Dilated Convolutions in Neural Networks for Left Atrial Segmentation in 3D Gadolinium Enhanced-MRI

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Introduction

- **Atrial fibrillation (AF)** is the most common type of cardiac arrhythmia, with higher rates of incidence among aging populations [1].

Aim:
- Automatic segmentation of the left atrial chamber:
  (1) Improve understanding of the electrical and structural remodelling characteristics of the human atria
  (2) Diagnosis, treatment planning and patient prognosis
  (3) Manual segmentation is highly subjective [2]

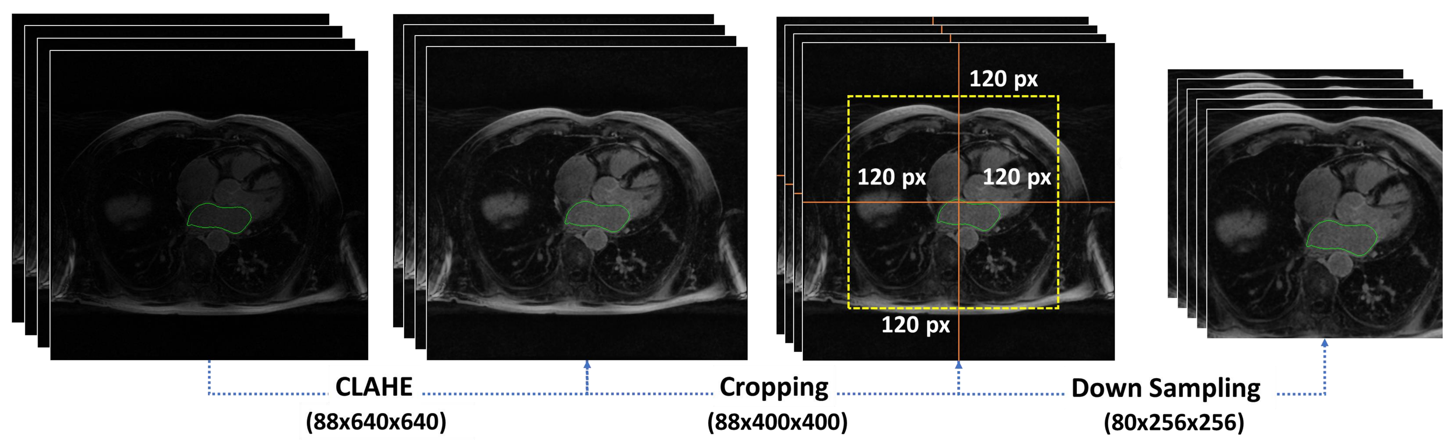
Material and Methods

Accurate organ segmentation requires incorporation of both local and global information.

3D U-Net + DR

- A modified version of the 3D U-Net, using **dilated convolutions** [3] in lowest part of the network (Fig. 1)
  → Extract features spanning a wider spatial range
- **Residual connections** to better incorporate **multi-scale** image information
- 3D convolutions to prevent loss of **inter-slice** information

Pre-Processing



Loss Function

- Binary Cross Entropy + Dice Coefficient Loss[4]

$$\zeta\,(y,\hat{y}) = \zeta_{bce}\,(y,\hat{y}) + \zeta_{dc}(y,\hat{y})$$

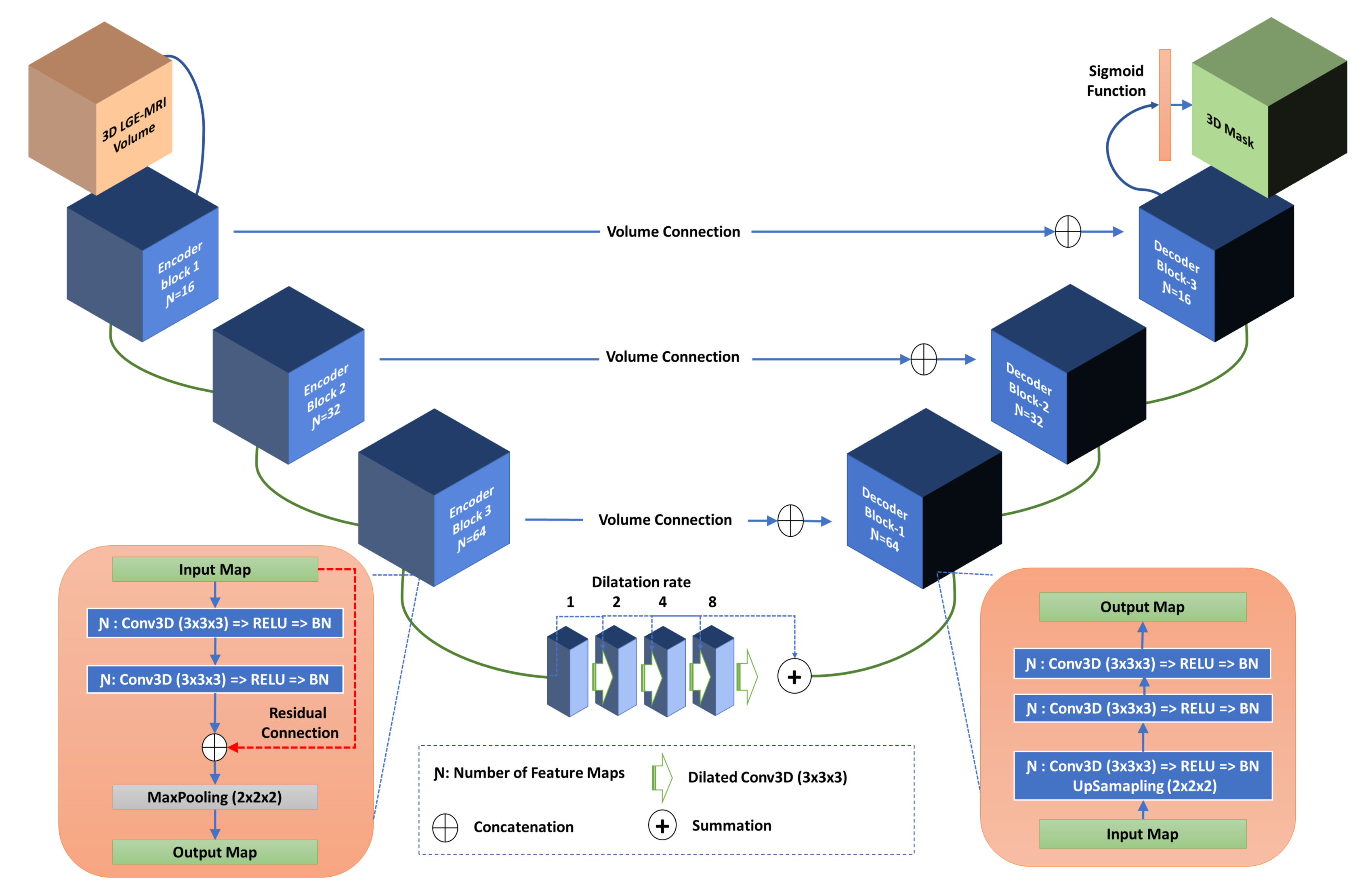


Figure 1: 3D U-Net + DR network architecture.

Results and Discussion

- Five-fold cross validation experiments using **80 Late Gadolinium Enhanced-MRI volumes**
  a) Significant improvements in segmentation accuracy
     → incorporating mutli-scale information using **residual connections**
     → adding dilated convolutions to expand field of view
     → dataset normalization using mean/std subtraction
- **90.1 %** Dice coefficient accuracy on **20 unseen LGE-MRIs**
- 3D U-Net + DR with **2.6 million** parameters

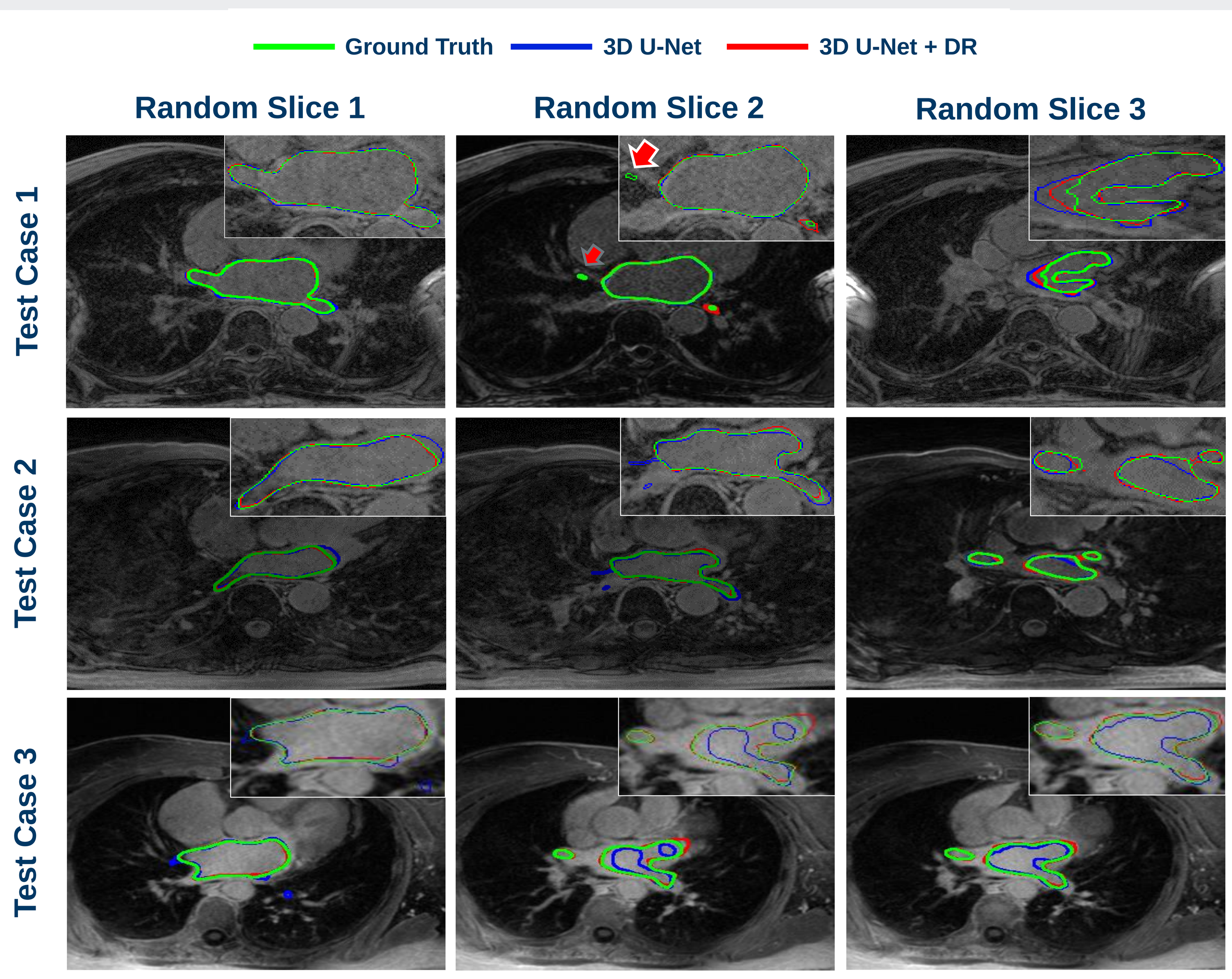


Figure 2: 3D U-Net and 3D U-Net + DR segmentation outputs.

Methods	Training			Validation			Testing		
	Loss	Dice	Jaccard	Loss	Dice	Jaccard	Loss	Dice	Jaccard
3D U-Net (Min max Normalisation)	0.126	0.896	0.844	0.227	0.818	0.728	0.223	0.818	0.74
3D U-Net + DR (Min max Normalisation)	0.093	0.923	0.873	0.179	0.858	0.768	0.185	0.848	0.77
3D U-Net (Mean/STD normalisation)	0.038	0.968	0.943	0.157	0.879	0.797	0.133	0.898	0.819
3D U-Net + DR (Mean/STD normalisation)	**0.030**	**0.975**	**0.951**	**0.125**	**0.902**	**0.826**	**0.129**	**0.901**	**0.825**

Conclusion

- Proposed segmentation network **3D U-Net + DR:**
  → Use of 3D convolutions prevented loss of inter-slice information
  → Achieved higher segmentation accuracy than 3D U-Net due to incorporation of global context via dilated convolutions
  → Fewer parameters **(2.6 million vs 3.3 million)**
  → Fast and robust segmentation (**2.2 seconds/volume**)

References

[1] Guang Y *et al.* Medical Physics. 2018
[2] Qian T *et al.* Magnetic Resonance Imaging Journal. 2018
[3] Yu F *et al.* ICLR. 2016
[4] Milletari F et al. 3D Vision. 2016

Contact

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