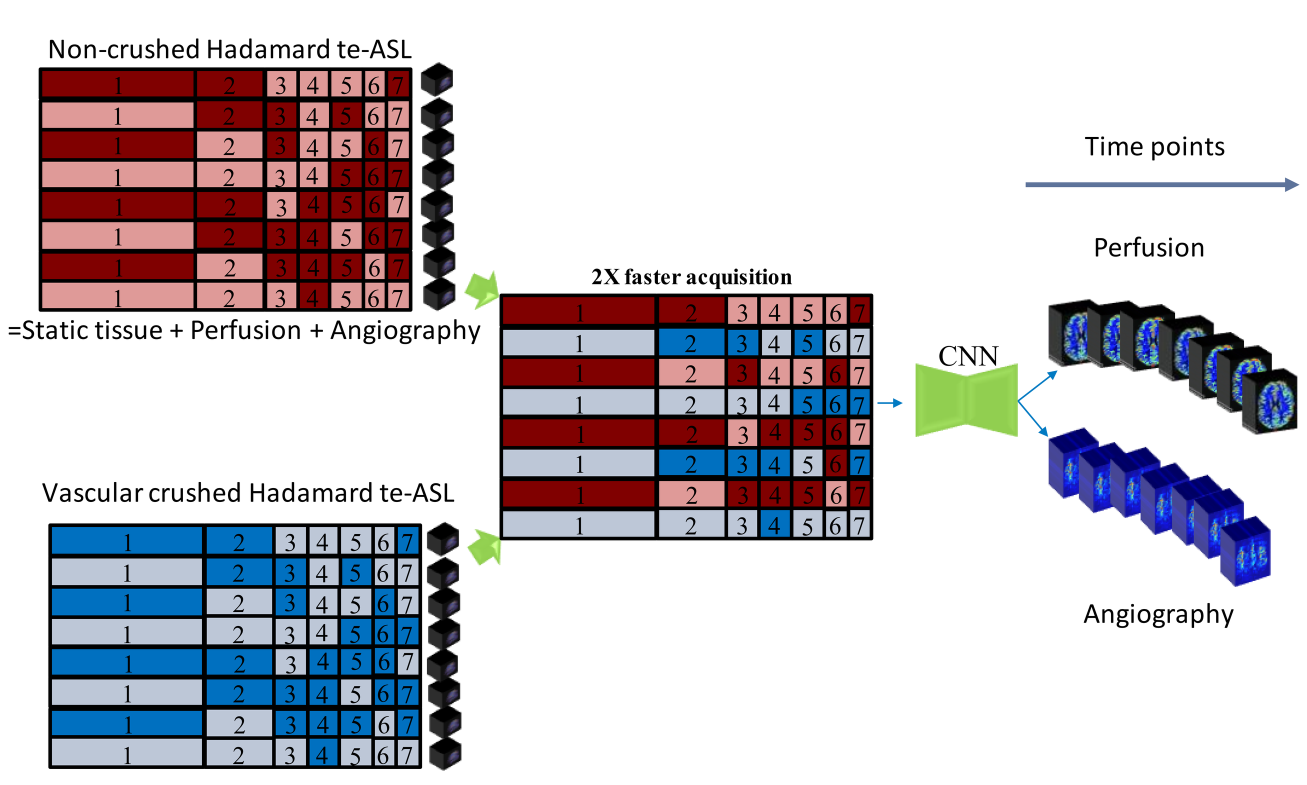
- Hadamard time-encoded arterial spin labeling (te-pCASL) is a SNR-efficient MRI technique for acquiring dynamic pCASL signals that encodes the temporal information into the labeling according to a Hadamard matrix




Hadamard time encoded (te)-ASL


## MOTIVATION

- Using Hadamard te-ASL both with and without flow-crushing, 4D perfusion and angiography images can be reconstructed -> two times longer acquisition times
- We proposed a 3D convolutional neural network (CNN) to accelerate Hadamard te-ASL quantification by a factor of two




Goal: accelerating 4D perfusion and angiography reconstruction two times faster

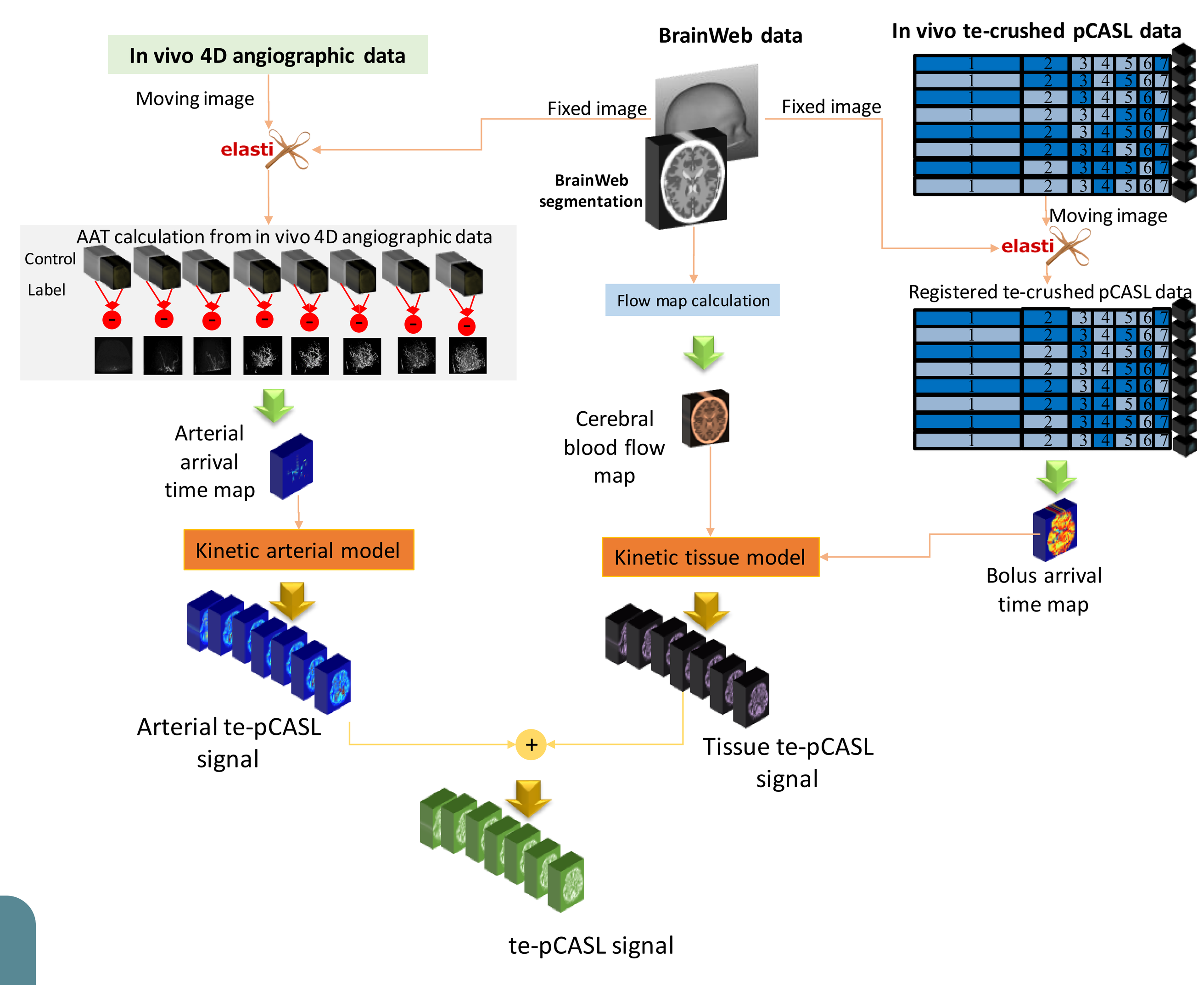
## METHODS- DATA

- Training a CNN needs too many volunteers & acquiring ASL data is time consuming
- Solution: simulated ASL data for training and validation sets
- Contribution (1): we customized kinetic models for Hadamard te-ASL

$$S_{tissue} = \begin{cases} 0;\ if\ t<\Delta t_a \\ M_{0a}.f.e^{\frac{-\Delta t_a}{T_{1a}}}.L_r(1).T_{1a}.\left(1-e^{-\frac{t-\Delta t_a}{T_{1a}}}\right);\ if\ \Delta t_a \le t < \Delta t_a+\tau_1 \\ M_{0a}.f.e^{\frac{-\Delta t_a}{T_{1a}}}.T_{1a}.\left[L_r(2)\left(1-e^{-\frac{t-\Delta t_a-\tau_1}{T_{1a}}}\right)+L_r(1)\left(e^{-\frac{t-\Delta t_a-\tau_1}{T_{1a}}}-e^{-\frac{t-\Delta t_a}{T_{1a}}}\right)\right];\ if\ \Delta t_a+\tau_1 \le t < \Delta t_a+\sum_{b=1}^{2}\tau_b \\ M_{0a}.f.e^{\frac{-\Delta t_a}{T_{1a}}}.T_{1a}.\left[L_r(B).\left(1-e^{-\frac{t-\Delta t_a-\sum_{b=1}^{2}\tau_b}{T_{1a}}}\right)+\sum_{b'=B-1}^{1}L_r(b')\left(e^{-\frac{t-\Delta t_a-\sum_{b=1}^{b'}\tau_b}{T_{1a}}}-e^{-\frac{t-\Delta t_a-\sum_{b=1}^{b'-1}\tau_b}{T_{1a}}}\right)\right];\ if\ \Delta t_a+\sum_{b=1}^{B-1}\tau_b \le t < \Delta t_a+\sum_{b=1}^{B}\tau_b;\ B\in[3,7] \\ M_{0a}.f.e^{\frac{-\Delta t_a}{T_{1a}}}.T_{1a}.\left[\sum_{b'=N}^{2}L_r(b')\left(e^{-\frac{t-\Delta t_a-\sum_{b=1}^{b'}\tau_b}{T_{1a}}}-e^{-\frac{t-\Delta t_a-\sum_{b=1}^{b'-1}\tau_b}{T_{1a}}}\right)+L_r(1)\left(e^{-\frac{t-\Delta t_a-\tau_1}{T_{1a}}}-e^{-\frac{t-\Delta t_a}{T_{1a}}}\right)\right];\ t\ge \Delta t_a+\sum_{b=1}^{N}\tau_b;\ N=7 \end{cases}$$

$$S_{artery} = \begin{cases} 0;\ t<\Delta t_a \\ M_{0a}.aCBV.L_r(b)\times e^{\frac{-\Delta t_a}{T_{1a}}};\ \Delta t_a+\sum_{b'=1}^{b-1}\tau_{b'} \le t < \Delta t_a+\sum_{b'=1}^{b}\tau_{b'} \\ 0;\ \Delta t_a+\tau_b \le t \end{cases}$$

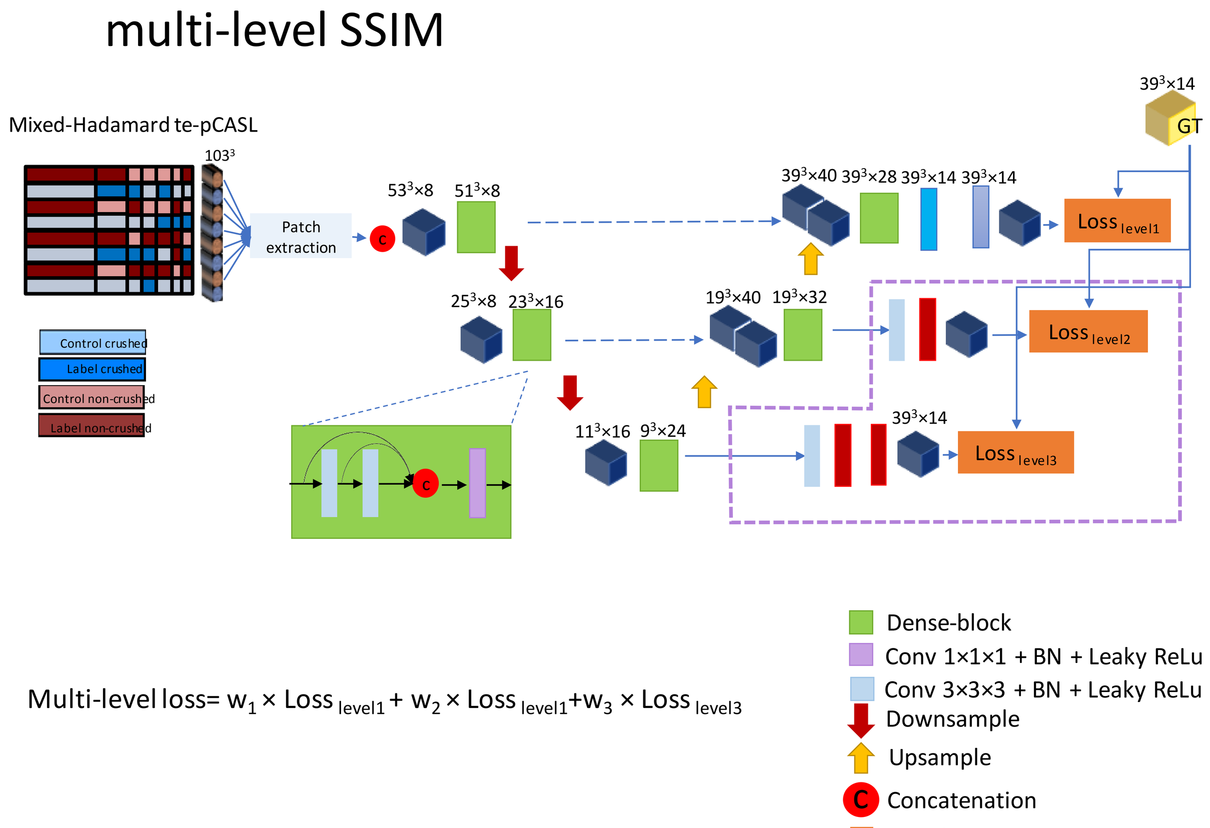
- Contribution (2): we designed a framework for generating the training and validation datasets




Data Generator framework

## METHODS-NETWORK

- Contribution (3): we designed an end-to-end DenseUnet network for performing the reconstruction
- We compared the performance of different loss functions: MSE, SSIM, Perceptual loss, and multi-level SSIM

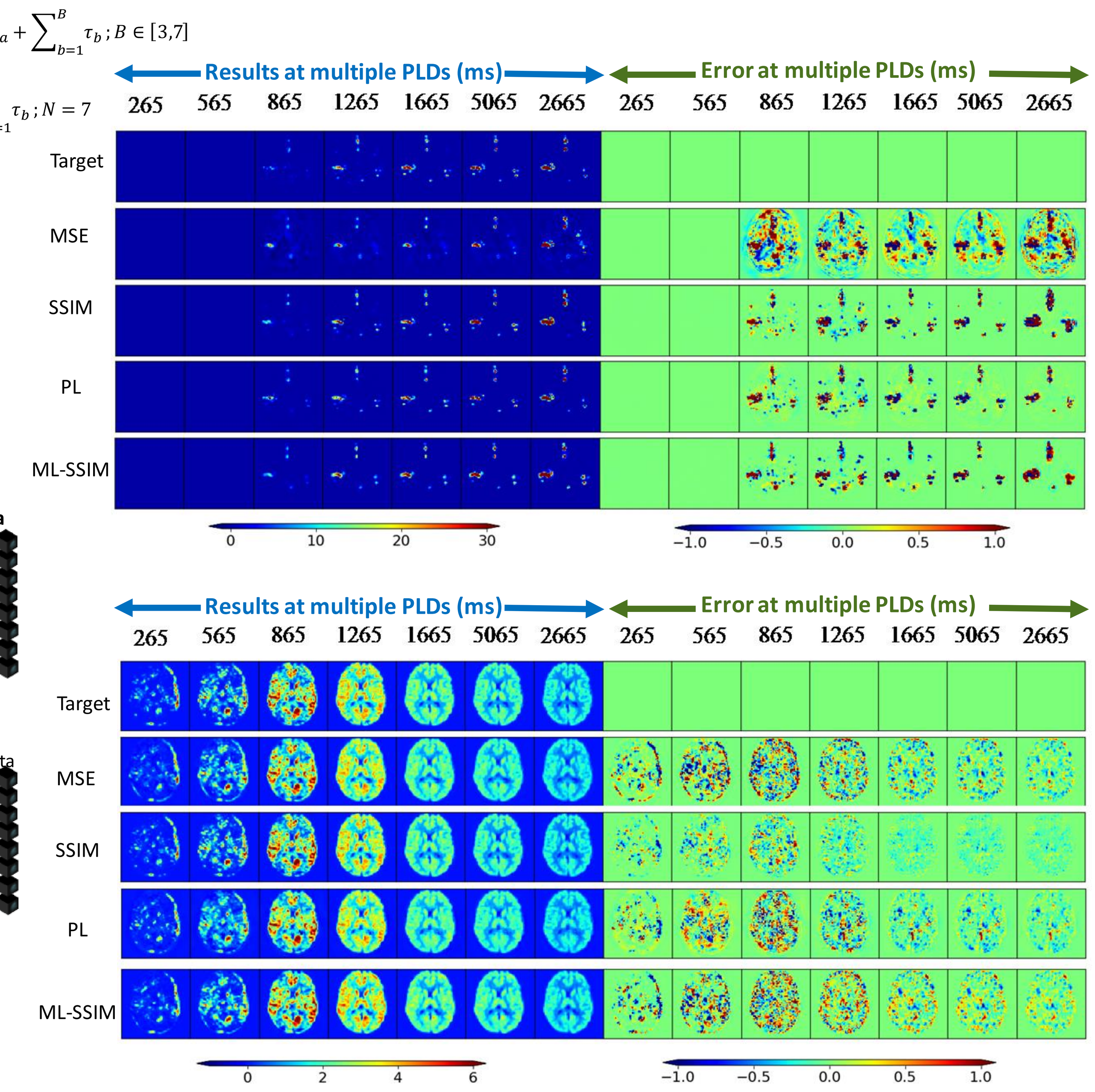



Multi-level loss= $w_1 \times Loss_{level1} + w_2 \times Loss_{level1} + w_3 \times Loss_{level3}$

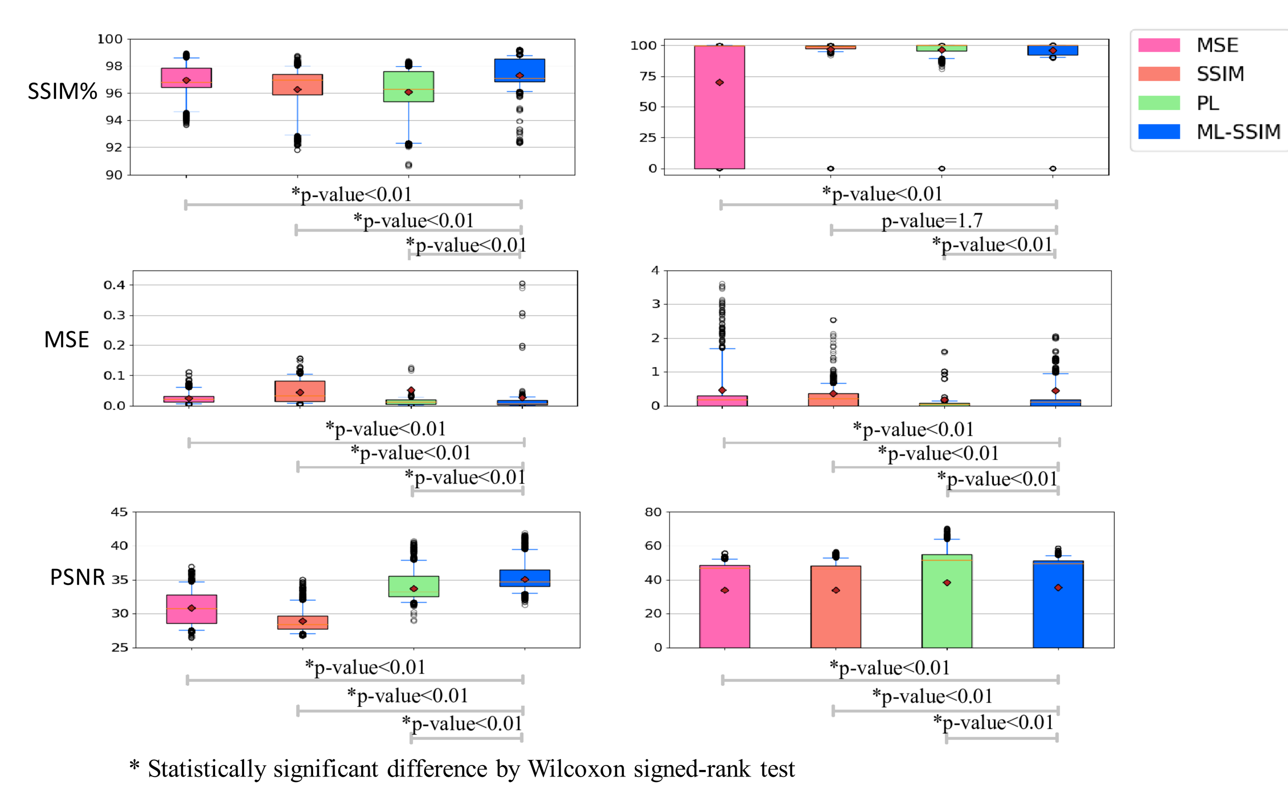
Proposed network

## RESULTS

- The dataset contains 1096 subjects for training, 155 for validation and 313 for testing
- 75% of the patches were extracted from the region containing arteries To tackle the sparsity of MRA with respect to the perfusion
- Augmentation methods: adding white noise extracted from a Gaussian distribution with μ=0 and random σ∈[0, 5], left-to-right flipping, and random rotation (up to 18°)




Qualitative results for dynamic perfusion reconstruction




* Statistically significant difference by Wilcoxon signed-rank test

Quantitative results

## CONCLUSIONS

- We proposed a CNN for accelerating dynamic angiography and perfusion reconstruction two times faster
- The proposed network obtained promising results for the challenging problem of 4D angiography and perfusion reconstruction
- Next step: enriching the training and validation datasets with in vivo data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