Master Internship 2022 - 2023

Self supervised representation learning for anomaly detection in MRI neuroimaging.

Host laboratory : Laboratoire CREATIS, 69 Villeurbanne- MYRIAD Team
Supervisors : Carole Lartizien -Nicolas Pinon
Key words : Neuroimaging, Deep learning, Self-supervised learning, Latent representation learning
Duration : 5-6 months
Starting date : Winter- Spring 2022-23 (flexible)

Scientific context

Recent advances in machine learning have led to very promising results in medical imaging for segmentation, registration or reconstruction as well as for the design of automated diagnosis or prognosis models. The vast majority of deep architecture for medical image analysis are based on supervised methods requiring the collection of large datasets of annotated examples. Building such annotated datasets is hardly achievable, especially for some specific tasks, including the detection of small and subtle lesions, which are sometimes impossible to visually detect and thus manually outline. This is the case for various brain pathologies including microbleeds, epilepsy or multiple sclerosis lesions as well as Parkinson's disease (PD).

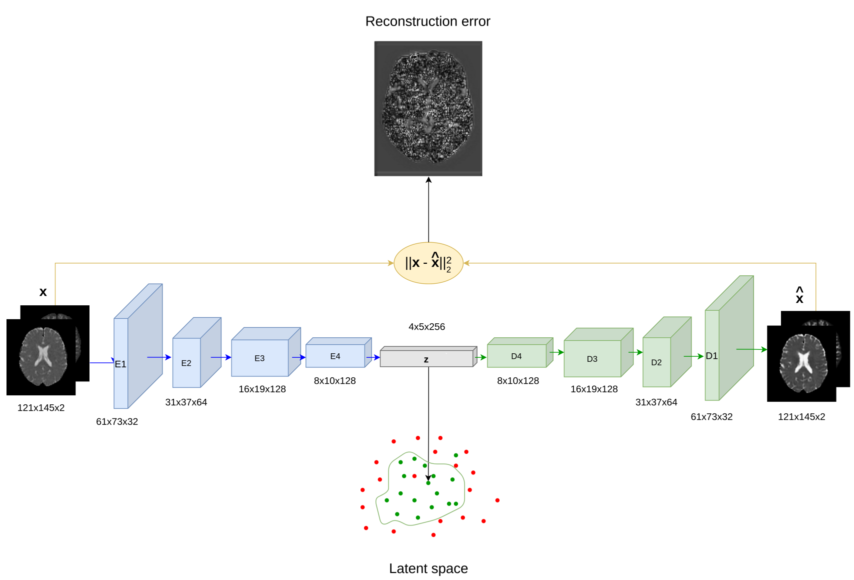

Figure 1: Self-supervised autoencoder trained to reconstruct the input image. The content of the input data is encoded into a latent representation variable z (centre). Anomaly detection is peformed either in the image space (top) based on the reconstruction error between the input and reconstructed images or in the latent space based on uniclass classifier (eg. oc-SVM) (bottom).

An alternative methodological framework is that of anomaly detection in an *unsupervised* context (also called *self-supervised*). It consists in learning a model of representation of normality from the healthy data only, and then to consider as anomalies (outliers) the test samples that deviate too much from normality. Self-supervised representation learning is based on the formulation of a "pretext" task that does not require annotations, or for which labels can be generated automatically. Autoencoders, for example, as shown in Figure 1 whose task is to reconstruct the input image, learn a compressed latent representation space (junction between encoder and decoder) without labeling the data.

The anomaly detection step is usually performed by computing the error between the original data and the data reconstructed by the autoencoder in the image data space [1], as shown in the upper part of figure 1. However, recent studies have highlighted the limitations of these approaches for the detection of very subtle abnormalities, such as those encountered in many brain pathologies (microhemorrhages, epilepsy, multiple sclerosis, Parkinson's disease...) [2]. The alternative approach that we are developing in the CREATIS laboratory focuses on the analysis of the latent representation space learned by the autoencoder model. These latent representations are used to train a uniclass classifier, e.g. OC-SVM, as shown at the bottom of figure 1. Anomaly detection is thus performed directly in the latent space, without reconstruction. We have recently shown that a Siamese autoencoder (SAE) gives good performances for the detection of epileptogenic lesions in multiparametric MRI [3]. Our current work focuses on the study of discrete models (Vector Quantized Variational Autoencoders (VQ-VAE)). First encouraging results have already been obtained (figure 2) on the public MVTec database of industrial images [4].

Objectives

The internship project is part of the research axis that we are developing in the CREATIS laboratory on unsupervised learning for the detection of brain anomalies in the latent space. The objective is to continue the ongoing work on discrete models such as VQVAE, to explore other learning models of the latent representation space based on Gaussian mixtures [5], and finally to explore alternative anomaly detection methods to OC-SVM, in particular LOF (local outlier factor) methods [6].

The internship program (non-exhaustive) will include:

- A bibliographical study of the state of the art in the various fields covered by the internship topic, in particular concerning
  - unsupervised anomaly detection methods for neuroimaging
  - one-class anomaly detection algorithms, with a particular focus on LOF (local outlier factor) and OC-SVM (One Class Support Vector Machine) methods
  - self-supervised variational latent representation learning methods
- Getting familiar with the code developed in the CREATIS laboratory (python, tensorflow) for the brain anomaly detection project,
- The implementation of the selected methods within the existing code,
- The performance evaluation of these methods, first on a public database of industrial images, the MVTec AD database, then on a neuroimaging database (WMH). The obtained performances will be compared to state of the art performance.

The selected candidate will be in constant collaboration with the CREATIS team that is carrying out this project and will also benefit from the expertise of researchers from the Hubert Curien laboratory in St Etienne (see below). He or she will have access to the laboratory's and national computing resources (CNRS Jean-Zay supercomputer) as well as to the MVTec and WMH medical imaging databases.

Skills

Candidate should have a background either in machine learning and/or deep learning or image processing as well as good programming skills. Experience with deep learning libraries (TensorFlow, Pytorch, scikit-learn) and with Linux systems

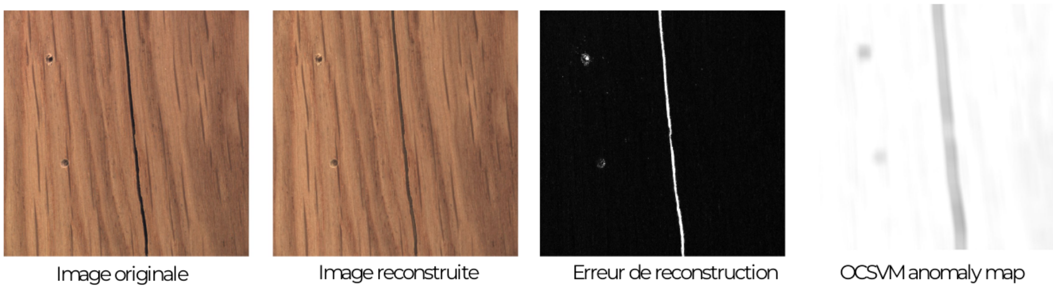

Figure 2: Preliminary results achieved with a siamese autoencoder : (middle left) of original image with a defect (left), reconstructed image (middle left), with anomaly detection maps derived from the reconstruction error in the image space (middle right) and from a uniclass classifier trained in the latent representation space (right)

would be apreciated.
We are looking for an enthusiastic and autonomous student with strong motivation and interest in multidisciplinary research (image processing and machine learning in a medical context).

The chosen person will be supervised by Carole Lartizien and in constant collaboration with a PhD student, Nicolas Pinon, working on this project. This internship is part of the *DAIAA* project funded by the Lyon Computer Science Federation (FIL) and gathering the MYRIAD team of CREATIS and the DI and ISCV teams of the Hubert Curien laboratory of St Etienne. The DI and ISCV teams will bring their expertise on the LOF (Local outlier factor) method and variational models.

Application

Interested applicants are required to send a cover letter, CV and any other relevant documents (reference letter, recent transcripts of marks, etc.) to:
carole.lartizien@creatis.insa-lyon.fr et **nicolas.pinon@creatis.insa-lyon.fr**

References

[1] Christoph Baur, Stefan Denner, Benedikt Wiestler, Nassir Navab, and Shadi Albarqouni. Autoencoders for unsupervised anomaly segmentation in brain mr images: A comparative study. *Medical Image Analysis*, 69:101952, 01 2021.

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[4] Paul Bergmann, Kilian Batzner, Michael Fauser, David Sattlegger, and Carsten Steger. The MVTec Anomaly Detection Dataset: A Comprehensive Real-World Dataset for Unsupervised Anomaly Detection. *International Journal of Computer Vision*, 129(4):1038–1059, April 2021.

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[6] Varun Chandola, Arindam Banerjee, and Vipin Kumar. Anomaly detection: A survey. *ACM Comput. Surv.*, 41(3), jul 2009.