MA Thesis: Multi-Modal Liver Segmentation in Privacy-Preserved Fashion

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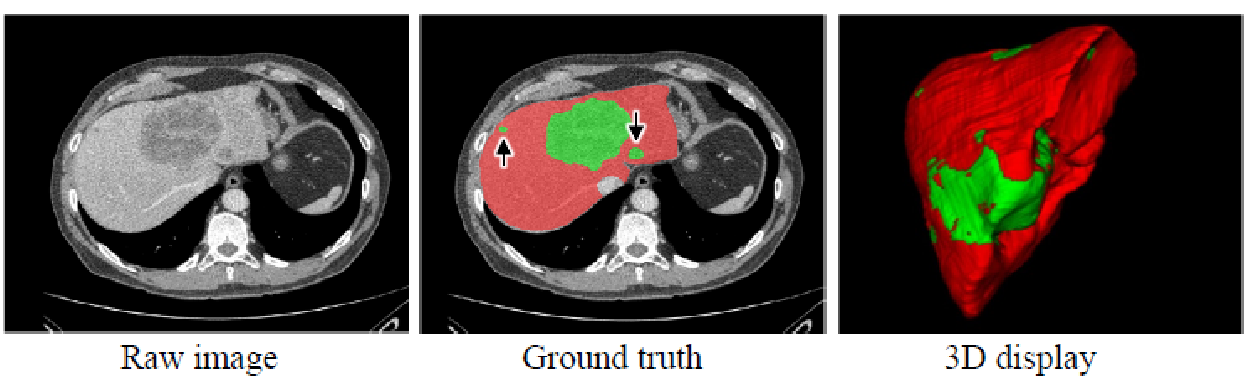
Abstract. Liver Cancer is one of the most common causes of cancer death in the world with an estimated around 782,000 deaths every year according to the World Health Organization [21]. Different Imaging modalities like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) play a major role in the diagnosis and treatment of various liver diseases, e.g., hepatocellular carcinoma (HCC). Automatic Liver segmentation has been extensively investigated in the literature to facilitate treatment planning in clinical routine. Early works investigated 3D statistical shape models as a geometric prior for automatic Liver segmentation [19-20, 22-23]. With the advent of convolutional neural networks and the availability of computational resources, deep learning-based methods are currently state-of-the-art [1,7,9]. In the last decade, a couple of multimodal abdominal databases were made publicly available; LiTS17 [2], CHAOS19 [3] Multi-Atlas [4], ~~Decathlon [5]~~, Visceral [6], and 3DIRCADb [8], to foster the research and development of automatic liver segmentation. Yet, many other valuable databases and cohorts are kept private for privacy issues. In this thesis, we aim to develop a liver segmentation model that could i) leverage multi-modal data, namely CT and MR scans, and ii) preserve privacy meaning training the model in a federated fashion [11].



Liver images are adopted from Li et al. [9]

Roadmap:

- Familiarize yourself with the current literature on:
    - Multi-Modal Liver Segmentation using Deep Learning [1,7,9,24]
    - Federated Learning with Medical Imaging [14 - 18]
    - Federated Learning with non-iid [10,12,13]
    - Disentangled Representations [25,26]
- Measure the A-distance between different domains [27]
- Build baseline models; local models (trained on each database, individually), global model (trained with all databases). Note that you need to train the models on CT scans and w/ and w/o MR scans.
- Develop the proposed method
- Run extensive experiments and analysis
- Write up your thesis

Research Questions:

Q1) Can we train a federated liver segmentation model with multi-modal data?
Q2) Would disentangling the shape feature (liver) from the appearance feature (CT, MR) promote generalizability (e.g, for new incoming participants) and personalization (e.g., for local models)?

Requirements:

- Solid background in Machine/Deep Learning
- Familiar with discriminative deep learning models and SOTA architectures
- Sufficient knowledge of Python programming language and libraries (Scikit-learn)
- Experience with a mainstream deep learning framework such as PyTorch.
- Machine/Deep learning hands-on experience

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[2] https://competitions.codalab.org/competitions/17094
[3] https://chaos.grand-challenge.org/
[4] https://www.synapse.org/#!Synapse:syn3193805/wiki/217789
[6] http://www.visceral.eu/closed-benchmarks/anatomy3
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