Unsupervised Region-based Anomaly Detection in Brain MRI with Adversarial Image Inpainting

Bao Nguyen*, Adam Feldman‡, Sarath Bethapudi†, Andrew Jennings†, Chris G. Willcocks*

* Department of Computer Science - Durham University, ‡ Department of Engineering - University of Exeter, † County Durham and Darlington NHS Foundation Trust

1. Motivation / Contribution

- Segmentation facilitates precise object measurement, quantifying the shape and volume of objects of interest that can impact prognosis and treatment options.
- Manual segmentation is time consuming and results are subject to large intra and inter expert variability, leading to considerable differences in extracted radiomic values [1].
- Supervised methods require annotated datasets, which are expensive and time consuming to procure.
- Other unsupervised methods require manual thresholding. There is a need for automatic methods to reduce cost, time and bias.

We propose a fully automatic, unsupervised image inpainting-based brain tumour segmentation system for T1 weighted MRI.

2. Intuition / Methodology

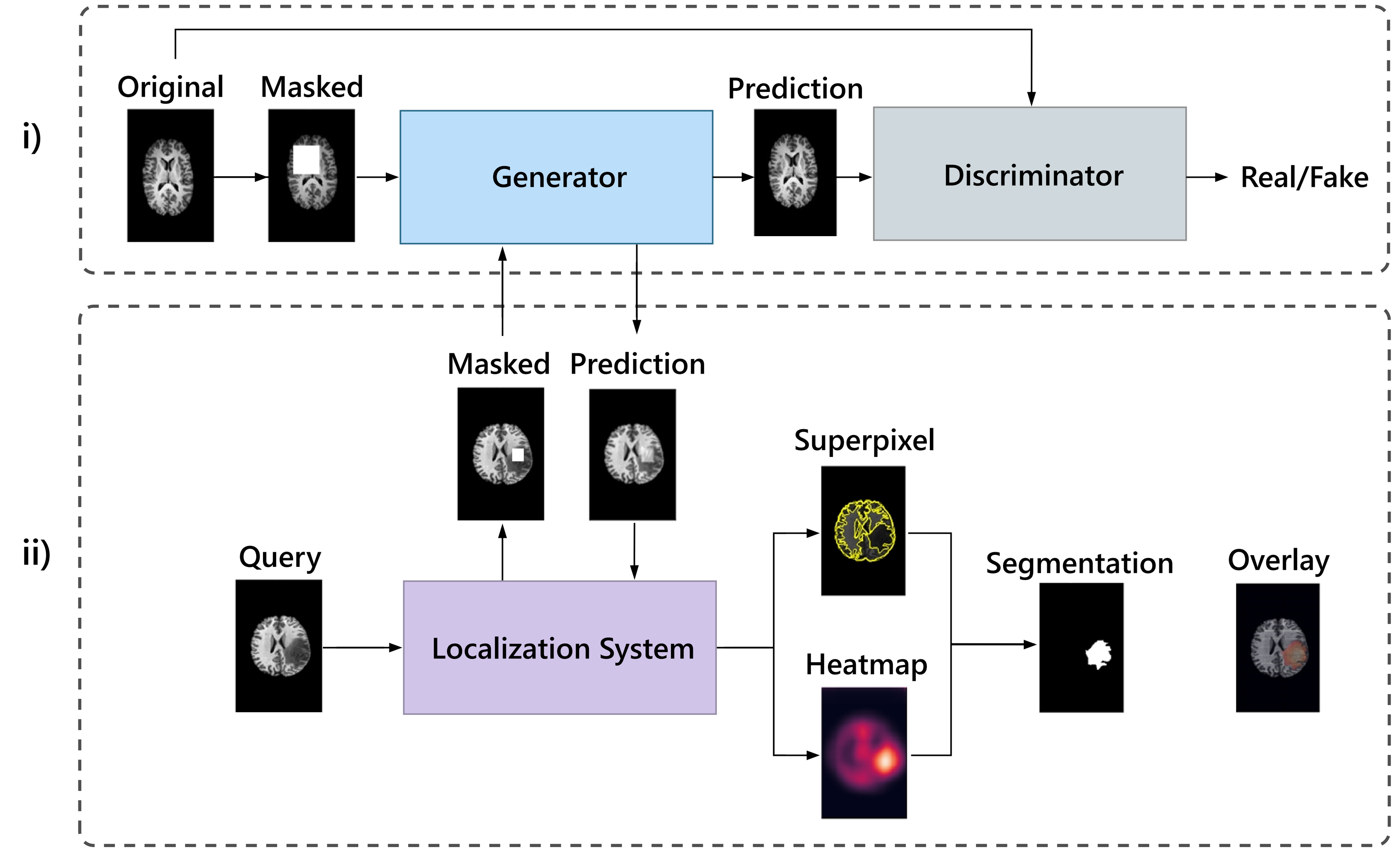

Fig. 1: *The Proposed System - i) Train Inpainting Network. ii) Predict anomalous regions and obtain segmentation.*

Brain tumour segmentation is performed in three steps:

1. Train a deep convolutional neural network, to reconstruct missing healthy brain regions, by jointly minimizing an L1 reconstruction loss and an adversarial loss [2]. The intuition is that at inference the network will fail to reconstruct unhealthy data that is not observed in training.
2. Given a query slice, perform a masked sliding window operation to obtain predictions for all regions.
3. Construct a heatmap indicating areas of highest reconstruction loss (measured by the L1 metric) and perform superpixel segmentation (Felzenszwalb's [3]) to better capture object boundary.

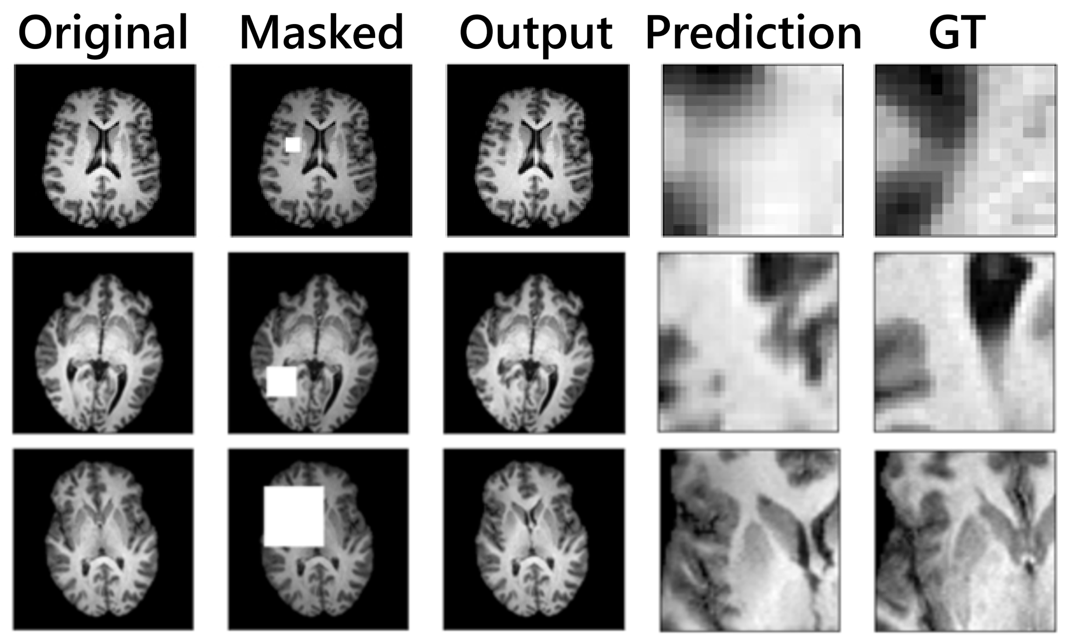

Fig. 2: *Inpainting results for window sizes 16, 32 and 64 respectively. From top to bottom.*

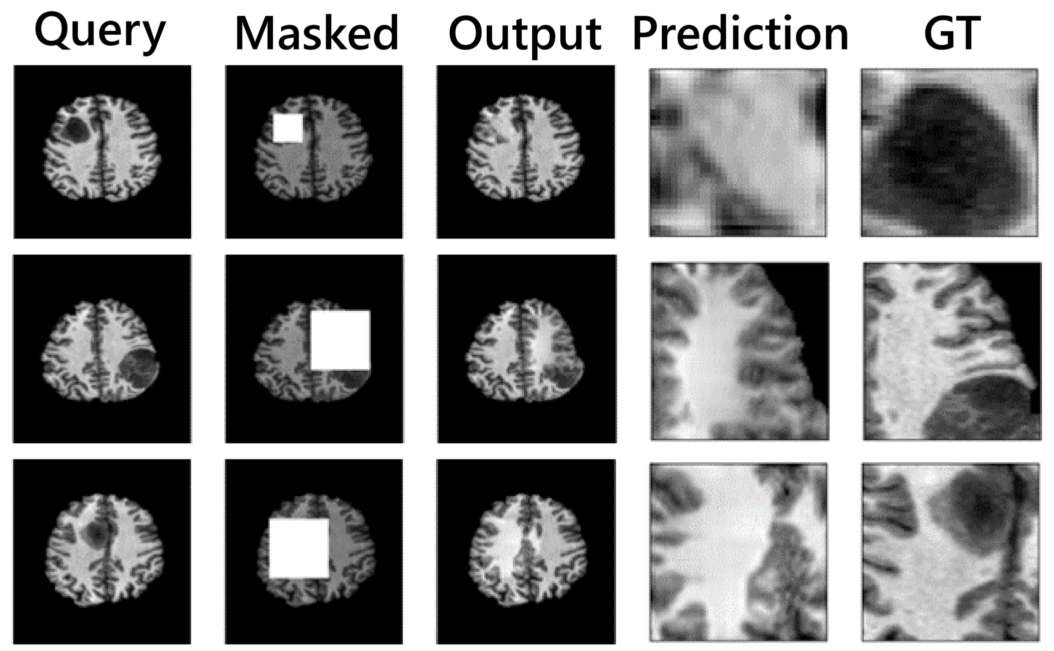

Fig. 3: *Examples of full and partial tumour coverage.*

3. Results

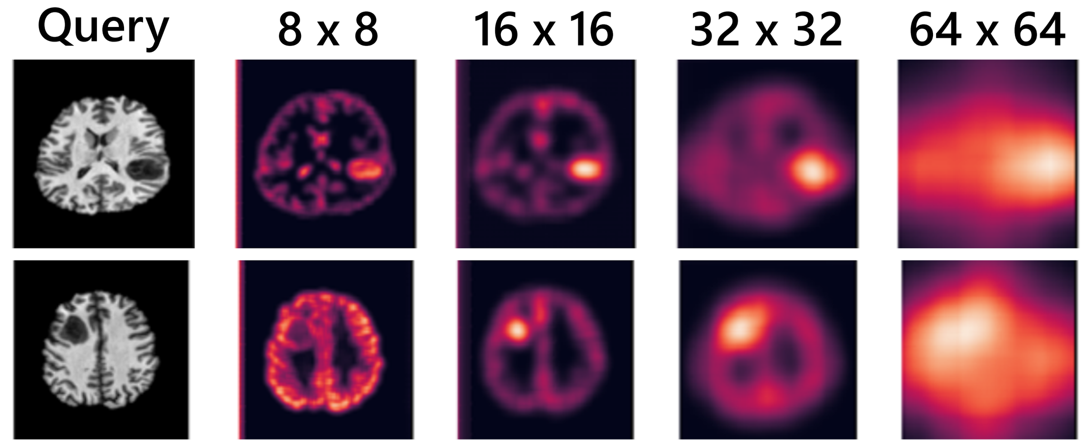

Fig. 4: *Heatmap for various window sizes.*

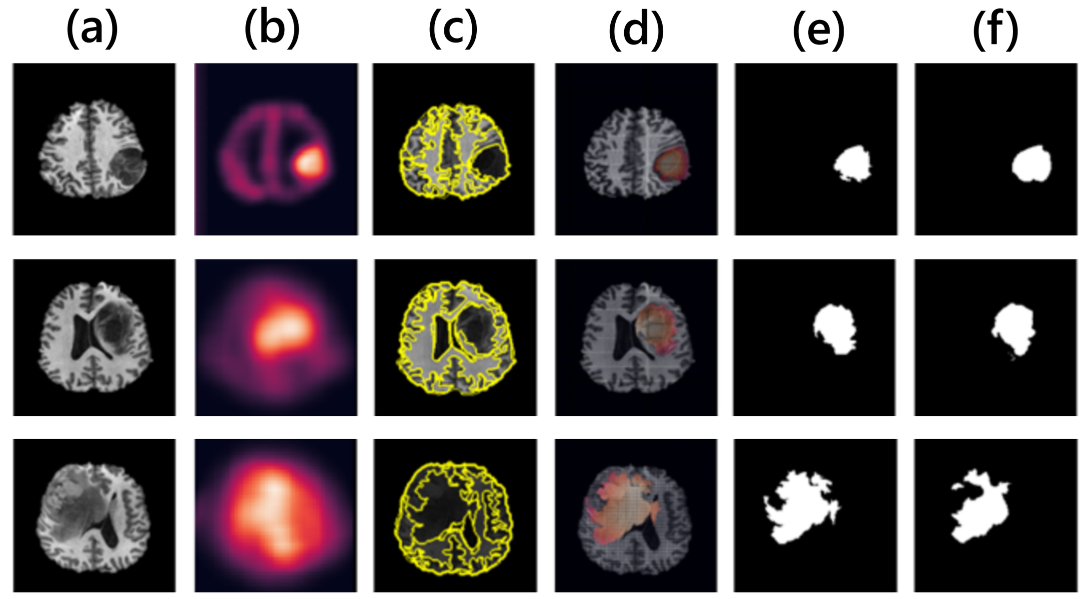

Fig. 5: *Segmentation Results - (a) Query, (b) Heatmap, (c) Superpixel, (d) Overlay, (e) Prediction, (f) Ground Truth*

- The effect of using superpixel results in higher definition segmentations, allowing the capture of regular and more abstract tumours, which would not be possible with manual thresholding.
- A window of size 32 indicates the highest accuracy and consistency in handling various sized tumours. Other window sizes express high variability, performing well either on small or large sized tumours.
- Heatmaps produced from smaller window sizes performed better on healthy regions, whereas larger window sizes appear to localize the tumour more effectively.
- It is important that the window covers most if not all the tumour to distinguish the reconstruction performance with other healthy areas of the brain.

	PSNR ($\mu \pm \sigma$)	SSIM ($\mu \pm \sigma$)	Dice ($\mu \pm \sigma$)
Ours - 8	38.61 ± 3.159	0.99 ± 0.006	0.49 ± 0.396
Ours - 16	37.94 ± 4.664	0.98 ± 0.022	0.66 ± 0.346
Ours - 32	35.63 ± 5.413	0.97 ± 0.002	**0.77 ±0.176**
Ours - 64	31.66 ± 6.491	0.96 ± 0.003	0.55 ± 0.380
AnoGAN [4]	-	-	0.38 ± 0.238

Table. 1: *Inpainting performance on unseen healthy samples and Dice scores.*

4. Limitations / Future Work

- Localization is only possible if the inpainting network performs well on non-anomalous regions, but fails otherwise.
- In Felzenszwalb's algorithm [2], the scale parameter influences the segment size. Careful selection of this value is required for optimal segmentation results.

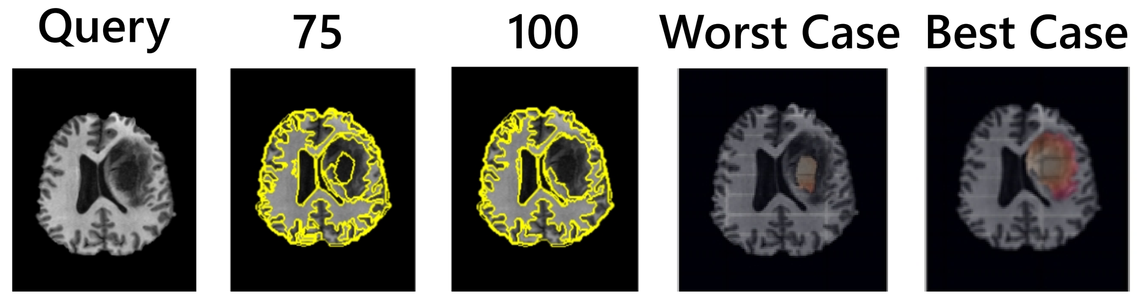

Fig. 6: *Superpixel segmentation with different scale values and possible outcomes.*

- In the future, we would like to investigate extending both Felzenszwalb's algorithm and our inpainting approach to handle 3D volumes. This is challenging due to the memory usage and computational overhead associated with 3D volumes.

5. References

[1] Chintan Parmar et al. "Robust radiomics feature quantification using semiautomatic volumetric segmentation," PLoS ONE, vol. 9, 2014.

[2] Ian J. Goodfellow et al. "Generative adversarial nets," in NIPS, 2014.

[3] Pedro F. Felzenszwalb and D. Huttenlocher, "Efficient graph-based image segmentation," International Journal of Computer Vision, vol. 59, pp.167–181, 2004.

[4] Thomas Schlegl et al. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery," in IPMI, 2017.