Patch2Loc: Learning to Localize Patches for Unsupervised Brain Lesion Detection

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AISTATS

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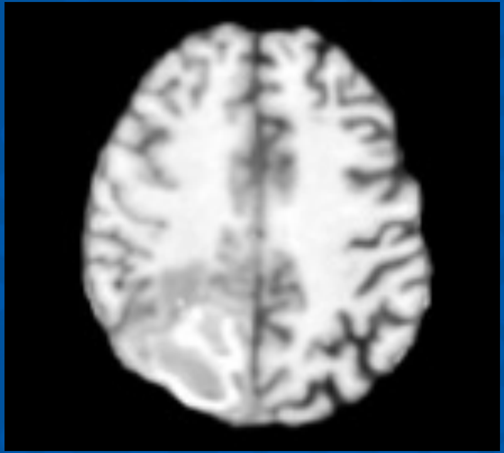
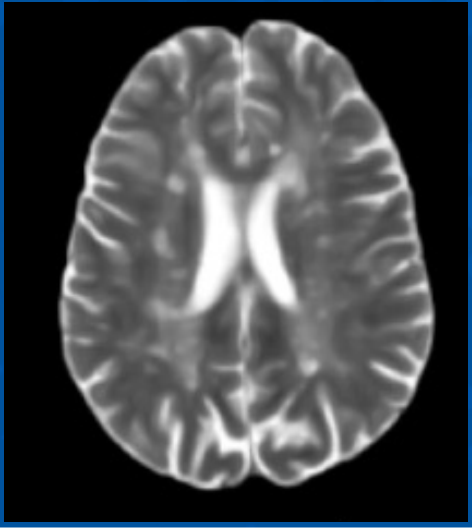
Goal: Find abnormalities in neuroimages.

There is a lack of neuroradiologists and they are over worked.

Could an unsupervised computer vision model **trained only with normal brains** help?

"All [normal brains] are alike; each [abnormal brain] is [abnormal] in its own way." Tolstoy (1877)





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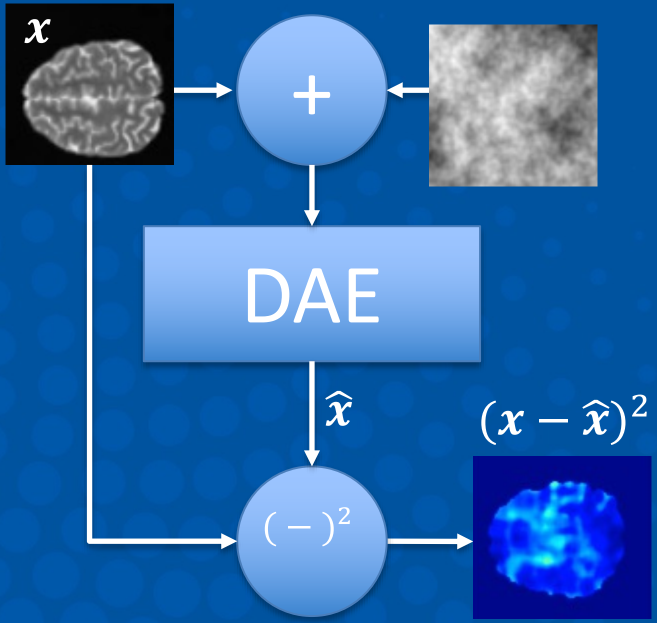
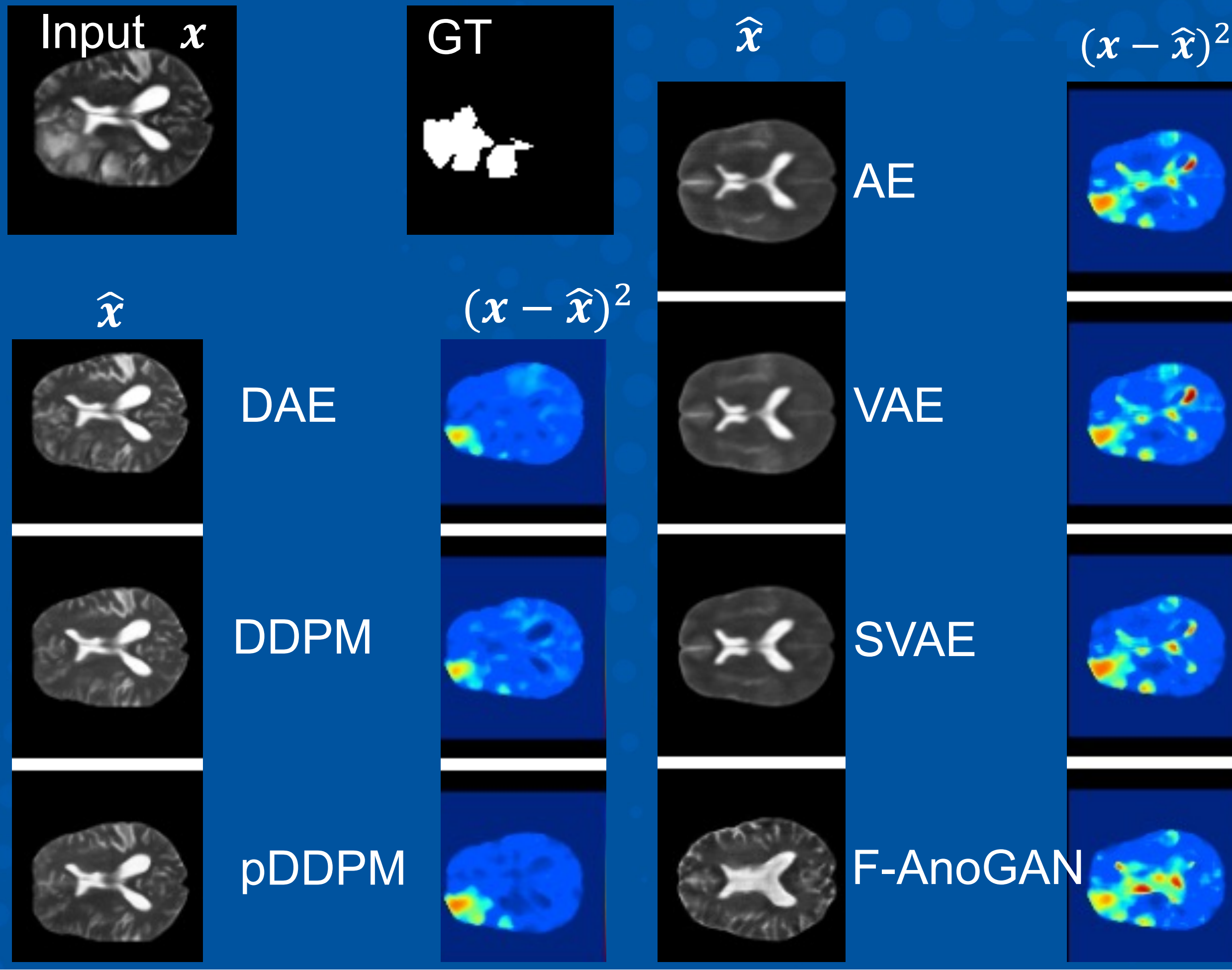
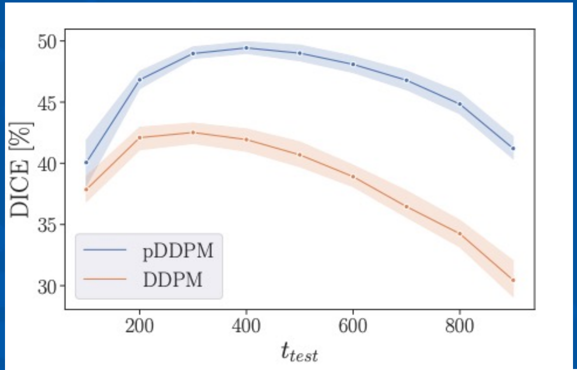
State-of-the-art and prior work uses global context of slice and (denoised) reconstruction

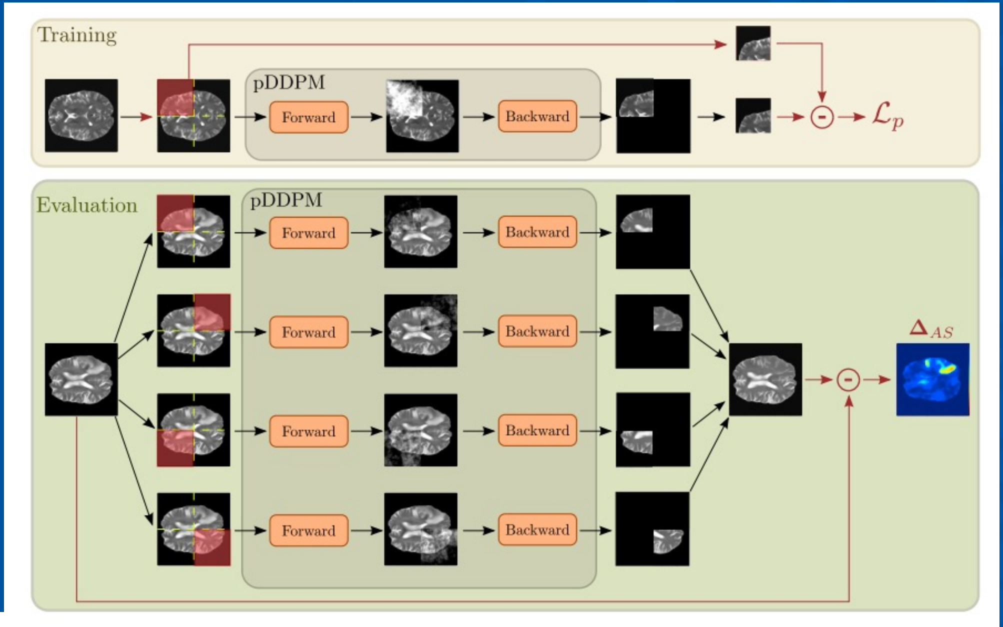


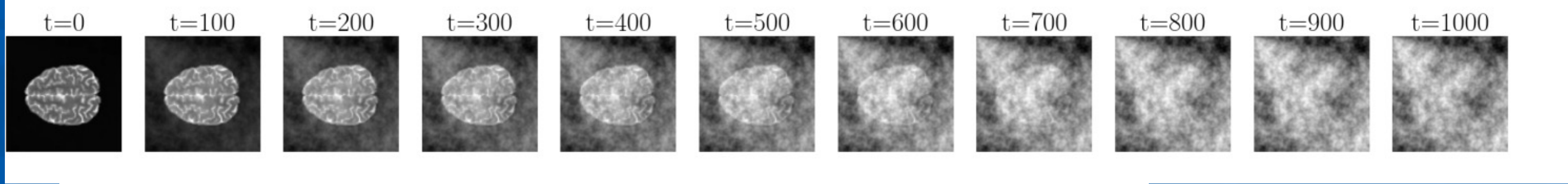


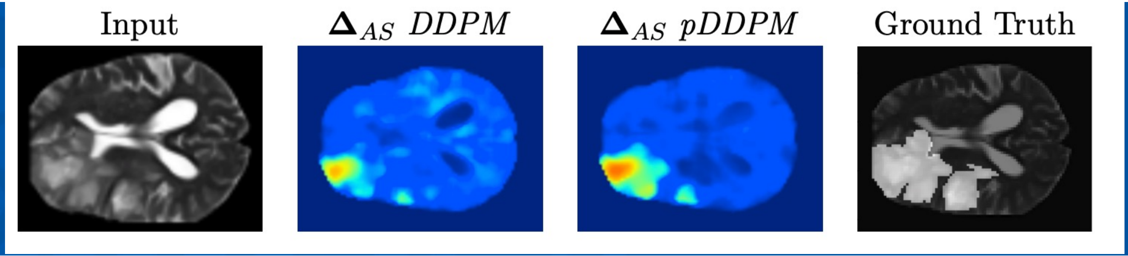
(Behrendt *et al.*, 2024)
“Patched Diffusion Models for Unsupervised Anomaly…”

State-of-the-art adds localized noise, but is limited by noise paradox









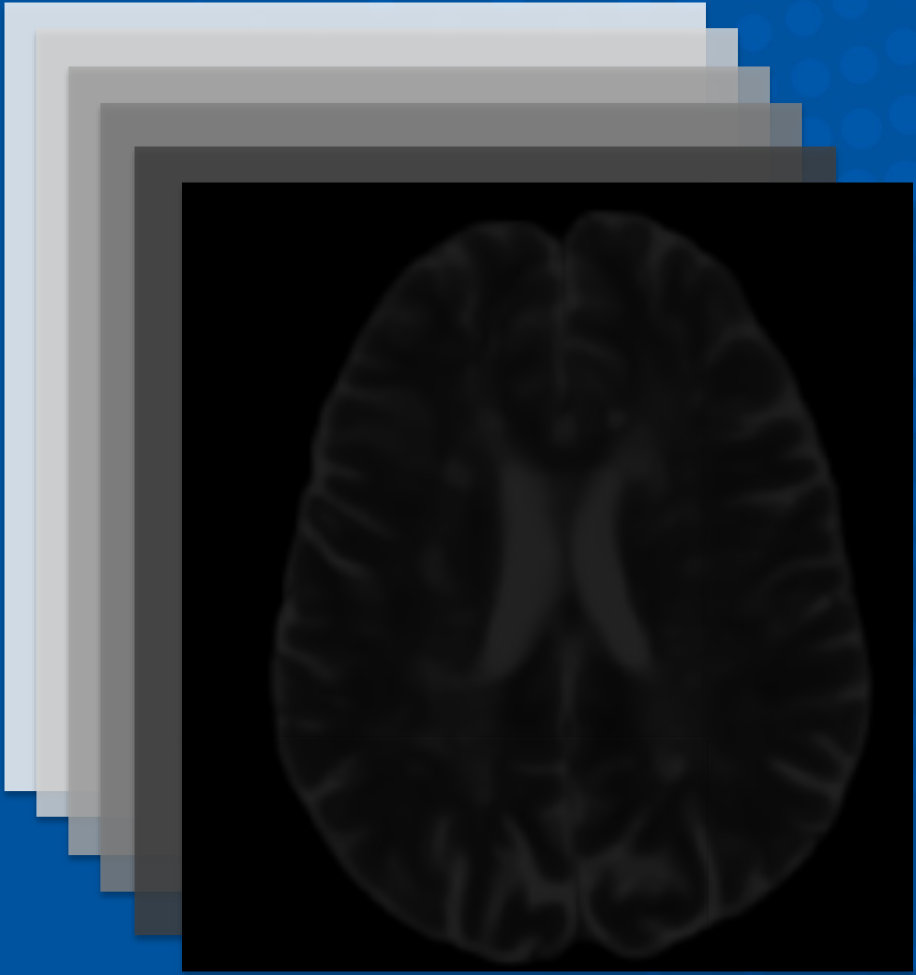
(Behrendt *et al.*, 2024) "Patched Diffusion Models for Unsupervised Anomaly.."

Our Insight:

Why not look locally?

X is a patch

Patch2Loc asks, “Which location does this come from?”



Our Insights:

Why not look locally?

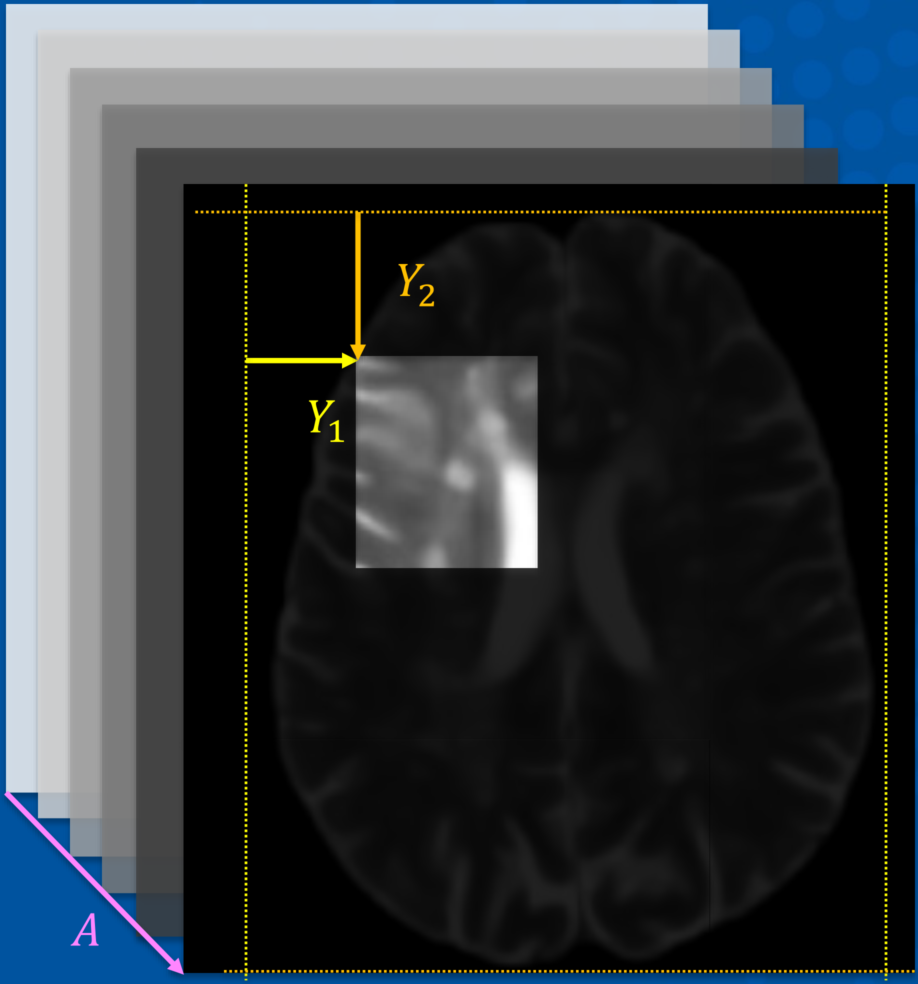
X is a patch

Patch2Loc asks, "Which location does this come from?"

$P_{\theta}(Y|X, A)$

Location $(Y, A) = (Y_1, Y_2, A) \subset \mathbb{R}^3$

A *axial coordinate*

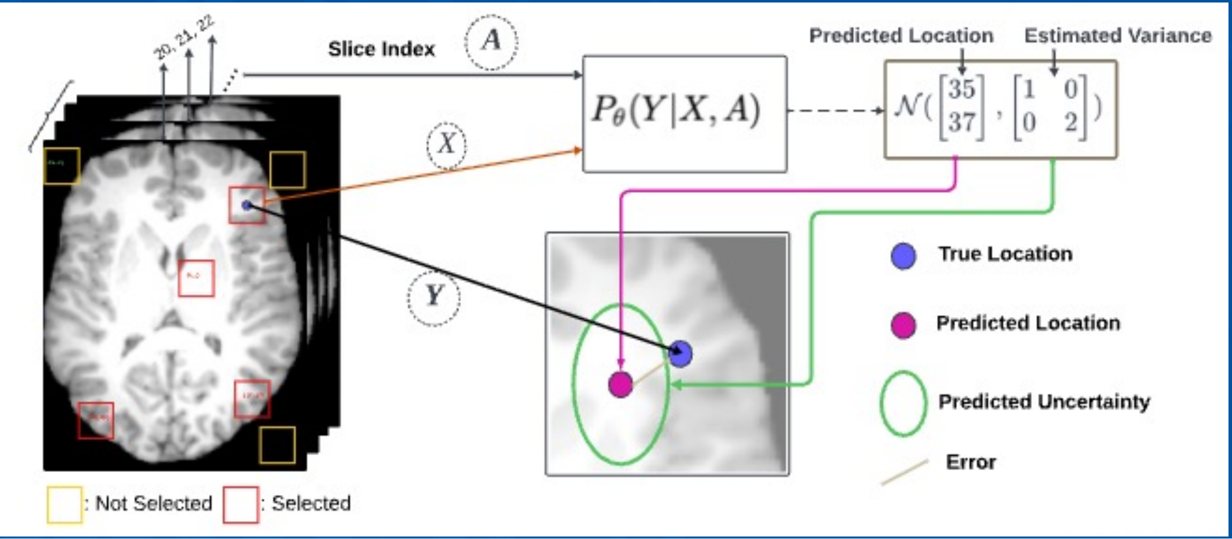


Patch2Loc Training via ~MLE of model relating Patch and Loc

$$P_\theta(Y|X,A) = \mathcal{N}(\mu^\theta(X,A), \Sigma^\theta(X,A)),$$
$$\Sigma^\theta(X,A) = \mathrm{diag}([\exp(\varsigma_i^\theta(X,A))]_i)$$

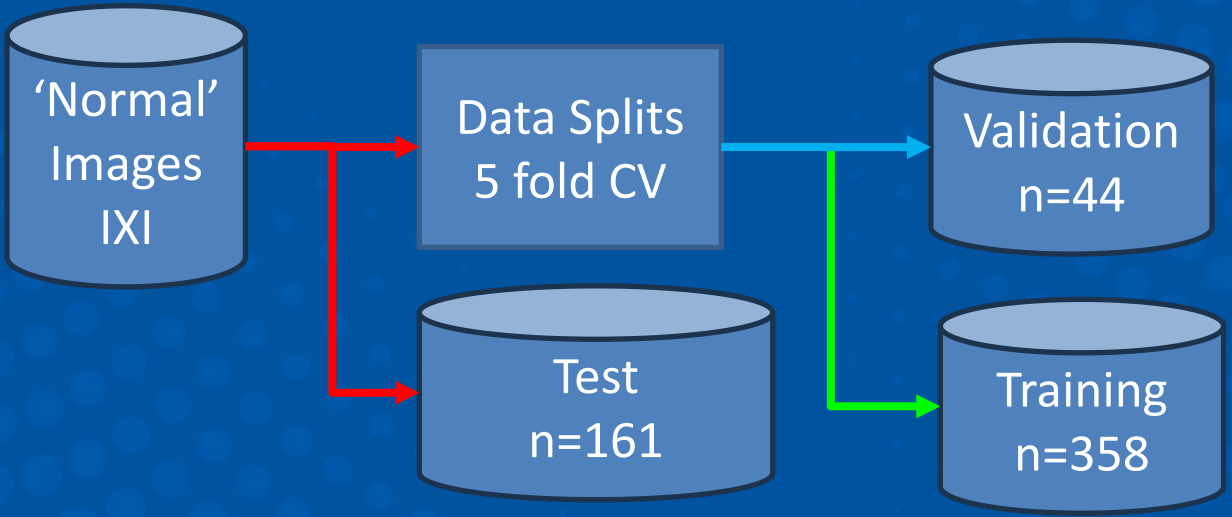
β-NLL [Seitzer et al., 2022] (for train and validation) where $\lfloor\cdot\rfloor$ is stop grad.

$$\min_\theta \mathbb{E}_{(X,Y,A)} \left[\sum_{i=1}^{2} \lfloor \exp(\varsigma_i^\theta(X,A)) \rfloor^\beta \left(\frac{|Y_i - \mu_i^\theta(X,A)|^2}{\exp(\varsigma_i^\theta(X,A))} + \varsigma_i^\theta(X,A) \right) \right]$$



Patch2Loc Training

IXI dataset from Biomedical Image Analysis Group, Imperial College London

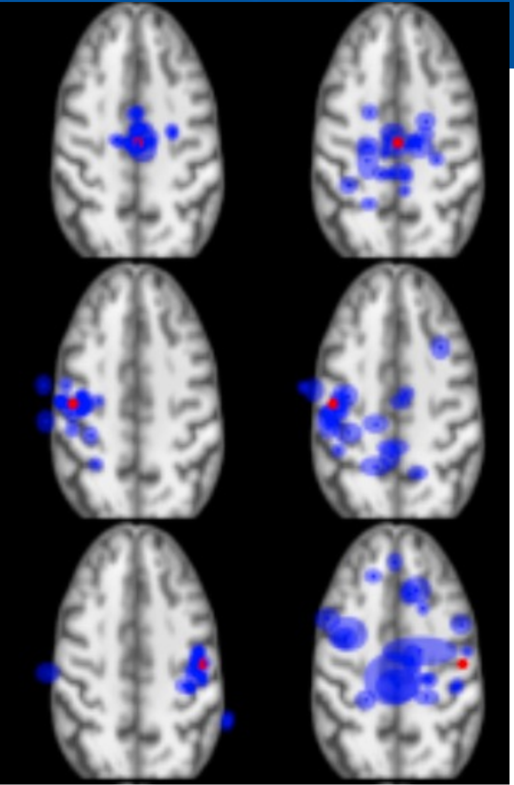


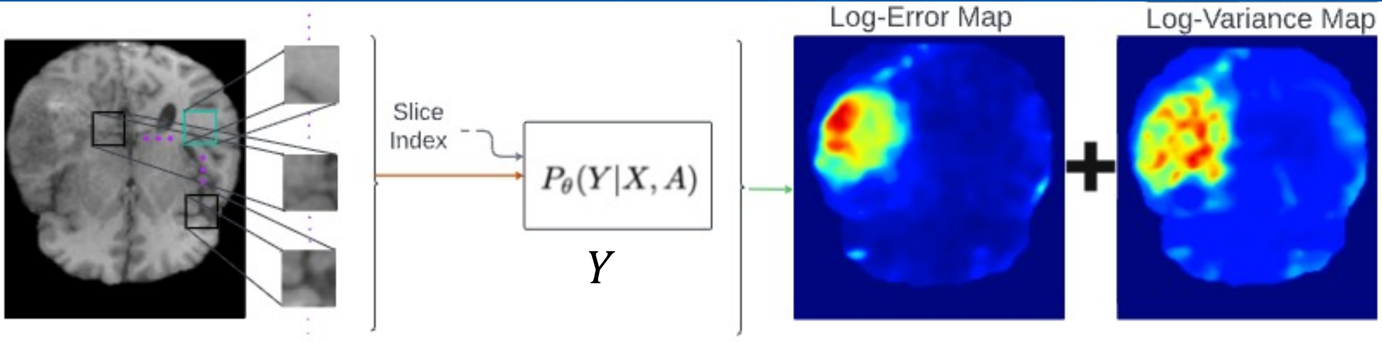
- Brain images are rigidly (affine) aligned and resampled.
- Histogram standardization (Nyúl et al., 2000) and normalization.
- Separate Patch2Loc model trained for T1 and T2

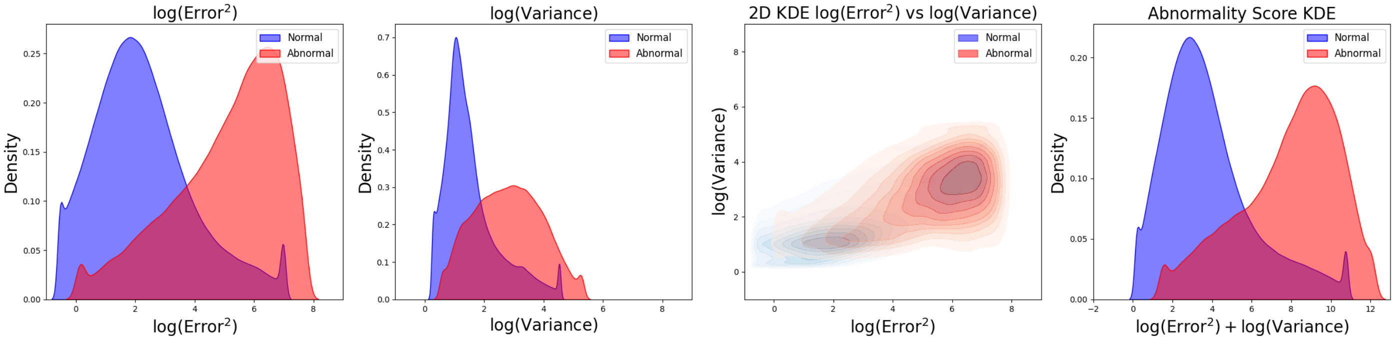
Inference: apply Patch2Loc convolutionally to make heatmaps

$$\mathrm{Score}(X, Y, A) = \underbrace{\log(\|Y - \mu^{\theta}(X, A)\|_2^2 + \varepsilon)}_{\mathrm{Log}(\mathrm{Error}^2)} + \underbrace{\frac{1}{2}\varsigma_1^{\theta}(X, A) + \frac{1}{2}\varsigma_2^{\theta}(X, A)}_{\mathrm{Log}(\mathrm{Variance})}$$

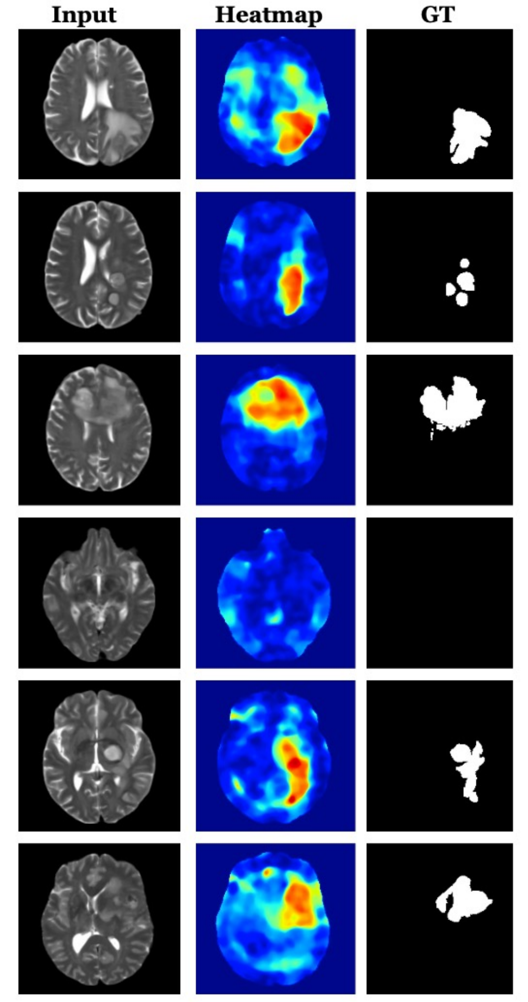
Normal Abnormal

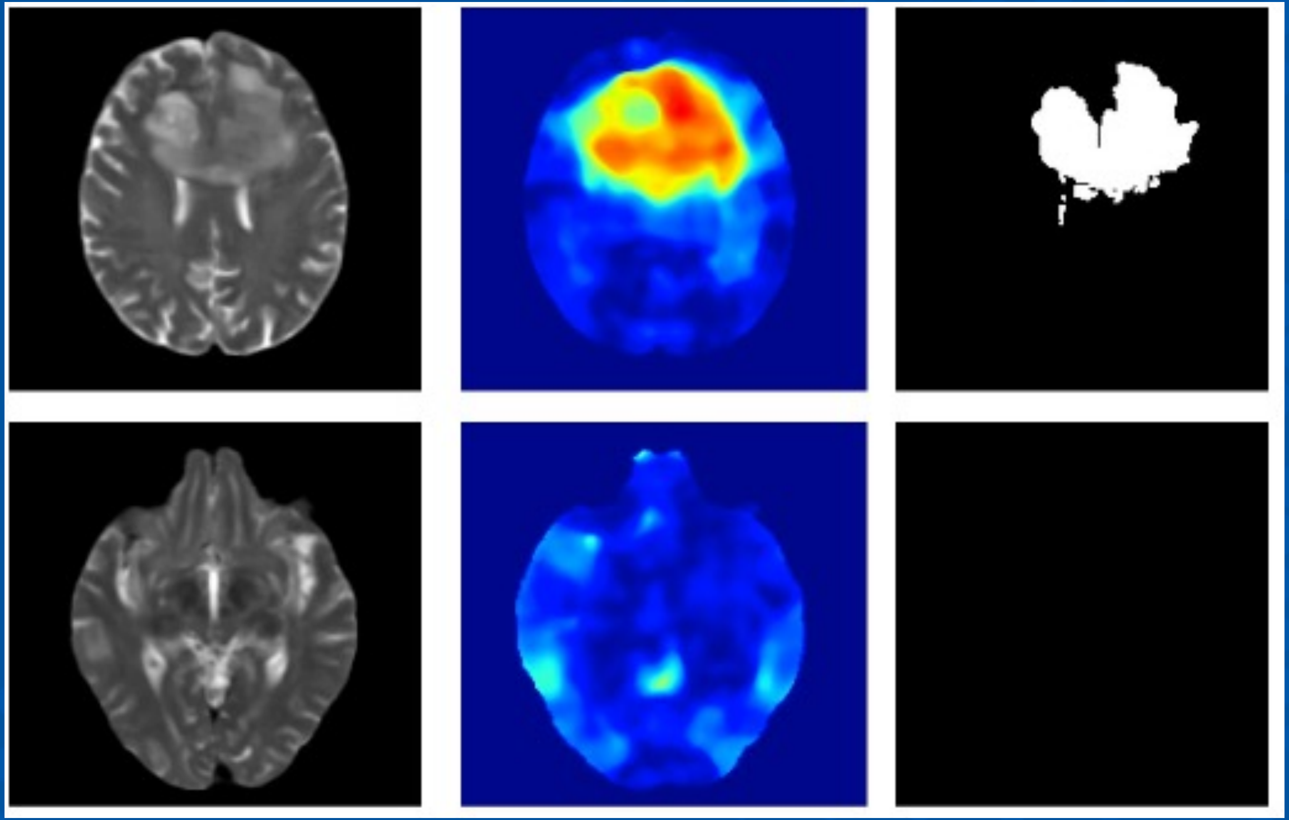






BraTS21, adult brain glioma, (Menze et al., 2015; Baid et al., 2021) n=1152

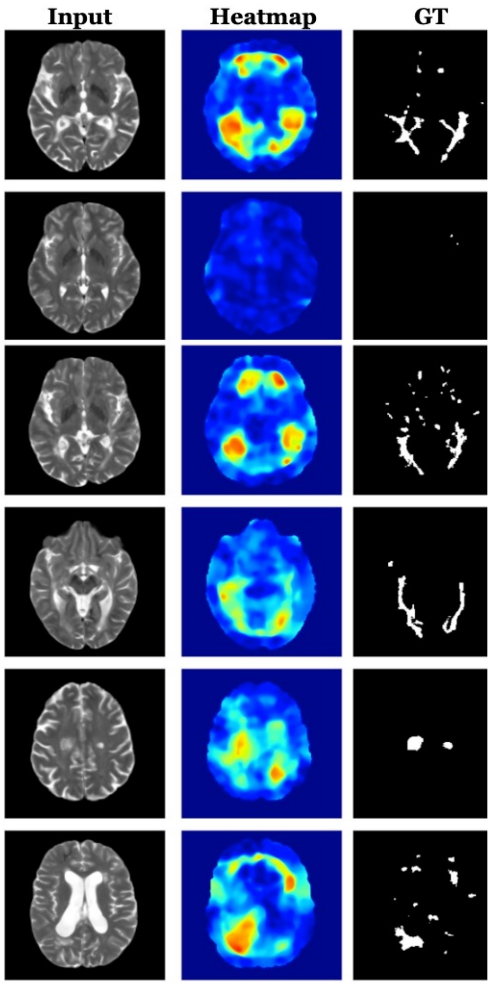


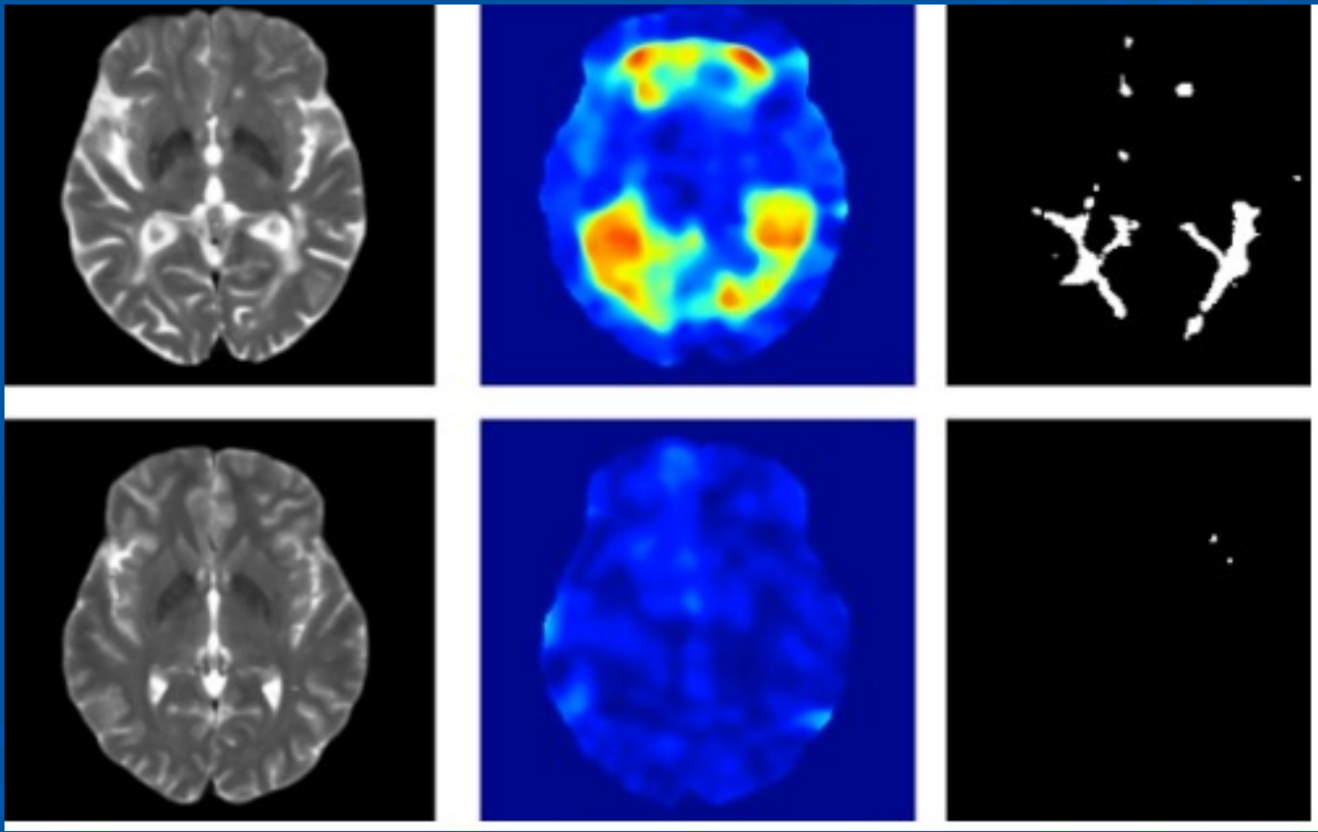


BraTS21, adult brain glioma, (Menze et al., 2015; Baid et al., 2021) n=1152

Model	BraTS21 (T2)	
	⌈DICE⌉ [%]	AUPRC [%]
Thresh (Meissen et al., 2022a)	30.26	20.27
VAE (Baur et al., 2021)	33.12 ± 1.12	25.74 ± 1.37
SVAE (Behrendt et al., 2022)	36.43 ± 0.36	30.3 ± 0.45
AE (Baur et al., 2021)	36.04 ± 1.73	28.8 ± 1.72
DAE (Kascenas et al., 2022)	48.82 ± 3.68	49.38 ± 4.18
RA (Bercea et al., 2023b)	16.75 ± 0.51	9.98 ± 0.43
PHANES (Bercea et al., 2023c)	28.42 ± 0.91	21.29 ± 1.06
FAE (Meissen et al., 2022b)	44.59 ± 2.19	43.63 ± 0.47
DDPM (Wyatt et al., 2022)	50.27 ± 2.67	50.61 ± 2.92
pDDPM (Behrendt et al., 2024)	53.61 ± 0.51	55.08 ± 0.54
cDDPM (Behrendt et al., 2025)	*56.30 ± 1.25*	**58.82 ± 1.56**
Patch2Loc (Ours)	**59.50 ± 1.45**	*55.40 ± 1.30*

MSLUB, multiple sclerosis, (Lesjak et al., 2018) n=30

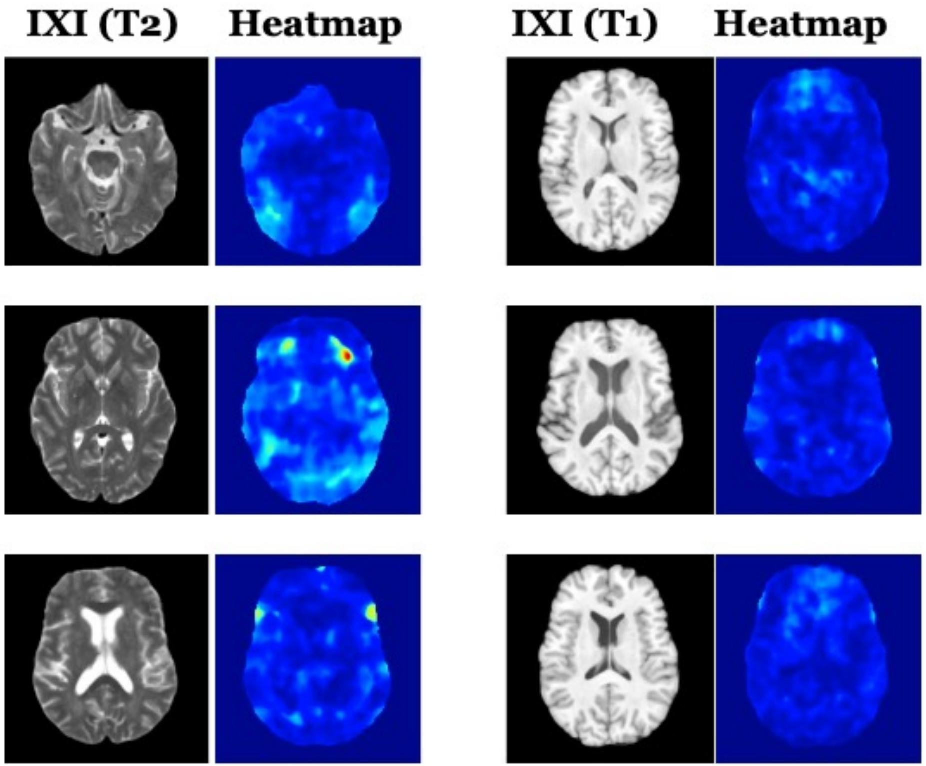


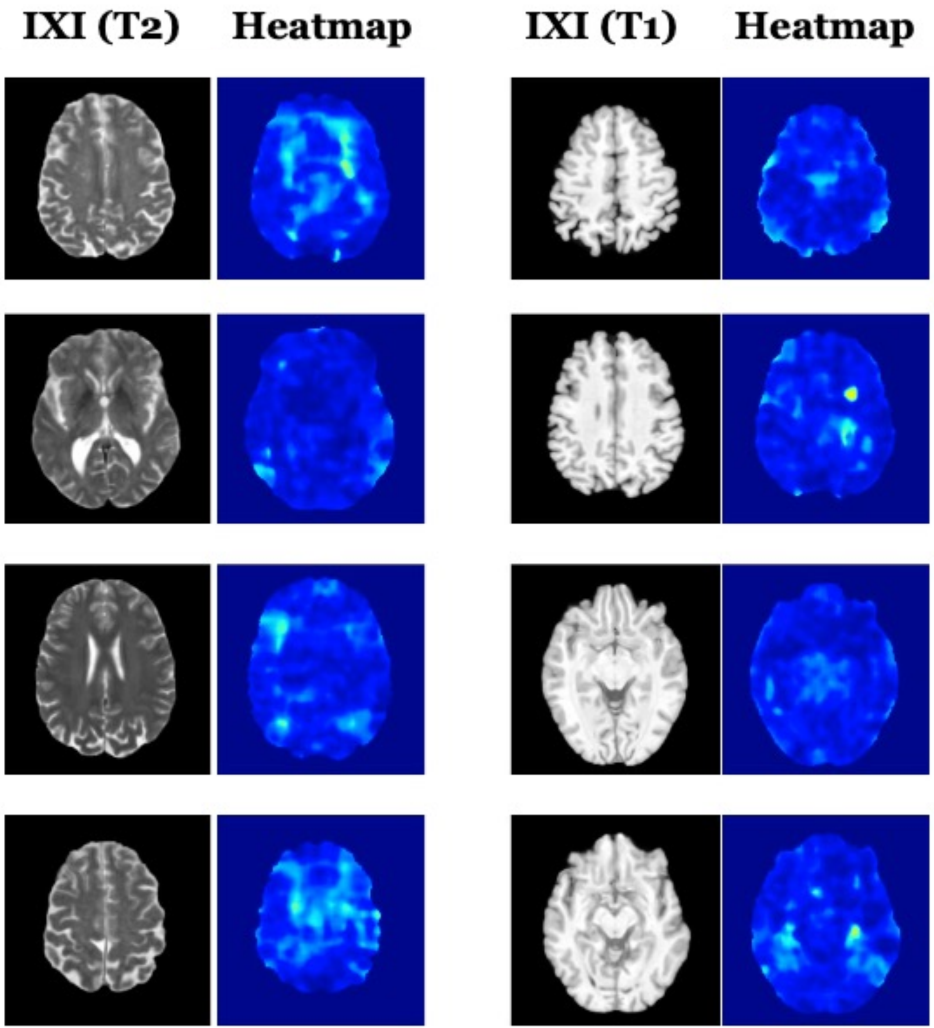


MSLUB, multiple sclerosis, (Lesjak et al., 2018) n=30

Model	MSLUB (T2)	
	[**DICE**] [%]	**AUPRC** [%]
Thresh (Meissen et al., 2022a)	7.65	4.23
VAE (Baur et al., 2021)	8.10 ± 0.18	4.48 ± 0.18
SVAE (Behrendt et al., 2022)	8.55 ± 0.11	4.8 ± 0.09
AE (Baur et al., 2021)	9.65 ± 0.97	5.71 ± 0.80
DAE (Kascenas et al., 2022)	7.57 ± 0.61	4.47 ± 0.69
RA (Bercea et al., 2023b)	3.96 ± 0.03	1.92 ± 0.04
PHANES (Bercea et al., 2023c)	6.11 ± 0.27	2.98 ± 0.07
FAE (Meissen et al., 2022b)	6.85 ± 0.65	3.85 ± 0.08
DDPM (Wyatt et al., 2022)	9.71 ± 1.29	6.27 ± 1.58
pDDPM (Behrendt et al., 2024)	12.83 ± 0.40	*10.02 ± 0.36*
cDDPM (Behrendt et al., 2025)	*14.04 ± 1.16*	**10.97 ± 1.17**
Patch2Loc (Ours)	**14.30 ± 1.40**	8.70 ± 1.20

Healthy controls





Future directions

Poster # 177

- Pediatric populations: sickle cell disease with silent infarcts, cortical malformations, epilepsy, TSC
- Multimodal fusion structural MRI (T1 and T2 and FLAIR)

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GitHub page

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