



Fully automated normal, infarcted and edema segmentation



Xiaoran Zhang¹, Michelle Noga², Kumaradevan Punithakumar²

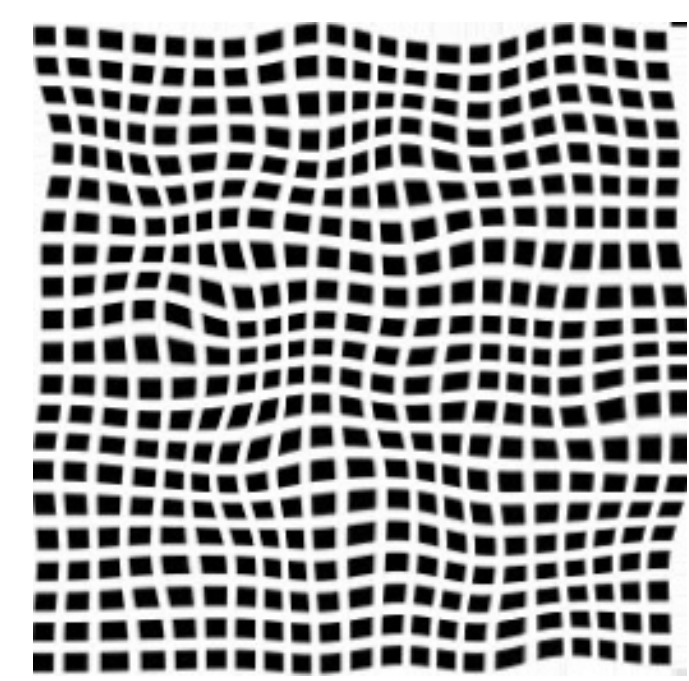
¹ Department of Electrical and Computer Engineering, UCLA ² Department of Radiology & Diagnostic Imaging, University of Alberta

Introduction

- Utilizing the combination of CMR sequences will allow a more robust and accurate diagnostic information for myocardial infarction^[1].
- The inter-observer variation of manual scar segmentation is high with a reported Dice score of 0.5243 ± 0.1578 ^[1].
- This study proposes a fully automated approach by utilizing deep convolutional neural networks to delineate left ventricular (LV) blood pool (BP), right ventricle (RV) BP, LV normal myocardium (NM), LV myocardial edema (ME) and LV myocardial scars (MS).

Augmentation Module

We utilize a non-rigid random warping and a random rotation scheme to augment our data.



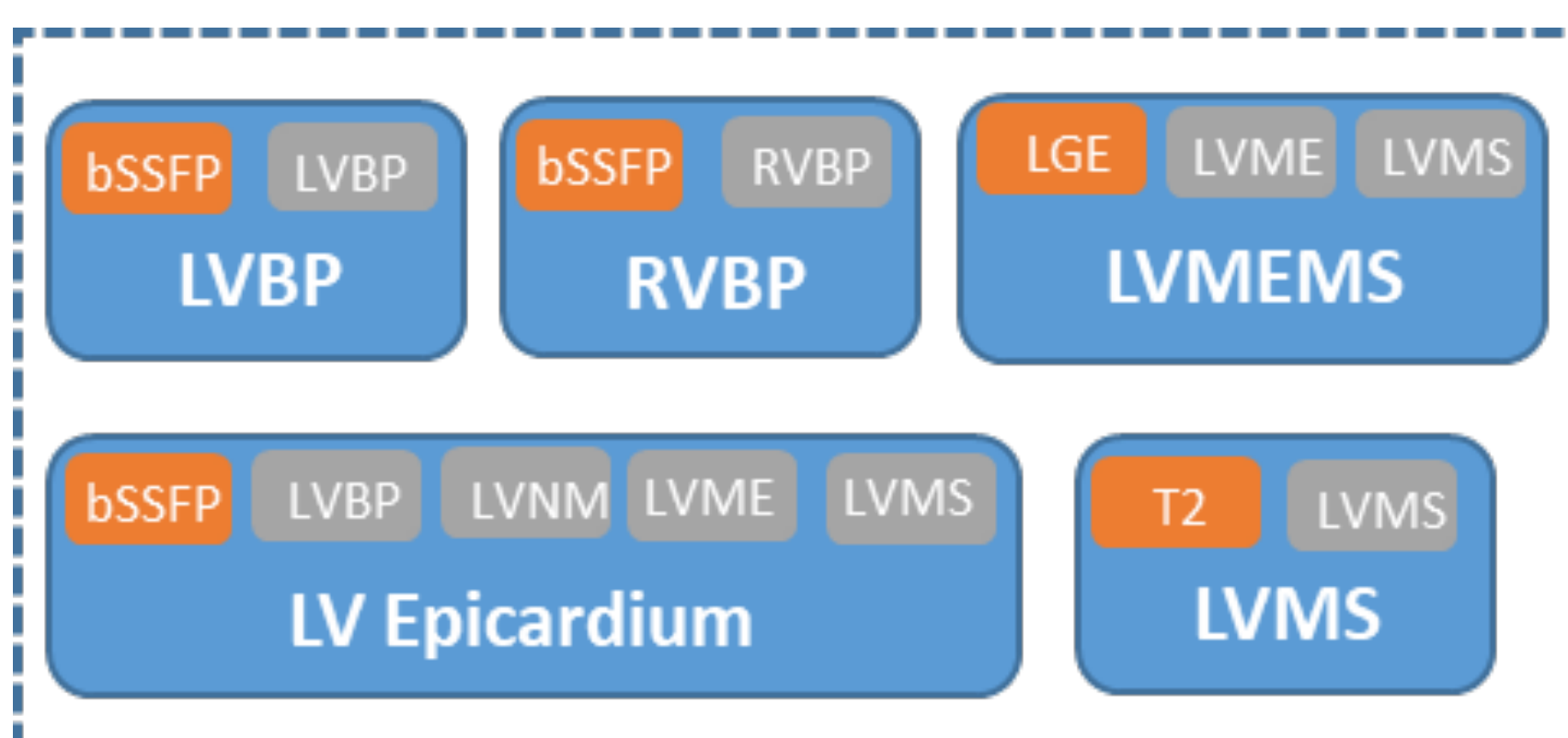
$$\begin{bmatrix} \cos(q) & \sin(q) & 0 \\ -\sin(q) & \cos(q) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Random warp

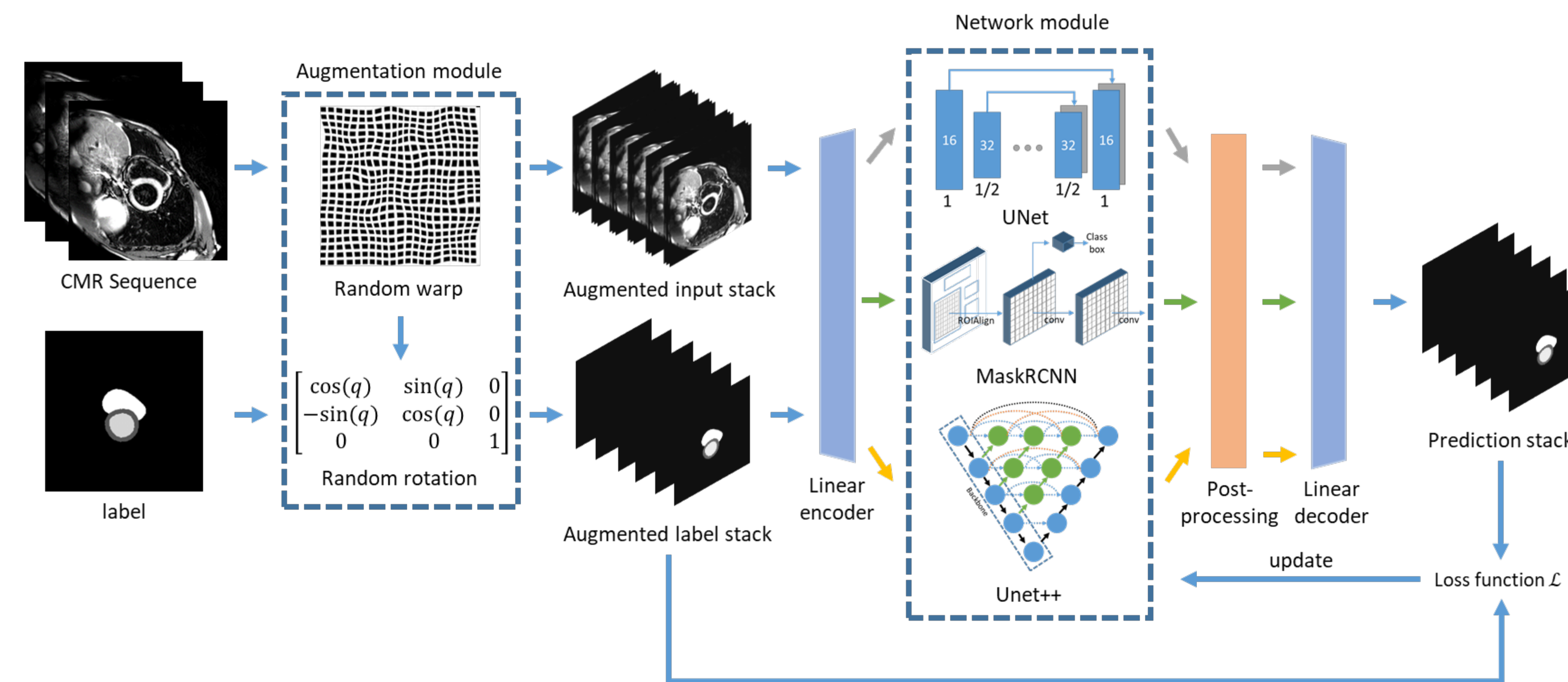
Random rotation

Linear Encoder

We encode the input and label sequences and produce five input blocks for network module.



Overall Architecture



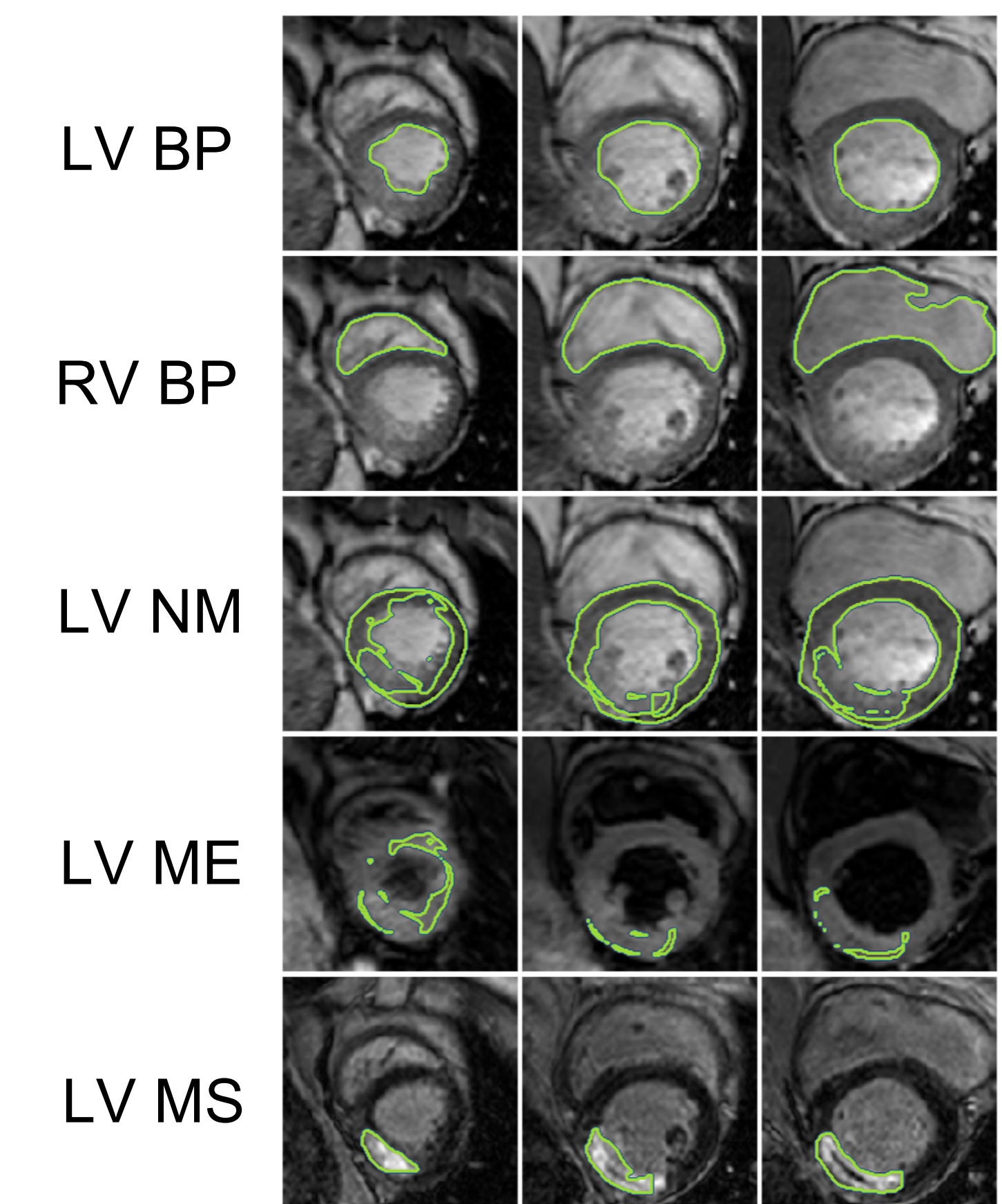
Linear Decoder

The linear decoder performs linear subtraction for predicted masks from the network module and includes a binary myocardium constraint for LV ME and LV MS.

$$P_i = \begin{cases} \sigma(\bar{P}_0) & i = 0 \\ \sigma(\bar{P}_1) & i = 1 \\ \sigma(\bar{P}_2 - \bar{P}_0 - \bar{P}_3) & i = 2 \\ \sigma(\bar{P}_2 - \bar{P}_0) \circ \sigma(\bar{P}_3 - \bar{P}_4) & i = 3 \\ \sigma(\bar{P}_2 - \bar{P}_0) \circ \sigma(\bar{P}_4) & i = 4 \end{cases}$$

Results

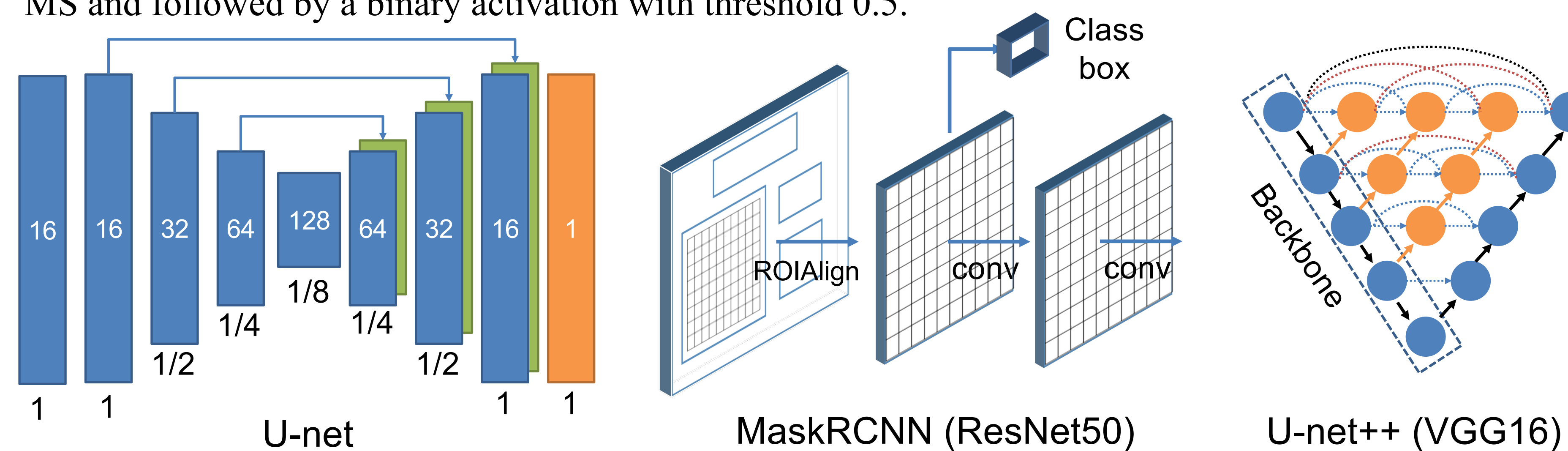
The proposed method is evaluated over images acquired from a total of 20 cases including CMR sequences after trained and validated using 25 cases.



Layer 1 Layer 2 Layer 3

Network Module

We utilize three different architectures including U-net^[2], MaskRCNN^[3], and U-net++^[4] with different input blocks for each model. The results are averaged from the three networks for LV ME+MS and LV MS and followed by a binary activation with threshold 0.5.



References

[1] Zhuang, Xiahai. "Multivariate mixture model for myocardial segmentation combining multi-source images." IEEE Transactions on Pattern Analysis and Machine Intelligence 41.12 (2018): 2933-2946.
 [2] Ronneberger, Olaf, et al. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2015.
 [3] He, Kaiming, et al. "Mask R-CNN." Proceedings of the IEEE International Conference on Computer Vision. 2017.
 [4] Zhou, Zongwei, et al. "Unet++: Redesigning skip connections to exploit multiscale features in image segmentation." IEEE Transactions on Medical Imaging 39.6 (2019): 1856-1867.

Methods	Dice metric (%)		Jaccard index(%)	
	MS	ME+MS	MS	ME+MS
UNet	36.2 ± 23.2	43.2 ± 16.0	24.5 ± 18.1	28.8 ± 13.1
Proposed [†]	38.5 ± 24.3	54.2 ± 17.1	26.5 ± 18.9	38.9 ± 15.0
Proposed	46.8 ± 26.8	55.7 ± 18.3	34.2 ± 22.2	40.5 ± 16.3

[†] indicates without the linear encoder and decoder module.