Towards reducing segmentation labeling costs for CMR imaging using explainable AI

Alessa Stria, BSc[1], Asan Agibetov, PhD[1]

[1] Institute of Artificial Intelligence and Decision Support – Medical University of Vienna; Währingerstraße 25a, 1090 Vienna, Austria
alessa.stria@meduniwien.ac.at; asan.agibetov@meduniwien.ac.at

MEDIZINISCHE UNIVERSITÄT WIEN

Introduction

Segmented cardiac magnetic resonance (CMR) images allow us to computationally quantify important morphological and pathological changes, such as stroke volume or ejection fraction. These features are essential in cardiac disease quantification and non-invasive pre-clinical diagnosis [1]. To facilitate the computation of such features, deep-learning-based cardiac segmentation algorithms have been recently proposed in literature [2-4].

While these algorithms promise the creation of (semi-) automatic segmentation tools, their successful application is heavily conditioned on the availability of large amounts of labeled segmented data. Unfortunately, obtaining segmented MR images is a tedious and time-consuming delineation task that represents a big challenge in the cardiac imaging domain. Compared to segmentation labels, classification labels, e.g., patient's diagnosis, are much easier to obtain. Indeed, a cardiologist may need to look at a few MR slices and establish the diagnosis, whereas manual segmentation may take hours. In Figure 1 the difference of a classification model and a segmentation model is shown.

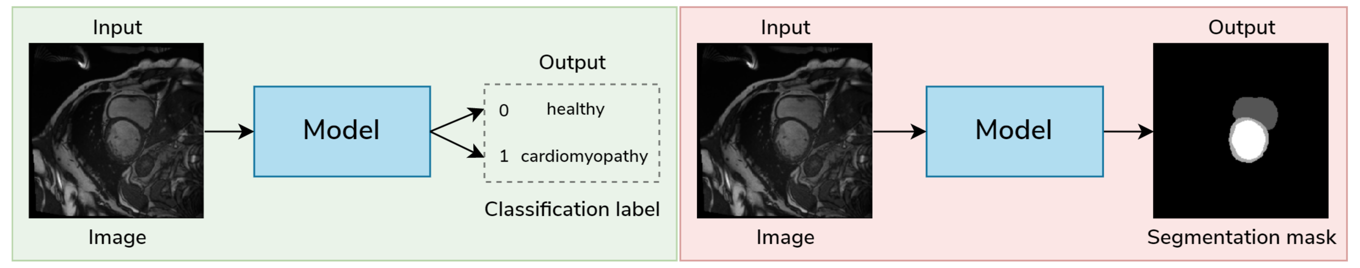

Figure 1: Green panel (left): A classification prediction model that takes an MR image as input and outputs a classification score, or a probability, of the input belonging to a specific category, e.g., disease or no disease. Red panel (right): A segmentation model takes as input an MR image and outputs a segmentation mask for the desired anatomical region in the image, e.g., delineation of heart chambers.
(MR images source: [2])

Here we present our preliminary results and a vision, for a computational framework to reduce sample size-dependence for automated segmentation in CMR imaging. Our main hypothesis is that a (pre-trained) AI classification model could be used as a template for segmentation labels. The segmentation framework uses the anatomical priors extracted from a classification model with explainable artificial intelligence (XAI) techniques.

Methods

The proposed methodology re-purposes a pre-trained classification model by obtaining the class activation maps (CAMs [5]) as segmentation priors. CAM is an explainable AI technique that generates a localization map, which highlights the relevant regions of the image with respect to the prediction of the deep learning model. These proxy labels guide the training process of a segmentation model, by penalizing the algorithm whenever it proposes segmentation maps that differ too much from the anatomical prior. An overview of the methodology is presented in Figure 2.

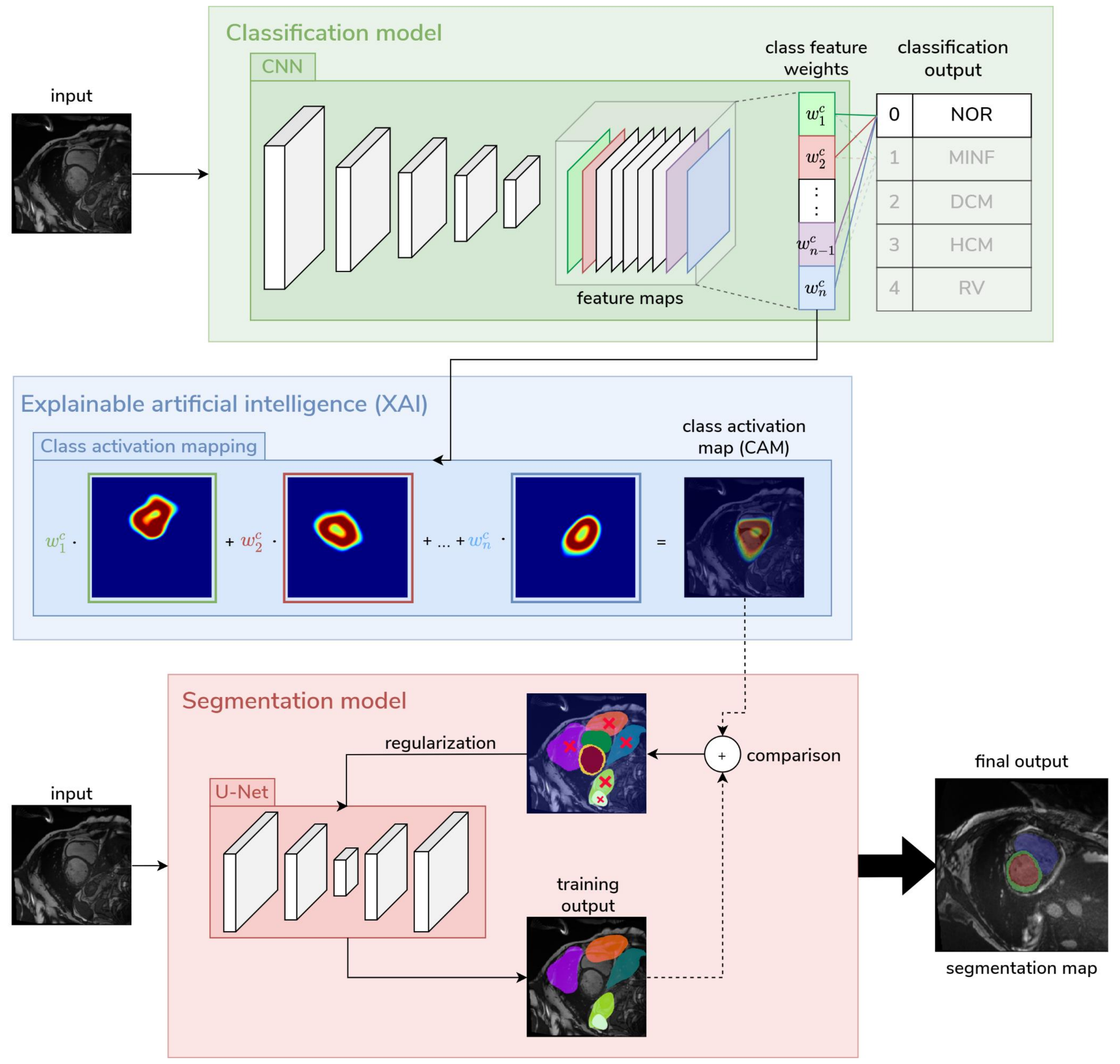

Figure 2: A high-level view of our methodology. Explainable AI techniques are used to extract the approximate positions (priors) of the desired anatomical region of interest in the MR image. These priors are then used to guide the segmentation model, and to reduce the overall search space of possible anatomical regions. (MR images source: [2])

Data

For development and evaluation, the Automatic Cardiac Diagnosis Challenge (ACDC) dataset from the University Hospital of Dijon is used [2]. The patients are split equally into five disease groups:

- Healthy
- Previous myocardial infarction
- Dilated cardiomyopathy
- Hypertrophic cardiomyopathy
- Abnormal right

Cine MR images of 100 patients as well as their segmentation ground truth masks from the ACDC datasets were used to train a convolutional neural network (CNN) as our multiclass classification model. The individual 2D image slices were stratified by patient split into training, validation, and test set resulting in 1150, 382, 370 images, respectively.

Evaluation

The performance of the trained classification model was evaluated according to accuracy metrics, area under the receiver-operating characteristic curve (ROC AUC), and F1-Score.

CAMs from our classification network were extracted and compared to the ground truth using the Jaccard index. This index measures the similarity of two segmentation masks by computing the ratio of overlapping area to their union.

Results

The ROC AUC scores and Jaccard scores for the different diagnoses are illustrated in (Table 1). A random model would have a ROC AUC of 0.5 for either of these categories. Jaccard score of 1 represents a perfect segmentation model.

Table 1: ROC AUC and Jaccard scores of the five different classes as well as the mean over all classes. NOR = normal/healthy, MINF = previous myocardial infarction, DCM = dilated cardiomyopathy, HCM = hypertrophic cardiomyopathy, RV = abnormal right

	Jaccard score				ROC AUC
Diagnosis class	Training set	Validation set	Test set	Mean	
NOR	0.15	0.26	0.11	0.16	0.55
MINF	0.20	0.21	0.16	0.20	0.41
DCM	0.26	0.26	0.23	0.25	0.80
HCM	0.14	0.13	0.17	0.14	0.40
RV	0.15	0.22	0.17	0.17	0.69
Mean	0.18	0.22	0.17	0.18	0.57

Overall, our pre-trained classification model achieved a weighted F1 score of 0.23 for this five-class prediction problem. This is only slightly superior to a pure random performance, which would have an F1 score of 0.2 for 5 categories. This is additionally supported by the mean ROC AUC of our model which equals 0.57. However, by visually examining the class activation maps of this pre-trained model we noticed that it was attending closer to the heart region. In fact, the produced segmentation maps from the model were of high quality, focusing on essential structures.

On some slices, the Jaccard score was as high as 0.8, i.e., 80% of overlap with the ground truth segmentation. The average Jaccard index for the whole holdout test set was 0.18, i.e., 18% overlap on all cine MR image slices. Figure 3 presents the two best and worst generated CAMs according to the Jaccard score, the input CMR slice as well as the ground truth mask are additionally displayed for comparison.

Conclusion

Our preliminary results open a promising research direction that shows that even a far from perfect pre-trained classification model could be used to produce sensible segmentation masks, with an average overlapping index of 18% (Jaccard score). This is particularly encouraging because the AI model was not trained on segmentation labels at all. The big assumption is that a good classification prediction model understands the underlying structure of the input image, by "attending" to the anatomic heart region in the image. We are currently testing the limits of our hypothesis and measuring the effective impact on the reduction of sample size dependency that it can bring.

Our generic methodology might well support the creation of automatic segmentation tools in cardiac MRI that drastically reduce the dependence and thereby the cost on time-consuming delineation labels. Furthermore, it could be incorporated into multi-modal prediction models to improve the research and development of cardiac clinical decision support tools, especially in rare diseases [6]. Eventually, we intend to open-source our framework for the cardiological community.

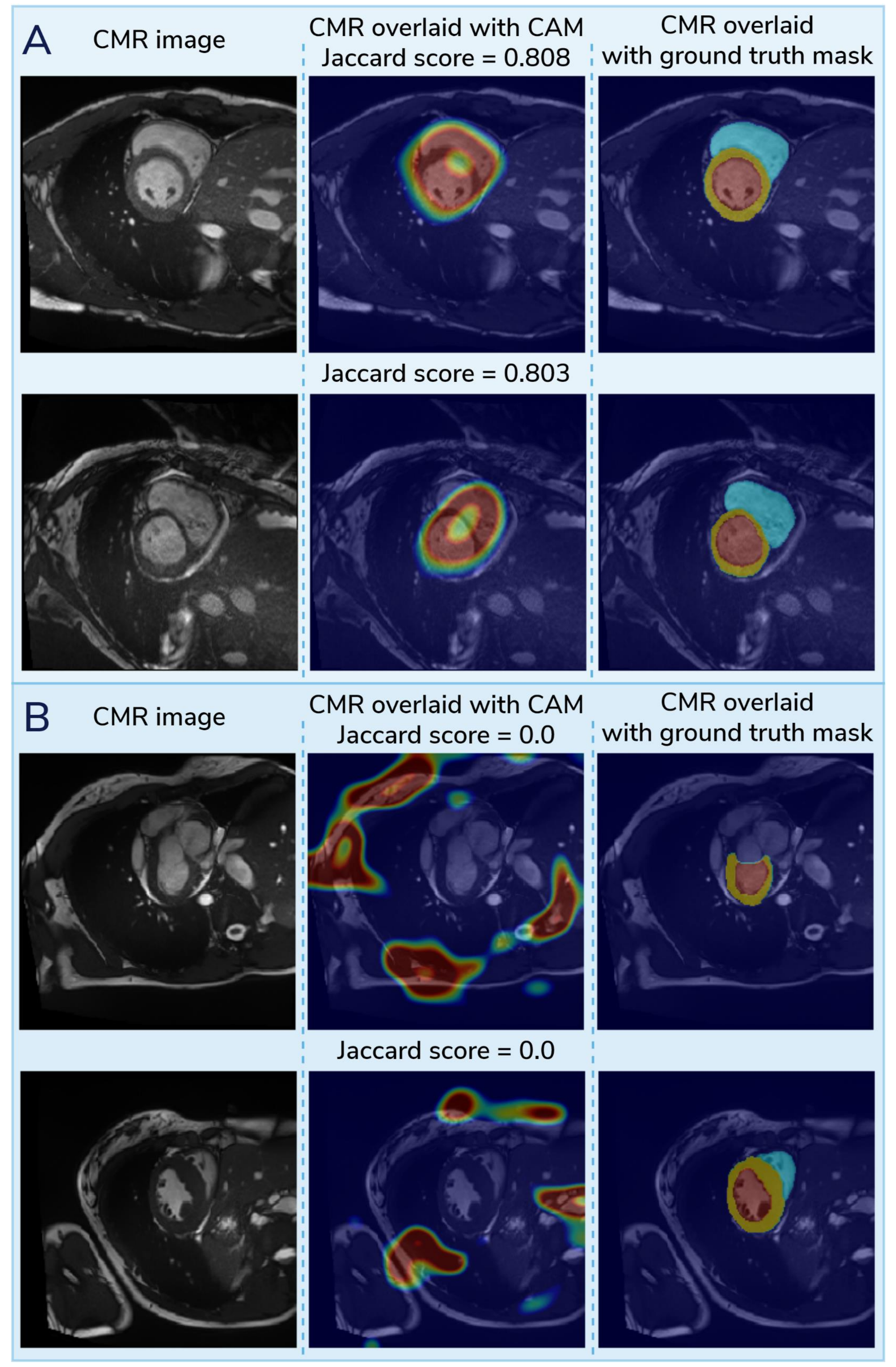

Figure 3: Panel A shows two different examples of one of the best CAM results. The CMR slice is on the left-hand side, the CMR slice with our generated CAM as overlay and the calculated Jaccard score for each example is in the middle. The CMR with the ground truth mask as overlay is on the right. Panel B shows the two worst cases.

Funding

AS, AA funding from ÖKG Forschungsstipendium "Reducing costs of segmentation labeling in cardiac MRI using explainable AI" May 2021 – April 2022.

Conflict of Interests

The authors declare no conflict of interest.

References

[1] Peng P, Lekadir K, Gooya A, Shao L, Petersen SE, Frangi AF. A review of heart chamber segmentation for structural and functional analysis using cardiac magnetic resonance imaging. Magnetic Resonance Materials in Physics, Biology and Medicine 2016;29:155-195.
[2] Bernard O, Lalande A, Zotti C et al. Deep Learning Techniques for Automatic MRI Cardiac Multi-Structures Segmentation and Diagnosis: Is the Problem Solved? IEEE Trans Med Imaging 2018;37:2514-2525.
[3] Chen C, Qin C, Qiu H et al. Deep Learning for Cardiac Image Segmentation: A Review. Front Cardiovasc Med 2020;7:25-25.
[4] Oktay O, Ferrante E, Kamnitsas K et al. Anatomically constrained neural networks (acnns): application to cardiac image enhancement and segmentation. IEEE Trans Med Imaging 2018;37:384-395.
[5] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, 'Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization', Int J Comput Vis, vol. 128, no. 2, pp. 336–359, Feb. 2020, doi: 10.1007/s11263-019-01228-7.
[6] A. Agibetov et al., "Machine Learning Enables Prediction of Cardiac Amyloidosis by Routine Laboratory Parameters: A Proof-of-Concept Study," Journal of Clinical Medicine, vol. 9, no. 5, Art. no. 5, May 2020, doi: 10.3390/jcm9051334.