# Segmentation of Axillary and Supraclavicular Tumoral Lymph Nodes in PET / CT: A Hybrid CNN / Component-Tree Approach
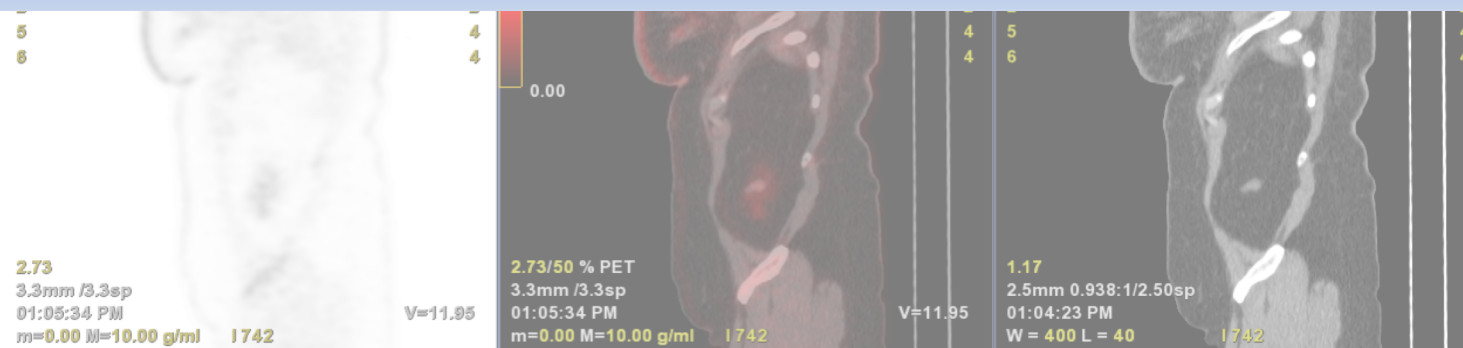
**D. L. Farfan Cabrera, N. Gogin, D. Morland, B. Naegel, D. Papathanassiou, N. Passat**

Université de Reims Champagne Ardenne, CReSTIC, EA 3804, 51097 Reims, France

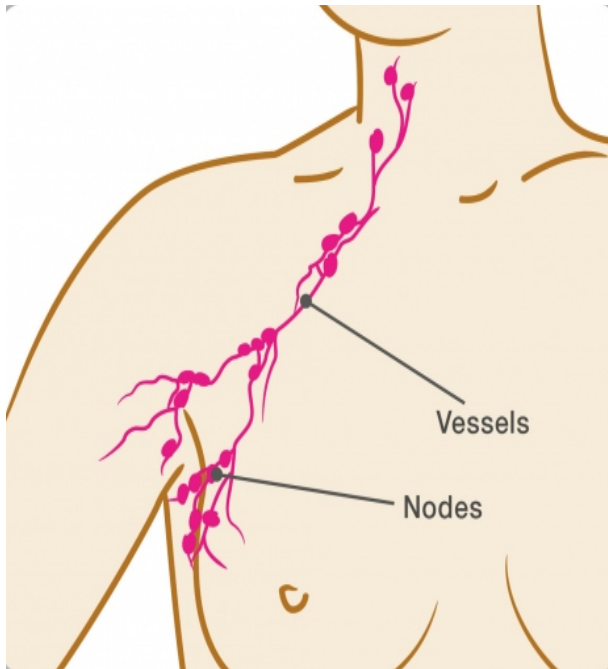General Electric Healthcare, Buc, France

Département de Médecine Nucléaire, Institut Godinot, Reims, France

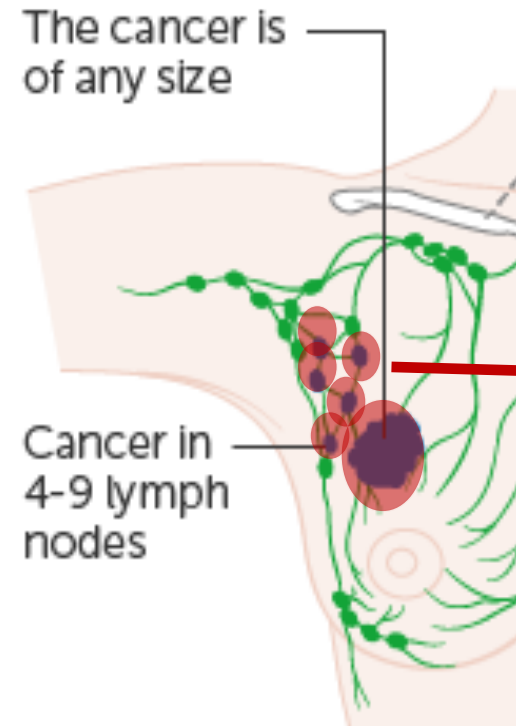Université de Strasbourg, CNRS, ICube, Strasbourg, France

# Automatic axillary lymph node tumor segmentation in PET/CT

**What are lymph nodes?**



**lymph nodes are the first organs reached by cancer**
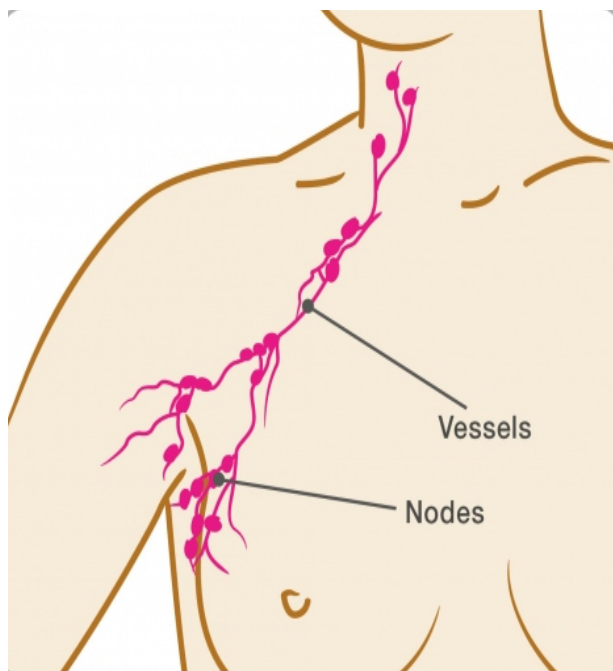
**Patient with no breast cancer**

**Patient with breast cancer**

# Automatic axillary lymph node tumor segmentation in PET/CT

## What are our contributions?



**Patient with no breast cancer**

Vessels

Nodes



The cancer is of any size

Cancer in 4-9 lymph nodes
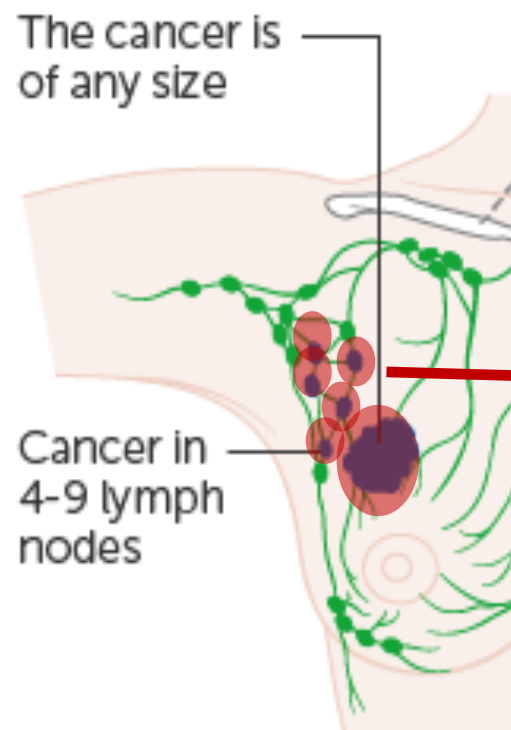
**Patient with breast cancer**

**1st Contribution:**
- Provide a prognostic factor for the staging of breast cancer

**lymph nodes are the first organs reached by cancer**

Cancer staging is determined by:
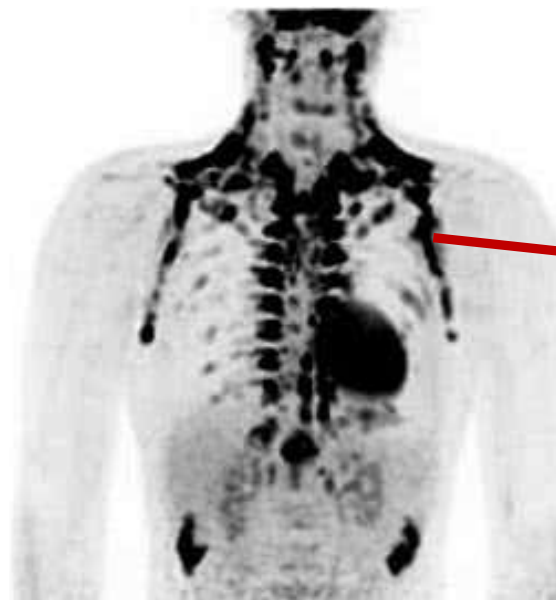N: number of lymph nodes with cancer
T: tumor volume
M: metastasis state

# Automatic axillary lymph node tumor segmentation in PET/CT

## What are our contributions?



**2nd Contribution:**
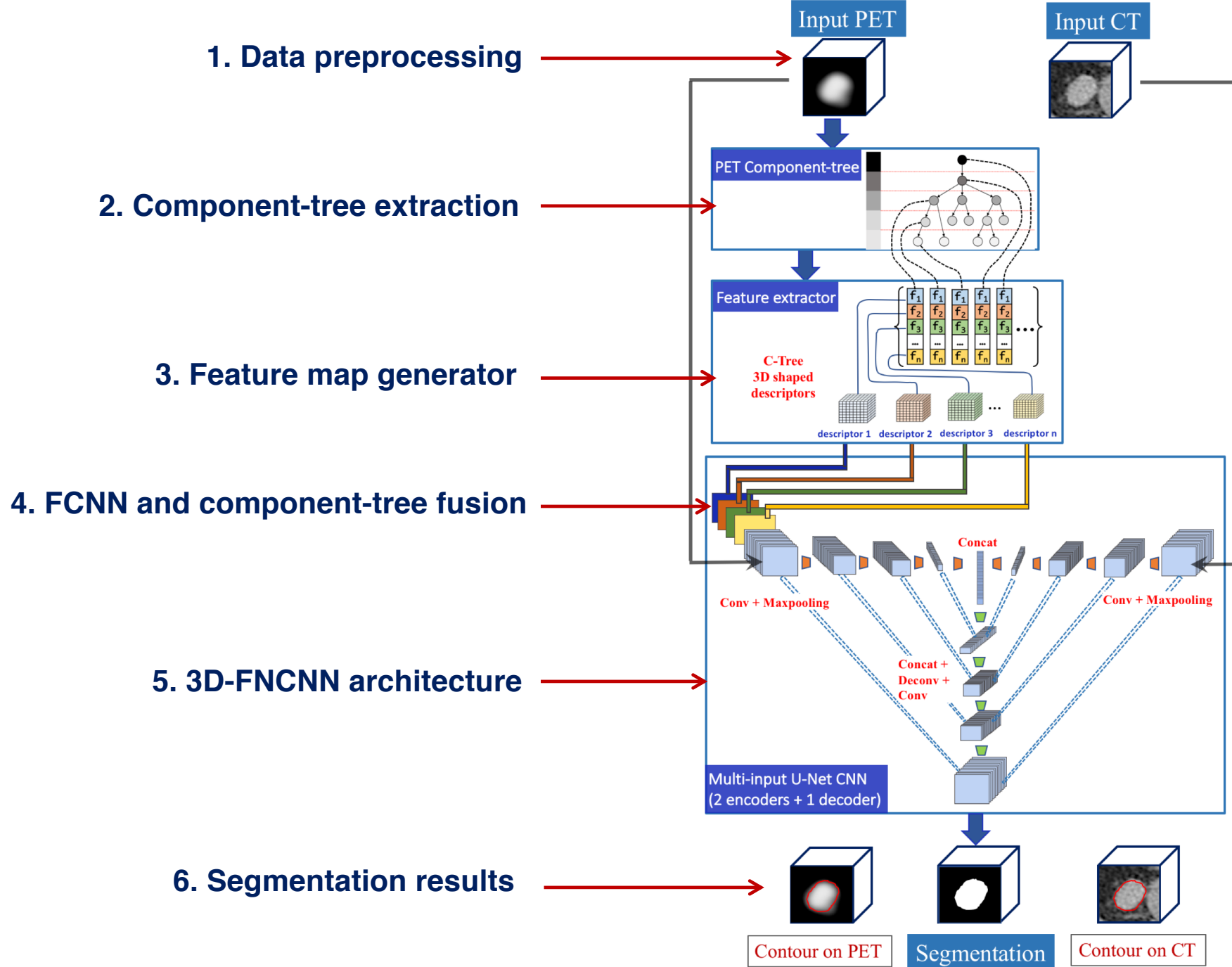- Help doctors to identify quicker false positive coming from brown fat

**brown fat**

**PET image**

**PET image**
**Brown fat shows up (due to exposure to cold)**

- Brown fat has the same metabolism as tumor cells
- Brown fat generates **false positives** that can be mistaken by tumors

1. Data preprocessing
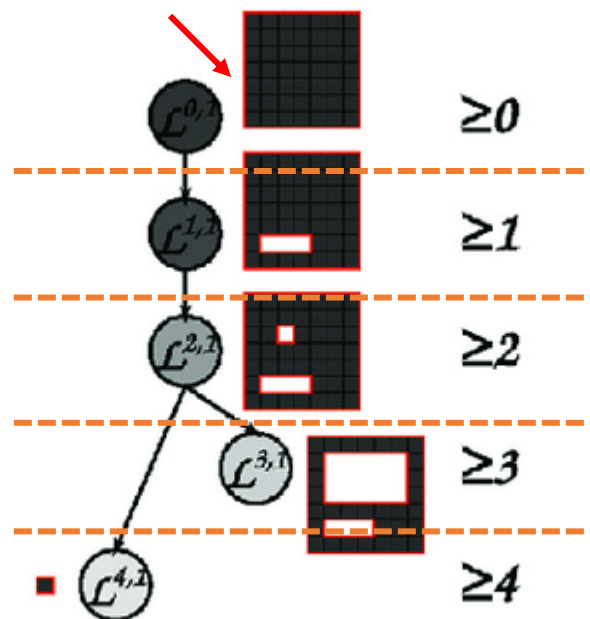
2. Component-tree extraction

3. Feature map generator

4. FCNN and component-tree fusion

5. 3D-FNCNN architecture

6. Segmentation results

Input PET

Input CT

PET Component-tree

Feature extractor

C-Tree
3D shaped
descriptors

descriptor 1   descriptor 2   descriptor 3   descriptor n

Concat

Conv + Maxpooling

Conv + Maxpooling

Concat +
Deconv +
Conv

Multi-input U-Net CNN
(2 encoders + 1 decoder)

Contour on PET

Segmentation

Contour on CT

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## 2. Component-tree extraction

### What is a component-tree?



Full image

- Each node is a connected component

- Root node contains all the image

- Follows a hierarchical structure according to gray levels

- Each tree level corresponds to a gray level

- Each node belongs to its ascendants nodes

# 2. Component-tree extraction



tumors

PET image
Coronal MIP view

Full PET image

tumors

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## 2. Component-tree extraction

For each node $N_i$, it is computed:

- **f1 → G($N_i$):** mean gradient of node contour in PET

- **f2 → H($N_i$):** mean HU value in CT

- **f3 → S($N_i$):** standard deviation of H

- **f4 → R($N_i$):** relative integral volume

- **f5 → L($N_i$):** position with respect to the lungs
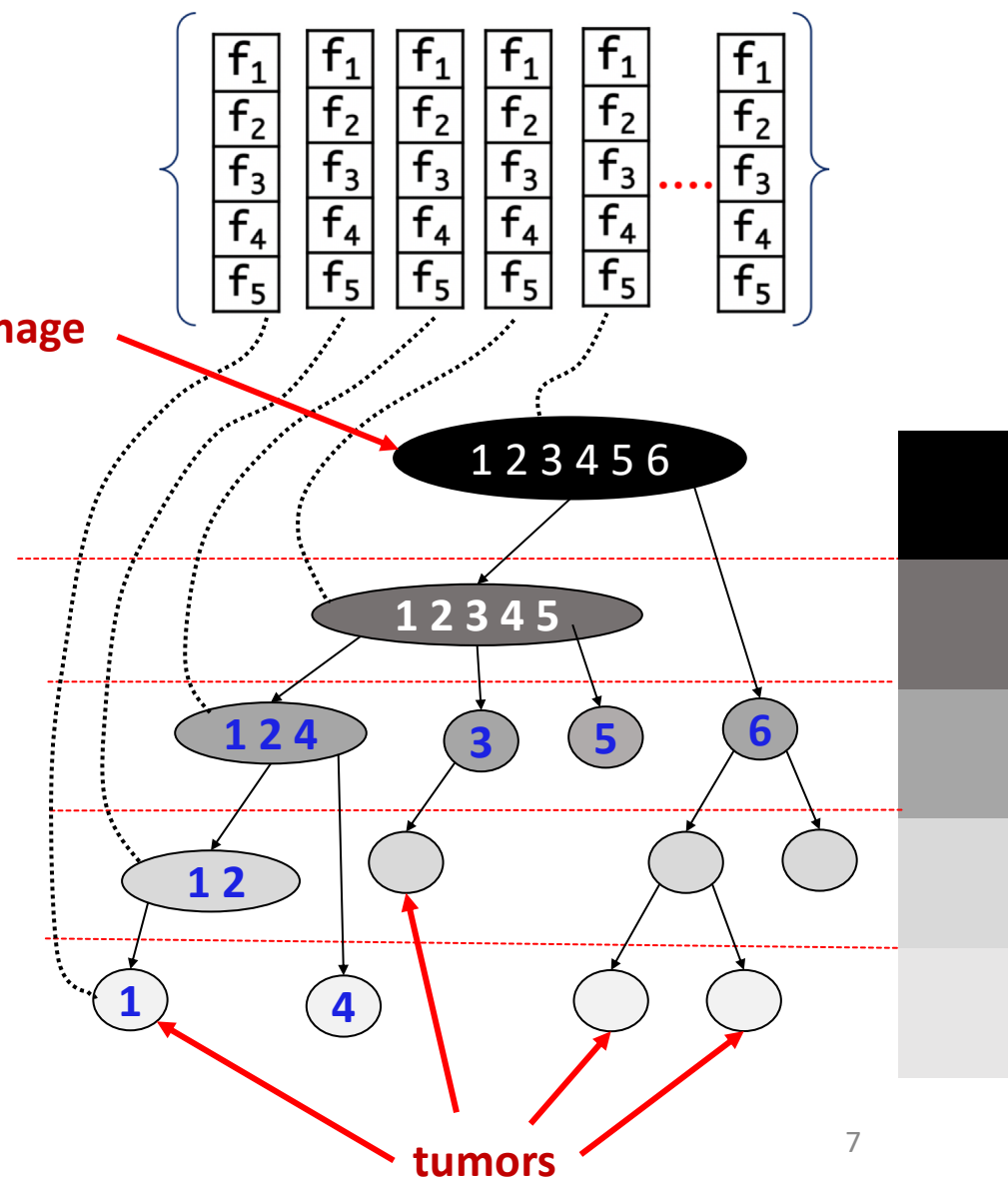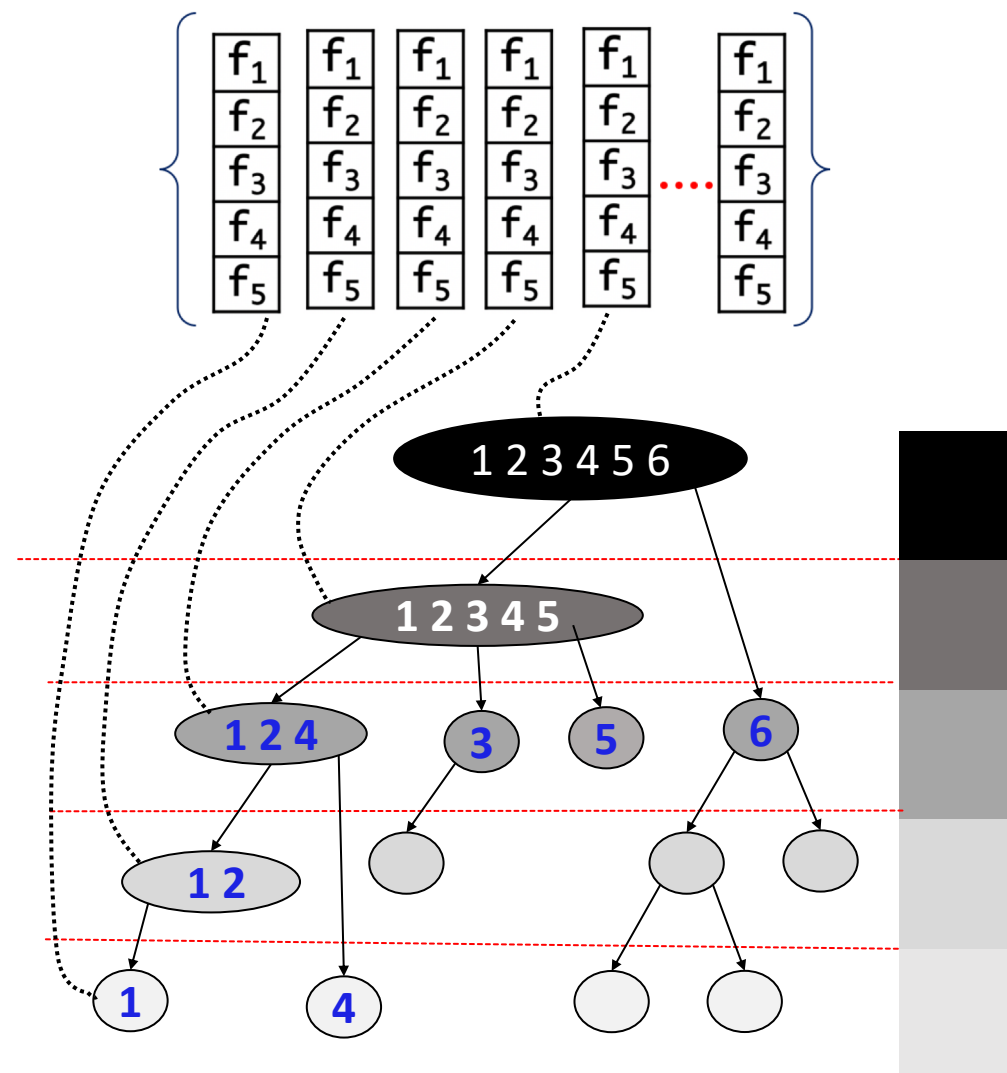
# Automatic lymph node tumor segmentation in PET/CT
## 2. Component-tree extraction

**Goal of these descriptors?**

For each node $N_i$, it is computed:

We assign to each **node** 5 descriptors

- **f1 → G($N_i$):** mean gradient of node contour  ⟶  lymph node have **high** contour gradient

- **f2 → H($N_i$):** mean HU value in CT  ⟶  lymph nodes have **positive** HU value
  brown fat has **negative** HU value

- **f3 → S($N_i$):** standard deviation of H  ⟶  lymph nodes have **low** standard deviation

- **f4 → R($N_i$):** relative integral volume  ⟶  lymph nodes have **high** contrast with their neighbourhood

- **f5 → L($N_i$):** position with respect to the lungs  ⟶  lymph nodes are **ouside** the lungs convexhull

## 3. Feature map generator

**From feature vectors to feature volumes?**

We assign to each **voxel** 5 descriptors

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

$$G(x) = \boxed{\max_i} G(N_i) \implies$$ lymph node have $\boxed{\text{high}}$ contour gradient

$$H(x) = \boxed{\text{mean}_i} H(N_i) \implies$$ lymph nodes have $\boxed{\text{positive}}$ HU value
brown fat has $\boxed{\text{negative}}$ HU value

$$S(x) = \boxed{\min_i} S(N_i) \implies$$ lymph nodes have $\boxed{\text{low}}$ standard deviation

$$R(x) = \boxed{\max_i} R(N_i) \implies$$ lymph nodes have $\boxed{\text{high}}$ contrast with their neighbourhood

$$L(x) = \boxed{\text{or}_i} L(N_i) \implies$$ lymph nodes are $\boxed{\text{ouside}}$ the lungs convexhull

## 4. CNN and component-tree fusion
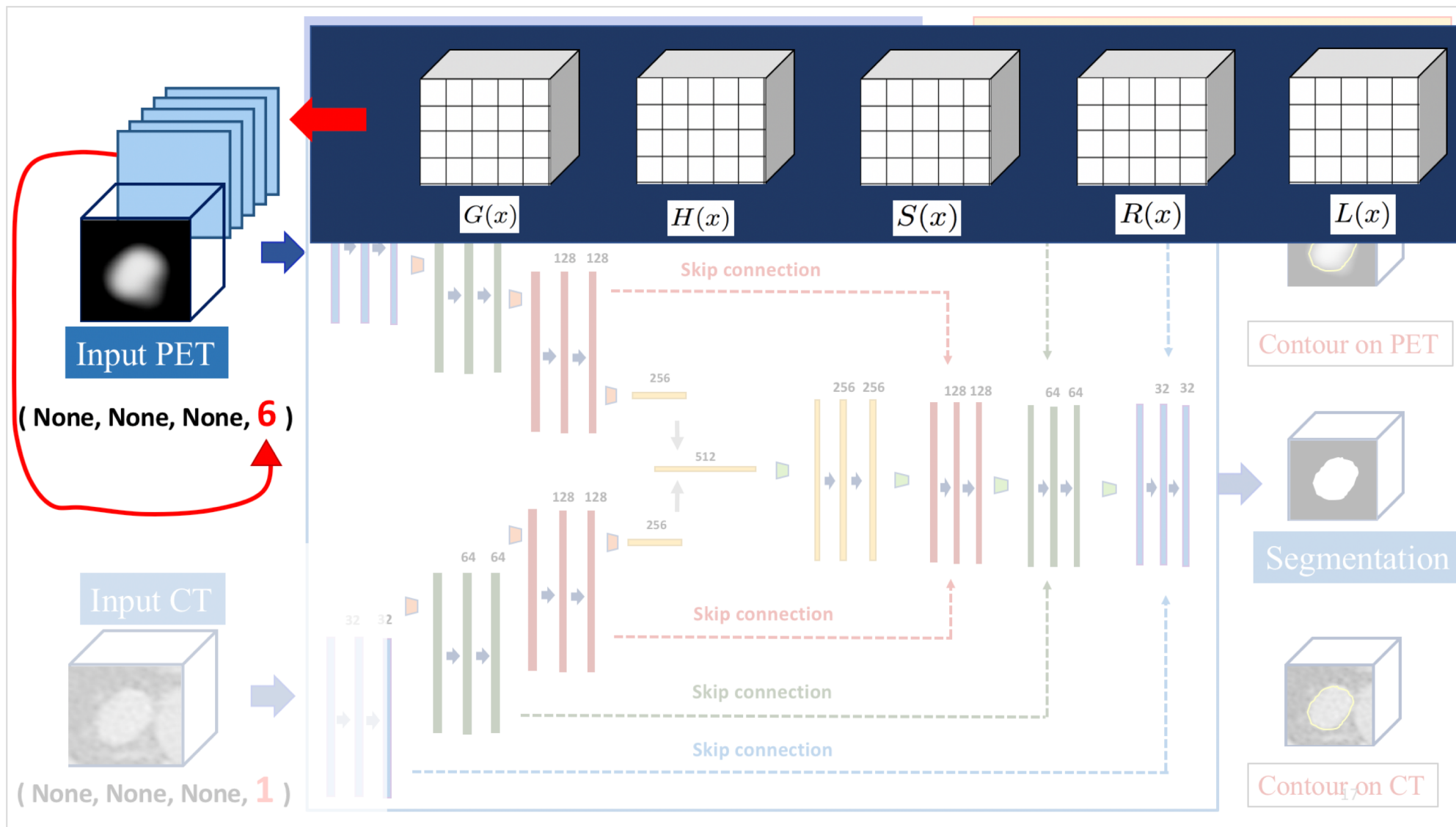
5. CNN

3D U-Net PET-CT for LN tumor segmentation
(2 encoders + 1 decoder)

Conv 3x3 Relu    Upconv 3x3 Relu
Maxpooling 3x3   Concatenation

Input PET

Input CT

Skip connection

Contour on PET

Segmentation

Contour on CT
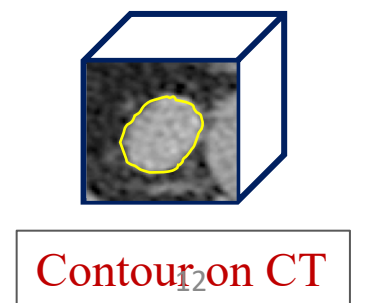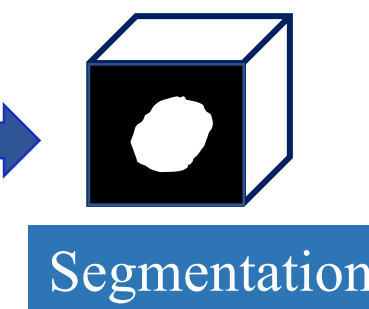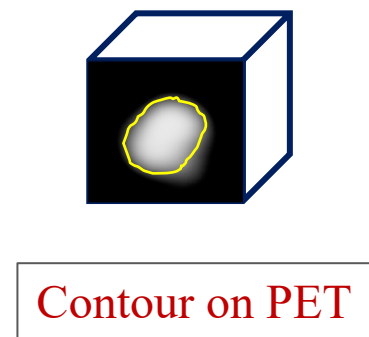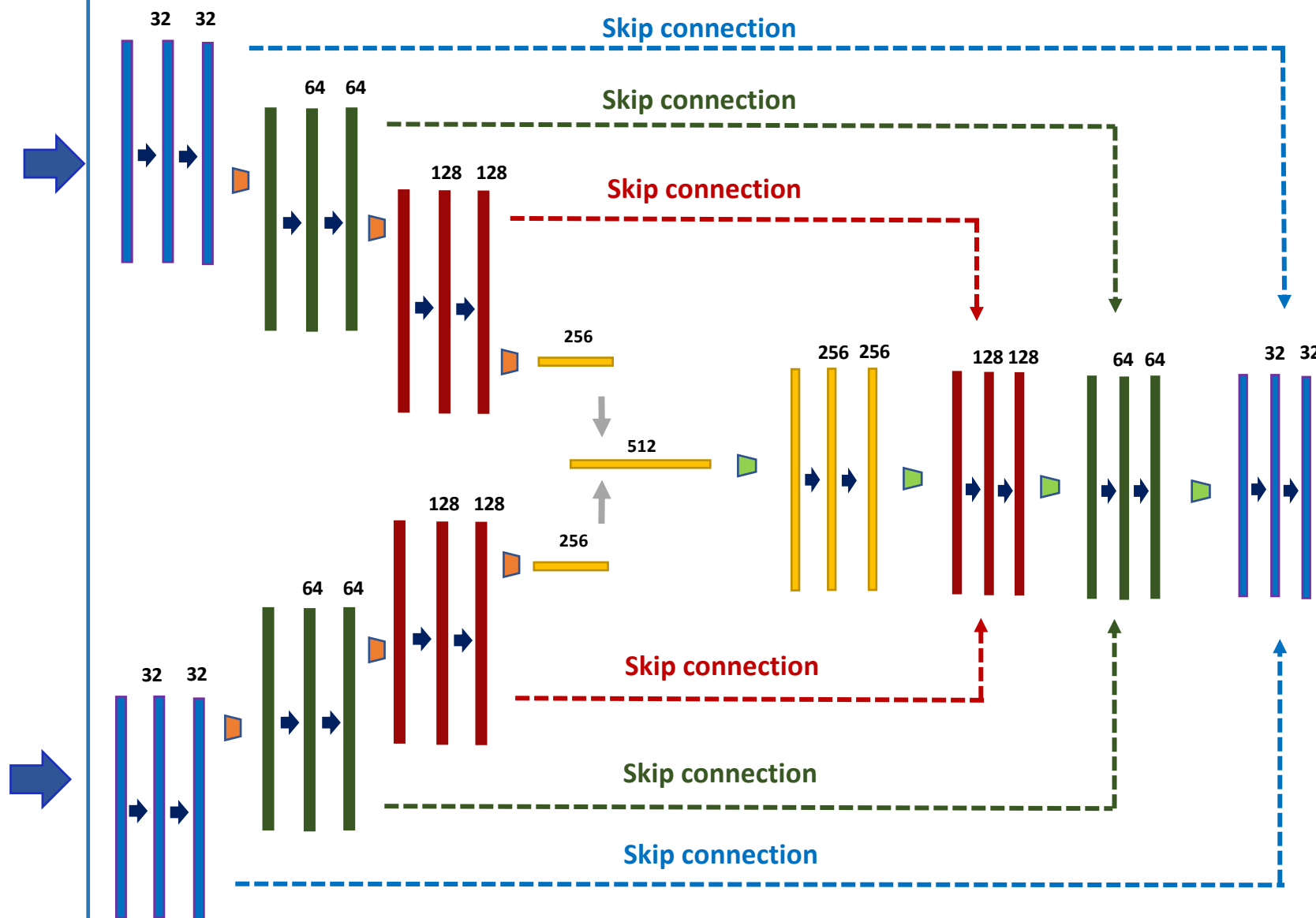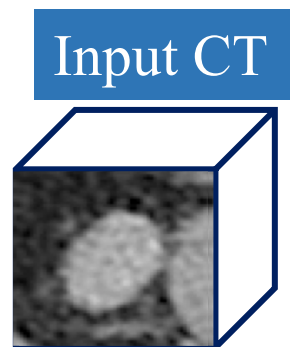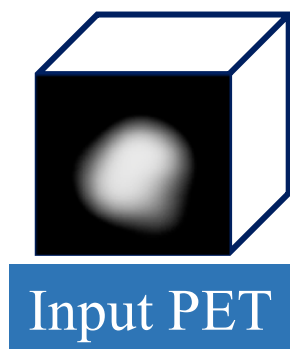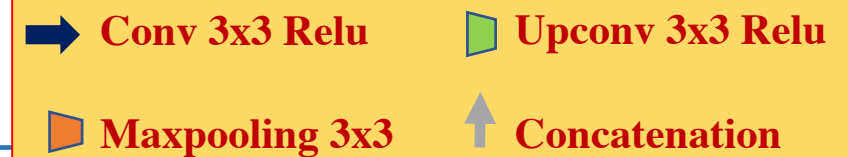
# Automatic lymph node tumor segmentation in PET/CT
# 6. Results

| | |
|---|---|
| **Training:** | **201 tumors (42 PET/CT exams)** |
| **Validation:** | **56 tumors** |
| **Patches for test:** | **63 tumors   (10 PET/CT exams)** |
| **Loss Function:** | **1 - Dice** |
| **Iterations:** | **1000** |
| **Type of CNN:** | **U-NET** |
| **Number of layers:** | **3** |
| **Resolution** | **1.2mm$^3$** |
| **3D Patch size:** | **80 mm$^3$** |

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

baseline →
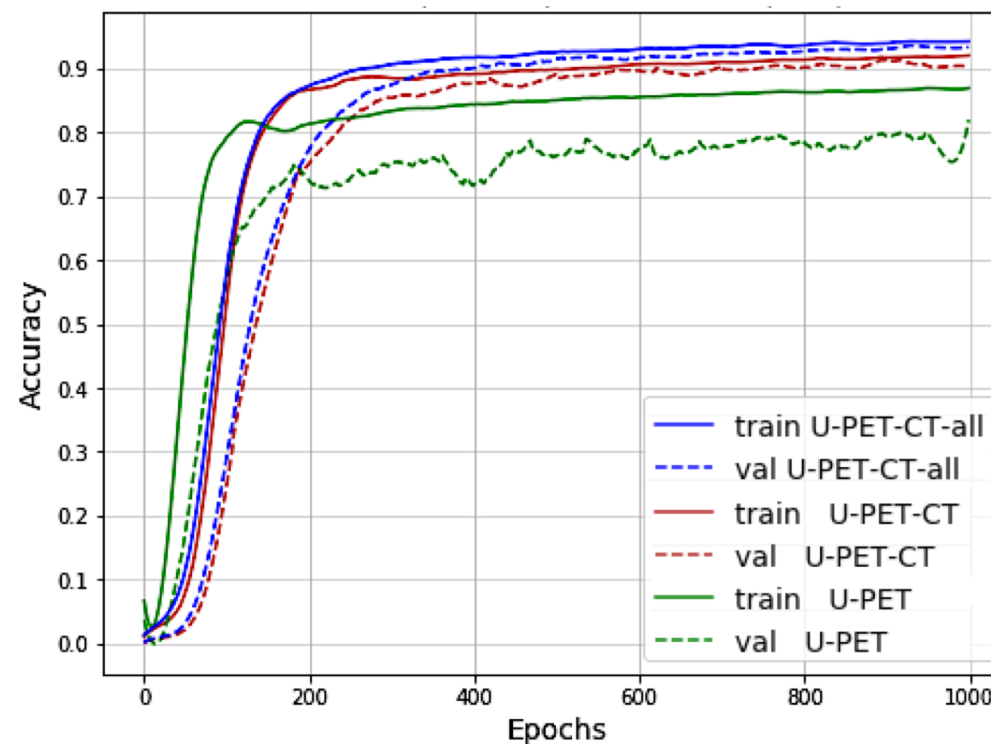
proposed method →



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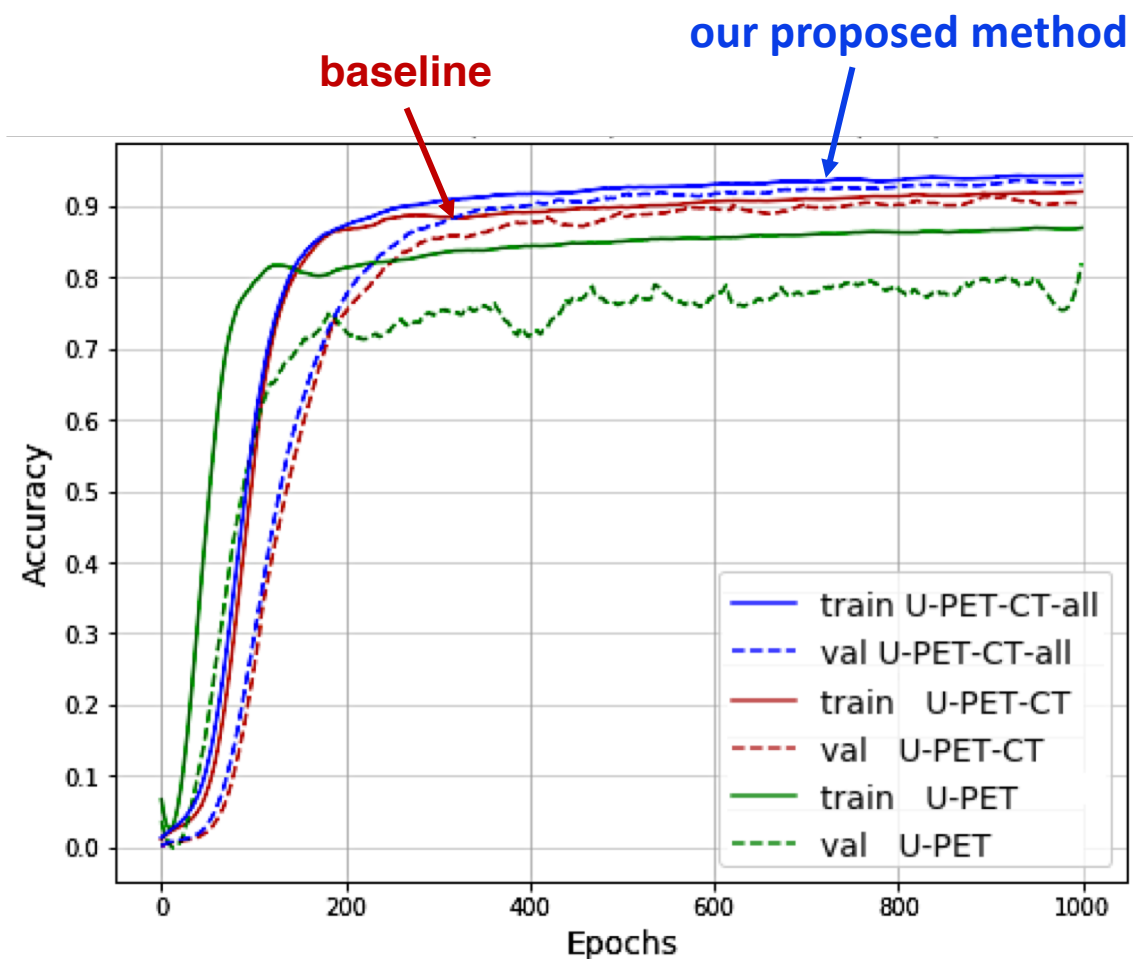
# Automatic lymph node tumor segmentation in PET/CT
# 6. Results

U-PET            →   inputs {PET}

U-PET-CT         →   inputs {PET, CT}

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



| 3D CNN Model | Voxel-based metrics (Segmentation) | | | Region-based metrics (Detection) | | |
|---|---|---|---|---|---|---|
| | DSC voxel | PPV voxel | SE voxel | DSC region | PPV region | SE region |
| 3D U-Net (PET) | 0.832703 +- 0.1327 | 0.827762 +- 0.1483 | 0.82478 +- 0.0868 | 0.798685 +- 0.1547 | 0.757925 +- 0.2206 | 0.890805 +- 0.0821 |
| 3D U-Net (PET-CT) | 0.865896 +- 0.08 | 0.844429 +- 0.1034 | 0.886527 +- 0.0465 | 0.871825 +- 0.1312 | 0.849864 +- 0.1893 | 0.926111 +- 0.0628 |
| 3D U-Net (PET-CT-all) | 0.867845 +- 0.1161 | 0.872781 +- 0.1425 | 0.896473 +- 0.0553 | 0.894624 +- 0.1431 | 0.851361 +- 0.1948 | 0.933135 +- 0.0756 |

baseline →

proposed method →

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## 6. Results

**Proposed method removes false positives coming from brown fat**

*false positive*

**Results shown on the PET/CT fusion images**



*false positive*

**U-PET**

**U-PET-CT**
*(baseline)*

**U-PET-all**
*(proposed method)*

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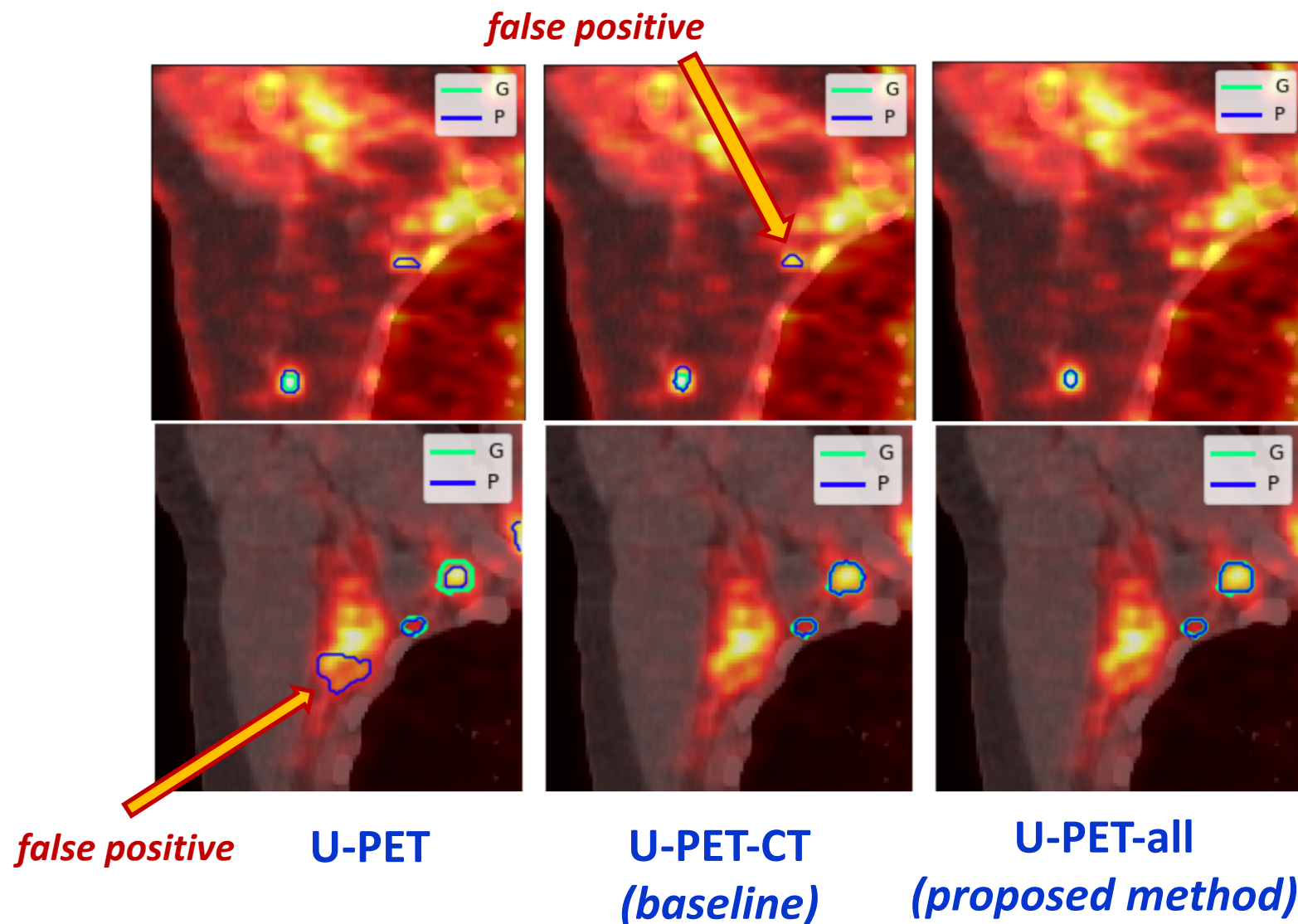
# Automatic lymph node tumor segmentation in PET/CT
# 6. Results

Proposed method separates visually connected tumors

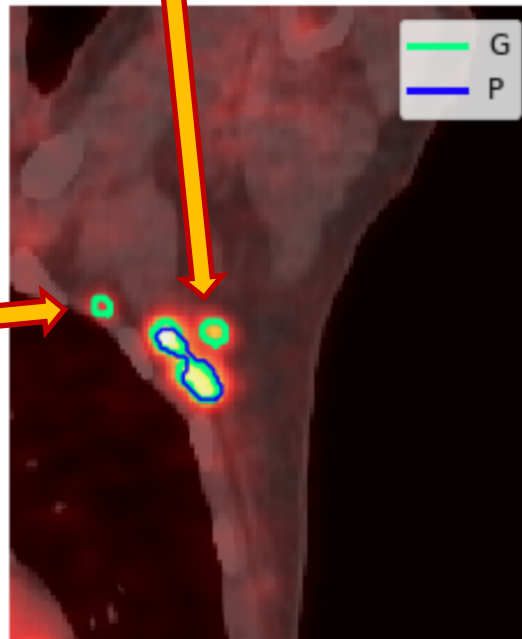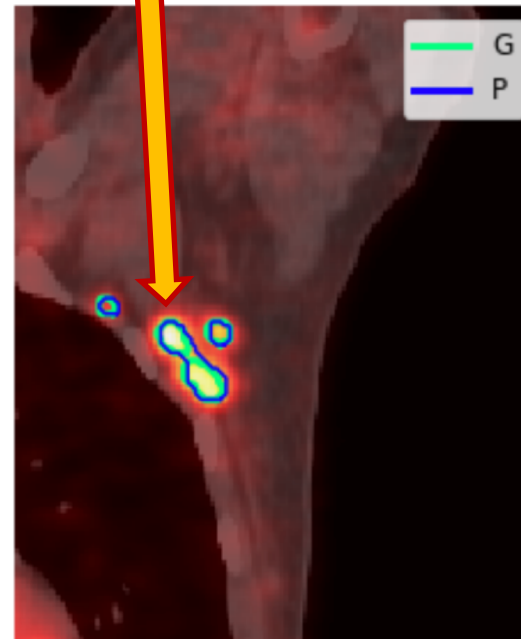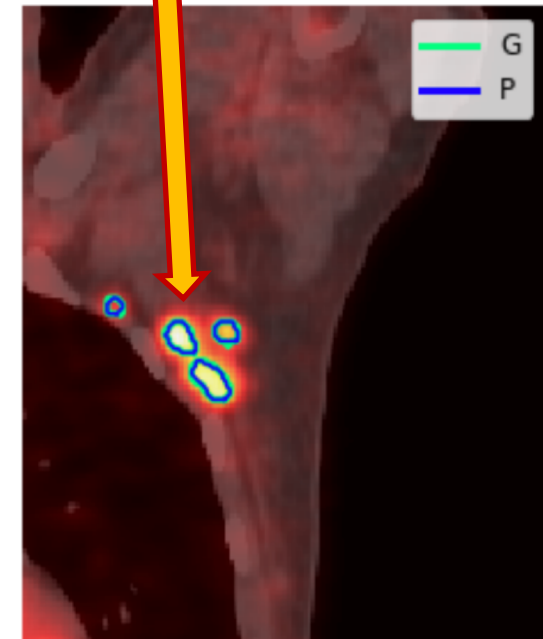Results shown on the PET/CT fusion images



false positive

joined contours

separated contours

false positive

**U-PET**

**U-PET-CT**
*(baseline)*

**U-PET-all**
*(proposed method)*

# Thank you for your attention

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