MSc Project: Uncertainty-Guided Registration of Normal Variability for Unsupervised Anomaly Detection

Abstract: Unsupervised anomaly detection methods aim to detect irregular and rare data instances that deviate from the normal, expected distribution. Although much work has been done on the use of auto-encoders (AE) to detect anomalies [1], it has been shown that learning the healthy distribution is stil cumbersome, with AEs being able to reconstruct some types of anomalies even better than samples from the trained distribution [2, 3]. Strategies to constrain the latent manifold of AE include adversarial training [4, 5], or probabilistic modeling [6, 7]. More recently, deformable auto-encoders [8] have been introduced to learn perceptually healthy priors and adapt their morphometry based on estimated dense deformation fields [9] to better match the input. However, this method does not guarantee that only healthy tissues will be deformed at inference time.

The objective of this project is to extend deformable auto-encoders with a localized, uncertainty-guided regularizaton of the deformaiton fields to avoid the registration of abnormal regions during inference. The prospective student will explore existing deep-learning-based uncertainty estimation methods, and develop a novel regularization for constrained registration to improve unsupervised anomaly detection.

Requirements:

- Prior experience and good understanding in machine learning and statistics.
- Very good programming skills in Python (and PyTorch).
- Interest in medical imaging.

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References

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