Deep-learning-based time-to-event prediction for a large multicentric cohort of H&N cancer patients

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What was your motivation for initiating this work?

A recent study by Diamant et al. [1] showed that the leveraging of deep-learning-based algorithms to extract relevant features automatically from images could lead to improved cancer outcome predictions compared with traditional radiomics. The main aims of this study were to extend the computed tomography (CT)-based 2D convolutional neural network (CNN) that was used by Diamant et al. to a 3D-CNN, to incorporate censoring information and to produce time-dependent predictions, and to analyse whether the models could successfully generalise the prediction of distant metastasis (DM) when applied to independent testing cohorts obtained from The Cancer Imaging Archive (TCIA) [2] as well as from collaborators. For that, we trained and validated the models on the data for the same 294 patients that had been used by Diamant et al. and we used as independent testing cohorts the data of 136 patients who had been treated at MAASTRO clinic in The Netherlands, 497 patients treated at Princess Margaret Cancer Centre (PMH) and 110 patients who had been treated at Centro di Riferimento Oncologico (CRO) in Italy. Moreover, we investigated the role of image texture for the CNNs by performing a binary masking experiment on the input CTs, inspired by work done by Welch et al. [3].

What is the most important finding of your study?

Both the 2D and the 3D CNNs achieved good DM discriminative performance on two (MAASTRO and CRO) out of three testing sets; these CNNs reproduced the good performance that had been reached on the validation cohort. Results of the study of the PMH cohort were substantially worse. Therefore we tried to train and validate CNNs through use of 50% of the PMH cohort and to test the obtained models on the remaining 50%. However, this led to only a small improvement. We hypothesise that the worse performance that was produced compared with those of the other test cohorts might have depended on certain unknown clinical backgrounds of this cohort, e.g. missing information on surgery in the TCIA dataset. No drop in performance was observed when a binary masked input CT was used for the 3D-CNN. Finally, stratification of the patients into high-risk vs. low-risk groups was significant for all three testing cohorts both for the 2D-CNN and the 3D-CNN. Full results can be found in [4].

What are the implications of this research?

CT-based CNN models showed good overall accuracy and could be used for DM risk-group stratification within personalised radiotherapy workflows. Unknown clinical backgrounds might bias the results, so large well-described datasets are required to validate the models further, ideally in a prospective fashion. The binary masking experiment showed CT texture feature to be irrelevant for the 3D-CNN; however, it remains to be seen whether incorporation of features from different imaging modalities (e.g. PET), as enabled by the implemented image-based deep learning models, might improve the CNN's performance.

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