Combining deep learning and radiomics-based machine learning to optimize predictions on medical images

Impact paragraph

This thesis investigated the individual and combined use of deep learning and handcrafted radiomics to improve the machine learning model predictions on different types of imaging data. Our first study was a systematic review about the strengths and weaknesses of handcrafted radiomics and deep learning methodologies, which informed the work conducted in this thesis. We were able to draw a number of important conclusions from this review:
(1) Researchers seems to either use handcrafted radiomics or deep learning based models, we were unable to identify a study which used these methods in combination.
(2) Having homogeneous datasets, which are independent from the machine they were acquired on, is very important for reproducibility and successful validation of the results.
(3) In order to increase usuability of our models, assessing performance on at least one external validation dataset and using cross-validation on a test dataset are key to success.

Scientific impacts

In the first part of this thesis, we compared and combined deep learning and feature-based machine learning. From our study, we concluded that the use of two different datasets, one containing histological information and the other one containing molecular information, might have complementary value for the prediction of dysplasia grades in Barrett's oesophagus. The analysis of the images with the molecular information was better in predicting dysplasia grade per image and progression of dysplasia to cancer whereas the images with the histological information were best to classify tissue type. This discovery might help clinicians to improve prediction of progression of dysplasia and hence could improve management of patients with Barrett's oesophagus. In another study on brain MRI, we discovered that combining the predictions of adverse radiation effect obtained with handcrafted features machine learning and deep learning method lead to better predictions than using one model alone. This important information might influence how MRI images are analysed in the future when trying to predict adverse effects of radiation therapy in patients with brain metastases.

In the second part of this thesis, we used feature-based models to augment deep learning predictions. We created a novel workflow based on histology images of lymph nodes and other tissues in order to detect and segment lymph nodes. We used first a deep learning model to segment the lymph nodes and then created a machine-learning model which takes those predicted segmentations as input and outputs a score from 0 to 1 quantifying the likelihood that the segmentation is indeed a lymph node which has been correctly segmented. Adding this step to a regular deep learning approach reduced the false positive results significantly as part of the false positive findings were reclassified in the uncertain category. This work could be used to detect and segment lymph nodes on histology images in a research setting as a prerequisite of performing detailed AI based analyses of the lymph node architecture (data of this study was used to successfully obtain funding for further investigations in lymph nodes). Our last study was performed on contrast enhanced mammography images. We trained a model to detect, segment and classify suspicious lesions. Interestingly, also in this study, the best results were obtained using a combination of deep learning and handcrafted radiomics features.

We have shown in this thesis for the first time the potential of utilizing the strengths of handcrafted features based models in combination with the strengths of deep learning models for multiple medical imaging datasets and diverse tasks. Although our results are promising and offer insights into new avenues of research, validation of our findings in independent series is required.

Social impacts and knowledge transfer

According to the GLOBACAN 2020, it is expected that 28 million people will be diagnosed with cancer in 2040, which represents an increase of almost 50% compared to the figures from 2020. Cancer is already a leading cause of death in 2022 and will become even more of a burden on society.

Although lot of published studies are presenting tissue-based biomarkers based on medical imaging data, none was introduced into the routine practice. Clinical decisions are still based on a clinician assessing medical images (CT, MRI, X-rays, H&E stained tissue, etc.). This approach is subjective as it depends on the experience of the observer and experts are not always available to review those images. Thus, there is a need for accurate and fast tools to assist and support decisions of the clinicians objectively. We contributed to advance the field of personalized medicine by showing that using handcrafted features in combination with deep learning helps improve predictions eventually for detections, delineation and diagnosis tasks, making another step towards clinical implementation.

We communicated all the results of our research: all our studies are either published or submitted to peer-reviewed journals and made open access. The work presented in this thesis has been presented and discussed at multiple national and international conferences to disseminate our findings with medical imaging experts: Presentations were given at the GROW science day of Maastricht University (2019, 2020), the European Congress on Digital Pathology (2020, 2021), the European Congress of Radiology (2020, 2022) and the conference of the Pathological Society of Great Britain and Ireland (Manchester Pathology) (2021). Moreover, our work presented Chapter 5 is planned to be implemented by our department first for research purpose and if the results show to be consistent, then it will be implemented in the clinic. The model presented Chapter 6 will be made available for use by a company in the next years and could have a positive impact on the clinical workflow. Research is currently being done to improve the detection and diagnosis of micro-calcifications within the breast on contrast-enhanced mammography.