Abstract

Glioblastoma multiforme is the most frequent and aggressive primary brain tumor in humans. Due to its fast growth and infiltrative nature, glioblastoma patients only have a median survival of 15 months. The fast disease progression and low overall survival time make close disease monitoring necessary. Currently, a patient's response to treatment is assessed based on Magnetic Resonance Imaging (MRI), acquired approximately every three months. Due to the prohibitively extensive effort to manually segment the tumor, two-dimensional surrogate measurements of the tumor burden are currently used to evaluate treatment response.

Advances in radiomics in conjunction with machine learning allow extraction of information from medical images beyond visual assessment and analysis of subtle changes. These radiomic features often lack robustness in multi-center settings with different MRI scanner vendors, models, and acquisition protocols.

This thesis investigates advanced machine learning techniques and radiomics on magnetic resonance imaging with radiomics for overall survival analysis, longitudinal volumetry, and disease progression biomarkers.

We first present data-driven insights from our single-center glioblastoma patient population, followed by studies on deep learning and machine learning approaches to overall survival prediction from pre-operative MRI. The challenge to find robust radiomic features is addressed by artificially perturbing single-center data to minimize a loss in machine learning performance when transferred to multi-center data.

We then evaluate the applicability of automated tumor volumetry for longitudinal response assessment and present a first study on evaluating and learning radiomic disease progression biomarkers.

Our results show that the performance drop on multi-center data can be effectively reduced with tailored robustness testing. Features showed a high sensitivity to histogram binning and other perturbations such as voxel size and slice spacing changes. Longitudinal volumetry and automated two-dimensional measurements simulating the current practice show a high agreement, but close expert monitoring and safeguards are still needed for response assessment. We further present encouraging results to use radiomic features as progression biomarkers, with the most promising candidates stemming from a deep multi-task neural network.