AI-based Prediction of Myocardium Viability Using [^{82}Rb] PET/CT

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Aim/Introduction: Myocardial viability assessment is crucial to determine the potential need for revascularisation after myocardial infarction (MI). While [^{18}F]FDG combined with [^{82}Rb] myocardial perfusion imaging is the gold standard, this study aims to detect non-viable tissues using only [^{82}Rb] PET and artificial intelligence (AI).

Materials and Methods: The cohort was retrospectively composed of MI patients who underwent clinically indicated [^{82}Rb] and [^{18}F]FDG at our institution. For ground truth, we computed the viability score by normalizing the FDG uptake map to the regions with normal [^{82}Rb], defined as $\geq 60\%$ maximum. Viability score bellow 50% defined non-viable regions. We propose two approaches to infer viability from Rubidium alone: the regression (Reg) approach predicts the viability score, while the classification (Cl) approach detects non-viable tissues. We compared two models for both methods, support vector models ($SVM_{Reg/Cl}$) using 93 radiomic features extracted from the segment uptake rate K_1 and a convolutional neural network ($CNN_{Reg/Cl}$) using myocardial blood flow segment. Only the best modality for each model is reported. For classification models, the static [^{82}Rb] is added to differentiate normal from abnormal. The metrics reported are positive predictive value (PPV), true positive/negative rate (TPR/TNR). For the regression approach, the predicted score is binarized using the 50% threshold for classification. Analysis was performed at the segmental level using the 17-segment American Society of Nuclear Cardiology model, excluding the apex. Training used five stratified folds, allowing us to compute the 95% confidence intervals assuming a Student-*t* distribution.

Results: The study includes 34 patients (29 male; mean age 70 $\pm$ 9 years), resulting in 544 segments. As normal segments are trivial to classify, evaluation is conducted on the 114 abnormal segments. For regression, CNN_{Reg} predicts the viability score with a mean absolute error (MAE) of 8.52[6.50,10.54], and achieves a PPV, TPR and TNR of 0.75[0.45,1.00], 0.80[0.63,0.98] and 0.89[0.77, 1.00]. Therefore, CNN_{Reg} slightly outperforms its classification counterpart CNN_{Cl}, which shows PPV, TPR and TNR of 0.74[0.53,0.94], 0.78[0.57,0.99] and 0.86[0.73, 1.00]. Radiomics-based models are slightly worst, SVM_{Reg} with an MAE of 9.04[7.19,10.90], PPV, TPR and TNR of 0.68[0.42,0.94], 0.62[0.30,0.95] and 0.85[0.72, 0.98] and SVM_{Cl} (PPV, TPR and TNR of 0.68[0.44,0.91], 0.87[0.70,1.00] and 0.80[0.62,0.97]).

Conclusion: AI may help predict segmental myocardial viability after an infarction using rest [^{82}Rb] PET alone and remove the costs associated with the use of [^{18}F]FDG.