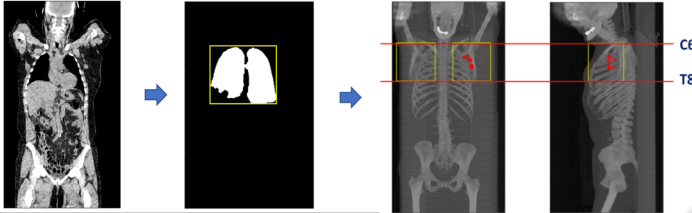


Segmentation of Axillary and Supraclavicular Tumoral Lymph Nodes in PET / CT: A Hybrid CNN / Component-Tree Approach

Diana Farfan Cabrera, Nicolas Gogin, David Morland, Benoit Naegel, Dimitri Papathanassiou, Nicolas Passat

ROI extraction

Axillary region extraction according to **vertebrae & lungs** position



Feature extractor

For each node N_i , it is computed:

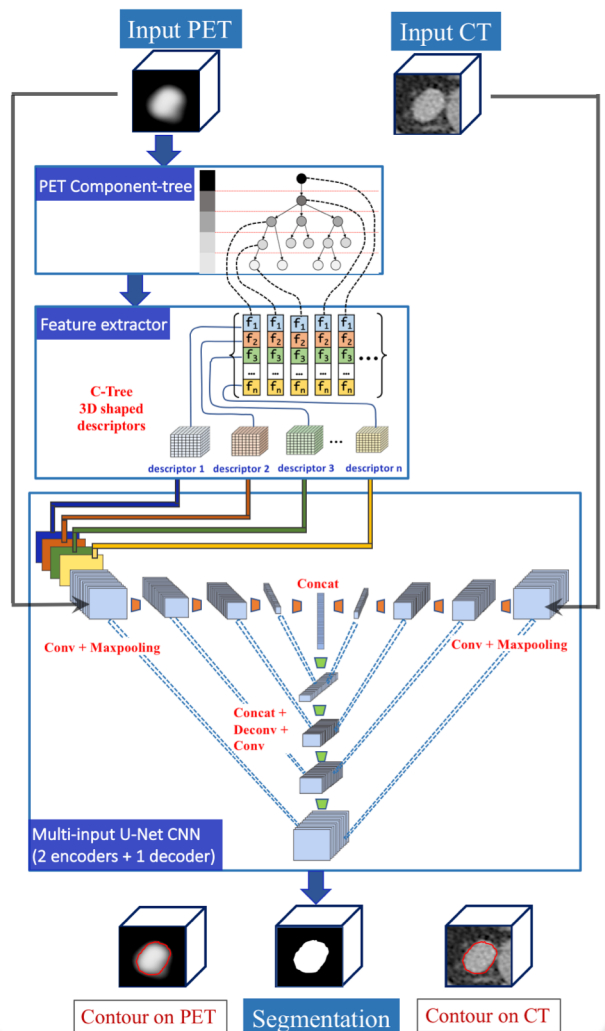
- $f_1 \rightarrow G(N_i)$: mean gradient of node contour in PET
- $f_2 \rightarrow H(N_i)$: mean HU value in CT
- $f_3 \rightarrow S(N_i)$: standard deviation of H
- $f_4 \rightarrow R(N_i)$: relative integral volume
- $f_5 \rightarrow L(N_i)$: position with respect to the lungs

Feature map generator

For each voxel x in the PET image, it is computed:

- $G(x) = \max_i G(N_i)$ → filters nodes with the maximum contour gradient
- $H(x) = \text{mean}_i H(N_i)$ → discards false positive nodes corresponding to brown fat
- $S(x) = \min_i S(N_i)$ → filters nodes with low standard deviation
- $R(x) = \max_i R(N_i)$ → filters nodes with highest contrast with its neighbourhood
- $L(x) = \text{or}_i L(N_i)$ → discards nodes outside the lungs convex-hull

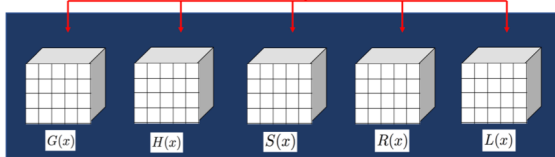
Proposed end-to-end flowchart



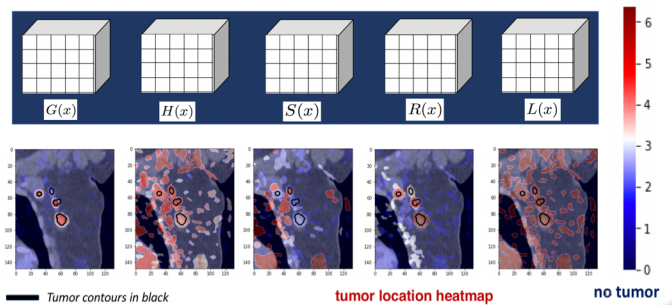
Why to go from feature vectors to feature volumes?

- $G(x) = \max_i G(N_i)$
- $H(x) = \text{mean}_i H(N_i)$
- $S(x) = \min_i S(N_i)$
- $R(x) = \max_i R(N_i)$
- $L(x) = \text{or}_i L(N_i)$

to maintain the same size as PET/CT input image



What do feature volumes contain?

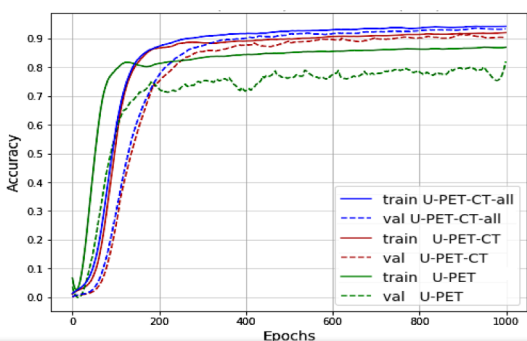


Data Training: 52 PET/CT scans (201 tumor lymph nodes)
Test: 10 PET/CT scans (63 lymph node tumors)

Experiments

CNN architecture: 3D U-Net (2 encoders – 1 decoder)

- U-PET → inputs {PET}
- U-PET-CT → inputs {PET,CT}
- U-PET-CT-all → inputs {PET,CT,feature maps}



Results

- Proposed method is robust to different contrasted PET/CT images
- Proposed method removes false positives coming from brown fat
- Proposed method separates visually connected tumors

