Improving Semantic Segmentation of 3D Medical Images on CNNs

Alejandra Marquez Herrera, Alex Cuadros Vargas, Helio Pedrini

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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**

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

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

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

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

2. V-Net (Fausto M.)

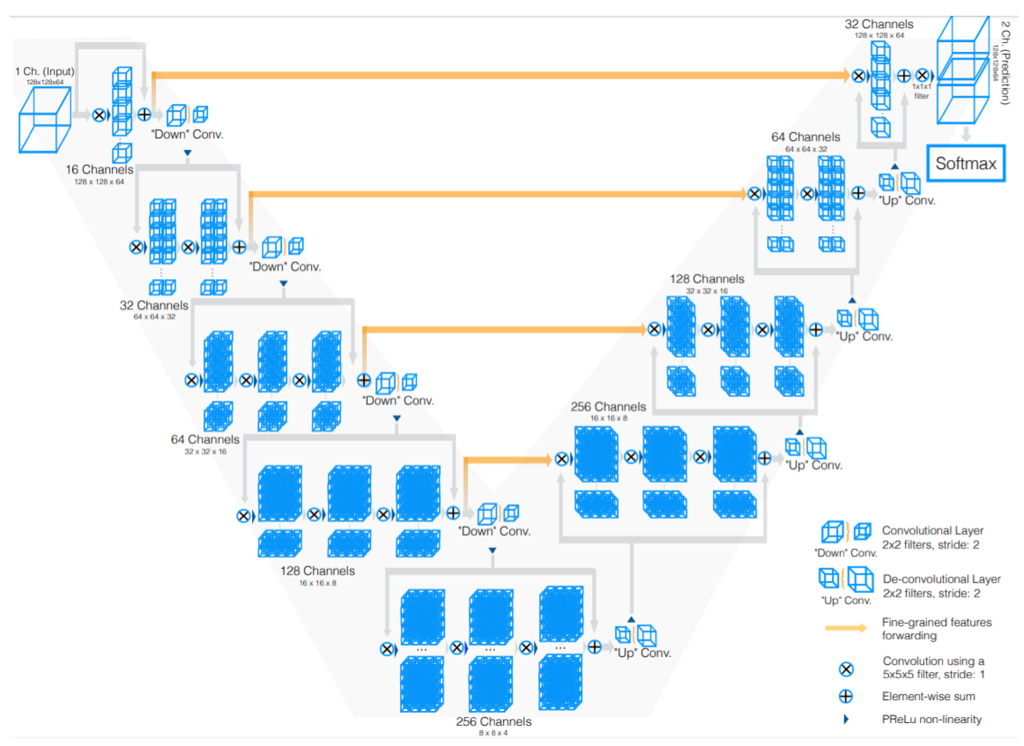
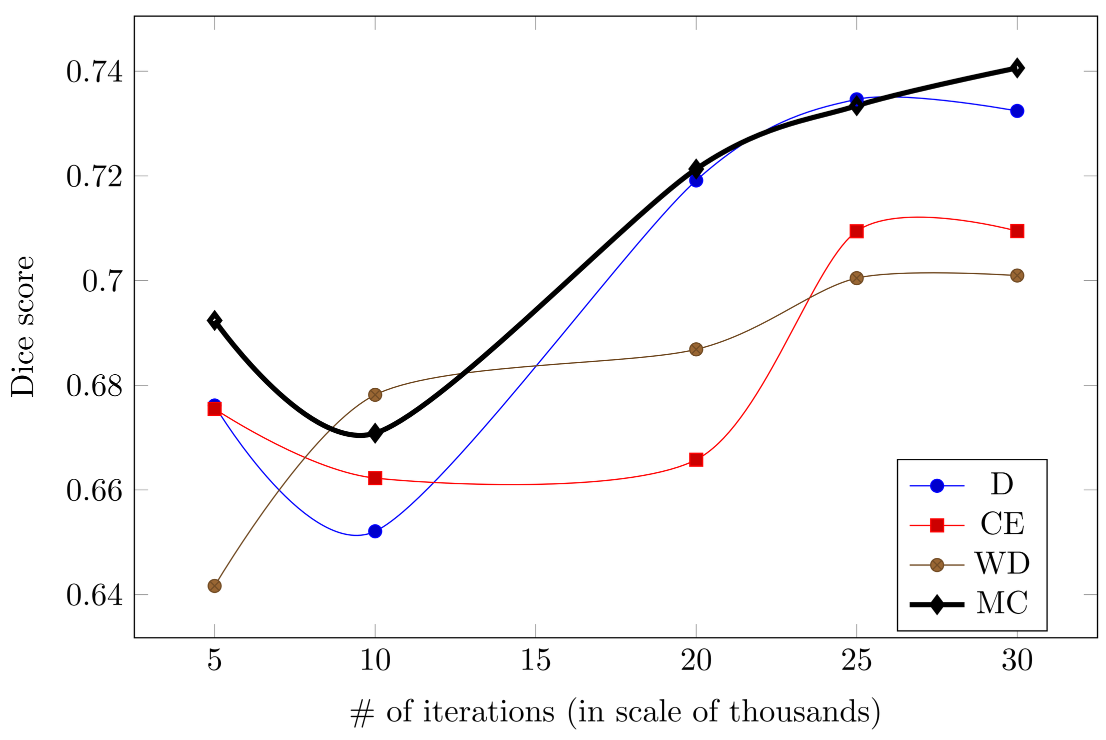


Fig. 1: 3D Medical Image Segmentation Network.

6.Accuracy Comparison (Plot)



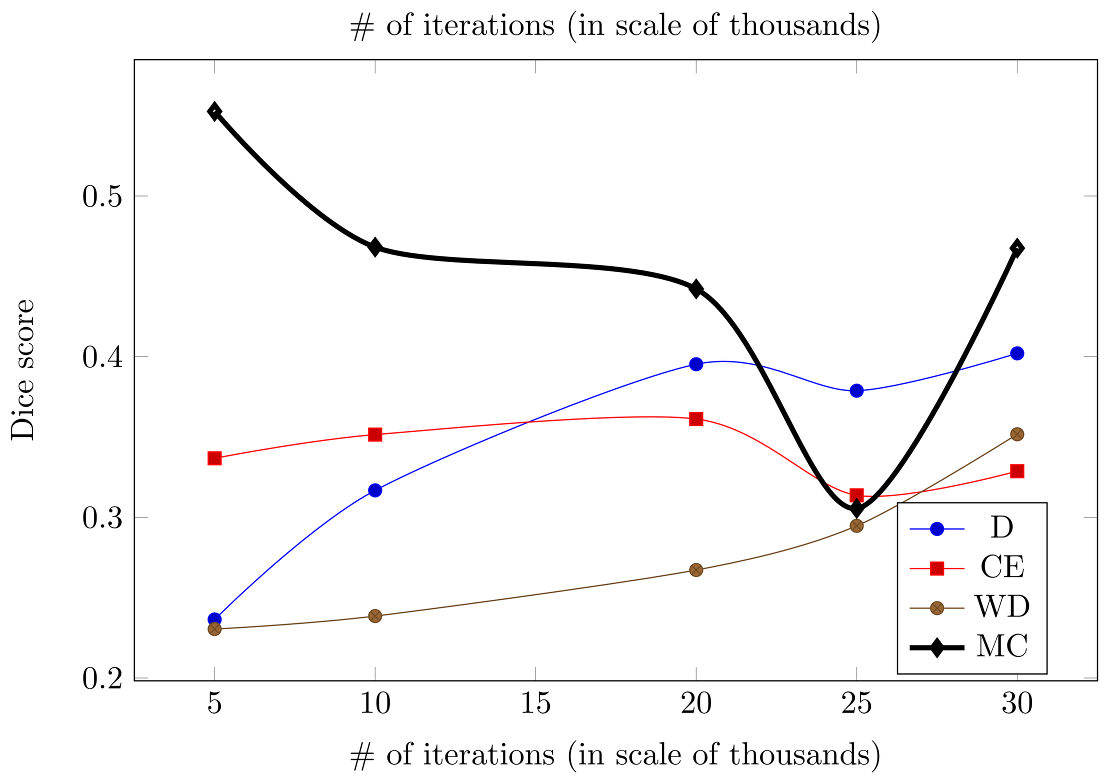
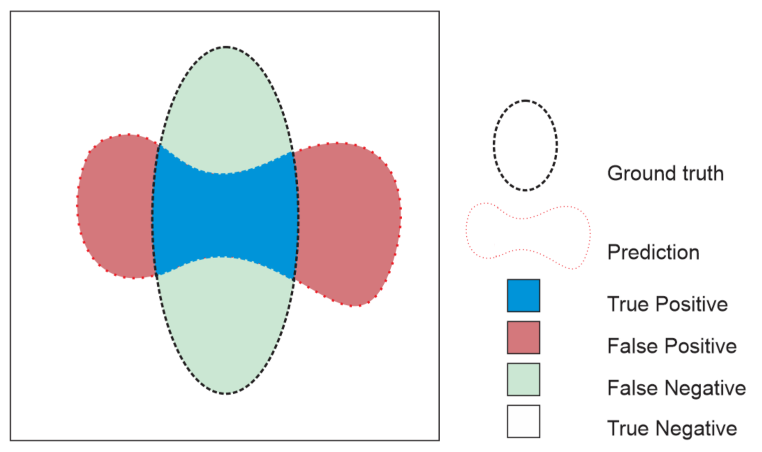


Fig. 2: Plots of the Dice scores shown in **Table 1**.

3. Matthews Correlation (MCC)

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



- 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.

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

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

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

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

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

$$\arg\min_{w} L = 1 - MCC \tag{6}$$

5. Segmentation Results

PROMISE12: PROSTATE SEGMENTATION DATASET

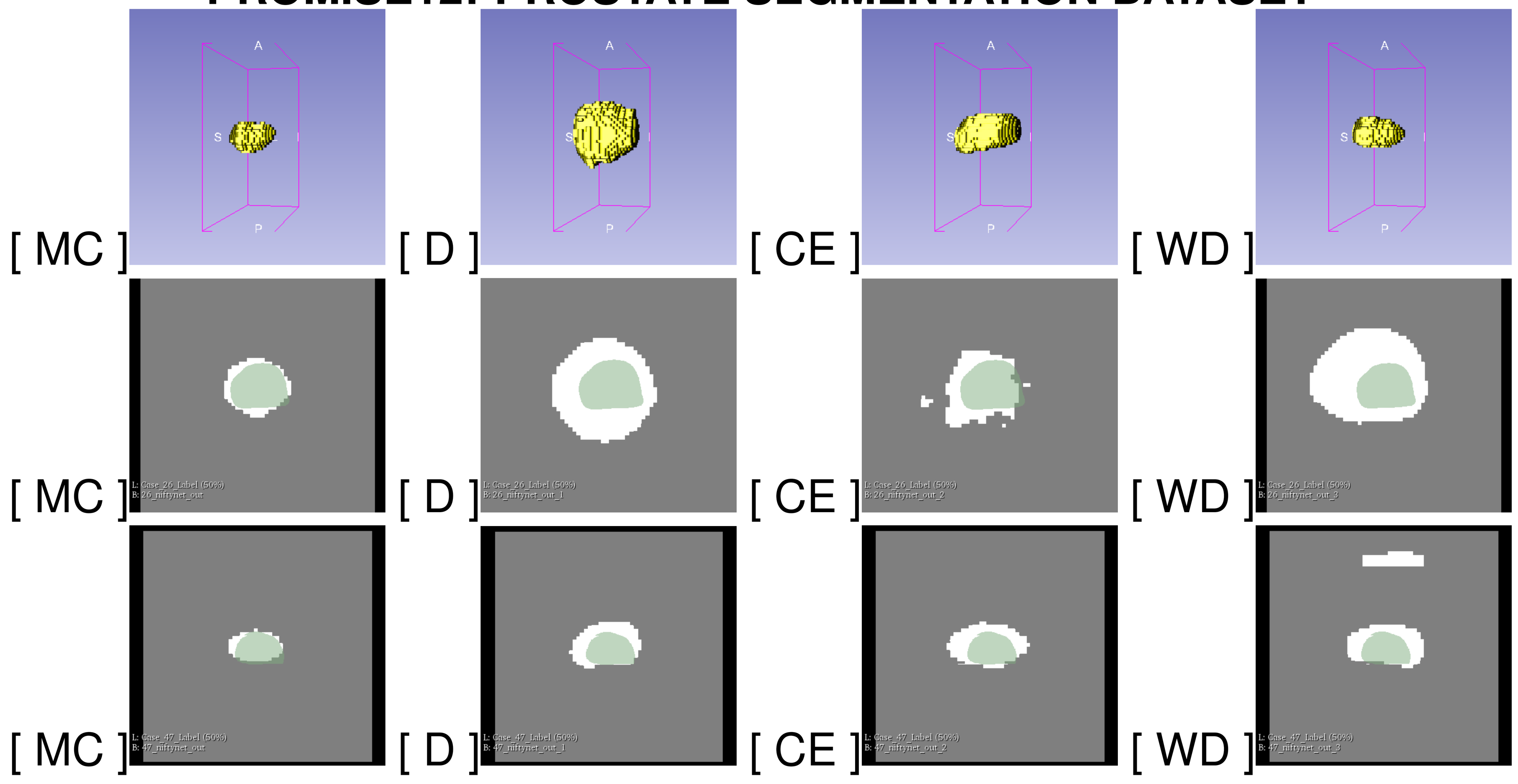


Fig. 3: Groundtruth (white pixels) and inference prediction results (semi-transparent green pixels).

BRATS15: BRAIN TUMOR SEGMENTATION DATASET

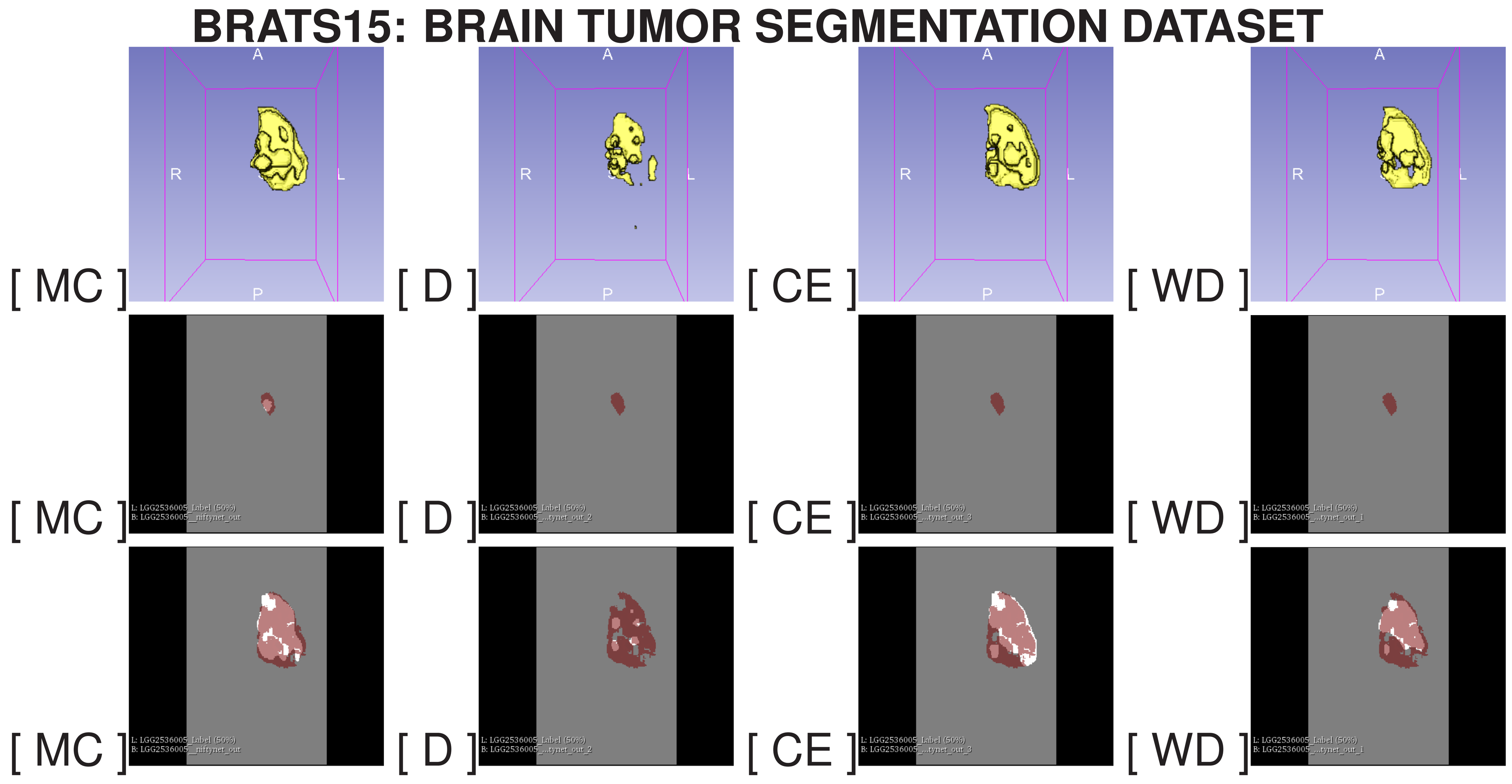


Fig. 4: Groundtruth (white pixels) and inference prediction results (semi-transparent red pixels).

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.