One-Class SVM on siamese neural network latent space for Unsupervised Anomaly Detection on brain MRI White Matter Hyperintensities

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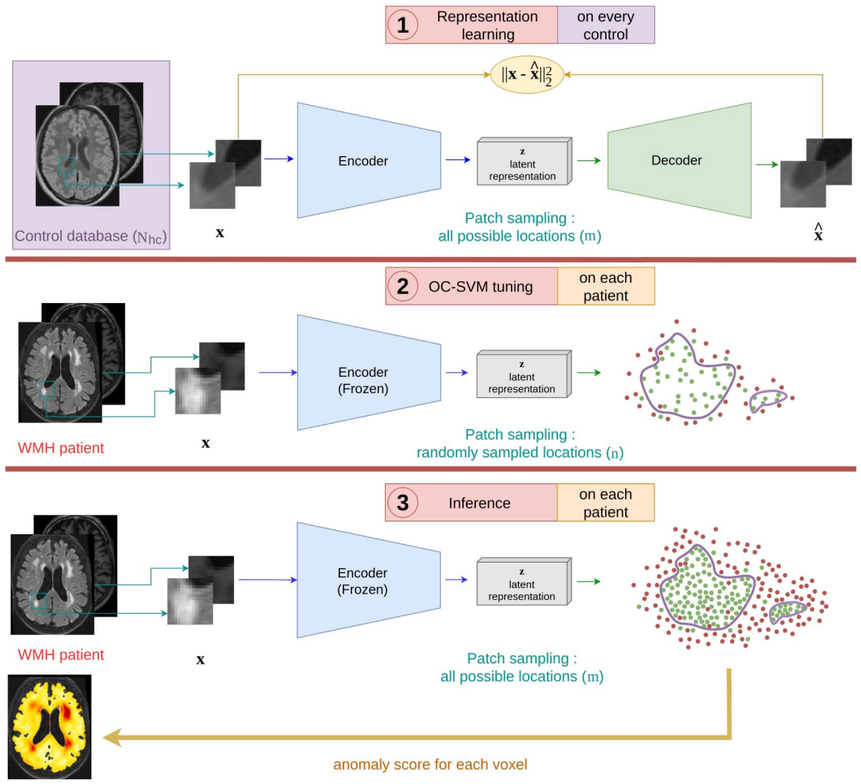
Introduction

- Unsupervised brain anomaly detection (**UAD**) methods have been proposed as an alternative to supervised models when the studied pathology is **rare** or when gathering fine expert **annotations** is too **challenging**.
- In this work, we propose a novel UAD method, with patient-specific characteristics, tailored to the task of lesion detection in multi-modal neuroimaging.

Unsupervised Anomaly Detection pipeline



1. **Representation learning**
   A siamese auto-encoder [3] is trained on **control** (healthy) patches **x** only. Every possible location in the brain is sampled, thus constructing a structured latent space based on a L_{SAE} loss function combining a standard *MSE* in the image space and cosine similarity in the latent space.

$$L_{SAE}(\mathbf{x_1}, \mathbf{x_2}) = \sum_{t=1}^{2} ||\mathbf{x_t} - \hat{\mathbf{x}}_\mathbf{t}||_2^2 - \alpha \cdot cos(\mathbf{z_1}, \mathbf{z_2})$$

2. **One-Class SVM tuning**
   For each **patient** (pathological), a subset of available patches is sampled, their latent representation extracted, and a One-Class SVM [2] trained to estimate the support of the normative latent density distribution.

3. **Inference**
   For each **patient**, latent representations of all patches are extracted and their distance to the boundary estimated. This will produce an anomaly score for each patch, that will be attributed to its central voxel to get the final anomaly map.

Experiments and Evaluation

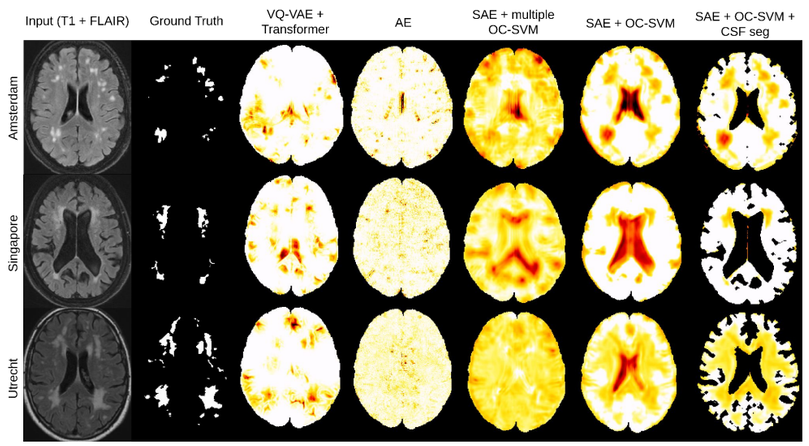
- **Control private dataset** : 75 paired T1w and FLAIR MRI on 1.5T Siemens Sonata scanner.
- **Patient pubic dataset (WMH Challenge dataset)** : 60 paired T1w and FLAIR on 3 different hospitals with 3 scanners of different manufacturers, with associated 3D lesion mask.
- Performances of our UAD model are compared to the **two best performing UAD models** [4] [5] on the WMH challenge dataset. We also compare to our previous model [3] where latent representations extracted from the control dataset are used to tune one OC-SVM per voxel.
- Performances are evaluated based on **AU ROC**, **AU PRC** and best achievable **Dice** metrics. We also investigate **AU PRO** [6] which acts as an AU ROC normalised by the size of the lesion (highlight good detection of small lesions). AU ROC and AU PRO are also studied by limiting the false positive rate to **30%**, above which the anomaly maps can be considered degenerated.

Results and Discussion

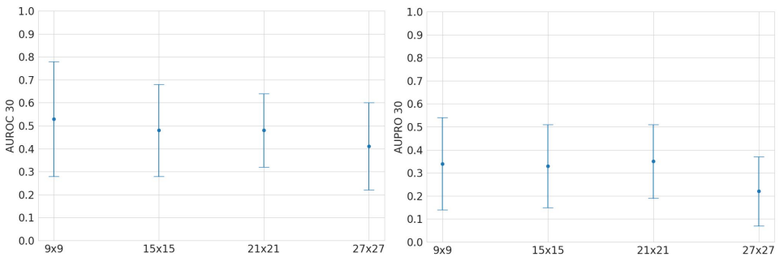
- On overall, **performances of our UAD model are higher than all three other methods for all the metrics.**
- The **patient-specific tuning** with one OC-SVM per patient performs better than with multiple OC-SVM (one per localisation) as in [3].
- Automatically masking the cerebrospinal fluid from the score maps ('CSF Seg' in the table above) improves performances due to a reduction of false positives.
- Comparative study by hospital reveals a high variance of performances, possibly due to the difference of manufacturer with the training dataset.
- Performance of our model seems robust to change of patch size.

3 hospitals	VQ-VAE + Transformer (Pinaya)	AE (Baur)	SAE + multiple OC-SVM (Alaverdyan)	SAE + OC-SVM (Ours)	SAE +OC-SVM +CSF seg (Ours)
AU ROC	0.69 ± 0.13	0.53 ± 0.09	0.52 ± 0.19	**0.80** ± 0.09	**0.81** ± 0.10
AU ROC 30	0.40 ± 0.20	0.20 ± 0.12	0.19 ± 0.16	**0.48** ± 0.20	**0.59** ± 0.17
AU PRC	0.065 ± 0.079	0.028 ± 0.030	0.023 ± 0.031	**0.084** ± 0.099	**0.165** ± 0.168
AU PRO	0.55 ± 0.10	0.50 ± 0.08	0.43 ± 0.17	0.71 ± 0.11	**0.80** ± 0.07
AU PRO 30	0.19 ± 0.13	0.15 ± 0.07	0.09 ± 0.13	0.33 ± 0.18	**0.48** ± 0.13
⌈ Dice ⌉	0.11 ± 0.10	0.06 ± 0.05	0.05 ± 0.05	**0.14** ± 0.13	**0.22** ± 0.17

Mean metric on every patient from the 3 different hospitals for each method. In bold are shown the best model and those for which Dunn's test with the best model returns a p-value > 0.01 .



Exemple performance of the different methods on one example from each of the 3 hospitals



Influence of patch size on AU ROC 30 and AU PRO 30

Conclusion and future work

- Performance gap is observed between the reported performances by [4] and [5] and our reimplementation, this could be caused by the huge pre-training done in [5] on 15 000 FLAIR volumes, and by their limitation to the 4 central slices of the volume. [4] and [5] work with FLAIR only, and implement data augmentation processes that may fill the domain adaptation gap.
- In comparison with [3], we report that the OC-SVM patient-specific training strategy seems to improve the performances on this task.
- Future work includes implementing domain adaptation strategies to account for the diversity of the scanners used, testing on other datasets and work with 3D patches.

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