DeePRAC PROJECT

Deep learning for segmentation of CT images to improve surgery in *Pediatric RenAl Cancers*

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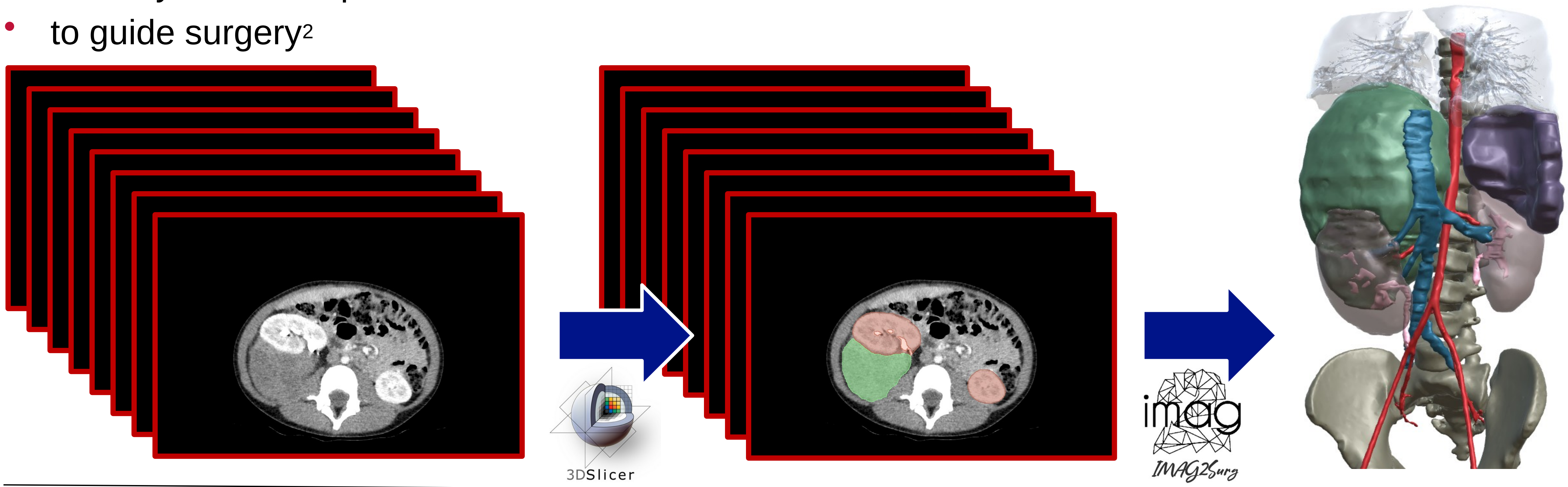
INTRODUCTION

Goal: assist in the creation of individual 3D model of pediatric patients affected by renal tumor

- to verify treatment protocol criteria[1]
- to guide surgery[2]

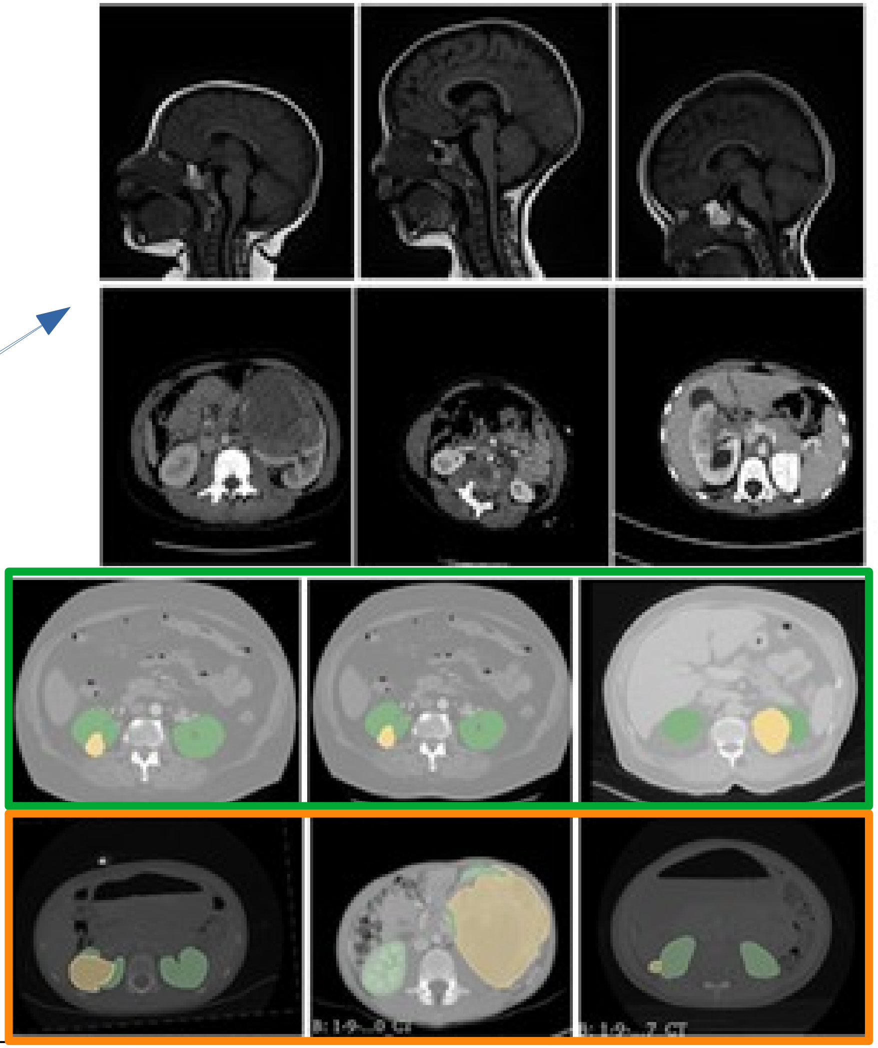


1. M. M. van den Heuvel-Eibrink, A. J. Hol, K. Pritchard-Jones, et al., “Position Paper: Rationale for the Treatment of Wilms Tumour in the UMBRELLA SIOP-RTSG 2016 Protocol,” *Nat Rev Urol., no. 14(12), pp. 743–752, 2017.*
2. F. Porpiglia, E. Checcucci, D. Amparore, et al., “Three-dimensional augmented reality robot-assisted partial nephrectomy in case of complex tumours (padua ≥ 10): A new intraoperative tool overcoming the ultrasound guidance,” *European Urology, no. 78(2), 2020*

INTRODUCTION

- **3D models are based on image segmentation**
  - Widely developed in adults[1] but not in children
    - Convolutional Neural Networks (CNN) are the State-Of-The-Art (SOTA)

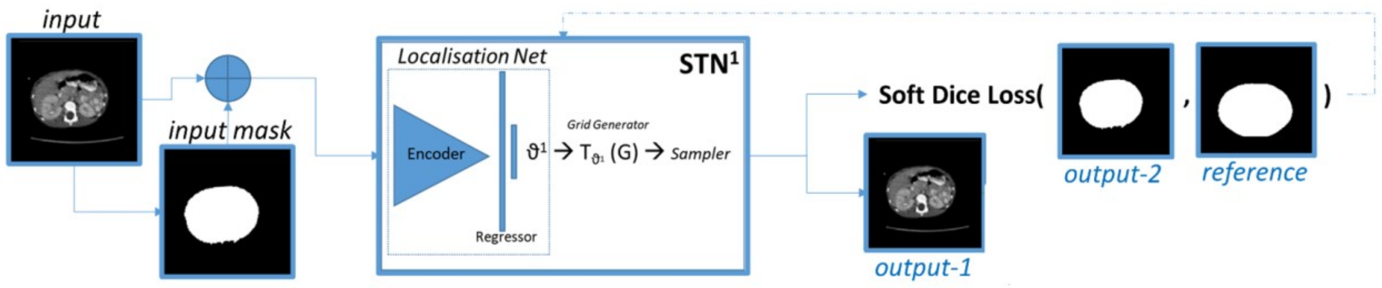
- **Challenges for segmenting pediatric data-sets**
  - Highly **heterogeneous** in terms of **size**
  - High **variability** in terms of **pose**
  - **Limited number** of images
  - **Differences** between **adults** **and** **children** data-sets



1. N. Heller, F. Isensee, K. H. Maier-Hein, X. Hou, C. Xie, F. Li, Y. Nan, G. Mu, Z. Lin, M. Han, et al., “The state of the art in kidney and kidney tumor segmentation in contrast-enhanced CT imaging: Results of the KiTS19 challenge,” *Medical Image Analysis, vol. 67, p. 101821, 2021.*

PROPOSED METHOD: Automatic size and pose homogenization with Spatial Transformer Network[1] to improve and accelerate pediatric segmentation[2]

- **Our first proposition:** reduce the data variability through an homogenization in terms of size and pose via STN



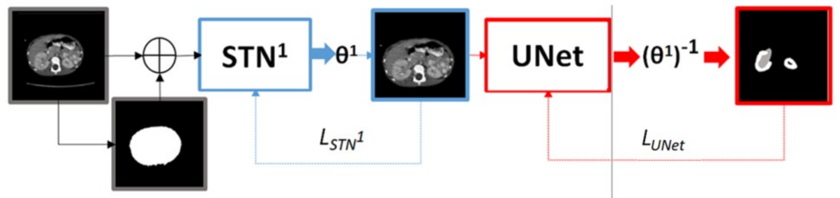


Image 128x128 with Batch Size of 32			
Architecture	Training Time	Dice Score Kidney	Dice Score Tumor
nnUNet	1h35	83.66 (7.88)	69.52 (24.61)
nnUNet (+ data augmentation)	2h15	**88.99 (3.71)**	74.18 (22.07)
STN pose-size + nnUNet	**1h45**	86.75 (6.47)	**77.31 (27.36)**
Image 512x512 with Batch Size of 12			
Architecture	Training Time	Dice Score Kidney	Dice Score Tumor
nnUNet	22h	88.07 (5.61)	78.14 (26.19)
nnUNet (+ data augmentation)	33h	**88.91 (5.08)**	85.52 (24.65)
STN pose-size + nnUNet	**25h**	88.01 (6.25)	**87.12 (23.39)**

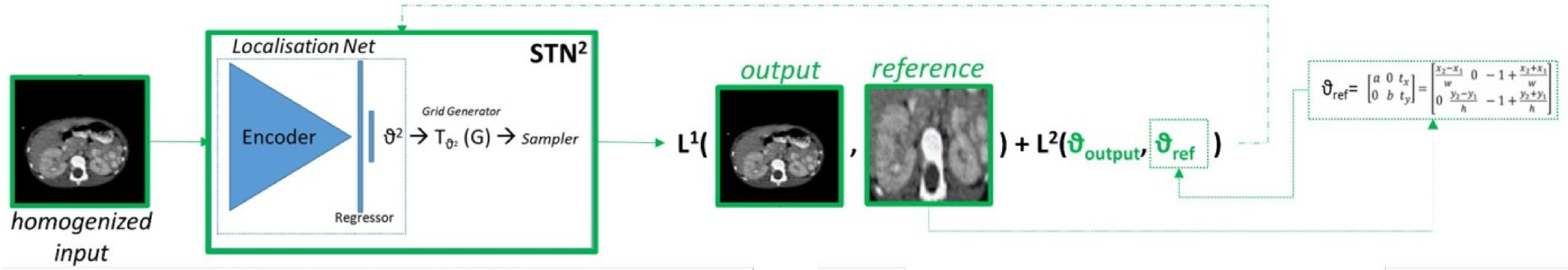
DATABASE: 80 pediatric pre-operative abdominal-visceral CT images with early arterial contrast injection.

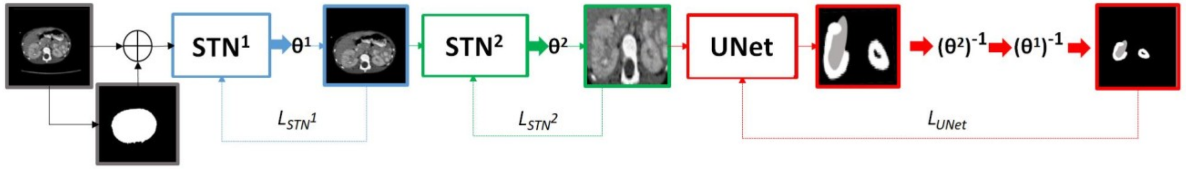
1. M. Jaderberg, K. Simonyan, A. Zisserman, and K. Kavukcuoglu, “Spatial Transformer Networks,” in *Neural Information Processing Systems (NIPS)*, 2015.

2. G. La Barbera, P. Gori, H. Boussaid, B. Belucci, A. Delmonte, J. Goulin, S. Sarnacki, L. Rouet and I. Bloch, “Automatic size and pose homogenization with Spatial Transformer Network to improve and accelerate pediatric segmentation,” in *IEEE International Symposium on Biomedical Imaging (ISBI), 2021* 〈 hal-03131980 〉

PROPOSED METHOD: Automatic size and pose homogenization with Spatial Transformer Network to improve and accelerate pediatric segmentation

- **Our second proposition:** learn to crop the region of interest (ROI) as a square patch via STN

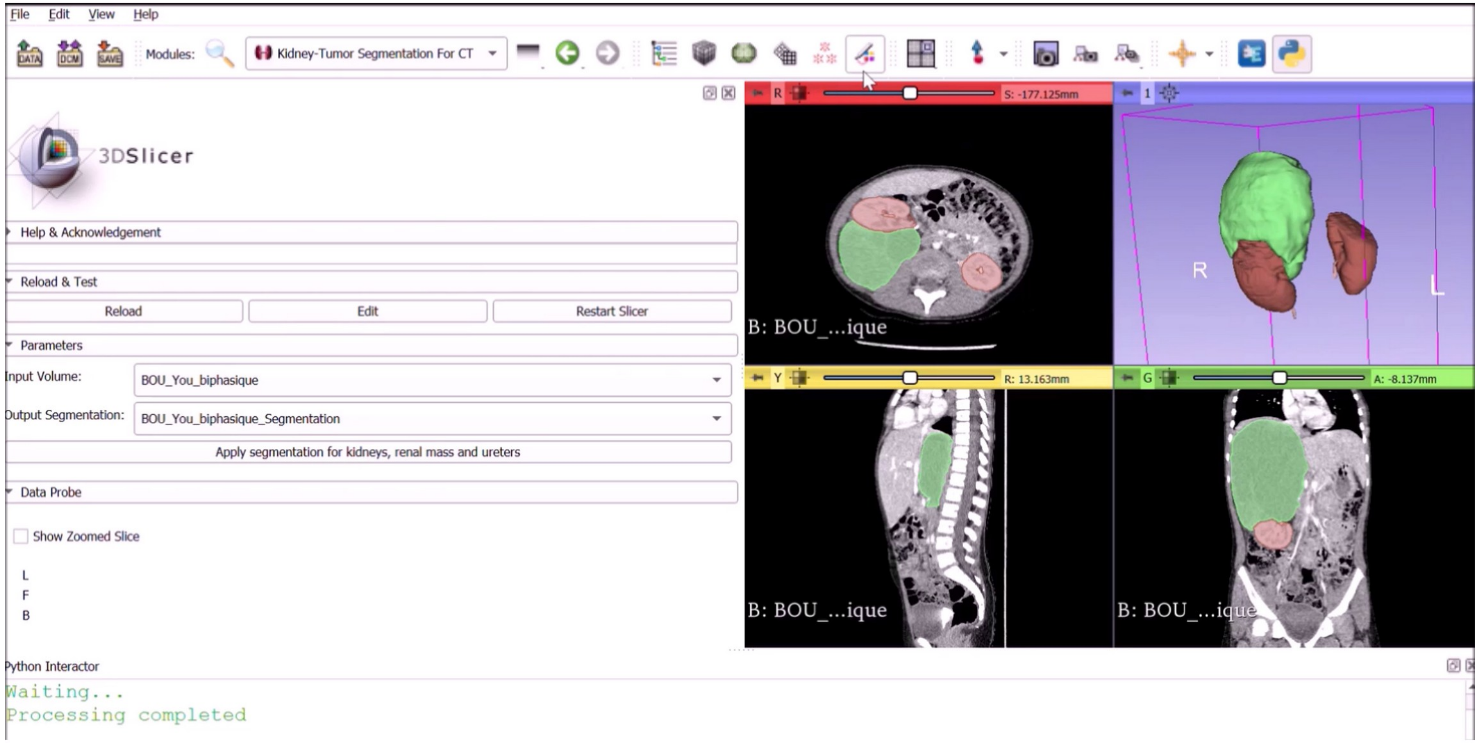




Architecture	Input size UNet	Training Time	Memory allocated	Dice score kidney	Dice score tumor
nnUNet	512×512	22h	10.05Gb	88.07 (5.61)	78.14 (26.19)
nnUNet (+ data augmentation)	512×512	33h	10.05Gb	88.91 (5.08)	85.52 (24.65)
STN pose-size + STN crop + nnUNet	512×512	28h	10.05Gb	88.84 (7.79)	84.25 (31.15)
STN pose-size + STN crop + nnUNet	256×256	**19h30**	**3.52Gb**	86.71 (19.36)	84.15 (30.11)

PERSPECTIVES

- **Future work:**
  - Improve the STN for cropping
  - Extend it to 3D
  - Use this method to improve transfer learning from adults to children
  - Insert the use of *diffeomorphism* for transfer learning



Inference phase implemented as plug-in for 3DSlicer via Docker