Late Gadolinium Enhancement

## Dark blood ischemic LGE segmentation using a deep learning approach

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Introduction: The extent of ischemic scar detected by Cardiac Magnetic Resonance (CMR) with late gadolinium enhancement (LGE) is linked with long-term prognosis, but scar quantification is time-consuming. Deep Learning (DL) approaches appear promising in CMR segmentation. Purpose: To train and apply a deep learning approach to dark blood (DB) CMR-LGE for ischemic scar segmentation, comparing results to 4-Standard Deviation (4-SD) semi-automated method. Methods: We trained and validated a dual neural network infrastructure on a dataset of DB-LGE short-axis stacks, acquired at 1.5T from 33 patients with ischemic scar. The DL architectures were an evolution of the U-Net Convolutional Neural Network (CNN), using data augmentation to increase generalization. The CNNs worked together to identify and segment 1) the myocardium and 2) areas of LGE. The first CNN simultaneously cropped the region of interest (RoI) according to the bounding box of the heart and calculated the area of myocardium. The cropped Rol was then processed by the second CNN, which identified the overall LGE area. The extent of scar was calculated as the ratio of the two areas. For comparison, endo- and epi-cardial borders were manually contoured and scars segmented by a 4-SD technique with a validated software. Results: The two U-Net networks were implemented with two free and open-source software library for machine learning. We performed 5-fold cross-validation over a dataset of 108 and 385 labelled CMR images of the myocardium and scar, respectively. We obtained high performance ( $> \sim 0.85$ ) as measured by the Intersection over Union metric (IoU) on the training sets, in the case of scar segmentation. With regards to heart recognition, the performance was lower (> ~0.7), although improved (~ 0.75) by detecting the cardiac area instead of heart boundaries. On the validation set, performances oscillated between 0.8 and 0.85 for scar tissue recognition, and dropped to ~0.7 for myocardium segmentation. We believe that underrepresented samples and noise might be affecting the overall performances, so that additional data might be beneficial. Figure 1: examples of heart segmentation (upper left panel: training; upper right panel: validation) and of scar segmentation (lower left panel: training; lower right panel: validation) dation). Conclusion: Our CNNs show promising results in automatically segmenting LV and quantify ischemic scars on DB-LGE-CMR images. The performances of our method can further improve by expanding the data set used for the training. If implemented in a clinical routine, this process can speed up the CMR analysis process and aid in the clinical decision-making.

## Abstract Figure.

