ETH zürich

CVL Computer Vision Lab

Guiding Unsupervised Image Restoration with few Annotated Subjects for Lesion Detection

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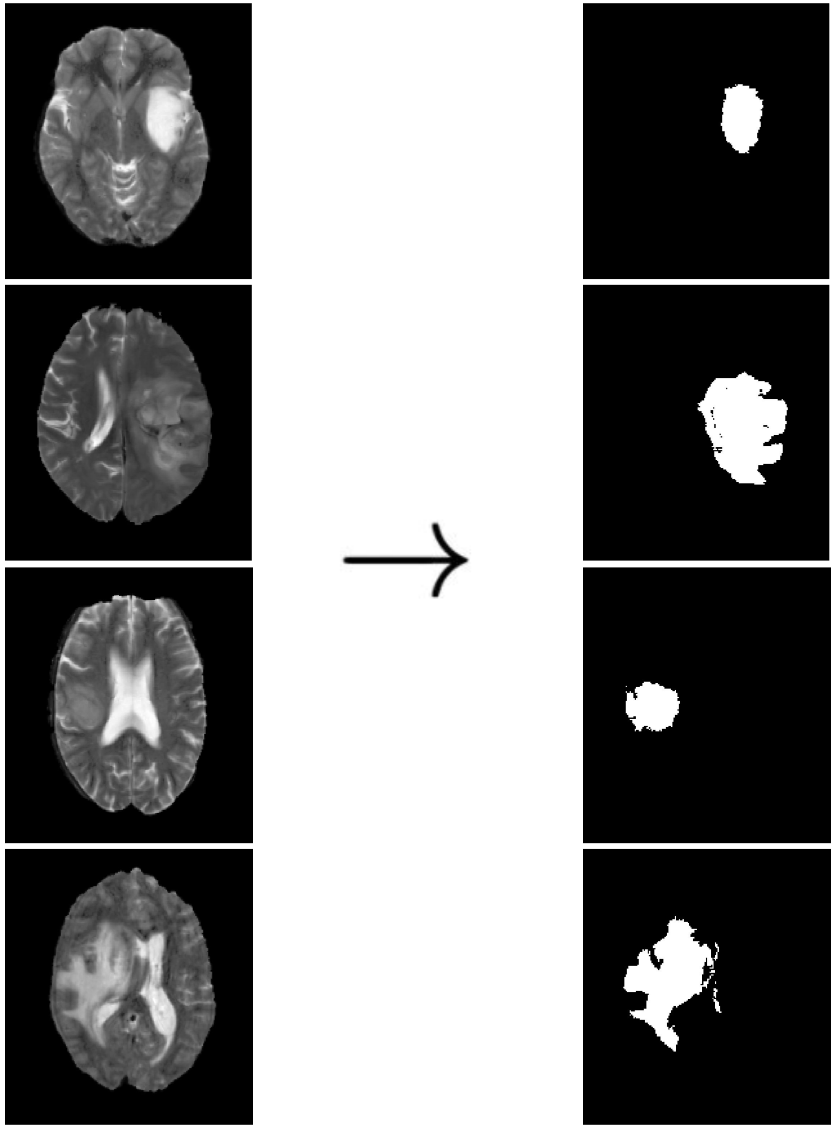
14 July 2020, Zürich

Lesion Detection

- Segmentation of lesions is important for diagnosis and treatment
- Manual segmentation is a tedious task
- Automatic measurements help clinicians be more efficient and precise



Problems of Previous Work

Supervised Methods

Well trained 3D U-Net [1]
Autoencoder Regularization [2]
Convolutional Neural Networks [3]

+ Good Performance
- Requires Large Datasets
- Bad Generalisation of Unseen Lesions

Unsupervised Methods

Constrained Adversarial Autoencoders [4]
Detection via Image Restoration [5]
Autoencoding models [7]

+ No Need of Annotated Datasets
+ Detects any Lesion
- Performance

Proposed Method

Semi-supervised method

+ Need of Only few Annotated Training data
+ Performance

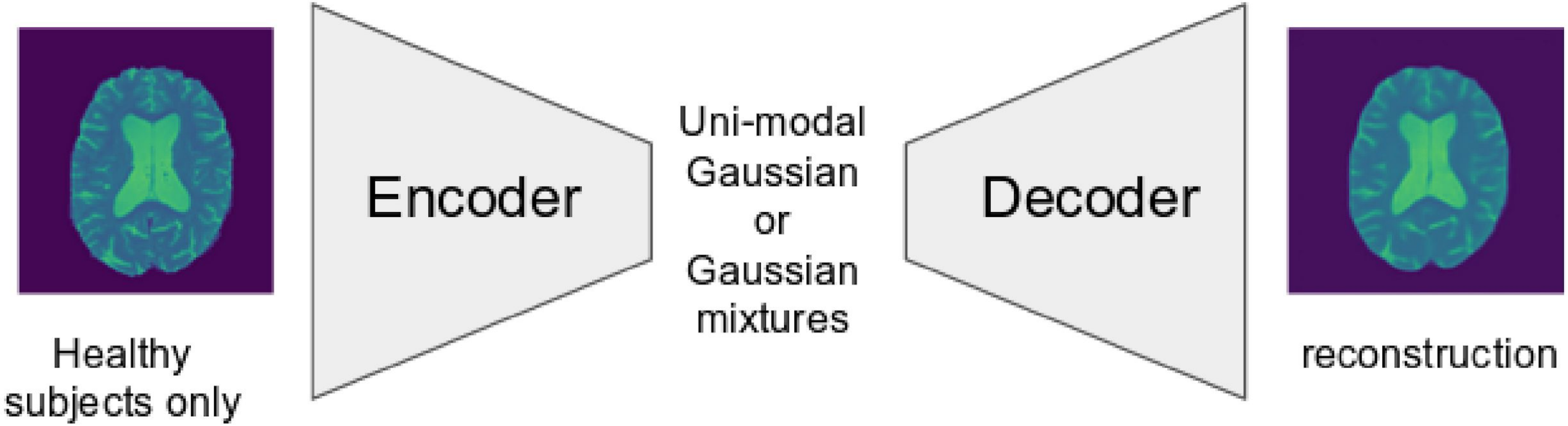
1. Isensee, Fabian, et al. "No new-net." *International MICCAI Brainlesion Workshop*. Springer, Cham, 2018.
2. Myronenko, Andriy. "3D MRI brain tumor segmentation using autoencoder regularization." *International MICCAI Brainlesion Workshop*. Springer, Cham, 2018.
3. Pereira, Sérgio, et al. "Brain tumor segmentation using convolutional neural networks in MRI images." *IEEE transactions on medical imaging* 35.5 (2016): 1240-1251.
4. Chen, Xiaoran, and Ender Konukoglu. "Unsupervised detection of lesions in brain mri using constrained adversarial auto-encoders." *arXiv preprint arXiv:1806.04972* (2018).
5. Baur, Christoph, et al. "Deep autoencoding models for unsupervised anomaly segmentation in brain MR images." *International MICCAI Brainlesion Workshop*. Springer, Cham, 2018.
6. You, Suhang, et al. "Unsupervised lesion detection via image restoration with a normative prior." *International Conference on Medical Imaging with Deep Learning*. 2019.

Agenda

1. Related Work
2. Proposed Methods
3. Experimental Setup and Baseline Methods
4. Results
5. Summary

Related Work - Detection with Normative Prior[1]

Step 1 - Learn normative prior from healthy data

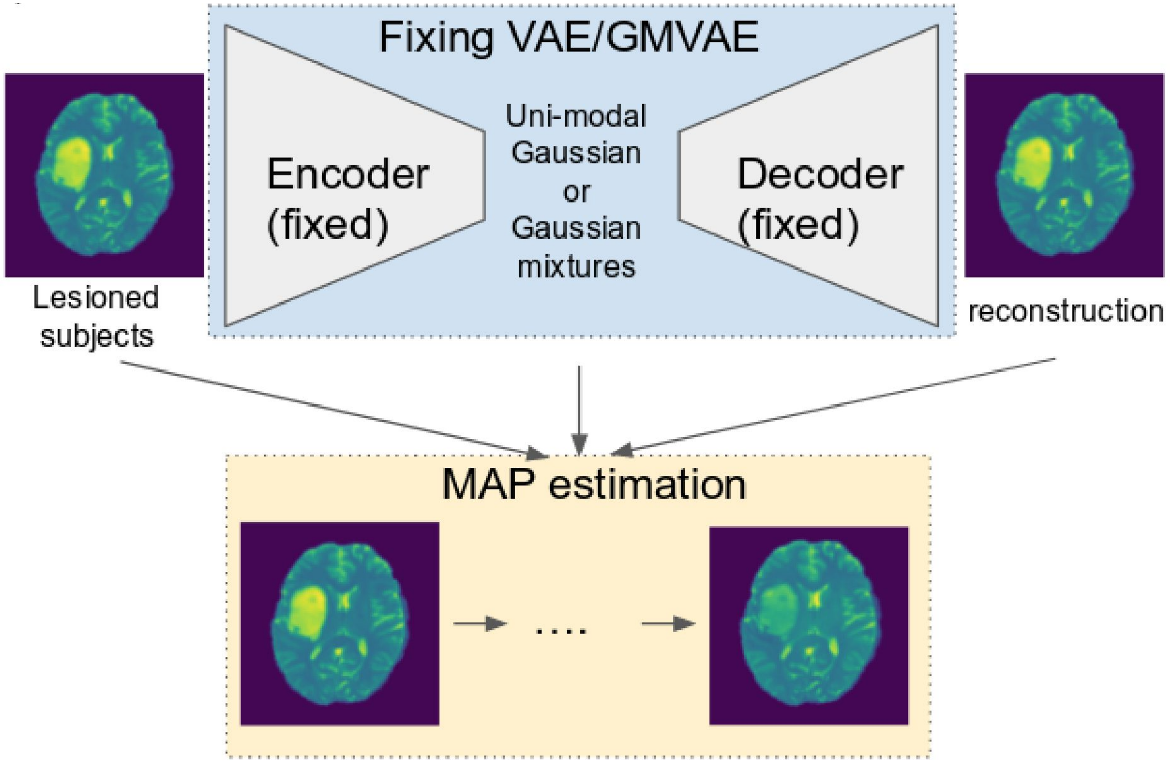


1. You, Suhang, et al. "Unsupervised lesion detection via image restoration with a normative prior." *International Conference on Medical Imaging with Deep Learning*. 2019.
Image source: Chen, Xiaoran, et al. "Unsupervised lesion detection via image restoration with a normative prior." *Medical Image Analysis* (2020): 101713.

Related Work - Detection with Normative Prior[1]

Step 2 - Detect Lesions via Image Restoration

$$\underset{X}{\operatorname{argmax}}\, p(X|Y) = \underset{X}{\operatorname{argmax}}\left[\frac{p(X)p(Y|X)}{p(Y)}\right]$$



1. You, Suhang, et al. "Unsupervised lesion detection via image restoration with a normative prior." *International Conference on Medical Imaging with Deep Learning*. 2019.

Image source: Chen, Xiaoran, et al. "Unsupervised lesion detection via image restoration with a normative prior." *Medical Image Analysis* (2020): 101713.

Proposed methods - Restoration

- **Lesions assumed as Additive Noise:**

Input MRI

Lesion

$$Y = X + D \Rightarrow D = |X - Y|$$

Healthy image

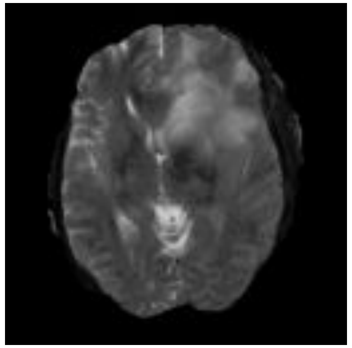
- **X is Found via Image Restoration with MAP estimation:**

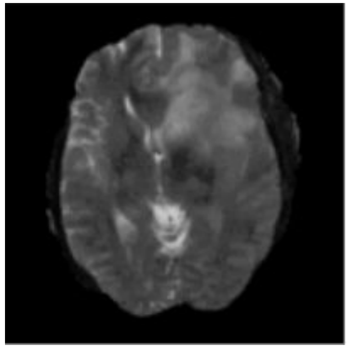
$$\underset{X}{\operatorname{argmax}} P(X|Y) = \underset{X}{\operatorname{argmax}}[\frac{P(X)P(Y|X)}{P(Y)}]$$
$$\propto \underset{X}{\operatorname{argmax}}[\log\big(P(X)\big) + \log(P(Y|X))]$$

- **MAP estimation is solved with gradient descent:**

$$X_{i+1} = X_i - \alpha\,[\frac{\partial}{\partial X_i}ELBO(X) - \frac{\partial}{\partial X_i}ELBO(X) \cdot NN(X, Y)]$$

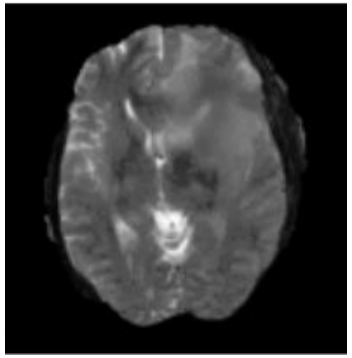
Proposed methods - Restoration

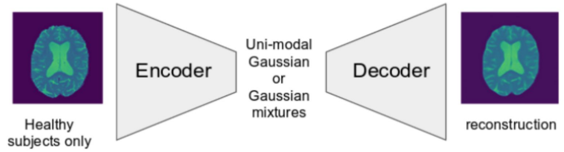




MAP estimation

$$X_{i+1} = X_i - \alpha \left[\frac{\partial}{\partial X_i} ELBO(X_i) - (\frac{\partial}{\partial X_i} ELBO(X_i)) \cdot NN_\theta(X_i, Y) \right]$$





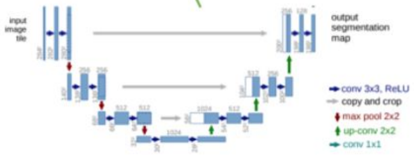
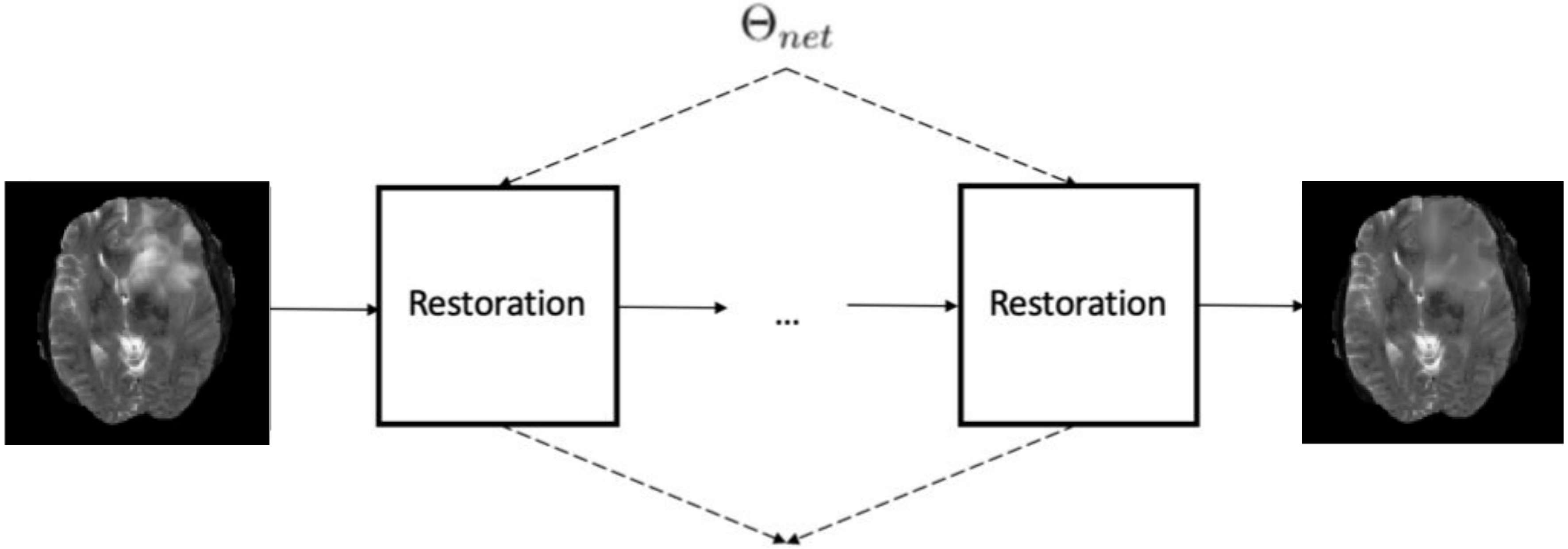
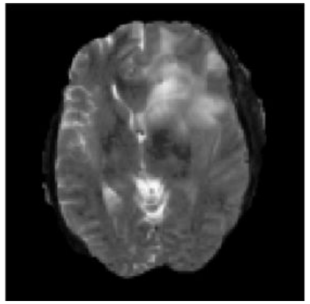
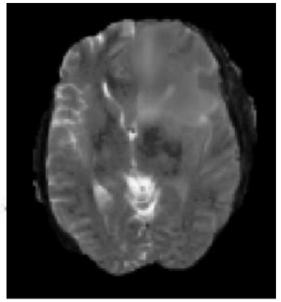
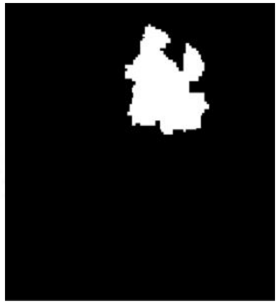


Image source 1: Chen, Xiaoran, et al. "Unsupervised lesion detection via image restoration with a normative prior." *Medical Image Analysis* (2020): 101713.
Image source 2: Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

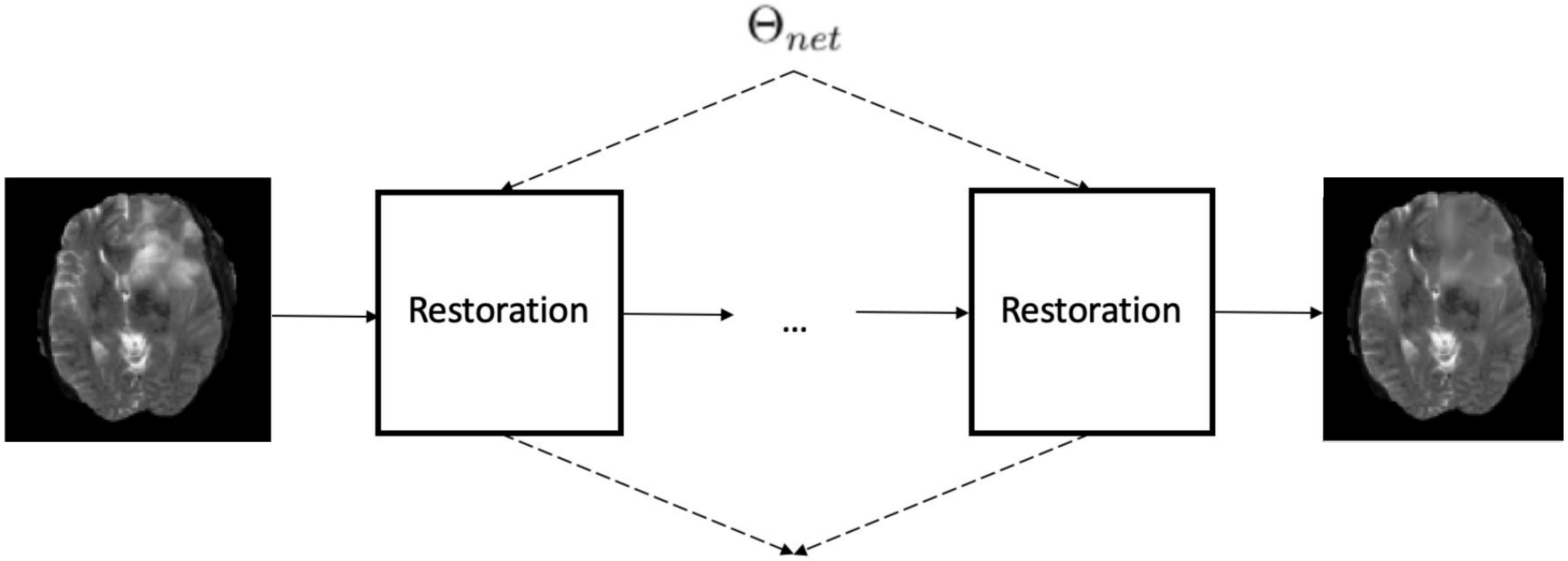
Learning the likelihood - Implicit Approach



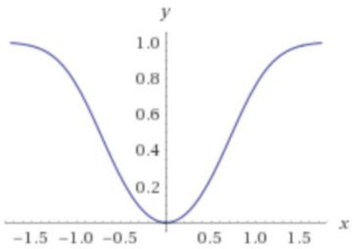
$$\text{Loss}_\theta = Dice_{Loss}(\text{NN}_\theta(Y, X_i), (1 - S))$$

$\text{Loss}_\theta = Dice_{Loss}(\text{NN}_\theta($  $,$  $), (1 -$  $))$

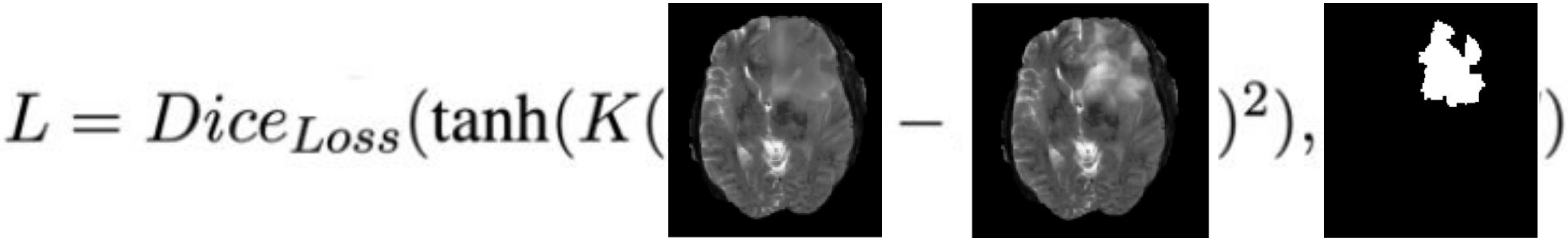
Learning the likelihood - Explicit Approach



$$L = Dice_{Loss}(\tanh(K(X_{i+1} - X_0)^2), S)$$



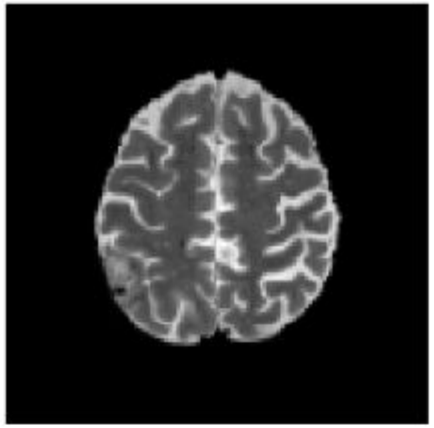
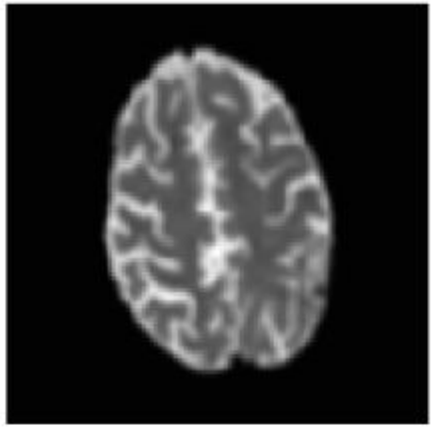
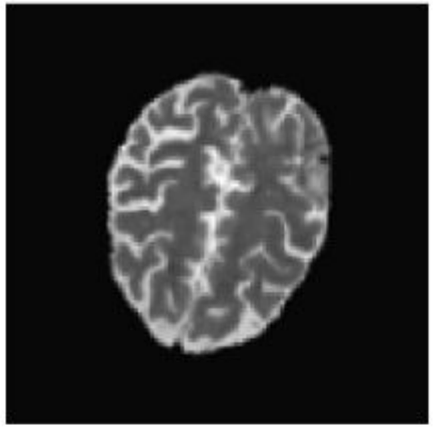
tanh(x^2)



Data Augmentation

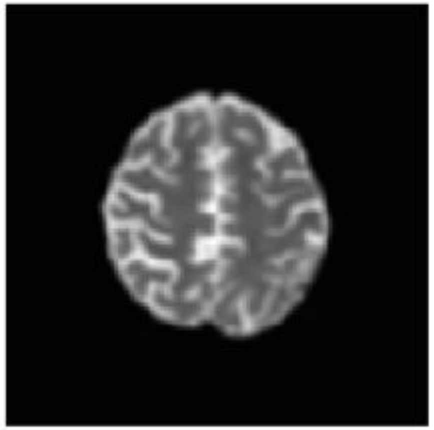
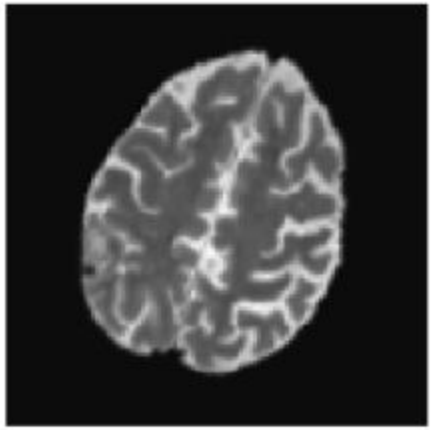
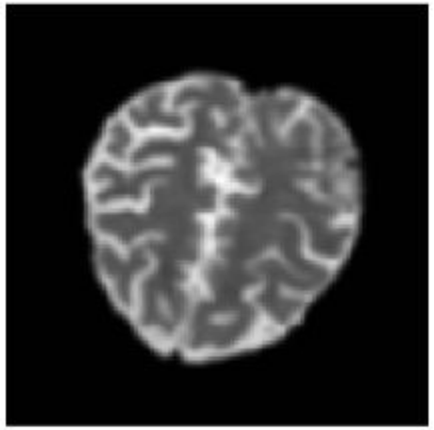
Weak Augmentation

Transform	Parameter
Horisontal Flip	0.5%
Rotate	random($\pm$10 deg)
Elastic Deformation	$\alpha = \text{random}(0, 100)$, $\sigma = 10$
Scale	random($\pm$0.20%)
Average Blur	random(0,4)
Linear Contrast	random($\pm$0.2)
Intensity Multiply	random($\pm$0.2)

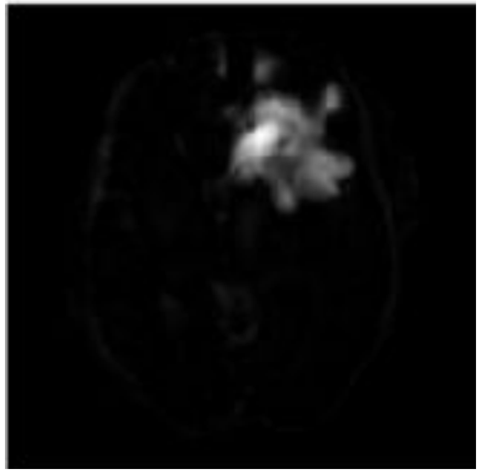
Strong Augmentation

Transform	Parameter
Horisontal Flip	0.5%
Vertical Flip	0.5%
Rotate	random($\pm$20 deg)
Elastic Deformation	$\alpha = \text{random}(0, 200)$, $\sigma = 20$
Scale	random($\pm$0.20%)
Average Blur	random(0,4)
Linear Contrast	random($\pm$0.3)
Intensity Multiply	random($\pm$0.2)

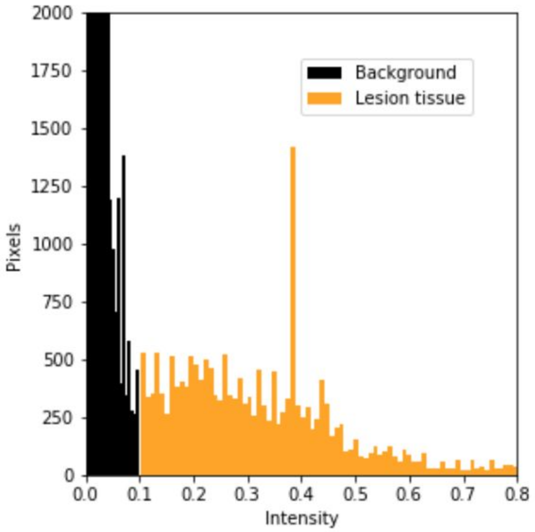




Selecting Threshold for Binary Segmentation

$$D = |Y - X| \qquad\qquad S$$



$$\rightarrow$$



Experimental setup

- Dataset: T2 weighted MRI axial slices
  - BraTS 2017: 283 subjects with labelled brain tumours
  - CamCAN: 652 healthy brain scans
  - 1/3/10/30/100 # of Subjects
- Data preprocessing
  - Bias field correction
  - Normalisation
  - Resize and Crop
  - Histogram Matching
- Hyperparameters for VAE and Segmentation network:
  - Batchsize: 32, Adam optimiser with learning rate: 10^-3
- Hyperparameters for restoration:
  - Step size: 3x10^-1, # of steps: 10
- Implementation using Pytorch

Baseline Methods

- Unsupervised detection via image restoration
- Supervised U-Net
- Semi-supervised U-Net trained with sim-CLR

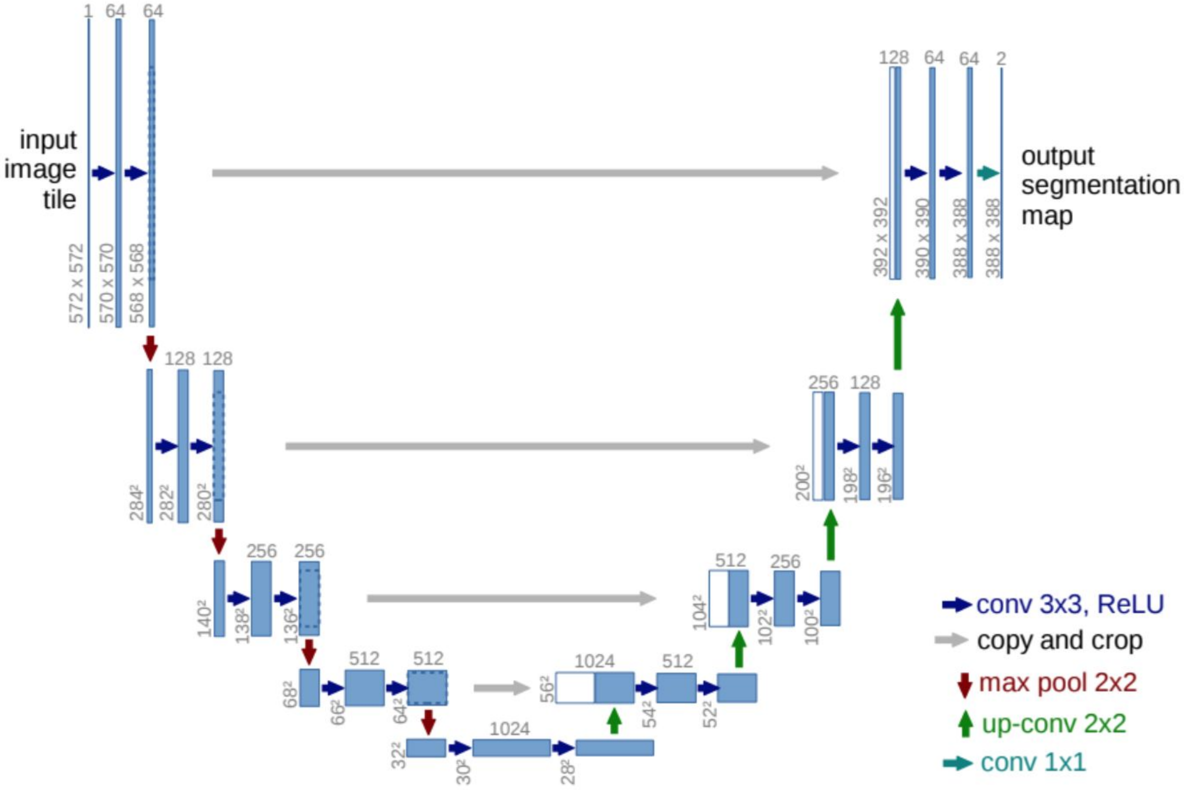
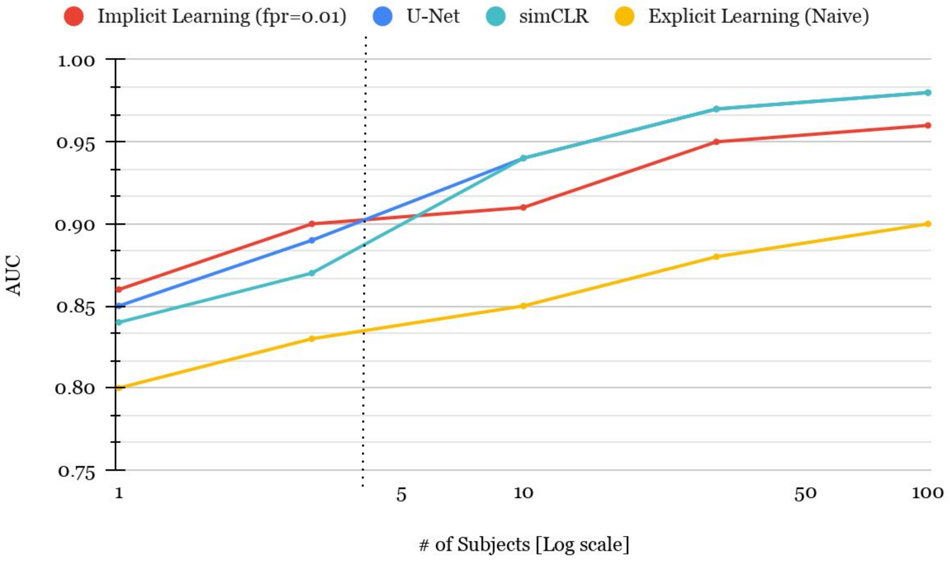
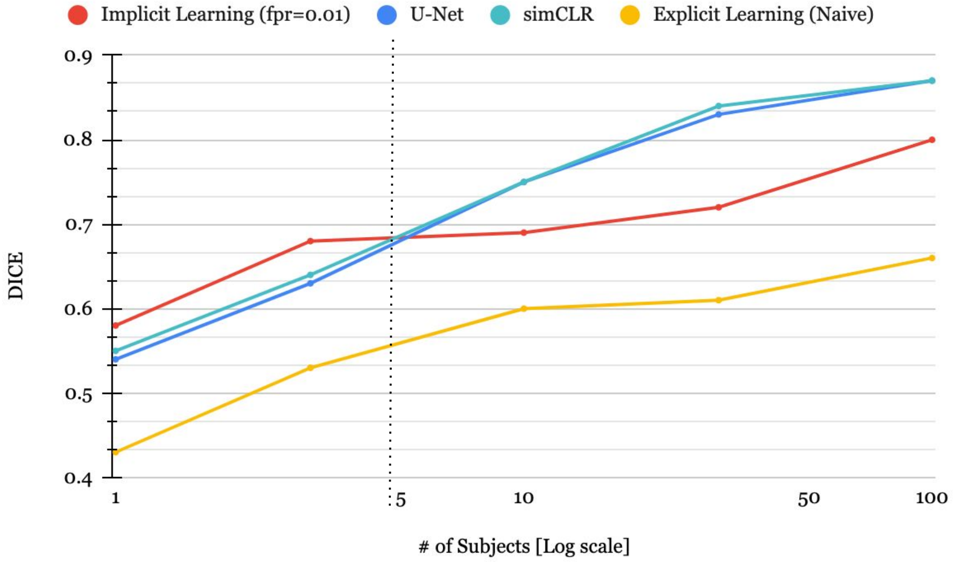


Image source 1: Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

Results





0 Subjects

Methods	AUC	Dice (naive)	DICE (fpr 0.01)	DICE (fpr 0.05)
You et al.	0.80	–	0.34	0.35

1 Subject

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	**0.86**(±**0.02**)	0.51(±0.05)	0.51(±0.07)	**0.53**(±**0.05**)
Explicit Learning *	0.80(±0.04)	0.38(±0.03)	0.41(±0.04)	0.41(±0.03)
U-Net	0.85(±0.02)	0.49(±0.06)	–	–
SimCLR / U-Net	0.84(±0.02)	0.50(±0.13)	–	–

10 Subjects

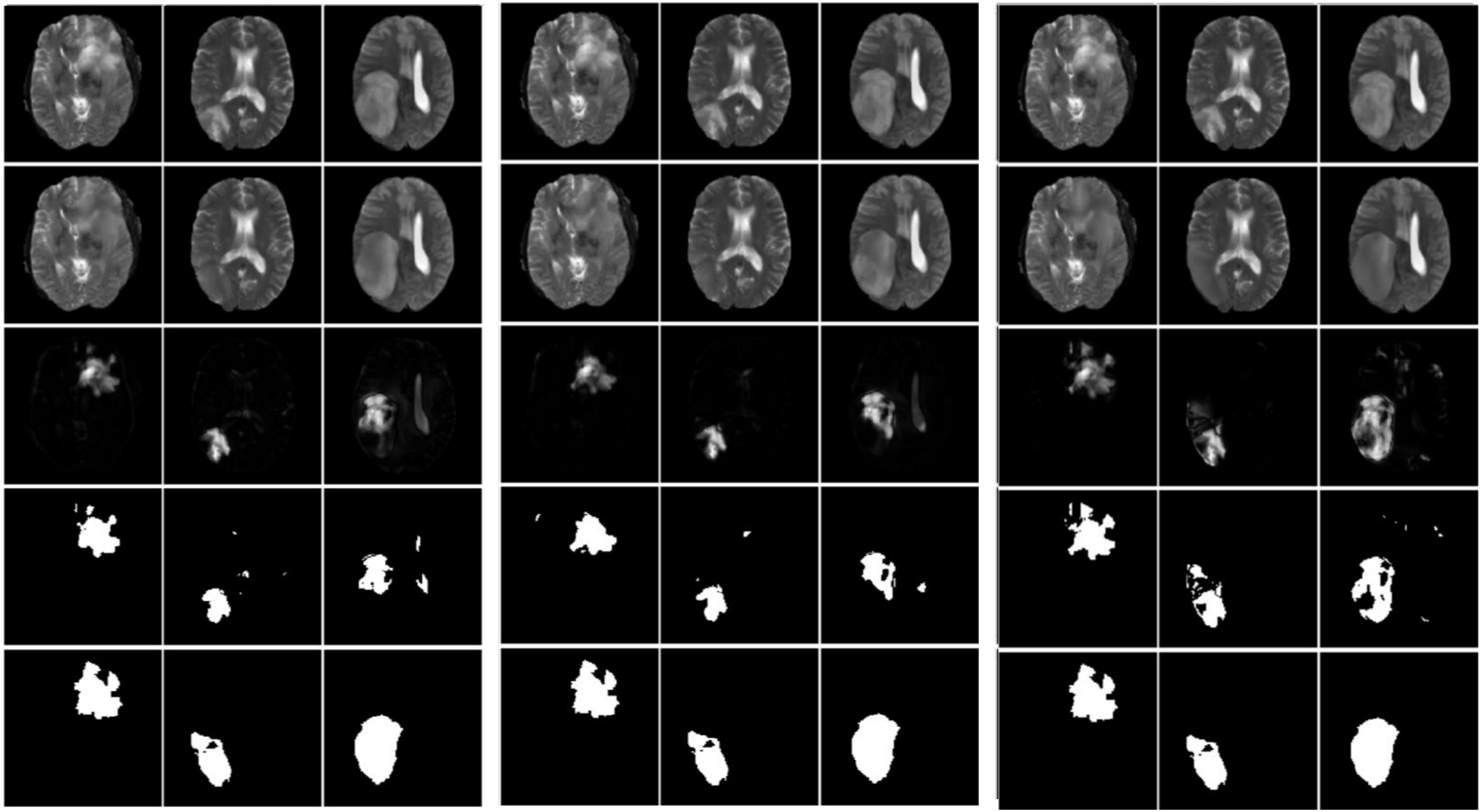
Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	0.91(±0.03)	0.64(±0.03)	0.54(±0.12)	0.64(±0.05)
Explicit Learning	0.85(±0.04)	0.55(±0.04)	0.45(±0.07)	0.48(±0.06)
U-Net	0.94(±0.01)	0.70(±0.03)	–	–
SimCLR / U-Net	**0.94**(±**0.01**)	**0.70**(±**0.04**)	–	–

100 Subjects

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	0.96	0.73	0.67	0.75
Explicit Learning	0.90	0.61	0.41	0.61
U-Net	**0.98**	**0.82**	–	–
SimCLR / U-Net	**0.98**	**0.82**	–	–

Results: Visualisation Implicit

1 training subject | 10 training subject | 100 training subject



Input

Restored

Lesion map

Output
(fpr = 1%)

Ground
truth

Results: Visualisation Explicit

1 training subject | 10 training subject | 100 training subject

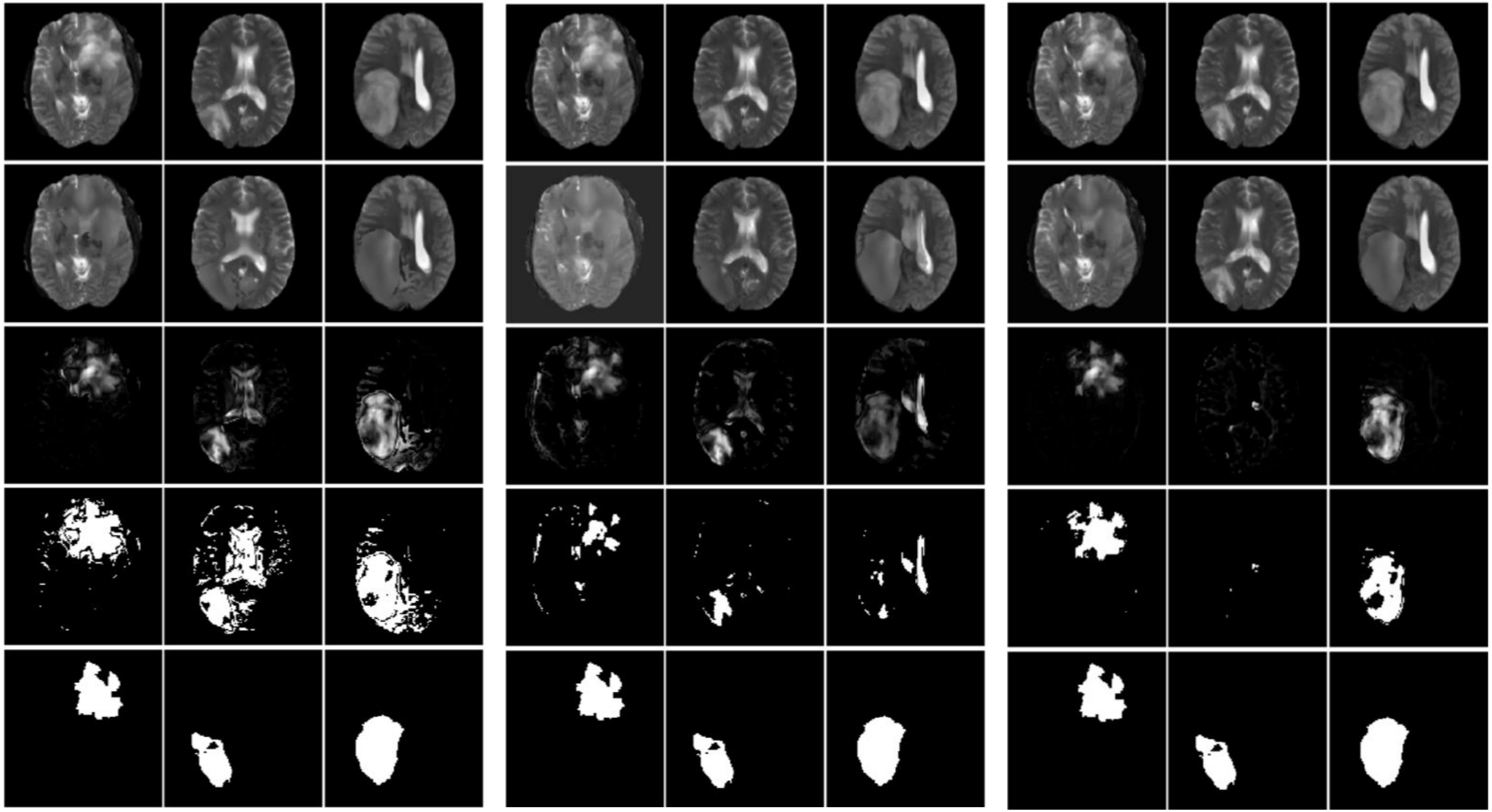
Input

Restored

Lesion map

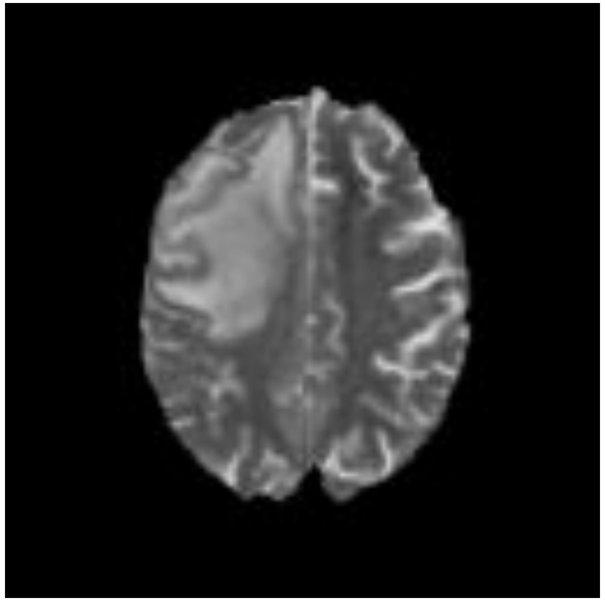
Output
(fpr = 1%)

Ground
truth



Summary

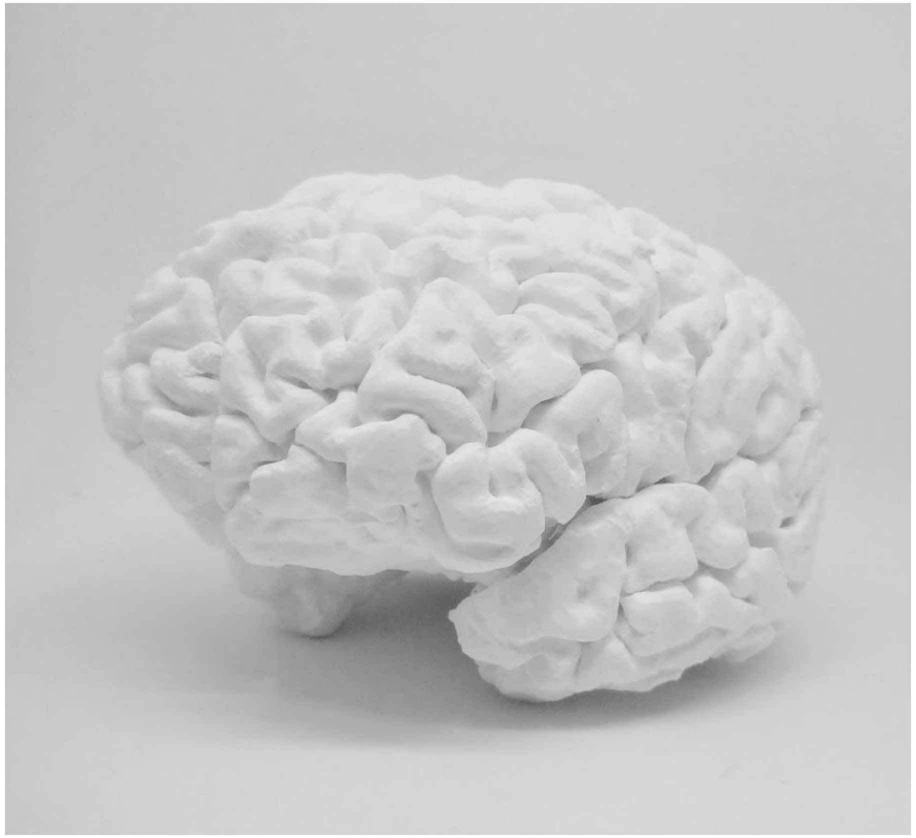
- The proposed supervised extension of You et al. increases performance
- Competes with supervised and semi-supervised baselines using few annotated training subjects
- Future work:
  - Improved optimisation
  - Better training of segmentation network
  - More accurate approximation of normative prior



Thank you!

Jonatan Kronander
jonatank@student.ethz.ch

Git Repository:
https://github.com/jkkronk/lesion_seg



Results: Visualisation 2 Implicit

1 training subject | 10 training subject | 100 training subject

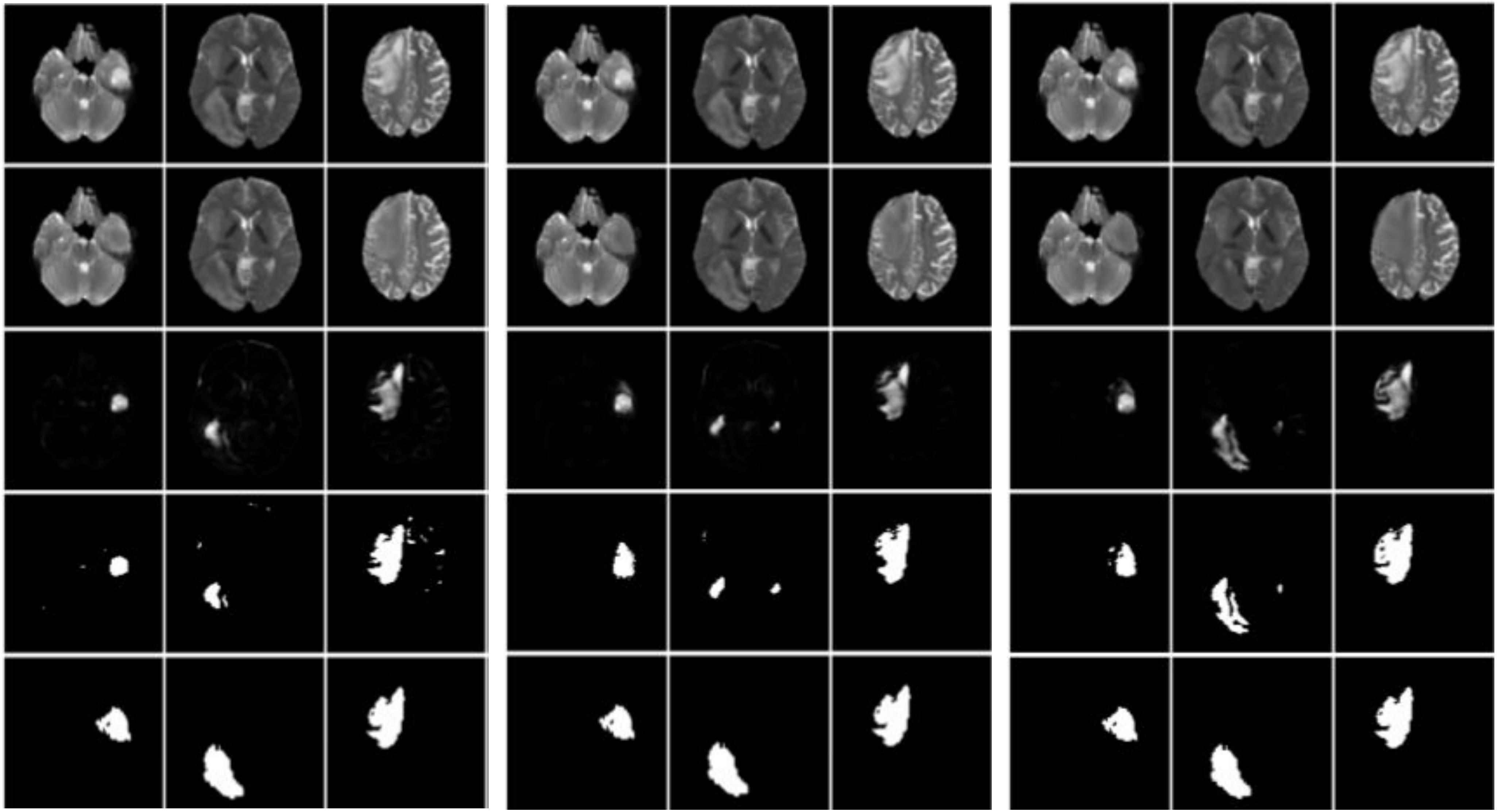
Input

Restored

Lesion map

Output
(fpr = 1%)

Ground
truth



Results: Visualisation 2 Explicit

1 training subject | 10 training subject | 100 training subject

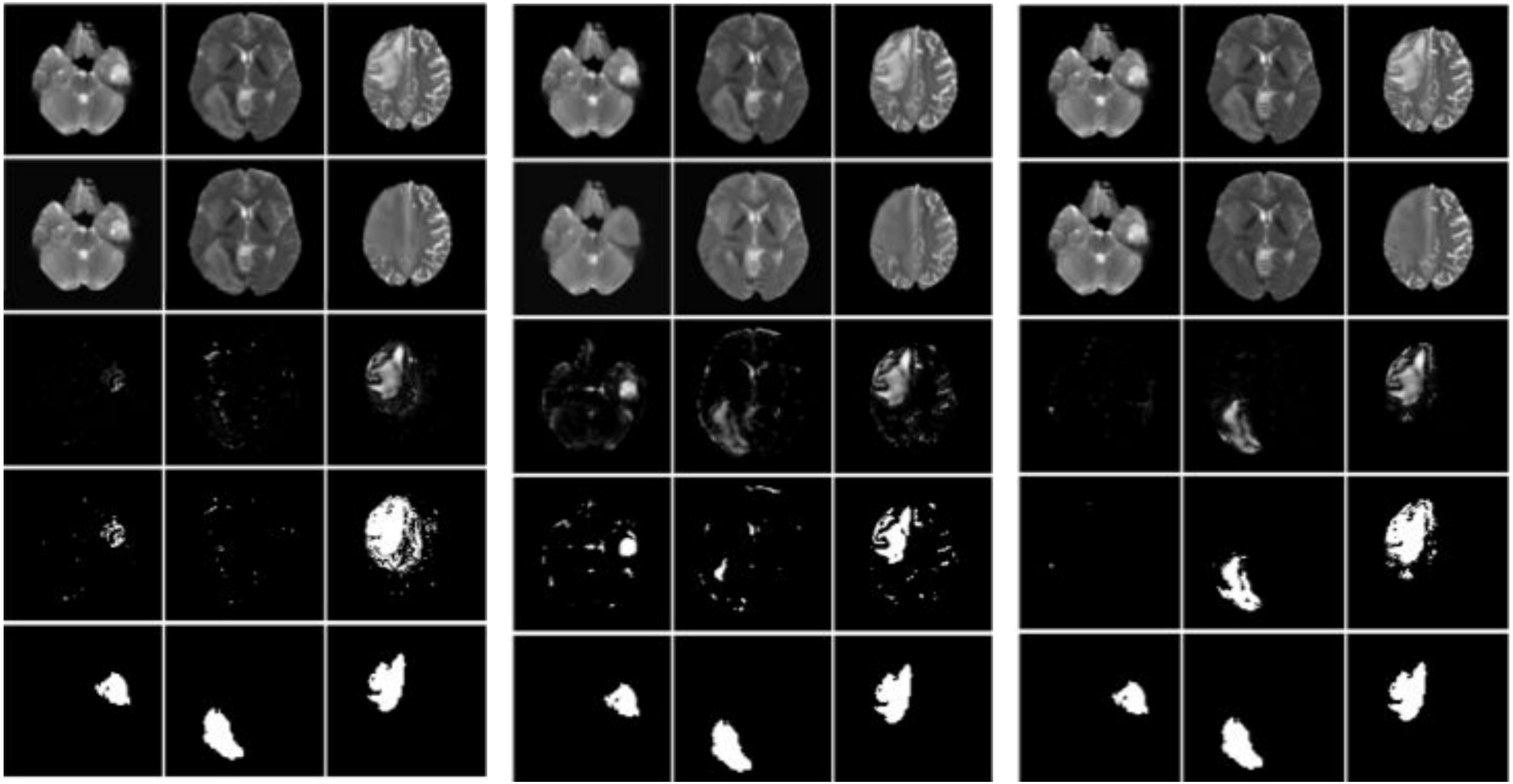
Input

Restored

Lesion map

Output
(fpr = 1%)

Ground
truth



Results:
Visualisation You et al.

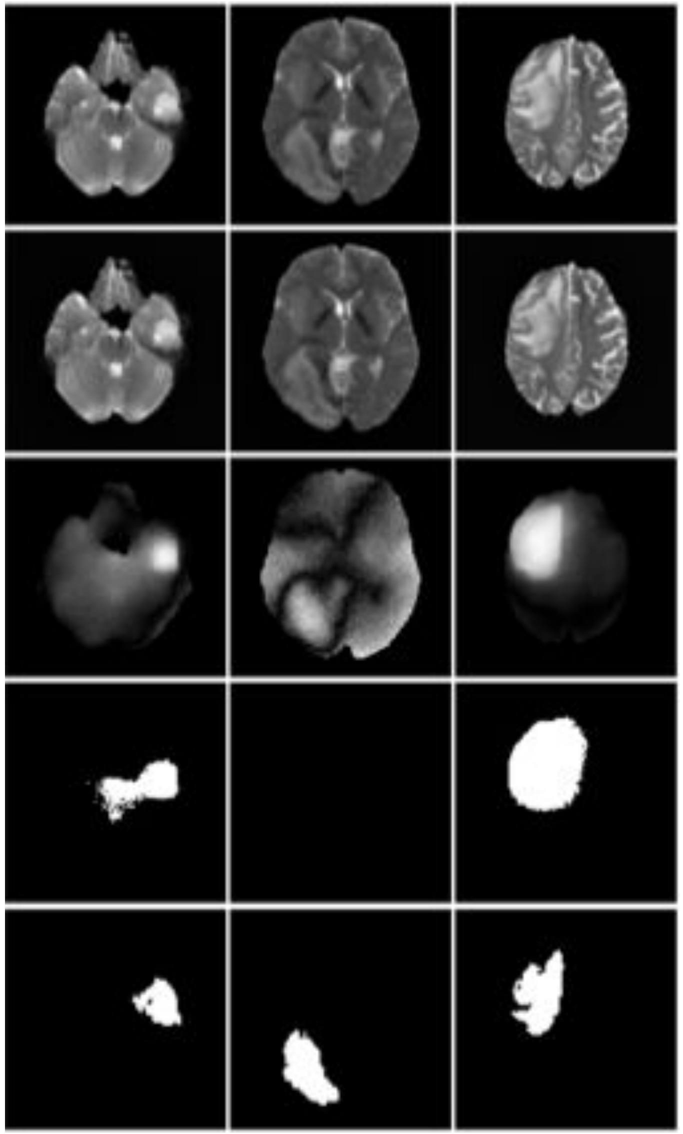
Input

Restored

Lesion map

Output

Ground truth



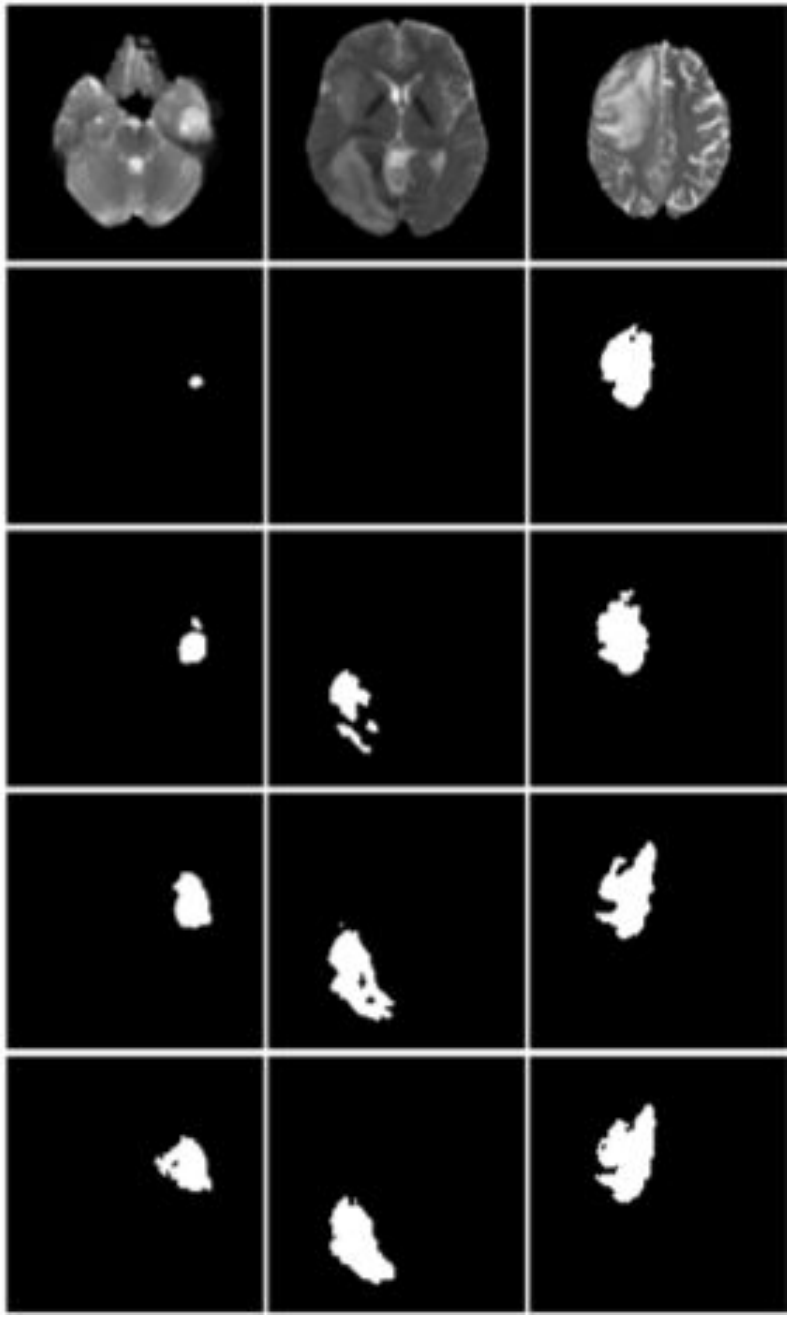
Results: Visualisation U-Net

1 training subject

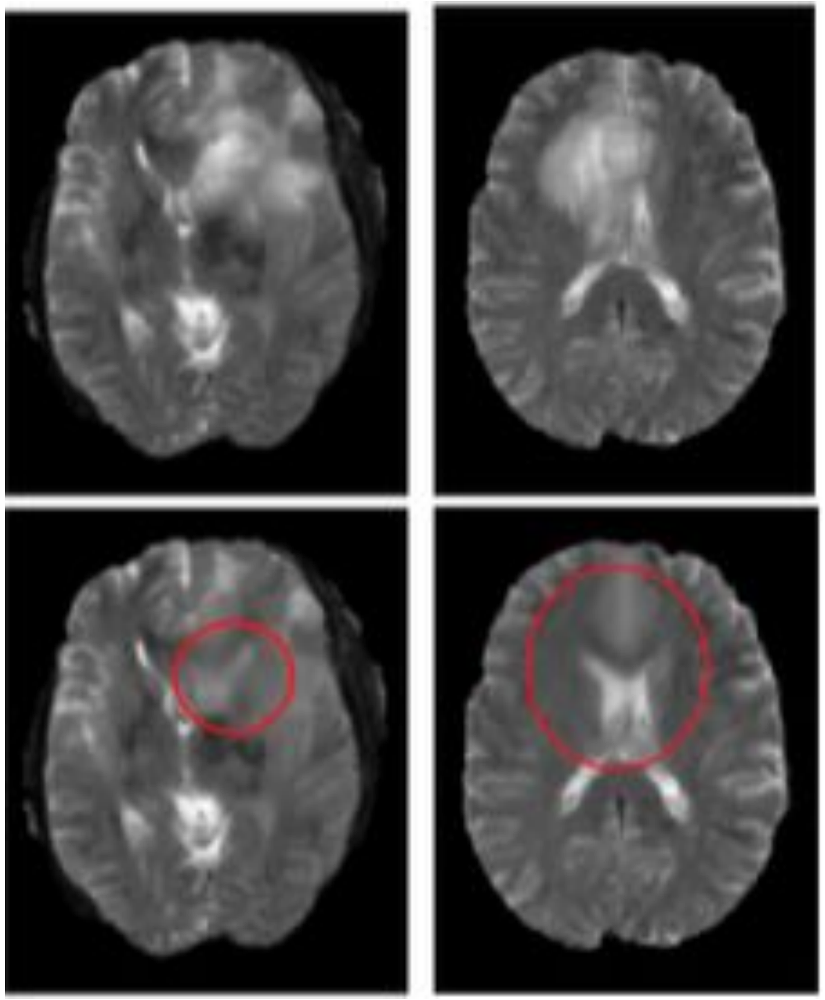
10 training subject

100 training subject

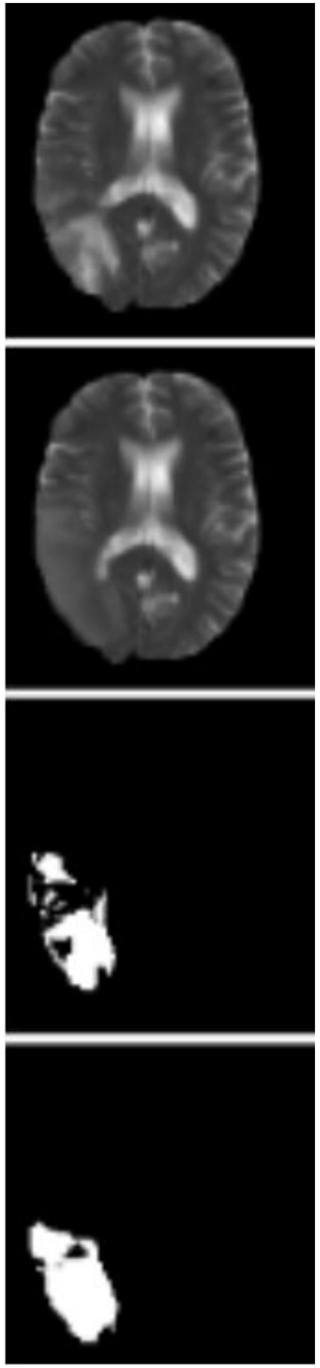
Ground truth



Results:
Restoration 1 subject



Results:
Results 100 subject



Restored

Predicted segmentation

Ground truth

Full results

Methods	AUC	Dice (naive)	DICE (fpr 0.01)	DICE (fpr 0.05)
You et al.	0.80	–	0.34	0.35

(a) Result comparison using 0 subjects.

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	**0.86**($\pm$**0.02**)	0.51($\pm$0.05)	0.51($\pm$0.07)	**0.53**($\pm$**0.05**)
Explicit Learning *	0.80($\pm$0.04)	0.38($\pm$0.03)	0.41($\pm$0.04)	0.41($\pm$0.03)
U-Net	0.85($\pm$0.02)	0.49($\pm$0.06)	–	–
SimCLR / U-Net	0.84($\pm$0.02)	0.50($\pm$0.13)	–	–

(b) Result comparison using 1 subject. * Uses one extra labelled subject for tuning the K-factor.

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	**0.90**($\pm$**0.02**)	0.61($\pm$0.03)	0.61($\pm$0.05)	**0.63**($\pm$**0.02**)
Explicit Learning	0.83($\pm$0.05)	0.48($\pm$0.09)	0.45($\pm$0.07)	0.47($\pm$0.07)
U-Net	0.90($\pm$0.02)	0.58($\pm$0.07)	–	–
SimCLR / U-Net	0.87($\pm$0.05)	0.59($\pm$0.07)	–	–

(c) Result comparison using 3 subjects.

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	0.91($\pm$0.03)	0.64($\pm$0.03)	0.54($\pm$0.12)	0.64($\pm$0.05)
Explicit Learning	0.85($\pm$0.04)	0.55($\pm$0.04)	0.45($\pm$0.07)	0.48($\pm$0.06)
U-Net	0.94($\pm$0.01)	0.70($\pm$0.03)	–	–
SimCLR / U-Net	**0.94**($\pm$**0.01**)	**0.70**($\pm$**0.04**)	–	–

(d) Result comparison using 10 subjects.

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	0.95($\pm$0.01)	0.67($\pm$0.04)	0.65($\pm$0.07)	0.67($\pm$0.03)
Explicit Learning	0.88($\pm$0.02)	0.56($\pm$0.04)	0.46($\pm$0.11)	0.49($\pm$0.10)
U-Net	0.97($\pm$0.01)	0.78($\pm$0.02)	–	–
SimCLR / U-Net	**0.98**($\pm$**0.01**)	**0.79**($\pm$**0.01**)	–	–

(e) Result comparison using 30 subjects.

Methods	AUC	Dice (naive)	Dice (fpr 0.05)	Dice (fpr 0.01)
Implicit Learning	0.96	0.73	0.67	0.75
Explicit Learning	0.90	0.61	0.41	0.61
U-Net	**0.98**	**0.82**	–	–
SimCLR / U-Net	**0.98**	**0.82**	–	–

(f) Result comparison using 100 subjects.