

Distill DSM: Computationally efficient method for segmentation of medical imaging volumes

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Overview

Aim: Given an medical imaging volume, output the segmentation map based on given classes

Challenges:

- 2D CNN is computationally efficient, but leads to poor performance for segmentation task of 3D volume
- 3D CNN is computationally inefficient, but leads to good performance for segmentation task of 3D volume.

Contribution:

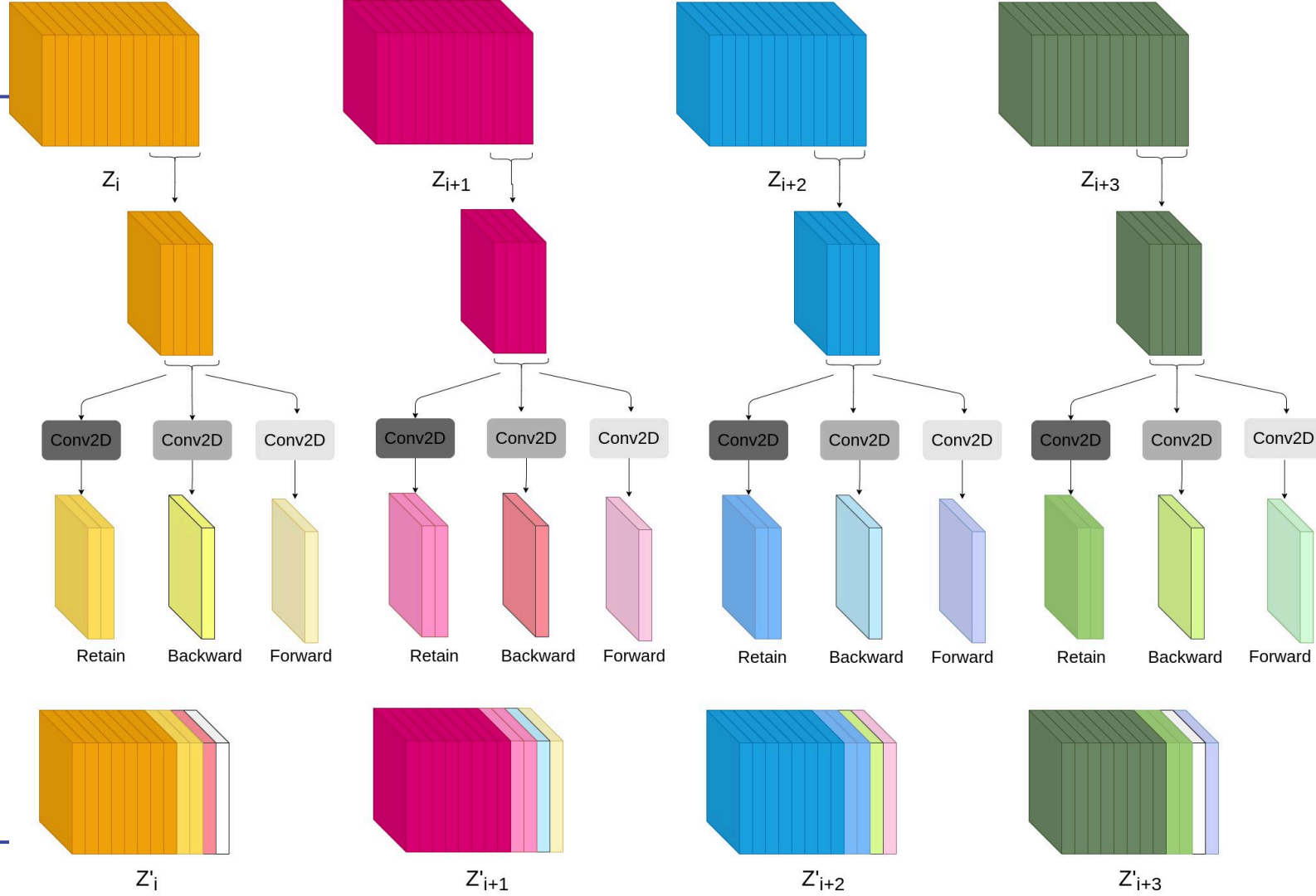
- Propose a framework for adapting a 2D CNN to process 3D volume by introducing cross depth modelling module
- Proposed solution is a plug and play module which could be into any 2D CNN architecture to model information along Z-dimension.
- A comprehensive evaluation is done on 5 Dataset to prove the effectiveness of solution.



Method

Proposed Approach: The proposed approach enables exchange of information among the neighbouring slice. It is done by exchanging the distilled information. Distilled information have three components of information.

- $\mathbf{R}_i \subseteq \mathbb{R}^{\alpha C/2 \times h \times w}$: Necessary information to retain in \mathbf{Z}_i
- $\mathbf{F}_i \subseteq \mathbb{R}^{\alpha C/4 \times h \times w}$: Necessary information to pass to forward slice \mathbf{Z}_{i+1}
- $\mathbf{B}_i \subseteq \mathbb{R}^{\alpha C/4 \times h \times w}$: Necessary information to pass to backward slice \mathbf{Z}_{i-1} .



Distill DSM





Result

	Class	2D UNet	Residual DSM	3D UNet	Distill DSM
BRATS	ET	0.712	0.732	0.704	0.753
	WT	0.861	0.867	0.879	0.873
	TC	0.687	0.704	0.796	0.742
Heart	1	0.9025±0.004	0.9076±0.009	0.9180±0.009	0.9235±0.011
Hippocampus	1	0.8802±0.002	0.8901±0.007	0.8993±0.004	0.8955±0.005
	2	0.8618±0.011	0.8648±0.010	0.8847±0.008	0.8786±0.008
Prostate	1	0.7847±0.041	0.7948±0.033	0.8164±0.041	0.8724±0.014
	2	0.6978±0.085	0.7021±0.07	0.7339±0.066	0.7804±0.081

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