

## Multi-planar heart segmentation of 3D CT images with 2D spatial propagation CNN

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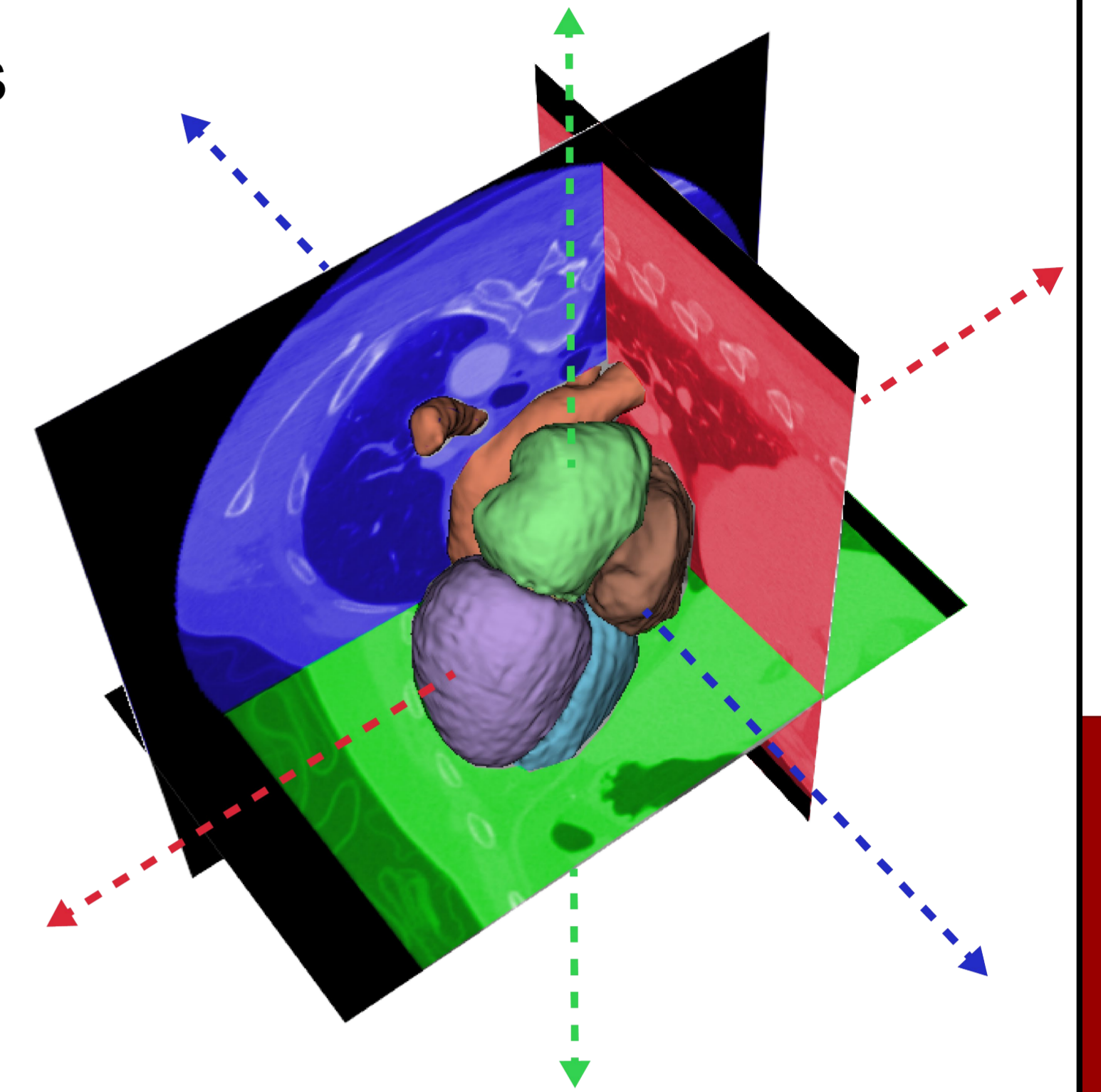
The combination of spatial propagation in the network structure and a multi-planar setup enables 2D networks to capture 3D information in cardiac CT scans

### INTRODUCTION

- Heart segmentation is a challenging and tedious task
- Automatic segmentation of the heart structures has thus become a popular challenge
- Aim is to utilize 2D networks in a multi-planar setup in order to create a multi-class segmentation of the seven major heart structures: right and left ventricle, right and left atrium, left myocardium, pulmonary arteries and aorta
- Attempts to include spatial consistency in the segmentation by employing a convolutional neural network with spatial propagation
- Cardiac CT scans from the MICCAI 2017 challenge "Multi-Modality Whole Heart Segmentation" is used

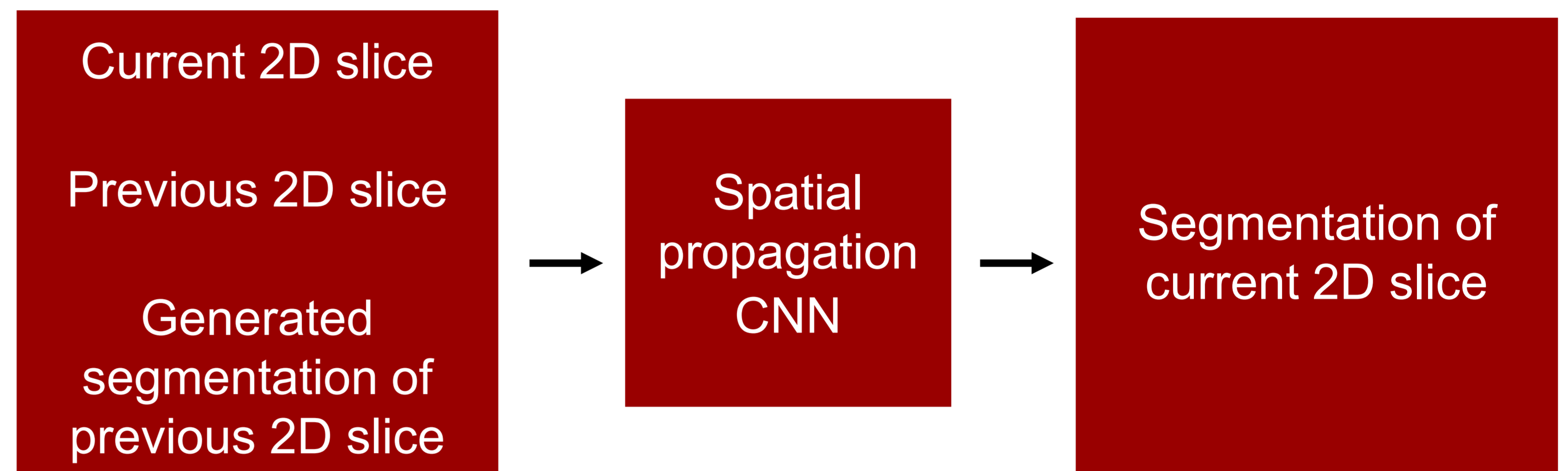
### METHODS – MULTIPLANAR SETUP

- Multi-planar setup analyses a 3D image volume using three 2D networks
- The 2D networks each generate a segmentation from a particular viewing direction.
- The three probability maps from the networks are merged into one final segmentation
- Attempts to include spatial information and avoid edges between slices

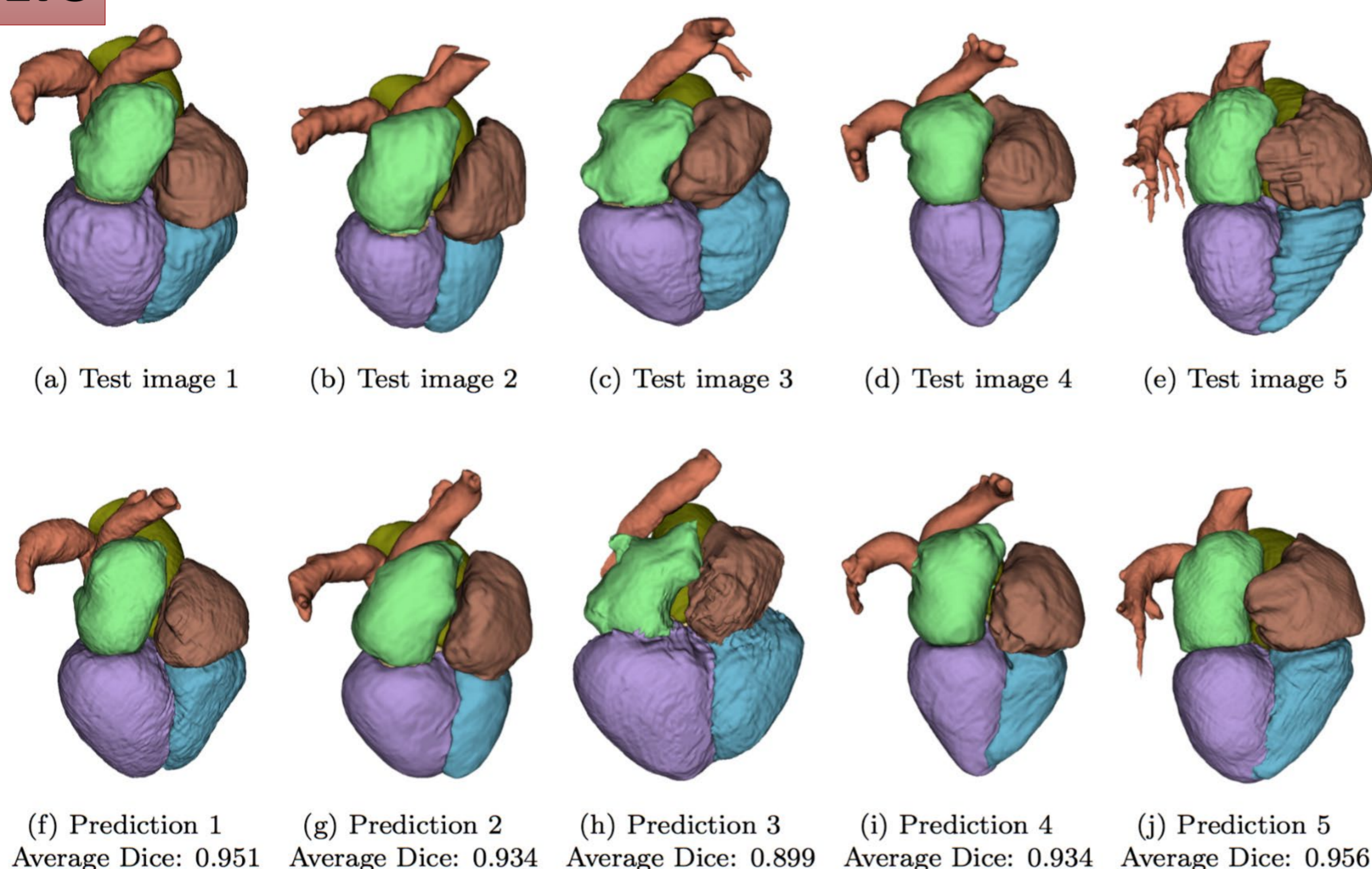


### METHODS – SPATIAL PROPAGATION CNN

- 2D segmentation are generated using spatial propagation convolutional neural network
- An extended version of the U-net [1] with an additional input, inspired by [2]
- Network structure has two contracting paths, one for current input, and one for additional information from previous input



### RESULTS



Approach	Dice	Jaccard	SD (mm)	HD (mm)
Payer et al.	0.908 ± 0.086	0.832 ± 0.037	1.117 ± 0.250	25.242 ± 10.813
Wang et al.	0.894 ± 0.030	0.810 ± 0.048	1.387 ± 0.516	31.146 ± 13.203
Yang et al.	0.890 ± 0.049	0.805 ± 0.074	1.432 ± 0.590	29.006 ± 15.804
Yang et al.	0.887 ± 0.030	0.798 ± 0.048	1.443 ± 0.302	55.426 ± 10.924
Shi et al.	0.886 ± 0.047	0.798 ± 0.072	1.681 ± 0.593	41.974 ± 16.287
This approach	0.886 ± 0.064	0.800 ± 0.089	1.428 ± 1.146	25.864 ± 12.965
Mortazi et al.	0.879 ± 0.079	0.792 ± 0.106	1.538 ± 1.006	28.481 ± 11.434
Yang et al.	0.879 ± 0.023	0.784 ± 0.036	1.705 ± 0.399	34.129 ± 12.528
Tong et al.	0.849 ± 0.061	0.742 ± 0.086	1.925 ± 0.924	44.880 ± 16.084
Galisot et al.	0.838 ± 0.152	0.742 ± 0.161	4.812 ± 13.604	34.634 ± 12.351
Wang et al.	0.806 ± 0.159	0.697 ± 0.166	4.197 ± 7.780	51.922 ± 17.482
Average	0.875 ± 0.083	0.784 ± 0.010	1.840 ± 2.963	38.510 ± 17.890

Table shows the results of the participants in the MICCAI 2017 challenge "Multi-Modality Whole Heart Segmentation" [3] challenge together with the results of this study

### CONCLUSION

- MICCAI rankings
  - Very similar Dice scores as the 4<sup>th</sup> and 5<sup>th</sup> best performing approaches
  - 4<sup>th</sup> best in regards to Jaccard index
  - 3<sup>rd</sup> best in regards to surface-to-surface distance
  - 2<sup>nd</sup> best in regards to Hausdorff distance
- This novel approach exploits the advantages of 2D CNN, while addressing the issues of spatial context in a 3D images volume
- Shows that 3D spatial context can be captured using 2D networks using this combination of spatial propagation network and a multi-planar approach

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### References

- [1] Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation  
[2] Zheng et al., 2018, 3D Consistent & Robust Segmentation of Cardiac Images by Deep Learning with Spatial Propagation  
[3] Zhuang et al., 2019, Evaluation of Algorithms for Multi-Modality Whole Heart Segmentation: An Open-Access Grand Challenge