A Mediterranean HUB for Translational Research

Prostate MRI Segmentation: A Comparative Analysis of U-Net and E-Net Deep Learning Models

Gaspare Centineo1, Leonardo Salvaggio[2] , Syed Ibrar Hussain[3] , Muhammad Ali[3] , Kristen Meiburger[1] , Filippo Molinari[1] , and Albert Comelli[3*]

[1] Department of Electronics and Telecommunications, Politecnico Di Torino, Turin, Italy ;[2] Department of Biomedicine, Neuroscience and Advanced Diagnostics (BiND), University of Palermo, Palermo, Italy; [3] Ri.MED Foundation, Via Bandiera 11, 90133 Palermo, Italy, Italy

.

INTRODUCTION

Prostate cancer (PCa) remains one of the most frequently diagnosed malignancies among men worldwide, with a significant public health challenge due to increasing incidence and mortality rate. This growing burden demands the urgent need for an accurate and early diagnosis to support effective treatment strategies and improve survival outcomes. Magnetic Resonance Imaging (MRI), particularly multiparametric MRI (mpMRI), has become a cornerstone in PCa detection, providing superior anatomical detail and tumor characterization. Radiomics and quantitative image analysis have further improved the diagnostic capabilities of mpMRI, but their efficacy is highly dependent on accurate seg mentation of the prostate and cancerous regions . Manual segmentation remains the clinical standard, but is labor intensive,timime-consuming, and prone to interobserver variability.

To address these lim- itations, deep learning-based approaches have emerged as powerful tools for automated prostate segmentation. Among these, convolutional neural network (CNN) architectures such as U-Net and E-Net have demonstrated exceptional. performance in capturing complex anatomical structures and enhancing seg mentation accuracy. These models offer improved reproducibility, reduced processing time, and facilitate real-time integration into radiology workflows. This paper focuses on evaluating the performance and clinical applicability of U-Net and E-Net architectures in automated segmentation of prostate anatomy and MRI, with the aim of supporting a more precise diagnosis and personalized treatment planning for patients with PCa.

MATERIALS AND METHODS

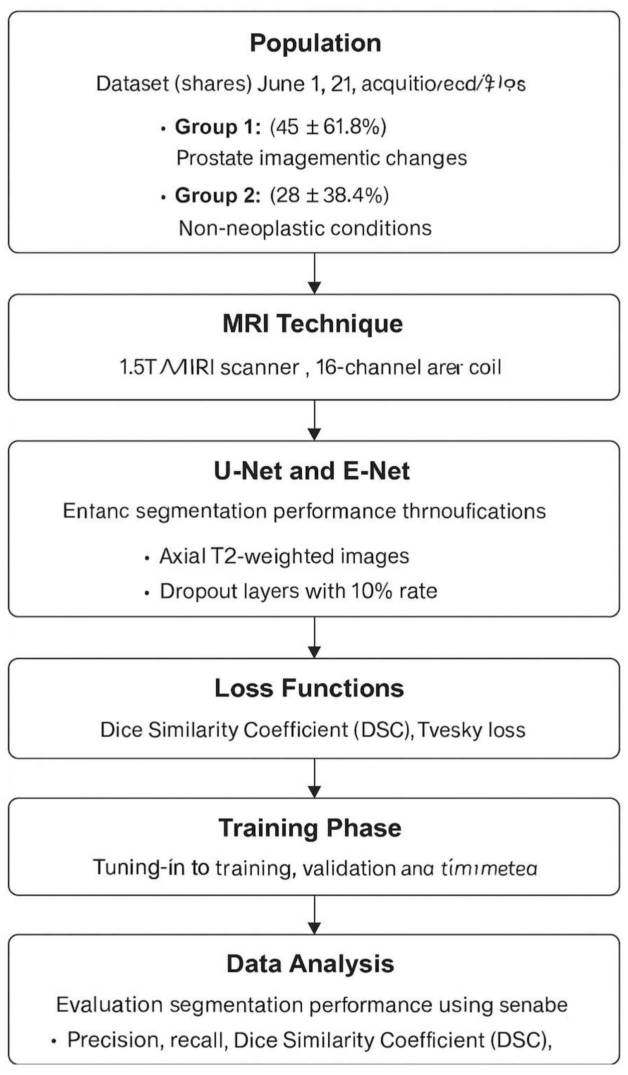

Fig.1: Workflow of the Prostate MRI Segmentation Study

MATERIALS AND METHODS

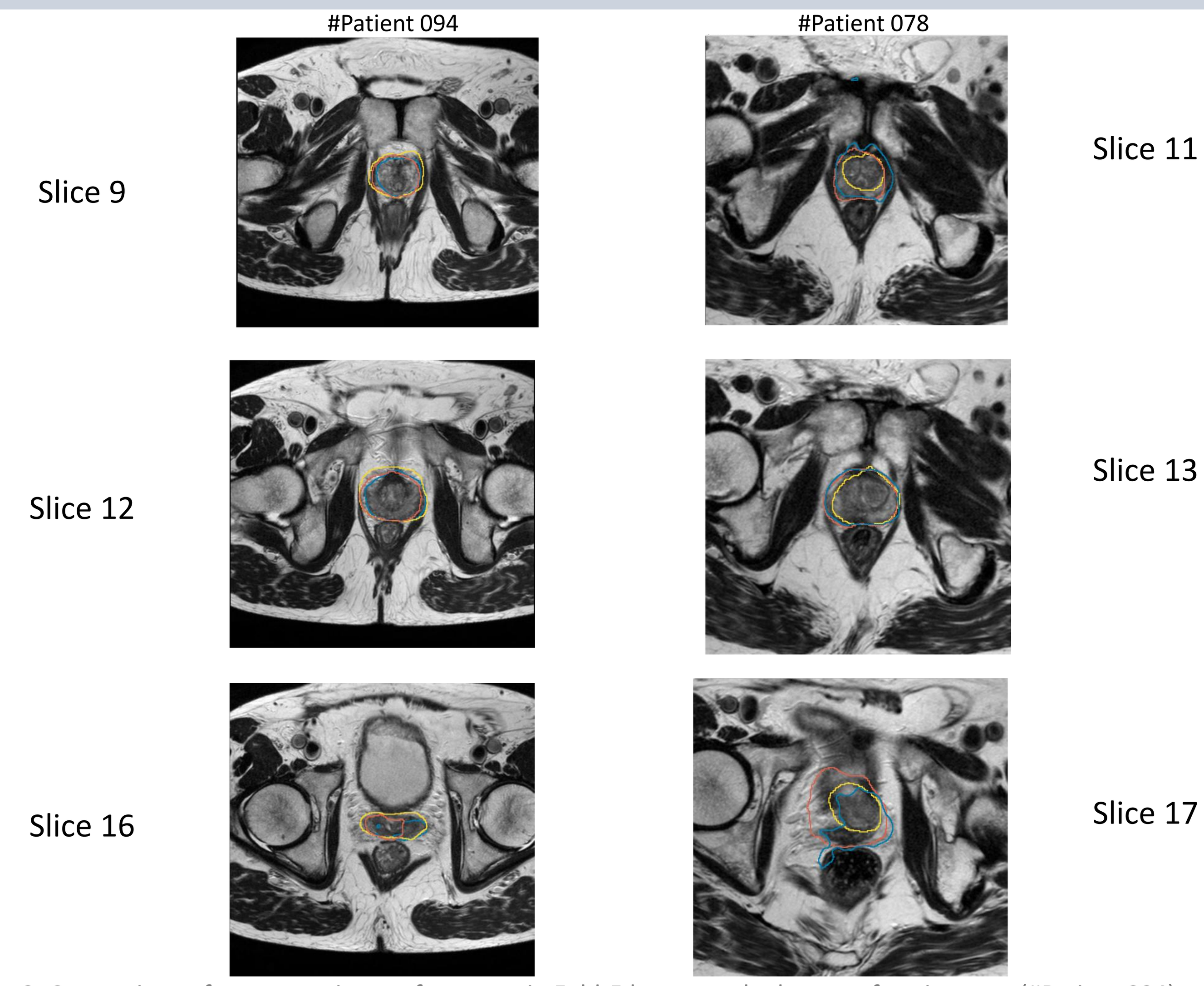

Fig. 2: Comparison of segmentation performance in Fold-5 between the best-performing case (#Patient 094) and the worst-performing case (#Patient 078). Ground truth (Yellow), U-Net predictions (Blue) and E-Net predictions (Red).

RESULTS AND DISCUSSION

The proposed segmentation methods were applied to automatically identify and delineate the prostate in MRI scans, comparing the performance of E-Net and U-Net. Overall, E-Net outperformed U-Net, achieving a mean Dice Similarity Coefficient (DSC) of 81.61 ± 2.80%, compared to 77.53 ± 2.59% for U-Net. The training profiles indicated that E-Net converged faster, while U-Net, despite achieving a slightly lower training loss, exhibited signs of overfitting. Statistical analysis using a paired t-test confirmed that the difference in DSC between the two networks was significant ($t = 2.88$, $p = 0.045 < 0.05$). In terms of computational efficiency, E-Net had far fewer trainable parameters (362,992 vs. 5.4 million), resulting in substantially faster inference times on both CPU (2.18 s vs. 11.61 s) and GPU (1.88 s vs. 4.66 s), making it more suitable for real-time clinical applications. Additionally, E-Net demonstrated higher recall and comparable precision across the validation folds, indicating robust detection of prostate regions with reduced computational cost. These results suggest that E-Net provides superior segmentation accuracy, faster convergence, and greater efficiency compared to U-Net.

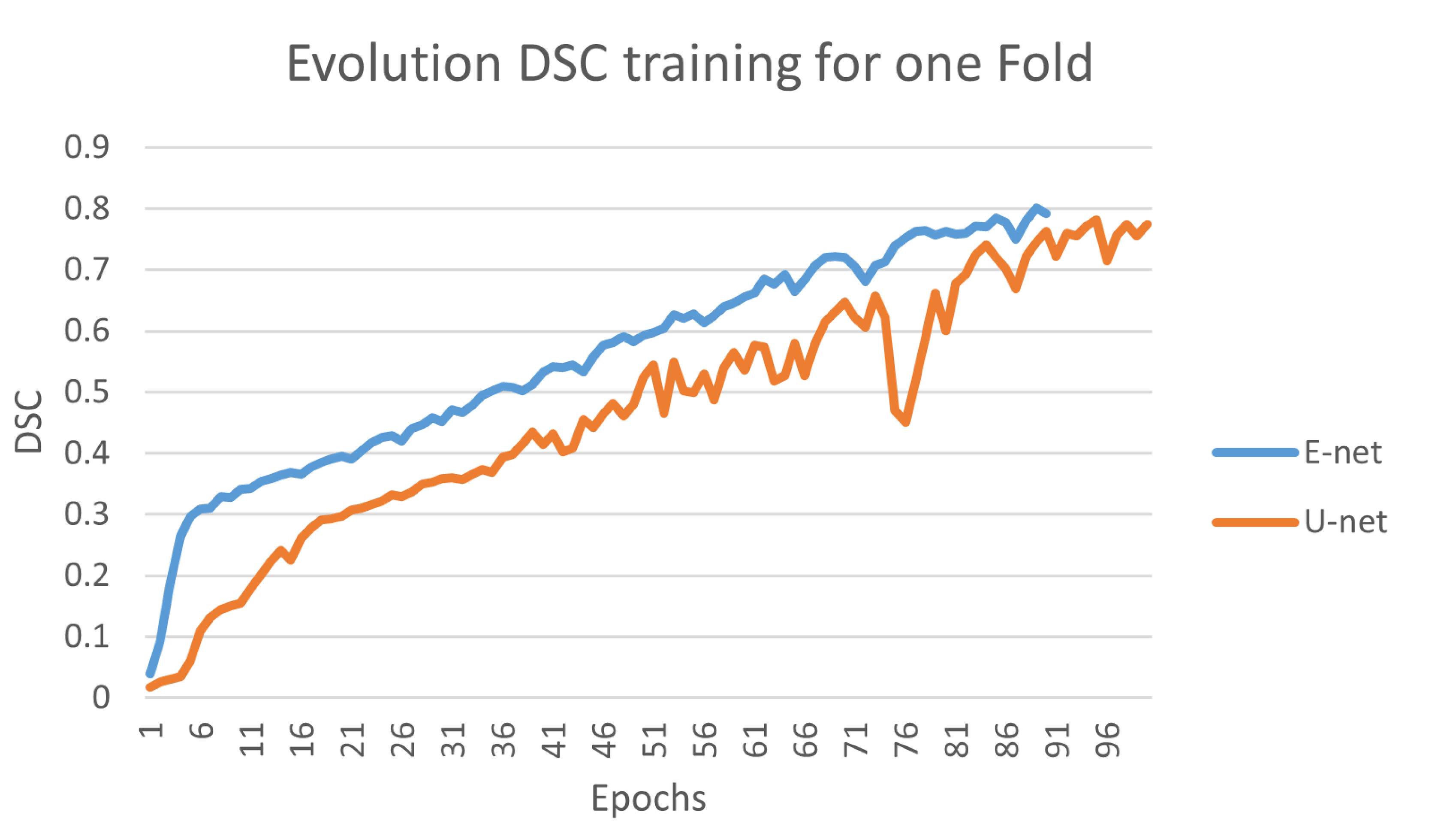

Fig. 3: Evolution of training DSC for both Networks

Fig.4: Evolution of training Tversky loss for both Networks

Model Name	Trainable Parameters	Non-Trainable Parameters	Size on Disk	CPU Inference Time (s)	GPU Inference Time (s)
E-Net	362,992	8,352	5.8 MB	2.18	1.88
U-Net	5,403,874	0	65.0 MB	11.61	4.66

Table 1: Segmentation metrics and model performance comparing U-Net vs. E-Net

Comparison	t-Value	p-Value
E-Net vs U-Net	2.88463755	0.044803672

Table 2: Two-tailed paired samples t-test on the dice similarity coefficient (DSC) showed statistical differences between segmentation methods.

CONCLUSIONS

Accurate prostate MRI segmentation is vital for prostate cancer diagnosis and treatment but manual methods are laborious and inconsistent. This study compared U-Net and E-Net architectures for automated segmentation. Both performed well, but E-Net outperformed U-Net in Dice Similarity Coefficient (81.61% vs. 77.53%) and other metrics, with statistical significance ($p = 0.0448$). E-Net was also more computationally efficient, with fewer parameters, faster inference, and lower storage requirements, making it suitable for clinical use

U-Net, while heavier, remained competitive, especially with architectural modifications. Both models showed robust results across cross-validation and a test set. Overall, E-Net offers the best balance of accuracy and efficiency, supporting its integration into clinical workflows, while future research should explore multimodal imaging, 3D segmentation, and domain adaptation

REFERENCES:

1. Ameen, Y.A., Badary, D.M., Abonnoor, A.E.I., Hussain, K.F., Sewisy, A.A.: Which data subset should be augmented for deep learning? a simulation study using urothelial cell carcinoma histopathology images. BMC bioinformatics 24(1), 75 (2023). https://doi.org/10.1186/s12859-023-05199-y
2. Canfora, I., Cutaia, G., Marcian`o, M., Calamia, M., Faraone, R., Cannella, R., Benfante, V., Comelli, A., Guercio, G., Giuseppe, L.R., Salvaggio, G.: A predictive system to classify preoperative grading of rectal cancer using radiomics features. In: Image Analysis and Processing – ICIAP 2022 Workshops, Lecture Notes in Computer Science, vol. 13373, pp. 431–440. Springer (2022). https://doi.org/ 10.1007/978-3-031-13321-3_38
3. Corso, R., Comelli, A., Salvaggio, G., Tegolo, D.: New parametric 2d curves for modeling prostate shape in magnetic resonance images. Symmetry 16(6) (2024). https://doi.org/10.3390/sym16060755
4. Litwin, M.S., Tan, H.J.: The diagnosis and treatment of prostate cancer: a review. Jama 317(24), 2532–2542 (2017). https://doi.org/10.1001/jama.2017.7248

www.fondazionerimed.eu

2022 Ri.MED Research Retreat