



Improving Semantic Segmentation of 3D Medical Images on CNNs

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1. Overview

► PROBLEM

- A good formulation of a loss function is crucial for training a segmentation network.
- Typical classification loss functions adapted to semantic segmentation may fail to measure error in a class-imbalanced context.
- Medical images suffer of class-imbalance.

► CONTRIBUTION

- A loss function for training a semantic segmentation CNN, that automatically deals with class imbalance on medical images.
- Compare our results against other pre-existing loss functions.

► PRE-EXISTING LOSSES

$$L = -\frac{1}{N} \sum_{n=1}^N \sum_{k=1}^K (G_k^n \log(P_k^n)) \quad (1)$$

$$2 \times \frac{\theta_{TP}}{(2 \times \theta_{TP} + \theta_{FP} + \theta_{FN})} \quad (2)$$

$$2 \times \frac{\theta_{TP}}{(\theta_{TP} + \theta_{FN})^2 + (\theta_{TP} + \theta_{FP})^2} \quad (3)$$

Cross-Entropy (1), Dice Loss (2) and Generalised Wasserstein Dice Loss (3).

2. V-Net (Fausto M.)

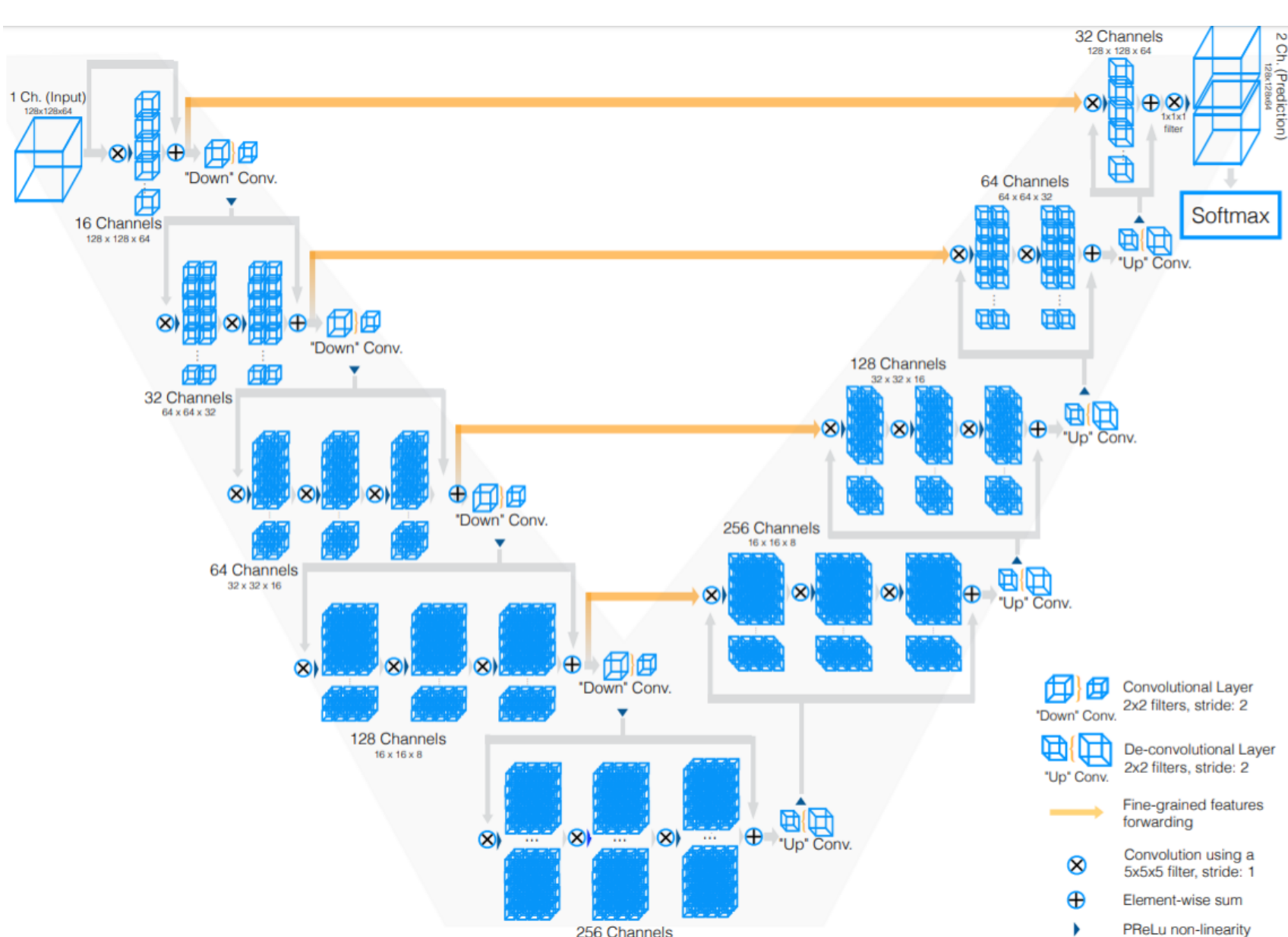


Fig. 1: 3D Medical Image Segmentation Network.

6. Accuracy Comparison (Plot)

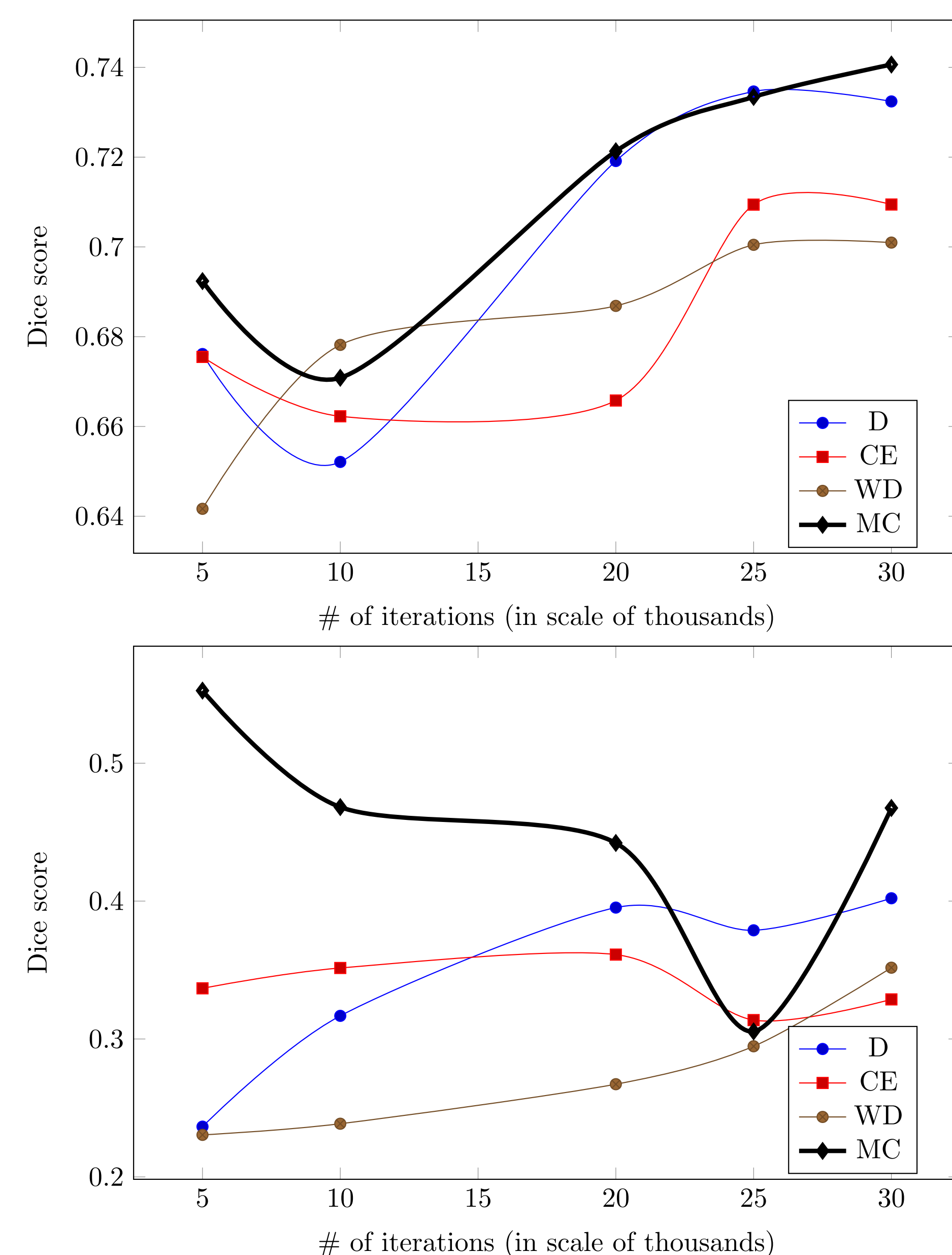
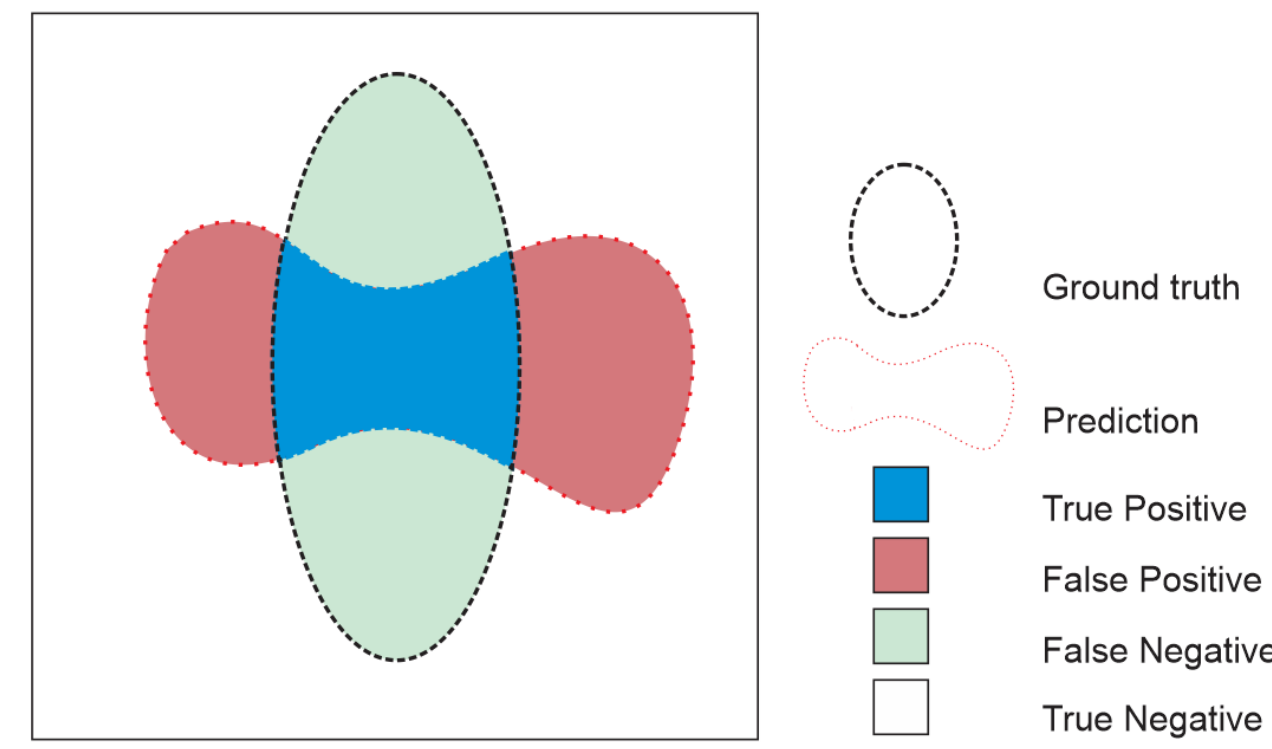


Fig. 2: Plots of the Dice scores shown in Table 1.

3. Matthews Correlation (MCC)

$$\frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP) \times (FN+TN) \times (FP+TN) \times (TP+FN)}} \quad (4)$$



- MCC is an efficient statistical measure for spatial overlap (**class imbalance**).
- The MCC formula as in Eq. (4), cannot be directly applied as a **loss function** for **semantic segmentation** training.

4. Adapting MCC as a Loss F.

$$TP = \sum_{n=1}^N \sum_{k=1}^K P_k^n * G_k^n \quad (5a)$$

$$TN = \sum_{n=1}^N \sum_{k=1}^K (1 - P_k^n) * (1 - G_k^n) \quad (5b)$$

$$FP = \sum_{n=1}^N \sum_{k=1}^K P_k^n * (1 - G_k^n) \quad (5c)$$

$$FN = \sum_{n=1}^N \sum_{k=1}^K (1 - P_k^n) * G_k^n \quad (5d)$$

Network parameters w can be optimised using Stochastic Gradient Descent (Eq. 6).

$$\arg \min_w L = 1 - MCC \quad (6)$$

5. Segmentation Results

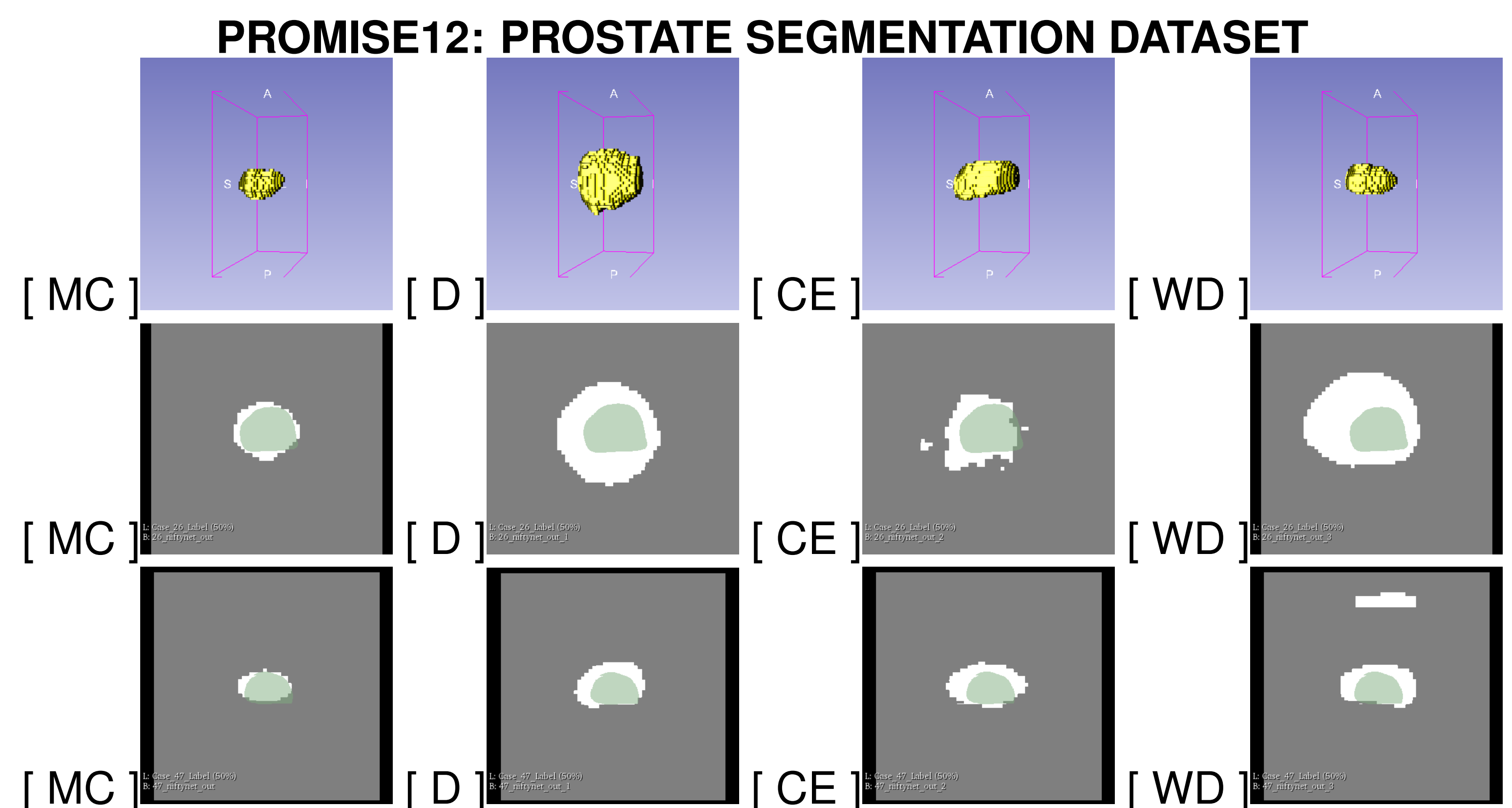


Fig. 3: Groundtruth (white pixels) and inference prediction results (semi-transparent green pixels).

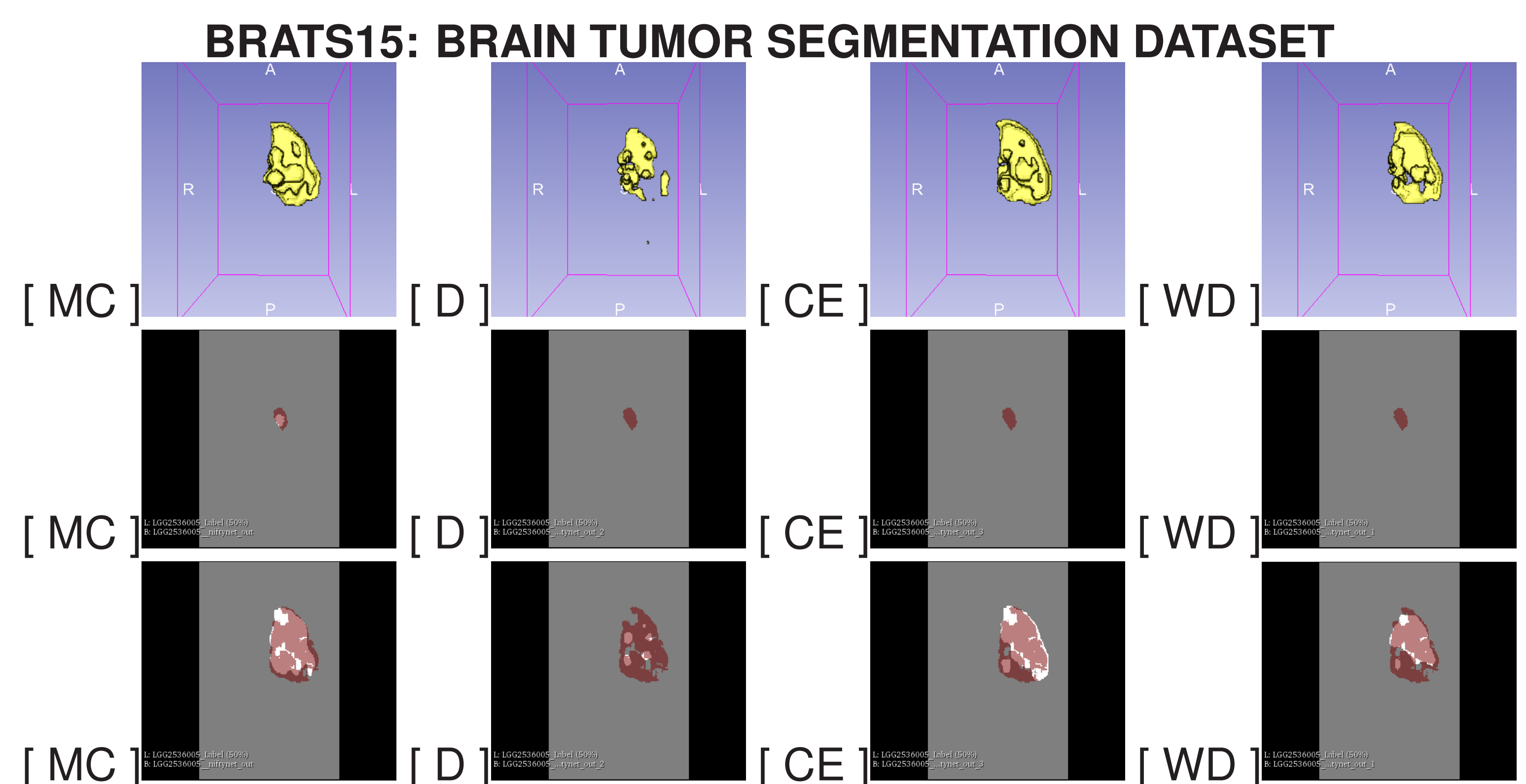


Fig. 4: Groundtruth (white pixels) and inference prediction results (semi-transparent red pixels).

Loss functions: [MC] Matthews Correlation loss (proposal), [D] Dice loss, [CE] Cross-Entropy loss, [WD] Wasserstein Dice loss.

7. Accuracy Comparison (Dice scores)

Loss Function	BRATS15					PROMISE12				
	Number of training iterations					Number of training iterations				
	5000	10000	20000	25000	30000	5000	10000	20000	25000	30000
Dice	0.676	0.652	0.719	0.735	0.732	0.236	0.317	0.395	0.379	0.402
Cross-entropy	0.675	0.662	0.666	0.709	0.709	0.337	0.351	0.361	0.314	0.329
Wasserstein	0.642	0.678	0.687	0.701	0.701	0.23	0.239	0.267	0.295	0.352
Matthews	0.692	0.671	0.721	0.733	0.741	0.553	0.468	0.442	0.306	0.468

Table 1. Average Dice scores obtained by the different loss functions after inference. Our proposed loss function achieves the overall highest performance in both datasets.