

## CONTEXT

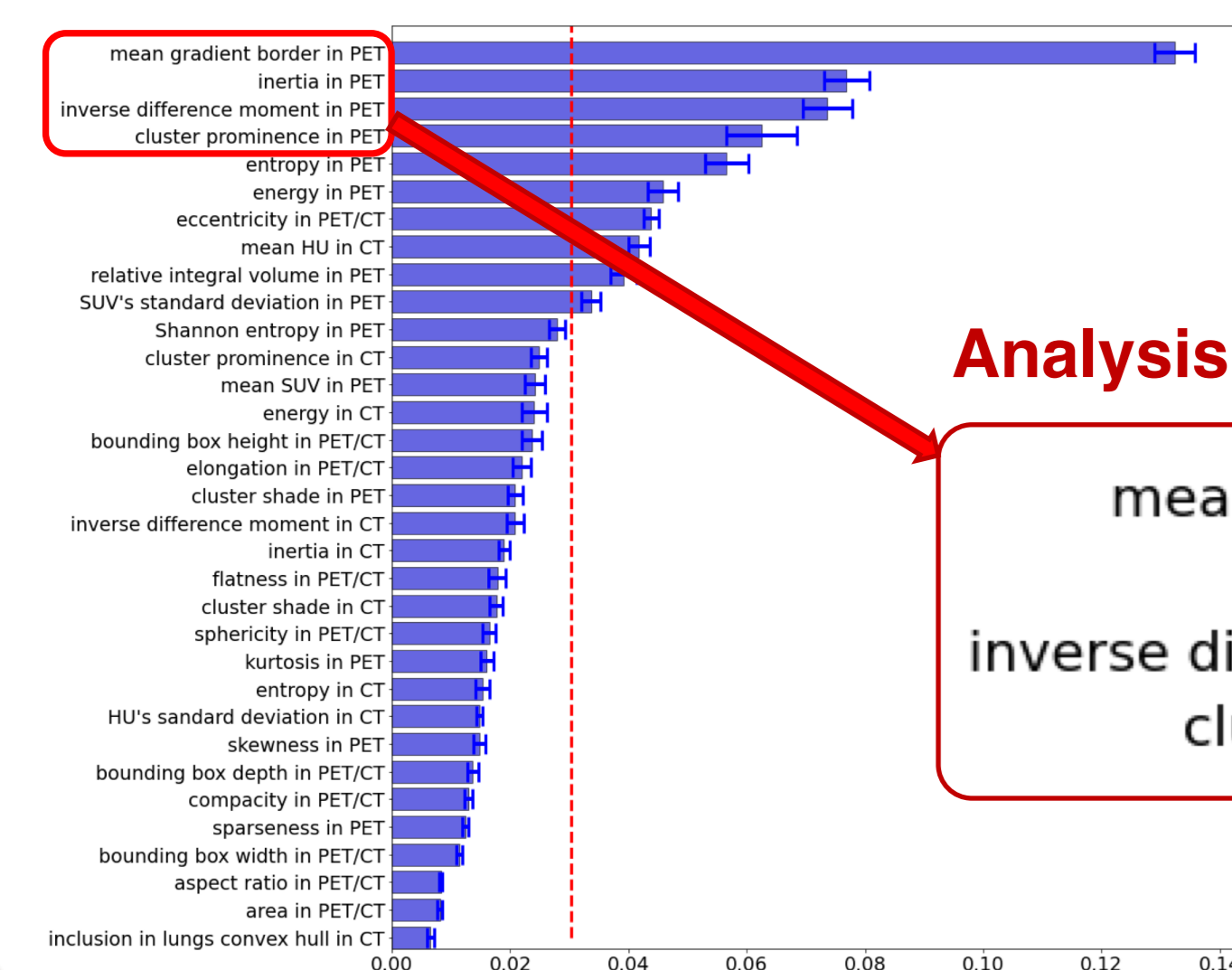
In the context of breast cancer, the detection and segmentation of cancerous lymph nodes in PET/CT imaging is of crucial importance, in particular for staging issues. We focus on the issue of choosing which features should be embedded for lymph node tumor segmentation from PET/CT.

## AIM

We first investigate the relevance of various features by considering a Random Forest framework. In a second time, we validate the expected relevance of the best scored features by involving them in a U-Net segmentation architecture.

## METHOD

### Relative importance of the 33 explored features from Random Forest Analysis



### Analysis of 4 most relevant features

- mean gradient border in PET
- inertia in PET
- inverse difference moment in PET
- cluster prominence in PET

## Feature extractor

For each node  $N_i$ , we compute:

- $f_1 \rightarrow MGB(N_i)$ : node's mean gradient of node in PET
- $f_2 \rightarrow Ine(N_i)$ : node's inertia in PET
- $f_3 \rightarrow IDM(N_i)$ : node's inverse difference moment in PET
- $f_4 \rightarrow CP(N_i)$ : node's cluster prominence in PET

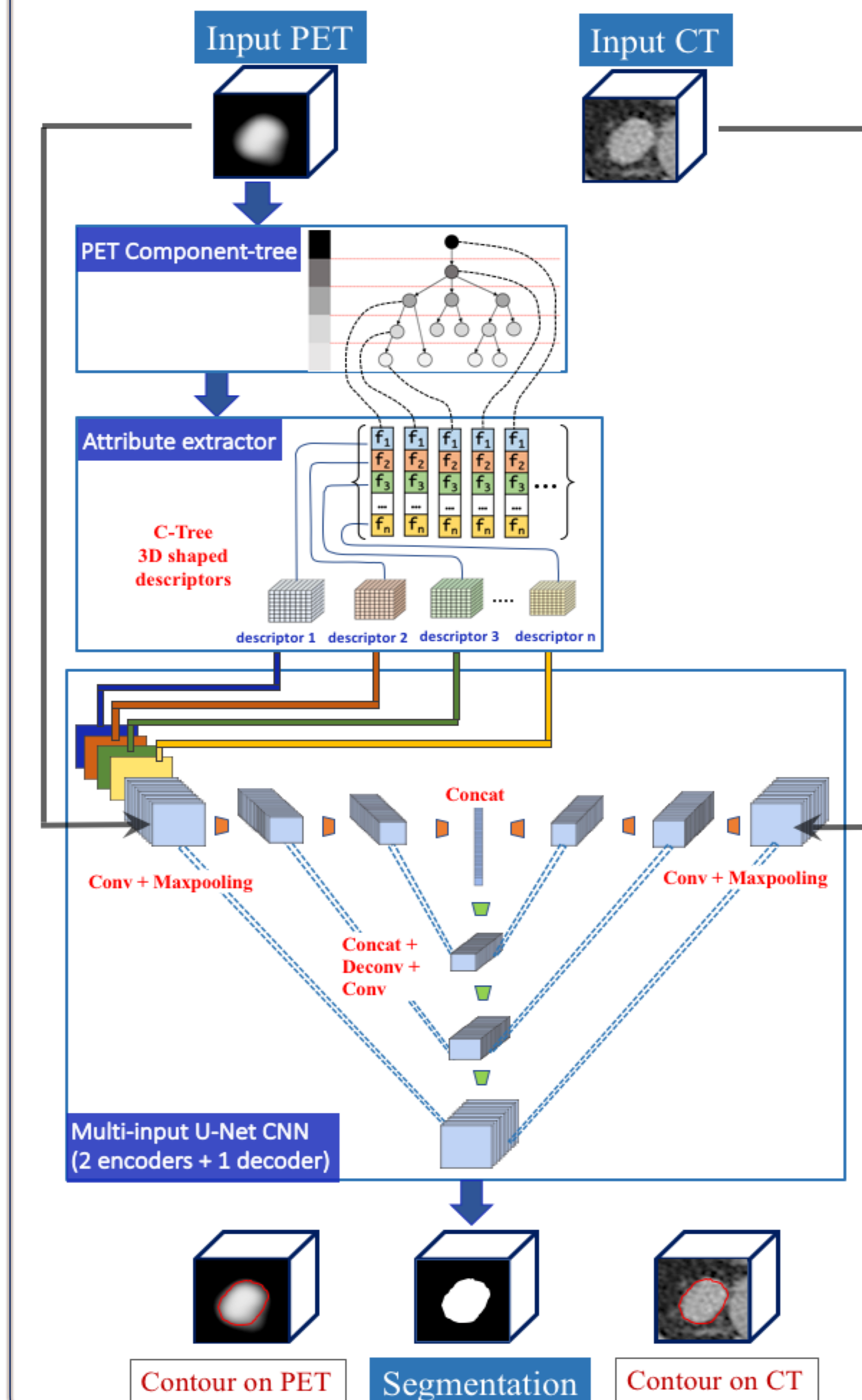
## Feature map generator

For each voxel  $x$  in the PET image, we compute:

- $MGB(x) = \max_i MGB(N_i) \rightarrow$  filters nodes with high contour gradient
- $Ine(x) = \max_i Ine(N_i) \rightarrow$  filters nodes with high inertia
- $IDM(x) = \min_i IDM(N_i) \rightarrow$  filters nodes with low cluster prominence
- $CP(x) = \max_i CP(N_i) \rightarrow$  filters nodes with high cluster prominence

## METHOD

### Proposed end-to-end flowchart



## METHOD

### Why to go from vector to feature volume?

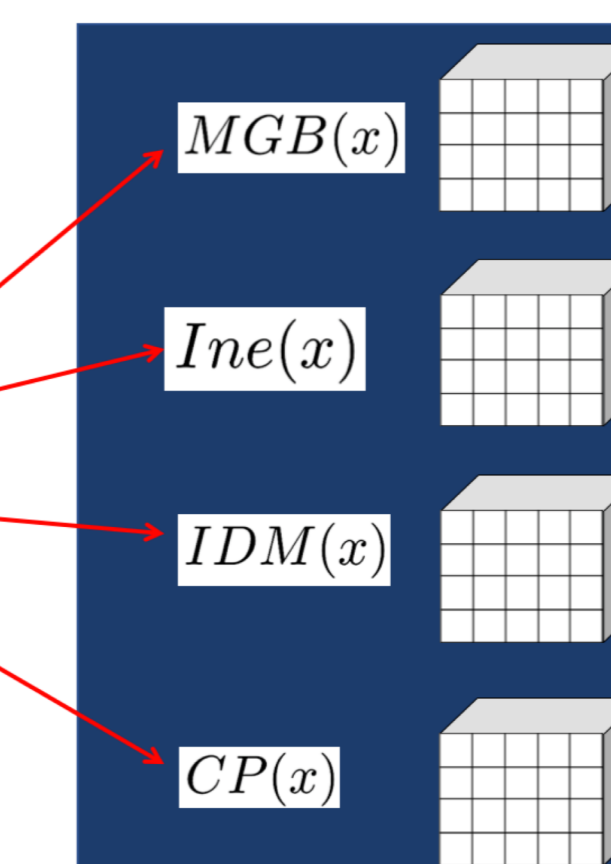
To maintain the same size as the PET/CT input image

$$MGB(x) = \max_i MGB(N_i)$$

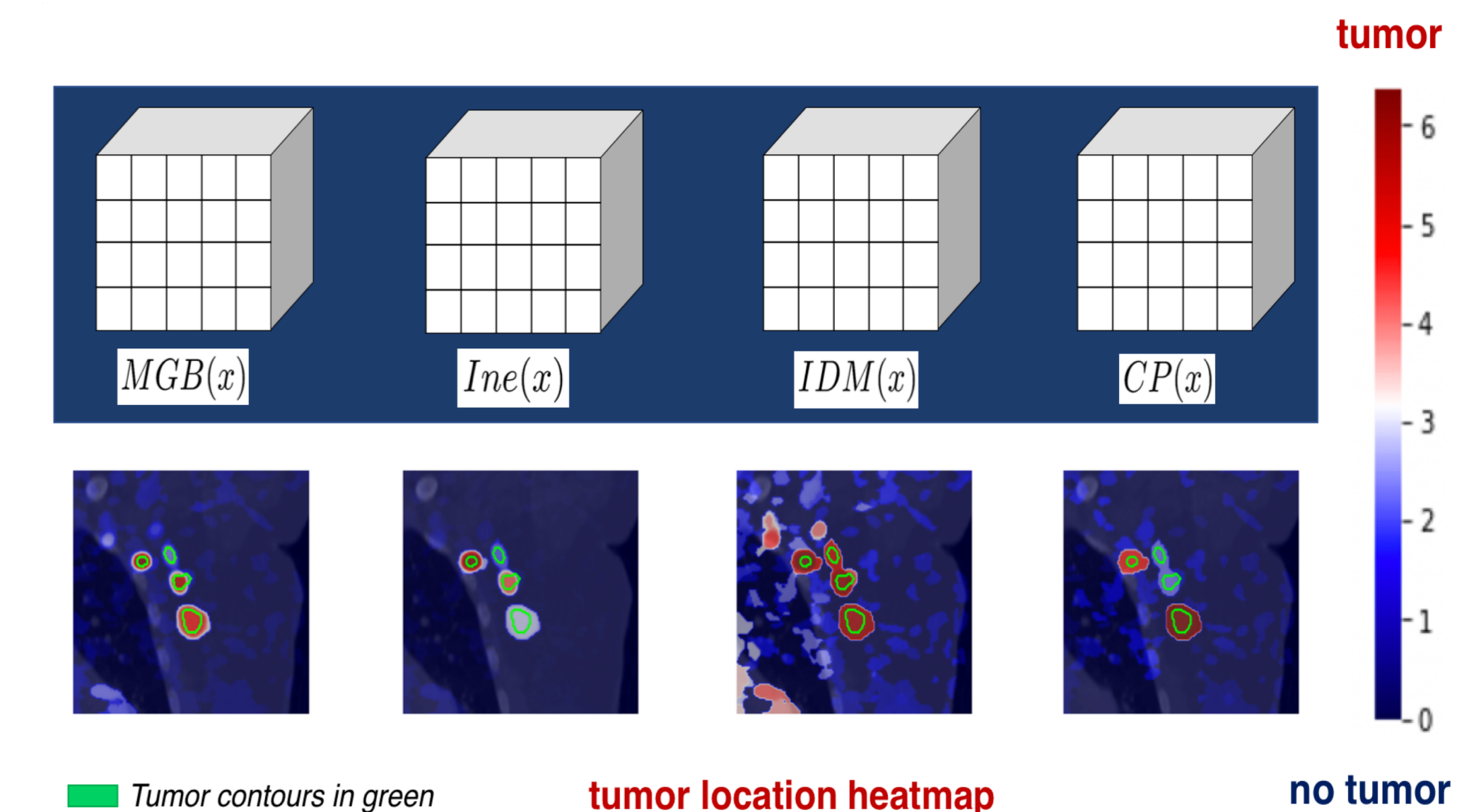
$$Ine(x) = \max_i Ine(N_i)$$

$$IDM(x) = \min_i IDM(N_i)$$

$$CP(x) = \max_i CP(N_i)$$



### What do feature volumes contain?



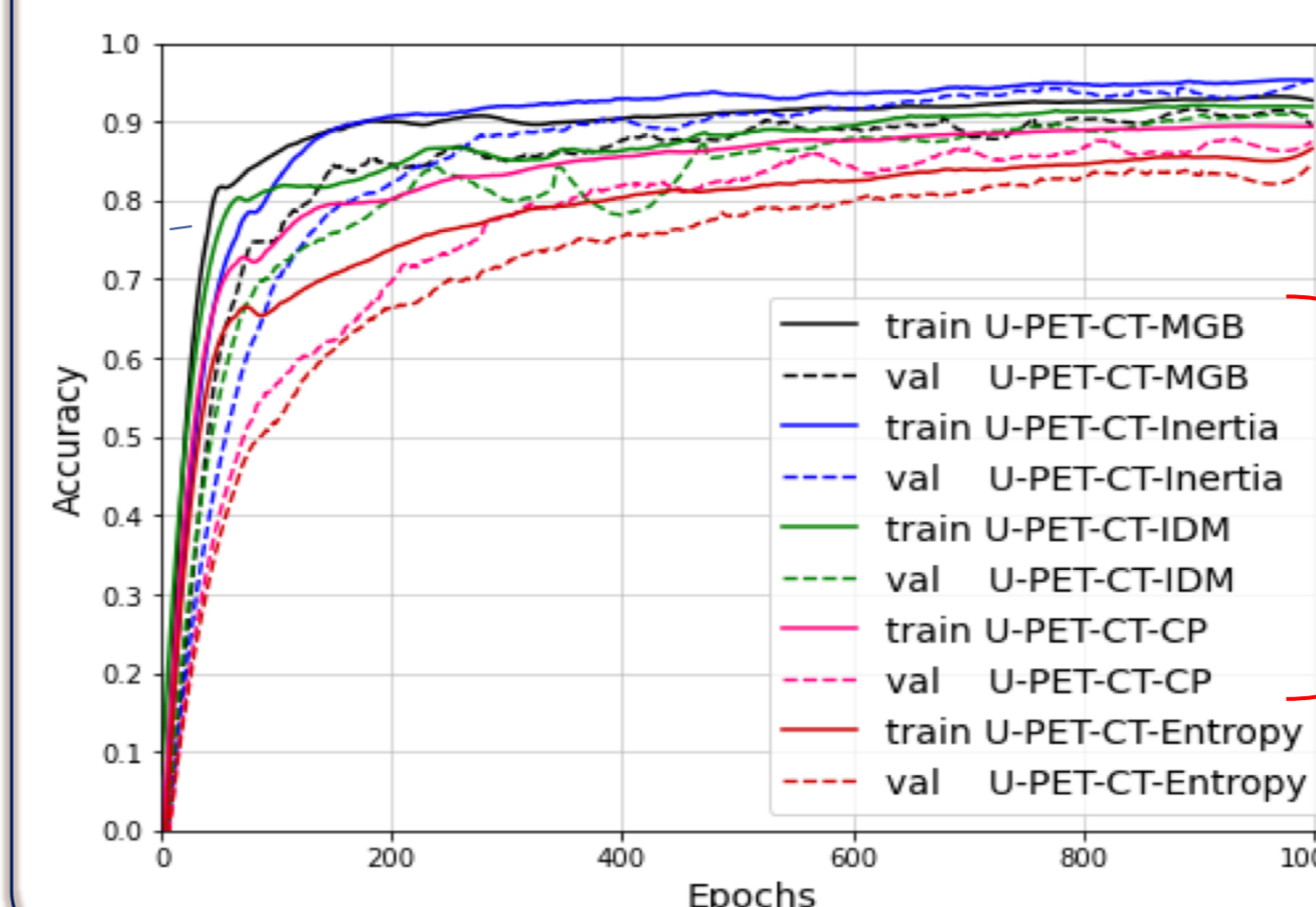
## EXPERIMENTS

**Training:** 52 PET/CT exams (201 lymph nodes tumors)  
**Test:** 10 PET/CT exams (63 lymph node tumors)

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

**Graphic:** 5 accuracy curves during training corresponding to 5 most pertinent features

- U-PET-CT-MGB  $\rightarrow$  inputs {PET,CT,MGB}
- U-PET-CT-Ine.  $\rightarrow$  inputs {PET,CT,Ine}
- U-PET-CT-IDM.  $\rightarrow$  inputs {PET,CT,IDM}
- U-PET-CT-CP  $\rightarrow$  inputs {PET,CT,CP}
- U-PET-CT-Entropy  $\rightarrow$  inputs {PET,CT,Entropy}



## RESULTS

• Proposed method allows tumor segmentation in regions where the baseline PET/CT experiences difficulties in tumor detection due to low image contrast.

• Proposed method eliminates false positives from regions with similar morphology and SUV value to those of tumors.

