Comparing ‘CutPaste: Self-Supervised Learning for Anomaly Detection and Localization’ and ‘Detecting Outliers with Foreign Patch Interpolation’

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Bridging the data gap through synthetic anomalies

Outliers in medical data can range from obvious lesions to subtle artifacts, making it difficult to detect all irregularities.

Both methods aim to learn a complete model of normal data through self-supervised deep learning techniques.

The common goal is to encourage the model to learn what features to expect normally and to be sensitive to subtle irregularities.

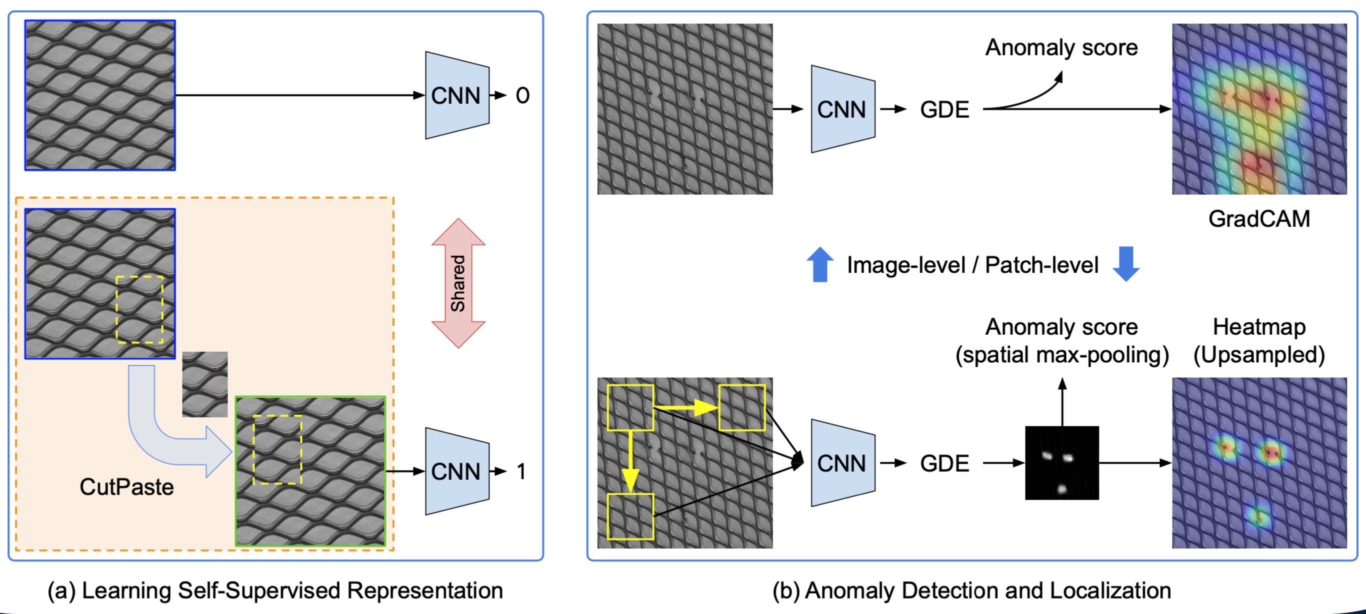
- Not necessarily computation intensive.
- Underlying algorithms are easy to understand.
- Use supervised paradigm without need for labeled datasets.

- Often fail for anomalies they weren’t developed.
- Highly dependent on data generation.

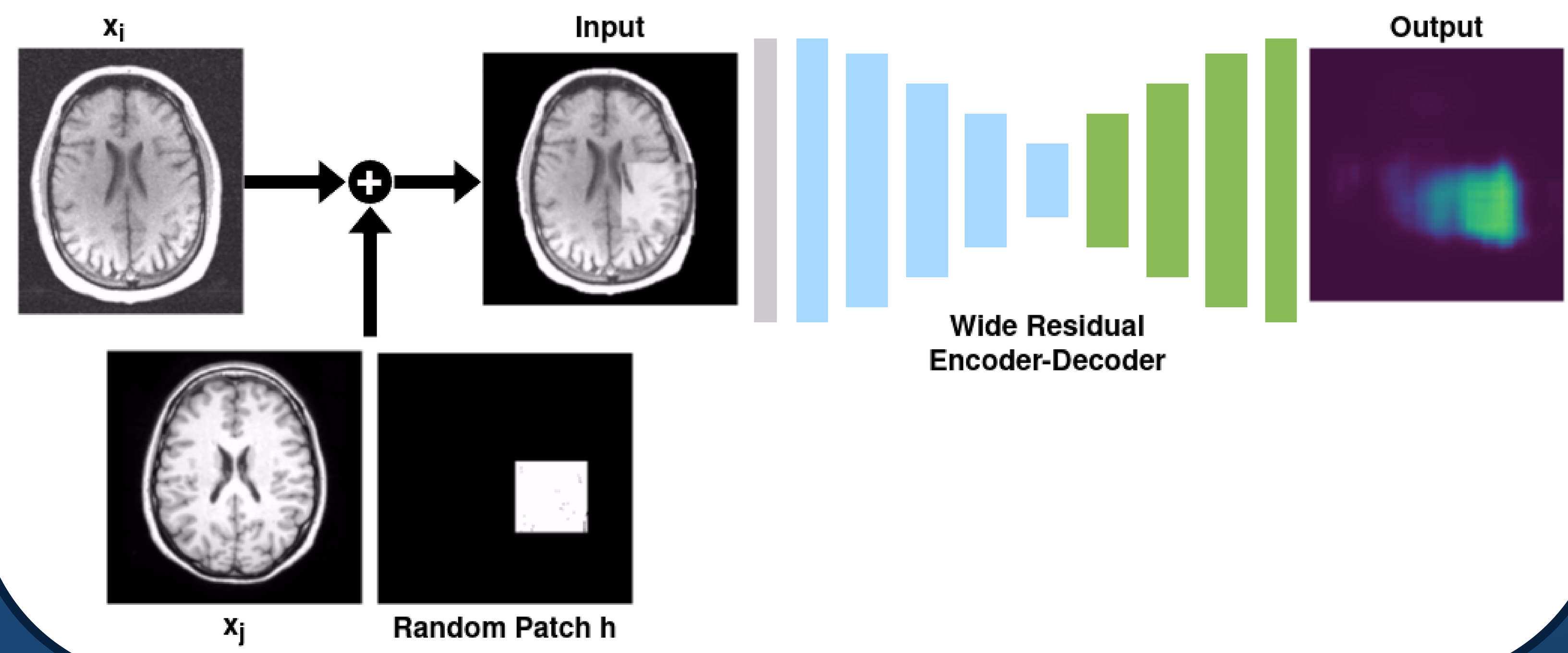
Generating Pacth-based Anomalies

A CNN model is trained to distinguish images from normal and augmented data distributions by ***CutPaste***;

1. Cut a small rectangular area from a normal training image.
2. Paste the patch back to the image at a random location.
3. Train a model to classify images with and without synthetic defects.
4. Use embedding distance from the normal data as anomaly score with ***Gaussian Density Estimator***.



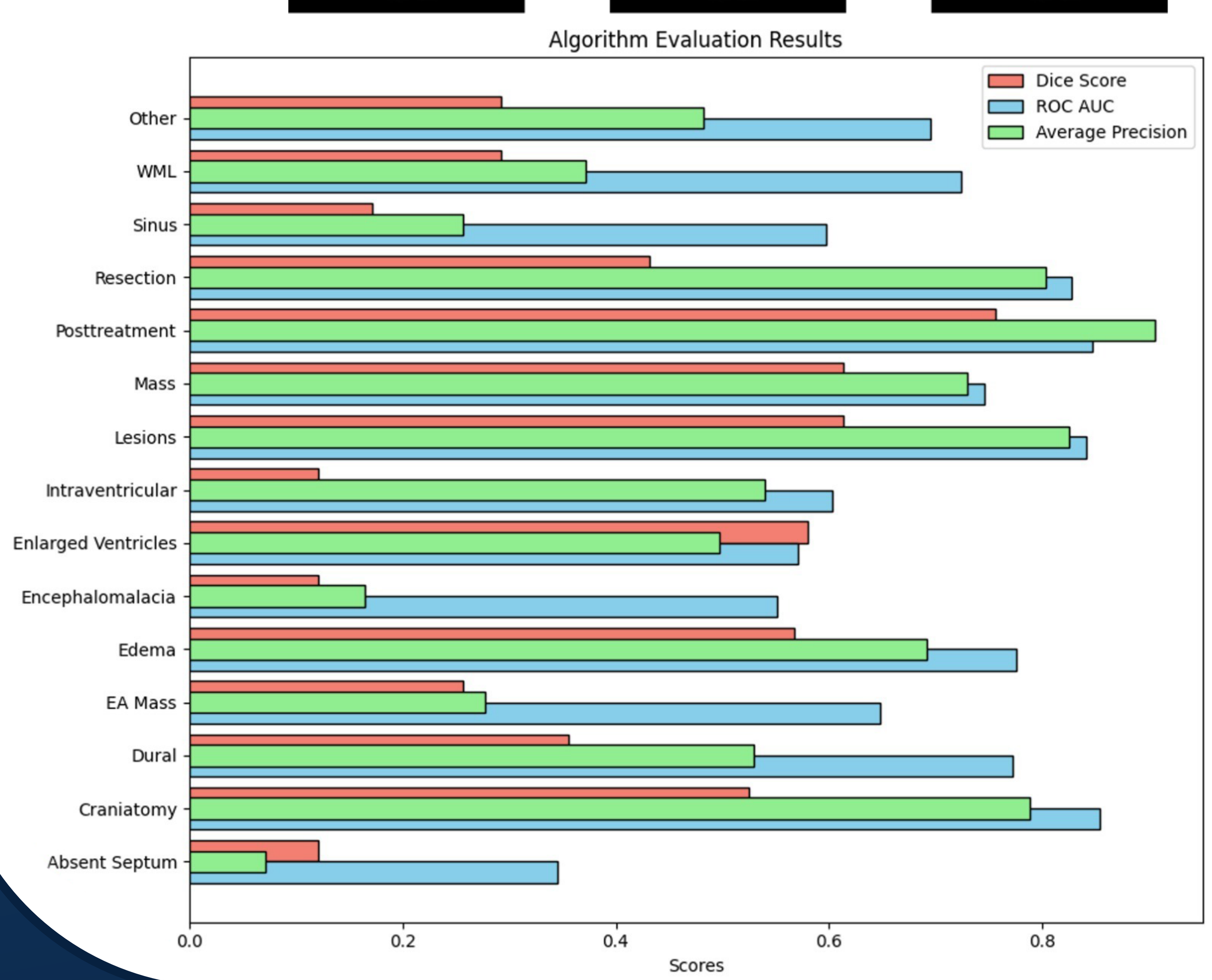
1. Extract two random patches from two training images.
2. Linearly interpolate between both patches and paste the patch back into an input image.
3. Train the model to identify the used interpolation factor used on a pixel-wise basis, subsequently serving as anomaly score.

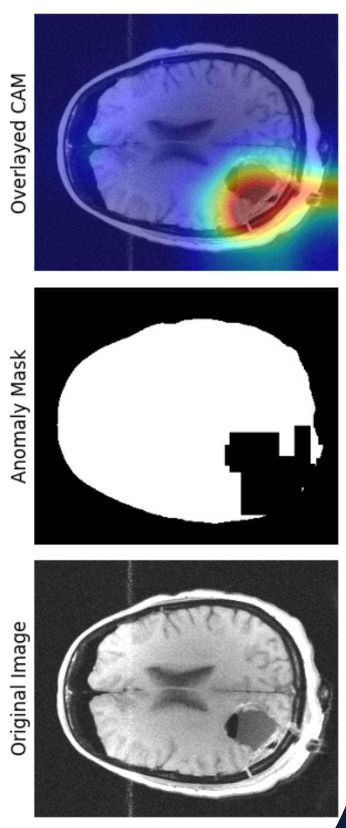


Experimental Results

*Experiments on 256x256 brain MRIs utilized the **3-way CutPaste** method for **256 epochs** with a **pretrained ResNet-18 in PyTorch**.*

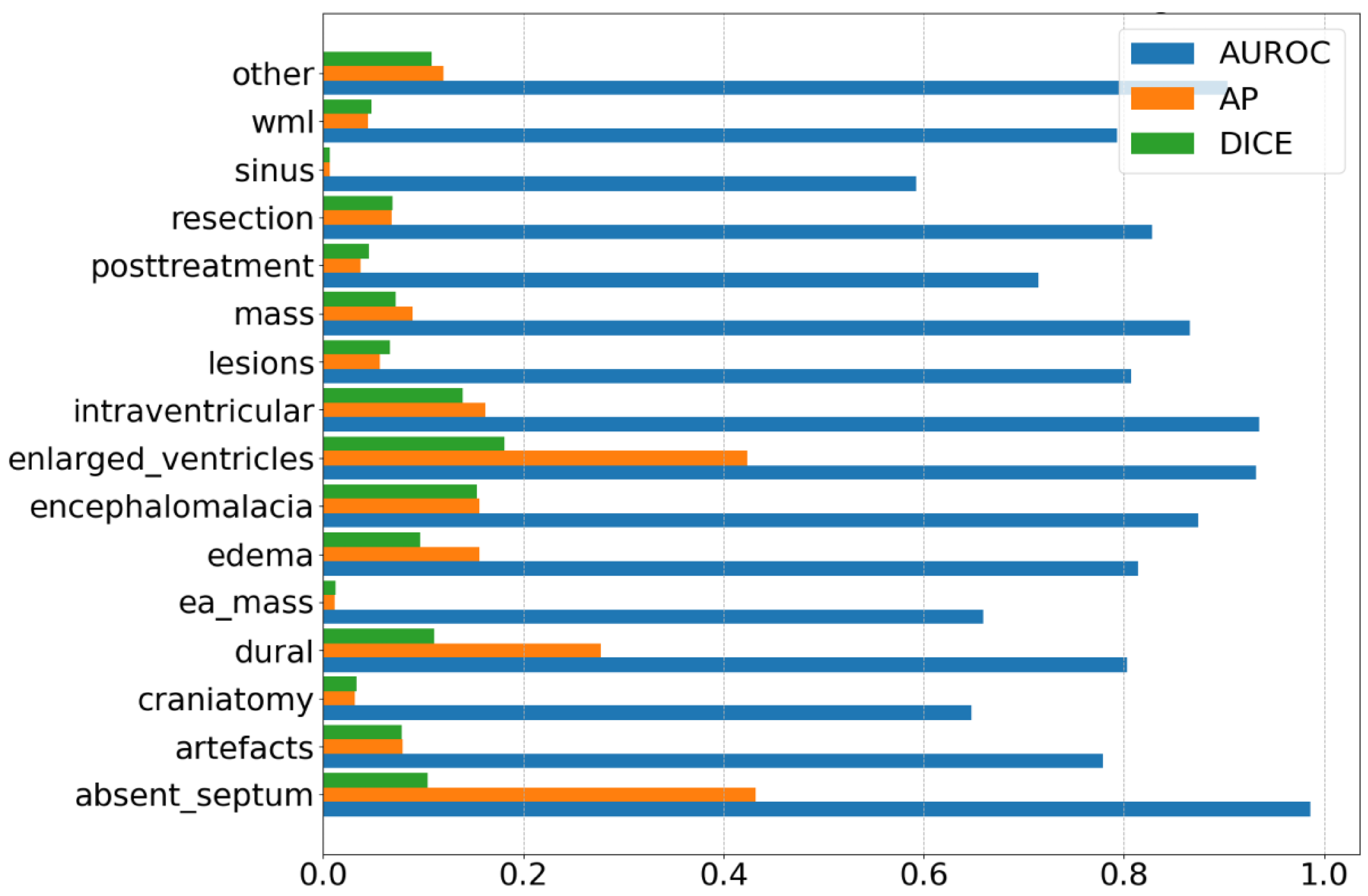
*Large patches in the **basic CutPaste** method did not align with typical brain anomalies, indicating that the use of **only the scar** method might be more effective in detecting such anomalies.*

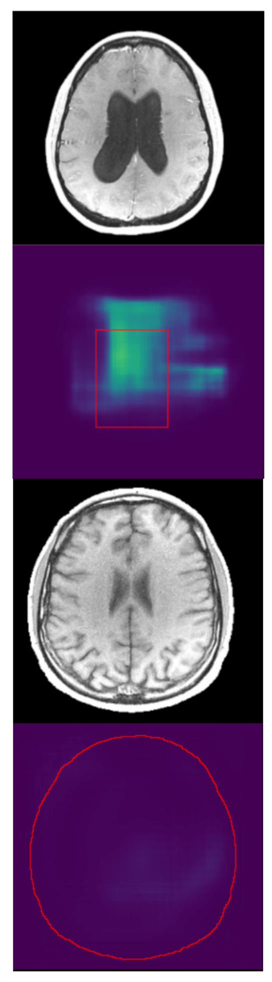




Experimental results after identical training procedure as in the paper (50 epochs with constant learning rate), using the continuous approach, focusing on the pixel-level task.

The resulting activation maps indicate overfitting to the rectangular shape of the patches.





FPI	AUROC	AP	DICE
Self-reported, synthetic test	0.985	0.731	0.709
Self-reported, DeepLesion	0.701	-	0.030
MOOD Challenge 2020	-	0.449	-
Tested (here)	0.791	0.135	0.069

References
1 Li, Chun-Liang, et al. "Cutpaste: Self-supervised learning for anomaly detection and localization." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021.
2 Tan, Jeremy, et al. "Detecting outliers with foreign patch interpolation." arXiv preprint arXiv:2011.04197 (2020).
3 Paszke, Adam, et al. "Automatic differentiation in pytorch." (2017).
4 Rippel, Oliver, Patrick Mertens, and Dorit Merhof. "Modeling the distribution of normal data in pre-trained deep features for anomaly detection." 2020 25th International Conference on Pattern Recognition (ICPR). IEEE, 2021.

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