Revolutionizing Cardiac Image Segmentation with AL/ML Techniques

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Abstract

AI/ML has become the most widely used approach for cardiac image segmentation in recent years. In this study, cardiac image segmentation is performed using deep learning on common imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound, and on major anatomical structures of interest (ventricles, atria, and vessels). The key anatomical structures of interest in cardiac image segmentation typically encompass the LV, RV, left atrium (LA), right atrium (RA), and coronary arteries. A large portion of these methods are designed for ventricle segmentation.

Keywords: Cardiac image segmentation, Machine learning (ML), MRI, CT, Ultrasound.

Objective

- Using the deep learning-based methods like Fully Convolutional Neural Networks (FCNs), Recurrent Neural Networks (RNNs) etc. in an efficient and effective way to segment particular organs or tissues (e.g., the LV, coronary vessels, scars) in different modalities, facilitating follow-up quantitative analysis of cardiovascular structure and function.
- The objective of ventricle segmentation is to delineate the endocardium and epicardium of the LV and/or RV. These segmentation maps are important for deriving clinical indices, such as left ventricular end-diastolic volume(LVEDV), left ventricular end-systolic volume (LVESV), RVEDV, RVESV, and EF.

Theory and Methodology

- **Vanilla FCN-based segmentation:** The FCN architecture consists of an encoder network, which processes the input image and extracts hierarchical features, and a decoder network, which upsamples the features to generate dense pixel-wise predictions.
- **Introducing spatial or temporal context:** 2D networks can fail to locate and segment the heart on challenging slices, such as apical and basal slices where the contours of the ventricles are not well-defined. To address this problem, we can introduce additional contextual information to guide 2D FCN. This contextual information can include shape priors learnt from labels or multi-view images
- **Applying anatomical constraints:** The pixel-wise loss functions may not be sufficient to learn features that represent the underlying anatomical structures. Therefore, we can focus on designing and applying anatomical constraints to train the network to improve its prediction accuracy and robustness.
- **Multi-task learning:** Training a network for multiple tasks simultaneously encourages the network to extract features that are useful across these tasks, resulting in improved learning efficiency and prediction accuracy.
- **Multi-stage networks:** By applying neural networks in a multi-stage pipeline that breaks down the segmentation problem into subtasks. For example, a region-of-interest (ROI) localization network followed by a segmentation network.
- **Hybrid segmentation methods:** Another stream of work aims at combining neural networks with classical segmentation approaches, e.g., level-sets, deformable models, atlas-based methods, and graph-cut based methods. Here, neural networks are applied in the feature extraction and model initialization stages, reducing the dependency on manual interactions and improving the segmentation accuracy of the conventional segmentation methods deployed afterwards.

Results1

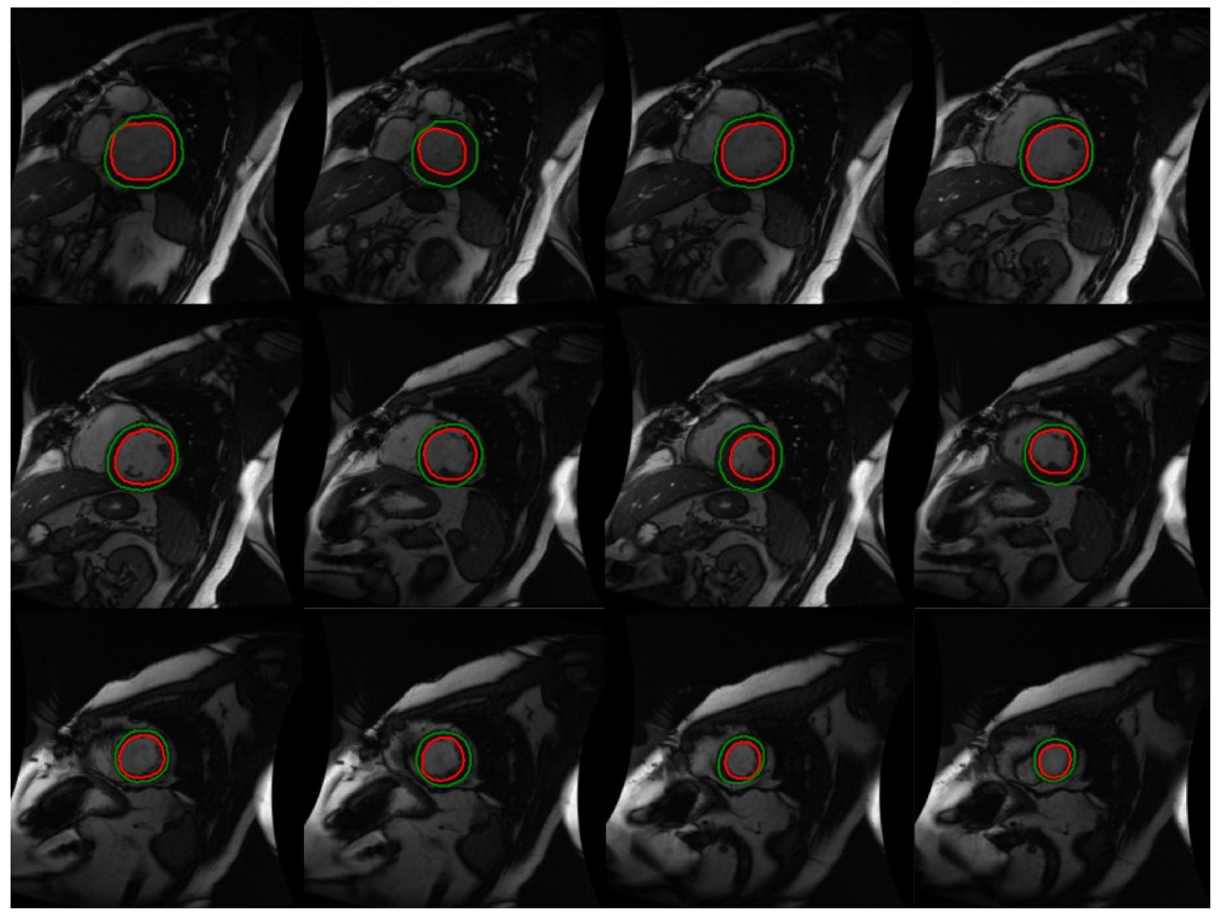

Figure 1: FCN segmentation result of an example test case in the Sunnybrook dataset for both ED and ES phases.Colors: red – endocardium; green – epicardium.

Results2

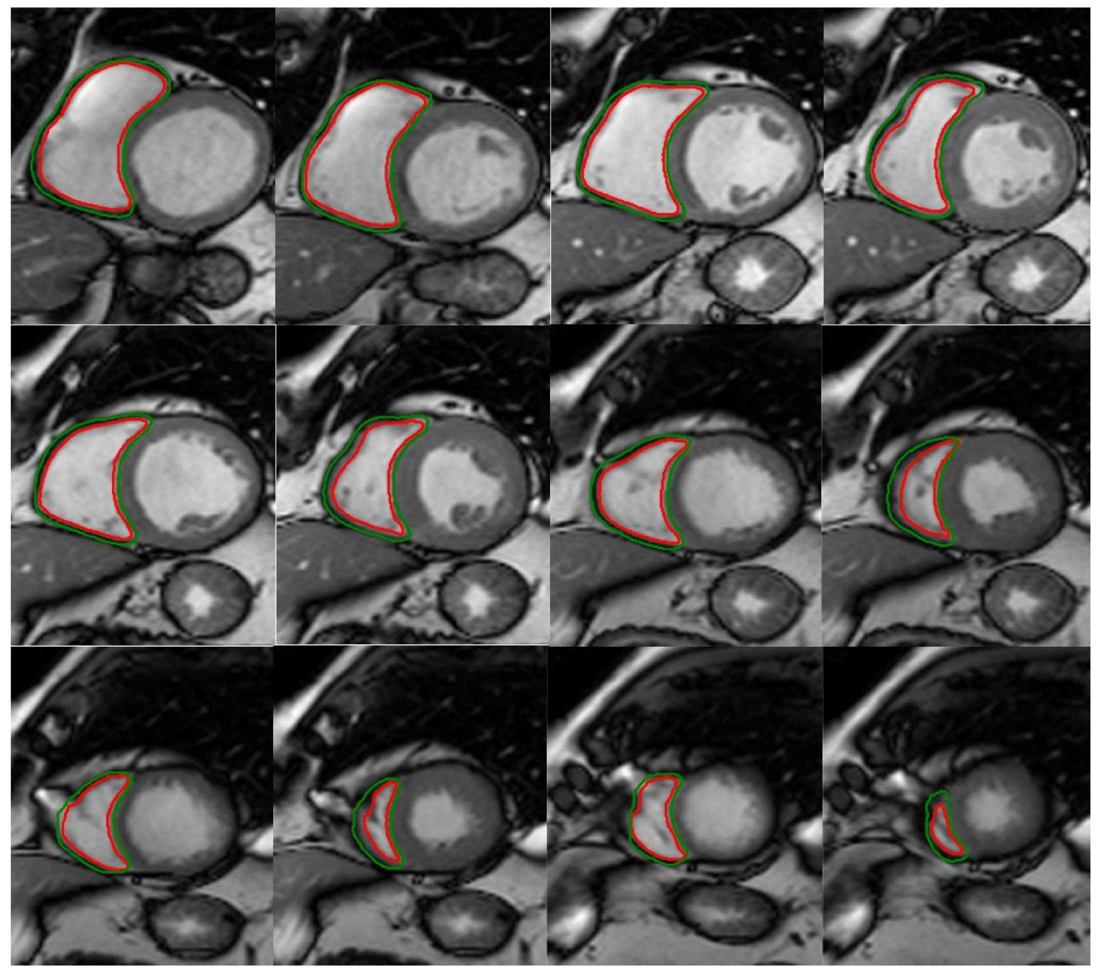

Figure 2: FCN segmentation result of an example test case in the RVSC dataset for both ED and ES phases. Colors:red– endocardium; green– epicardium.

Discussion and Conclusion

In this paper, we demonstrated the utility and efficacy of a fully convolutional neural network architecture for semantic segmentation in cardiac MRI. We showed that a single FCN model can be trained end-to-end to learn intricate features useful for segmenting both the left and right ventricle. Comprehensive empirical evaluations revealed that our FCN model achieves state-of-the-art segmentation accuracy on multiple metrics and benchmark MRI datasets exhibiting real-world variability in image quality and cardiac anatomical and functional characteristics across sites, institutions, scanners, populations, and heart conditions.Moreover, the FCN model is fast, and can run on commodity compute resources such as the GPU to enable cardiac segmentation at massive scales.

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