**Literature Review- MyoPS 2020**

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| Paper | Stacked BCDU-Net with Semantic CMR  Synthesis: Application to Myocardial  Pathology Segmentation Challenge |
| Dataset | 45 cases of multi-sequence CMR.  Each case refers to a patient with three CMR sequences, i.e., LGE, T2 and bSSFP CMR.  Pre-processed using MvMM Method  Online Augmentation: Like random rotations between *−*15*◦* and 15*◦* and random scaling and offsets of a maximum of 30 pixels  Offline augmentation: Semantic Image Synthesis with Spatially Adaptive Normalization (SPADE) method |
| Architecture | Two Steps:   1. Localization Network: Use of U-Net on the Cine MRIs to generate bounding box around myocardium. 2. Segmentation Network: Above outputs were cropped across the bounding box, normalized using histogram method then fed into BCDU-Network |
| Performance Metrics | 2D Dice Score:  Using Style transfer: Scar- 0*.*548 *±* 0*.*250  Scar + Edema- 0*.*640 *±* 0*.*192  3D Dice Score:  Using 15 model’s ensemble + post-processing:  Scar- 0.665 *±* 0.241  Scar + Edema- 0.698 *±* 0.128 |

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| Paper | Myocardial Edema and Scar  Segmentation Using a Coarse-to-Fine  Framework with Weighted Ensemble |
| Dataset | 45 cases of multi-sequence CMR.  Each case refers to a patient with three CMR sequences, i.e., LGE, T2 and bSSFP CMR.  25 for training, 20 for testing  Pre-processed using MvMM Method  Cropping for coarse segmentation  Data augmentation before fine segmentation network was implemented using nnU-Net |
| Architecture | Two Steps:   1. Coarse Network: In coarse segmentation, training vanilla U-Net to segment 4 categories (i.e. background, complete ring-shaped myocardium, left ventricular (LV) blood pool and right ventricular (RV) blood pool) 2. Fine Segmentation Network: The fine segmentation framework of which input is concatenation   of coarse network output prediction serving as prior location information and three sequences of CMR images to conduct detailed target prediction. Here, the author also introduced a novel weighted  ensemble method that gives a specific weight to 2D and 2.5D fine segmentation network |
| Performance Metrics | Dice Score: Scar- 0.6723  Scar + Edema- 0.7314 |

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| Paper | EfficientSeg: A Simple But Efficient  Solution to Myocardial Pathology  Segmentation Challenge |
| Dataset | 45 cases of multi-sequence CMR.  Each case refers to a patient with three CMR sequences, i.e., LGE, T2 and bSSFP CMR.  25 for training, 20 for testing  Pre-processed using MvMM Method |
| Architecture | Two Steps:   1. ImageNet-pretrained EfficientNets as feature   extractor in the encoder, aiming to extract strong features from CMR sequences.   1. Considering the objects (*i.e.* scars and edema) with different shapes and sizes, the author employ BiFPN as the decoder to fuse the multi-scale features produced by the encoder and predict the segmentation mask.   Apart from this used cross-entropy loss, dice loss and boundary loss for improved performance |
| Performance Metrics | Dice Score: Scar- 0.6471  Scar + Edema- 0.7087 |

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| Paper | Two-Stage Method for Segmentation of  the Myocardial Scars and Edema on  Multi-sequence Cardiac Magnetic  Resonance |
| Dataset | 45 cases of multi-sequence CMR.  Each case refers to a patient with three CMR sequences, i.e., LGE, T2 and bSSFP CMR.  25 for training, 20 for testing  Image Pre-processing: histogram equalization and random gamma technique |
| Architecture | Two Steps:   * A U-net is applied to extract the entire myocardial part to obtain the prior constraint. * In the second stage, an M-shaped segmentation network based on the   attention mechanism and residual connection is adopted, which can improve segmentation accuracy of myocardial scars and edema |
| Performance Metrics | Dice Score: Scar- 0*.*570 *±* 0*.*283  Scar + Edema- 0*.*634 *±* 0*.*164 |

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| Paper | Multi-modality Pathology Segmentation  Framework: Application to Cardiac  Magnetic Resonance Images |
| Dataset | 45 cases of multi-sequence CMR.  Each case refers to a patient with three CMR sequences, i.e., LGE, T2 and bSSFP CMR.  25 for training, 20 for testing |
| Architecture | Three Steps:   * Anatomical Structure Segmentation Network (ASSN): the ASSN performs pixel-wise classification based on processing   the intensity value of *Image.* However, the pathology usually leads to abnormal intensity  distribution in CMR images.   * In order to tackle this, a denoising   auto-encoder (DAE) is adopted to reconstruct the segmentation results with realistic shapes.  Finally, the complementary information from DAE is taken as an input for Pathological Region Segmentation Network to get the segmented mask |
| Performance Metrics | Dice Score: Scar: 0.6409 *± 0.*2596  Scar + Edema: 0.7024 *± 0.*1298 |

Detailed:

**Myocardial Edema and Scar Segmentation Using a Coarse-to-Fine Framework with Weighted Ensemble**

Introduce a novel ensemble method that train and predict the scar and edema regions in 2 and 2.5 dimensions. Counting for the performance in the two models, they introduce two weights to better ensemble models’ performance.

**Method:**

Our proposed framework for myocardial edema and scar segmentation can be summarised as data prepossession, coarse-to-fine segmentation, and model ensemble.

Data pre-processing: Crop the original images with cardiac bounding box. In coarse segmentation, due to the imbalance of foreground and background, we count the coordinate range of the targets in the training data. They expanded 30 voxels along each dimension and crop the images accordingly. In the fine segmentation, we similarly crop out the targets based on coarse segmentation results to reduce false positive.

Graphical user interface, application, website

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Coarse to fine segmentation: Because it is hard to segment the myocardial edema and scar directly, they split this task into two steps: a coarse step of LV myocardium segmentation and a fine step of edema and scar segmentation. scar. In coarse segmentation, we train a vanilla U-Net to segment 4 categories (i.e. background, complete ring-shaped myocardium, left ventricular (LV) blood pool and right ventricular (RV) blood pool). The input data set contains three sequences of CMR images: bSSFP, LGE and T2 which we directly concatenate to form 3-channel input. They use cross entropy loss and Dice loss for coarse segmentation training.

In the fine segmentation, the input images are cropped according to coarse predictions,and then they concatenate the coarse segmentation map and the croppedimages to form a 4-channel input to feed into the fine segmentation network. Ourfine segmentation network’s architecture is a variant of U-Net, as presented, where we add instance normalization (IN) and leaky rectified linearunit (Leaky ReLU) following every convolution layer.

2.5D CNN for Segmentation of Images with Anisotropic Resolutions:

For these images with high in-plane resolution and low through-plane resolution, 2D CNNs applied slice-by-slice will ignore inter-slice correlation. Isotropic 3D CNNs may need to upsample the image to an isotropic 3D resolution to balance the physical receptive field (in terms of mm rather than voxels) along each axis, which requires more memory and may limit the depth or feature numbers of the CNNs. Therefore, it is desirable to design a 2.5D CNN that can not only use inter-slice features but also be more efficient than 3D CNNs. In addition, to make the receptive field isotropic in terms of physical dimensions, the number of convolution along each axis should be different when dealing with such images.

A picture containing text, electronics, screenshot

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Model ensemble: A weighted ensemble method of 2D and 2.5D is exploited to get better prediction for each class. The author used a weighted ensemble strategy, where the prediction maps have 6 channels, and each channel represents one segmentation target.

Diagram

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