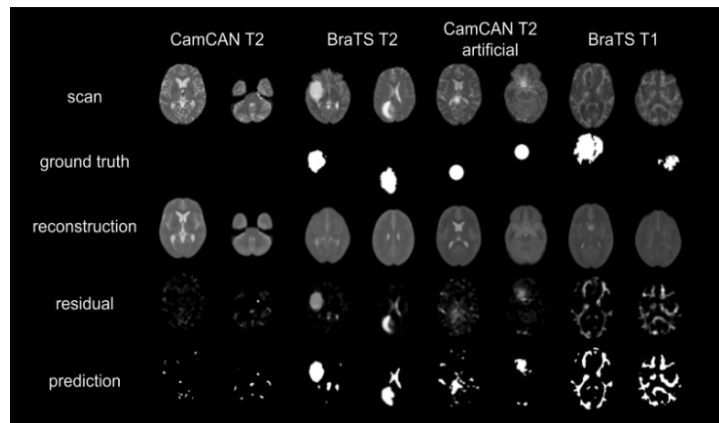


MA Thesis: Robust unsupervised anomaly detection for medical imaging

Supervisors: [Xiaoran Chen](#), [Janis Postels](#), [Shadi Albarqouni](#), [Ender Konukoglu](#)

BMIC/CVL, ETH Zurich, Zurich, Switzerland
Helmholtz AI, Helmholtz Center Munich, Munich, Germany

Unsupervised anomaly detection holds great promise for automatically detecting medical conditions (e.g. brain lesions) in image data since it alleviates the need for costly annotations [5]. Typically, one trains a generative model, e.g. a Variational Autoencoder (VAE), on data (e.g. brain scans) of healthy patients and detects pathological conditions at test time as out-of-distribution (OOD) data. This detection is commonly performed using the reconstruction



[1] or restoration loss [2]. A comparative study of all these methods can be found in [6].

However, it was previously established that these unsupervised anomaly detection approaches are fundamentally unable to differentiate between real OOD data (e.g., healthy with domain shift) and medical anomalies [3]. Therefore, in this work we are trying to develop an approach that bypasses this shortcoming. We will start with a model trained on unsupervised anomaly detection following the common procedure [1-3, 6, 9]. Subsequently, the goal is to gain additional information about the target domain where the model is destined to be deployed. Therefore, we envision two potential strategies: 1) Apply few-shot domain adaptation strategies to our model (e.g. [4], [8]) such that healthy/non-anomalous samples are not wrongly detected or/and 2) use techniques from online learning to understand which reconstruction error patterns belong to “real” anomalies at inference time.

Roadmap:

- Familiarize with relevant literature (i.e. unsupervised anomaly detection, domain adaptation, online learning).
- Familiarize with existing codebase used in [3]
- Apply domain adaptation strategies and quantify impact in terms of anomaly detection performance and robustness
- Apply online and quantify impact in terms of anomaly detection performance and robustness

Prerequisites:

- Fundamental knowledge of deep learning and computer vision
- Proficiency in at least one deep learning framework (preferably PyTorch)
- Experience or knowledge about generative models is an advantage

Databases:

- Healthy Brain MR Imaging (CamCAN, OASIS, ADNI)
- MS/GB Lesion (BRATS, MS-LUB, MS-ISBI, ...)
- MOOD (<http://medicalood.dkfz.de/web/>)

If you are interested in this project, please write an email to:

shadi.albarqouni@helmholtz-muenchen.de , jpostels@ethz.ch , chenx@vision.ee.ethz.ch

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