Constrative Learning for Kidney Transplant Analysis using MRI data and Deep Convolutional Networks

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Abstract

In this work, we propose contrastive learning schemes based on a 3D Convolutional Neural Network (CNN) to generate meaningful representations for kidney transplants associated with different relevant clinical information. To deal with the problem of a limited amount of data, we investigate various two-stream schemes pre-trained in a contrastive manner, where we use the cosine embedding loss to learn to discriminate pairs of inputs. Our universal 3D CNN models identify low dimensional manifolds for representing Dynamic Contrast-Enhanced Magnetic Resonance Imaging series from four different follow-up exams after the transplant surgery. Feature visualization analysis highlights the relevance of our proposed contrastive pre-trainings and therefore their significance in the study of chronic dysfunction mechanisms in renal transplantation, setting the path for future research in this area. The code is available at https://github.com/leomlck/renal_transplant_imaging.

Keywords: Renal transplantation, contrastive learning, MRI, representation learning.

1. Introduction

Renal transplantation has emerged as the most effective solution for end-stage renal disease. Nevertheless, a substantial risk of chronic dysfunction persists and may lead to graft loss or ultimately patient death. Indeed, if blood tests are irregular, the gold standard method to assess transplant status is needle biopsy, a surgical operation. Thus, the need for a non-invasive alternative that could provide valuable information in transplant monitoring post-transplantation is crucial.

Imaging data has proved to carry essential information in several medical applications, mainly by exploiting learned feature representations, instead of measurements or features designed by experts. Recent advances in self-supervised learning enable the training of powerful deep learning representations with a limited amount of data (Taleb et al., 2020). Renal transplantation data sets usually belong to this case, and diverse imaging modalities have been investigated to assess renal transplant functions in several studies (Sharfuddin, 2014). In this work, we propose contrastive learning schemes incorporating clinically valuable information to pre-train deep Convolutional Neural Networks (CNN), in order to generate relevant features for compact and informative representations of Dynamic Contrast-Enhanced (DCE) MRI of renal transplants.

2. Contrastive models for kidney transplant

In this work, we propose two contrastive learning schemes to explore meaningful imaging representations: (a) a self-supervised scheme, where we learn features by solving the task of determining if two MRI belong to the same patient, and (b) a weakly-supervised scheme, where we discriminate samples based on the differences in the value of various clinical variables. The variables were suggested by nephrology experts to encode clinical priors and information, as they are significantly linked to graft survival. We investigate three variables: (1) transplant incompatibility, (2) age of the transplant's donor, and (3) Glomerular Filtration Rate (GFR) value. Let us denote $(v_1, v_2) \in (\mathbb{R}^{N_x \times N_y \times N_z})^2$ a pair of 3D MRI regions of interest (ROI). Each stream $i = 1, 2$ consists of a ResNet18 model to extract a latent representation from the ROI, which takes v_i as input and outputs features $z_i \in \mathbb{R}^{D_f}$. Then, a feature embedding head associates these features with the underlying task. This is modeled by a Multi-Layer Perceptron (MLP) mapping the features to $(z'_1, z'_2) \in \mathbb{R}^{D_{fe}}$.

Training loss. From the embedded features (z'_1, z'_2), the optimization is done by the following cosine embedding loss:

$$\text{CosEmbLoss}(z'_1, z'_2, y) = \begin{cases} 1 - \cos(z'_1, z'_2), & \text{if } y = 1, \\ \max(0, \cos(z'_1, z'_2), & \text{if } y = 0, \end{cases} \tag{1}$$

where *cos* refers to the cosine similarity. This loss enforces the model to build relevant features that express adequately the kidney transplant imaging, incorporating clinical information, constrained by the strategies (a) or (b) to label each pair y.

Training scheme & curriculum learning. Since the dimensionality of our data is high and the tasks we investigate are challenging, we apply curriculum learning to facilitate the training process. In particular, for the self-supervised task (a) at the patient level, pairs from the same patient and the same exam are enabled in the beginning until half of the training, while they are discarded in the second half. For the weakly-supervised task (b) based on a clinical variable, the perplexity of the task is determined by the thresholds used to set the labels y. More specifically, the training labels are adjusted every 20 epochs and thus we strengthen the constraint through epochs on the difference of clinical variable value between the two pairs to be correctly arranged. Having approximately a set of pairs of $\binom{V}{2} \sim V^2$, where V is the number of available volumes, we propose to set the training set size to $V_t = 10000$, fix the positive samples, as well as its balance to 25%, and to randomly sample every epoch the remaining from the negative samples.

Dataset & Implementation details. The DCE MRI series were acquired at 4 follow-up exams post-transplantation for 89 subjects, resulting in respectively 68, 75, 87, and 83 available series at each exam. Volumes were cropped around the transplant using an automatic selection of the ROI (Milecki et al., 2021) and intensity normalization was executed.

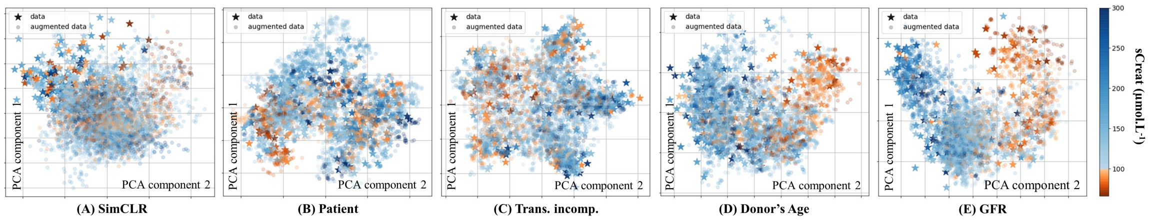

Figure 1: Generated features from DCE MRI visualization using PCA decomposition. Their association with sCreat (μmol.L^{-1}) is depicted.

We use data augmentation with horizontal flipping and random affine transformation with a 0.5 probability, as well as random Gaussian blur and noise ($\sigma \in [0, 0.5]$). The SGD optimizer with a momentum equal to 0.9 is used with a starting learning rate of $1e^{-2}$ following a cosine schedule and preceded by a linear warm-up of 5 epochs. The batch size was set to 48 and the model trained for 60 epochs on 4 NVIDIA Tesla V100 GPU.

3. Results & Discussion

In Figure 1, using Principal Component Analysis (PCA) decomposition, we visualize the generated features from the different models (A) SimCLR (Chen et al., 2020), (B) identifying exams of the same patient, (C) transplant incompatibility (Tran. incomp.), (D) donor's age, and (E) GFR variables. The colormap is set by the serum creatinine (sCreat) mean value around 1 year post-transplantation. Resulting from blood tests, sCreat is clinically used as a primary indicator of transplant dysfunction, where $< 100\mu$mol.L^{-1} corresponds to abnormal kidney function. Overall, the Donor's Age and the GFR based pre-trainings seem to provide better representations with respect to the sCreat.

To conclude, we proposed various contrastive learning schemes incorporating valuable clinical priors to learn generic and informative manifolds for patients undergoing renal transplantation. Our approach generated MRI features that encourage the use of medical imaging in order to assist clinical practice for fast and robust monitoring of kidney transplants. In future work, we aim to use those models to perform clinically relevant downstream tasks such as disease diagnosis or prognosis, survival analysis of kidney transplants events, and imaging features analysis through follow-ups.

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