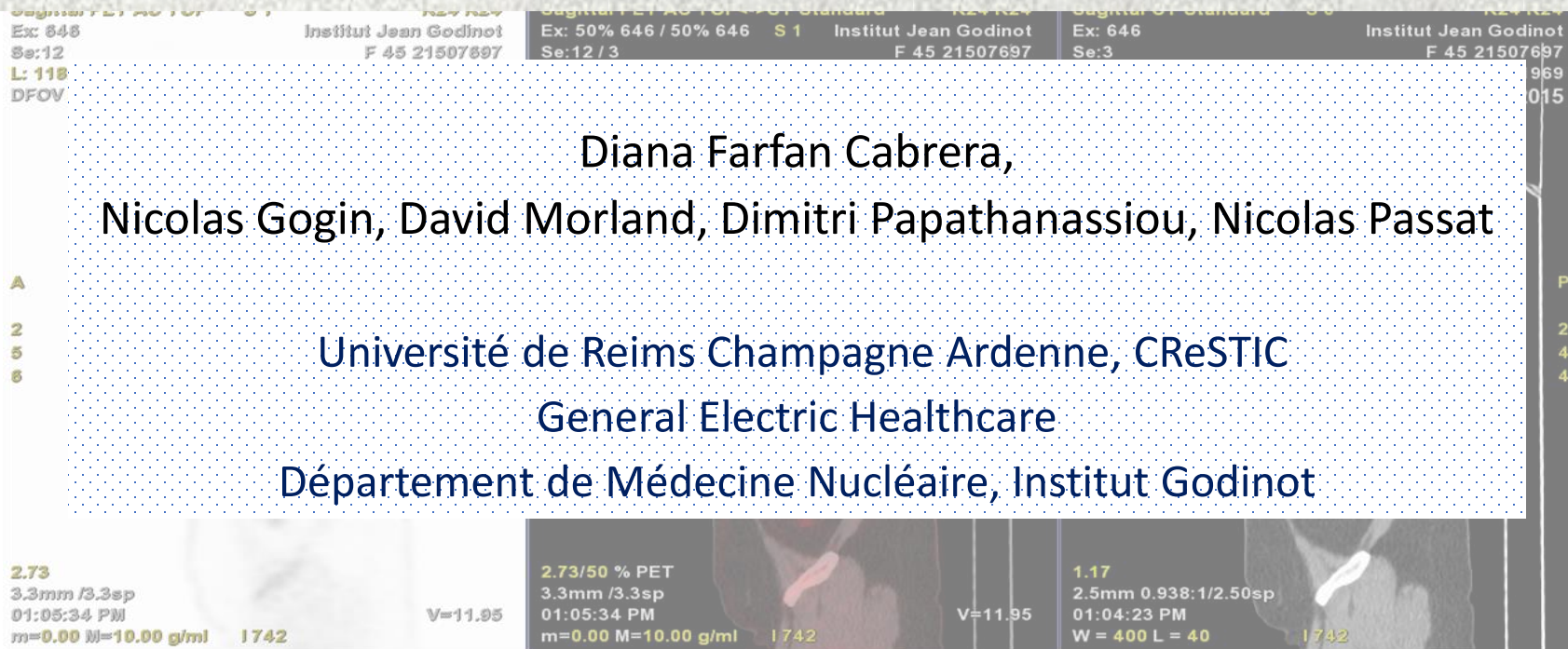


Segmentation of axillary lymph nodes in PET/CT scans: First experiments



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

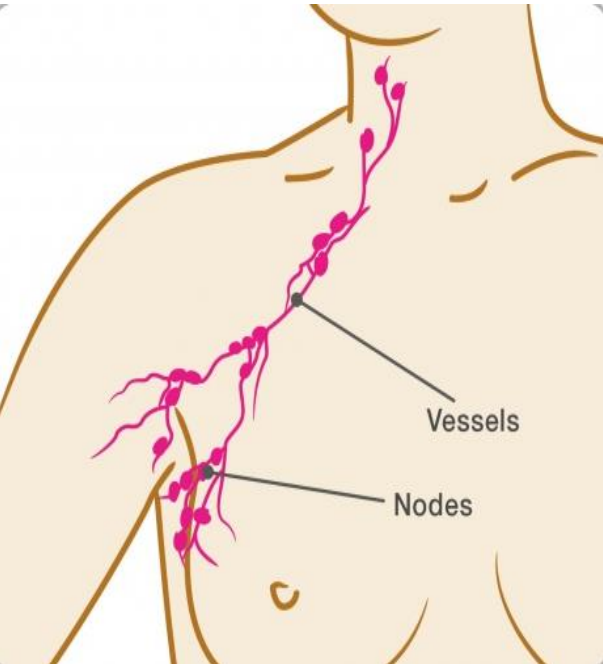
Université de Reims Champagne Ardenne, CReSTIC
General Electric Healthcare
Département de Médecine Nucléaire, Institut Godinot



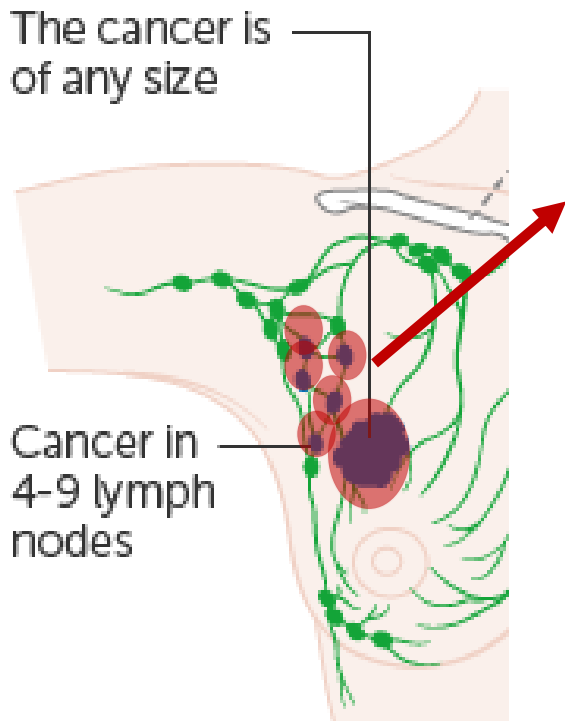
Automatic axillary lymph node segmentation in PET/CT volumes - Context

- Context: Breast cancer and axillary lymph nodes

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



Normal patient with no breast cancer



Patient with breast cancer

Diagnosis:

- Doctors proceed to do a surgical procedure to remove all the branches of vessels where a lymph cancer node is present

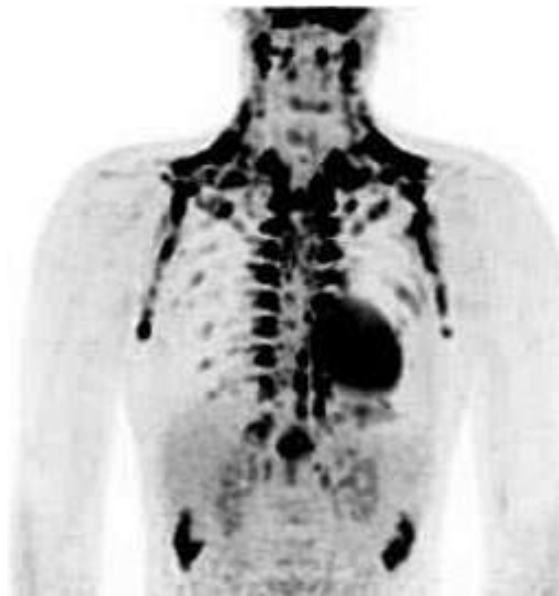


Automatic axillary lymph node segmentation in PET/CT volumes - **Contribution**

- Brown fat has the same metabolism as tumor cells
- They generate **FALSE POSITIVES** that require extra-time to be visualized by doctors



Ideal PET acquisition



Brown fat shows up(due to exposure to cold). Brown fat has the same metabolism as tumor cells

Contribution:

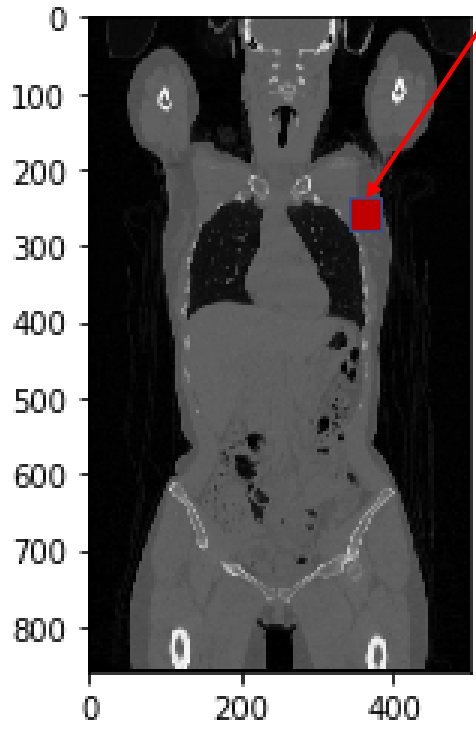
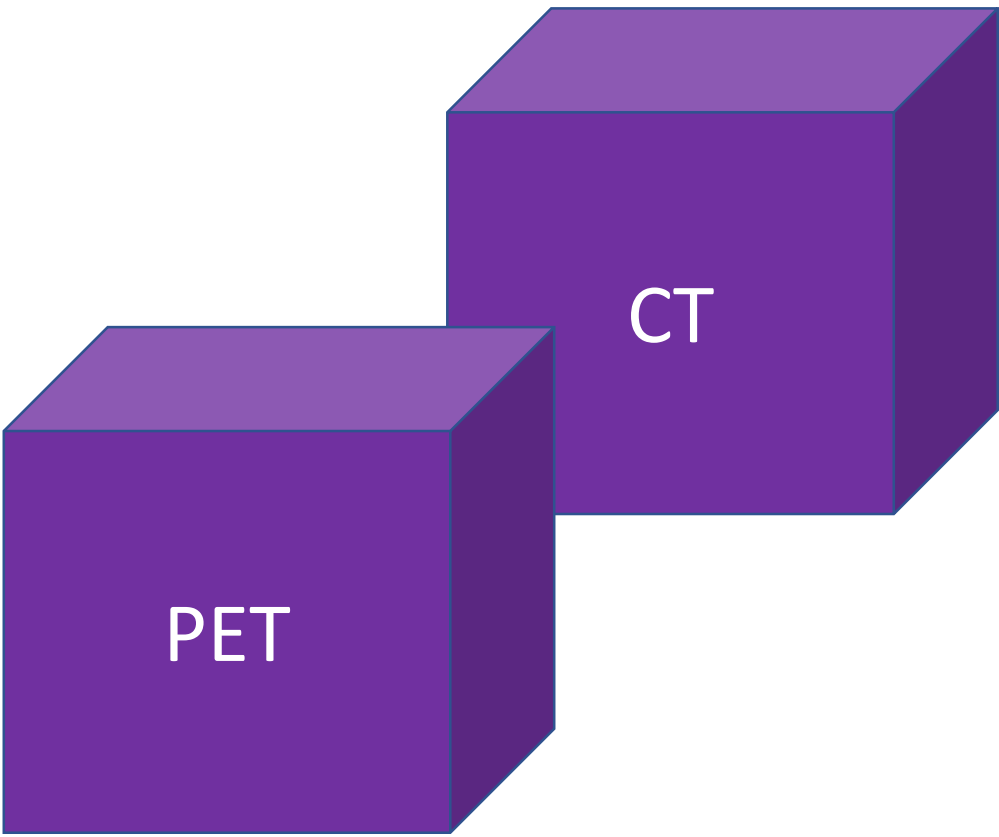
- Algorithm can automatically detect **N** (number of lymph nodes with cancer cells) and contribute to the determination of cancer staging
- Help doctors to identify quicker false positive cancer lymph nodes



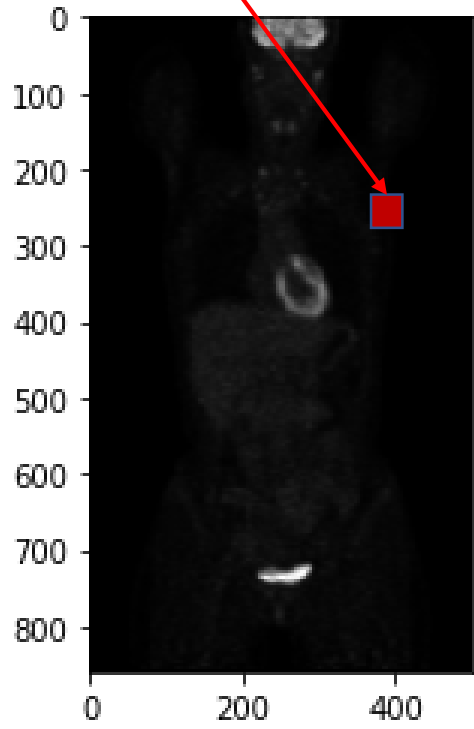
Automatic axillary lymph node segmentation in PET/CT volumes – Preprocessing

- Rigid transformation in order to register PET and CT
- Voxel normalisation of isotropic size of 1.5mm^3 for both PET and CT

Same coordinate corresponds to the same location in PET and CT



CT

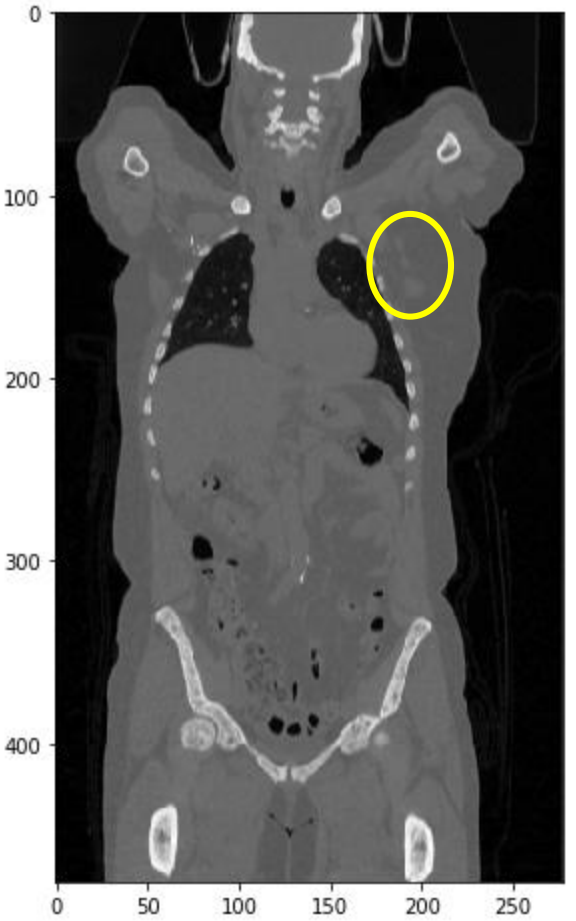


PET

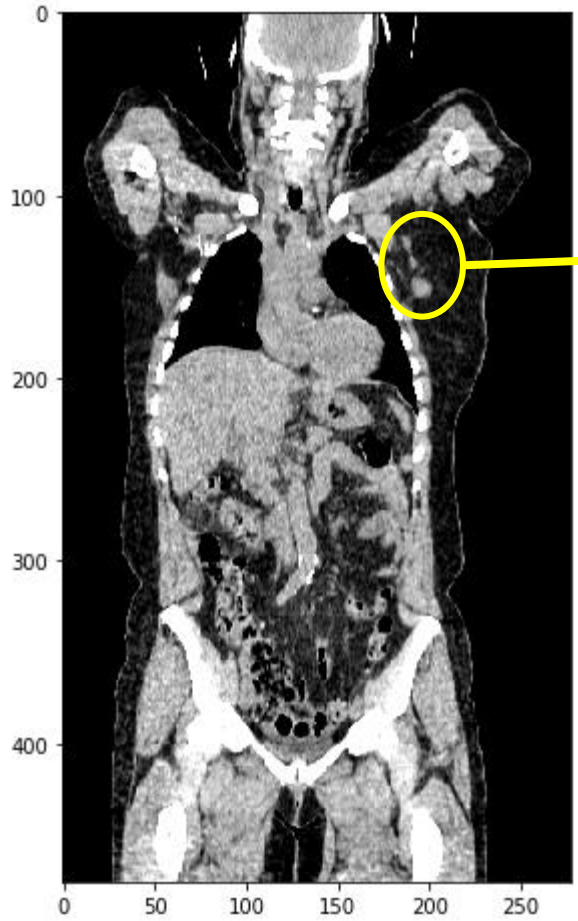


Automatic axillary lymph node segmentation in PET/CT volumes – Preprocessing

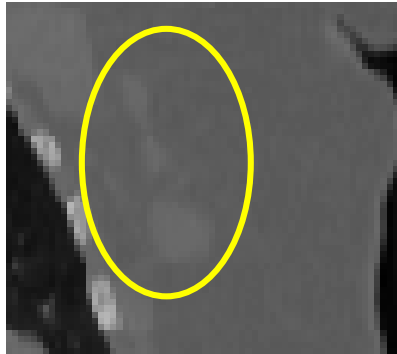
- Perform windowing in CT scans to enhance lymph node visualization



CT volume before windowing
Coronal slice view



CT volume after windowing
Coronal slice view



Windowing in CT:
Remove gray values bellow **- 120 HU**
Remove gray values above **+ 120 HU**

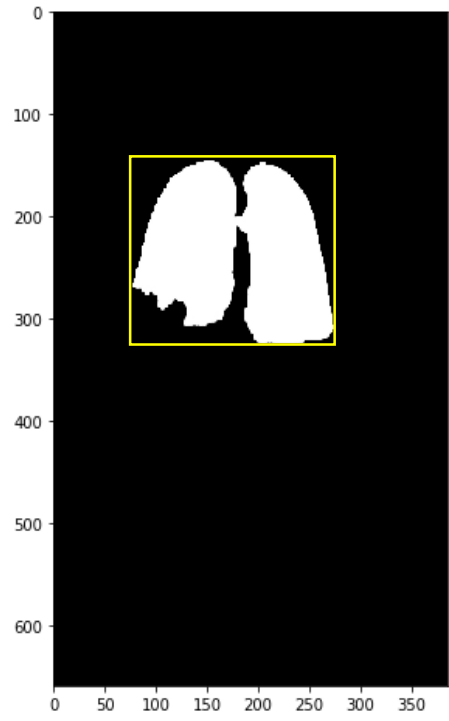


Automatic axillary lymph node segmentation in PET/CT volumes – Preprocessing

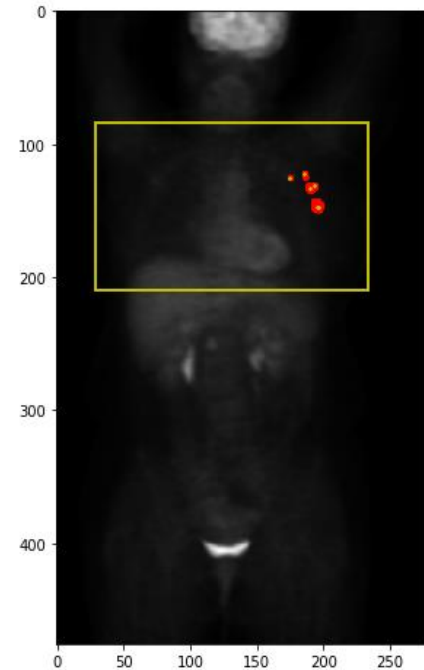
- Perform lung segmentation in CT scans to extract axillary ROI



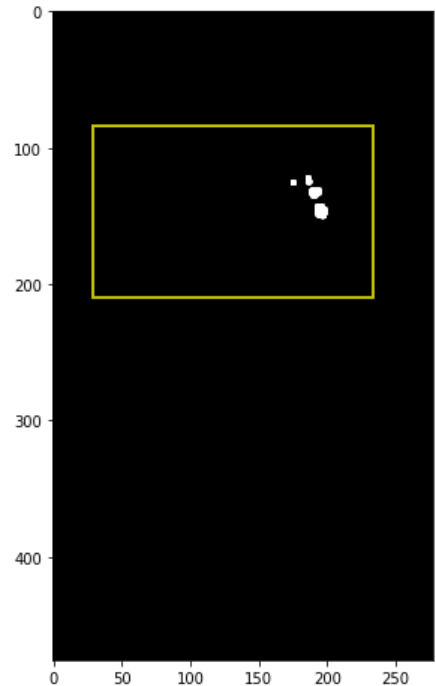
CT volume
Coronal slice view



Bounding box around lungs segmentation mask
Coronal MIP view



Bounding box around region of interest in PET
(landmarks in yellow, masks in red)
Coronal MIP view

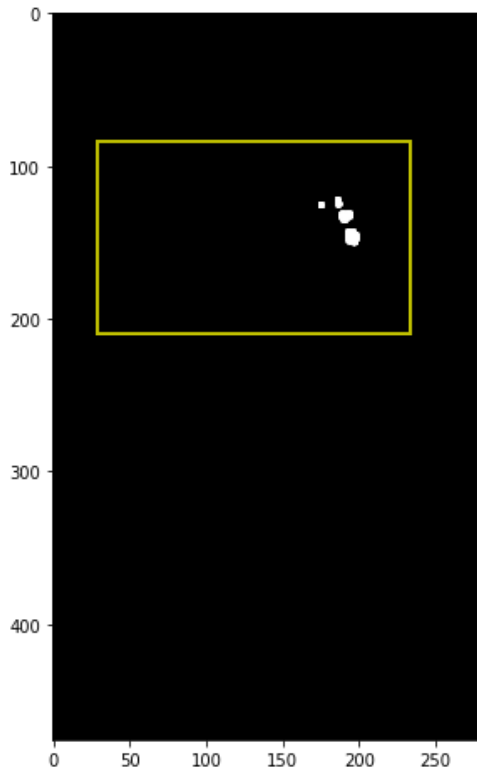


Bounding box around region of interest in ground-truth mask
Coronal MIP view



Automatic axillary lymph node segmentation in PET/CT volumes – Patch Extraction for CNN

- Positive patches (white bounding boxes) - contain a whole lymph node
- Negative patches (red bounding boxes) - contain a piece of lymph node or no lymph node at all



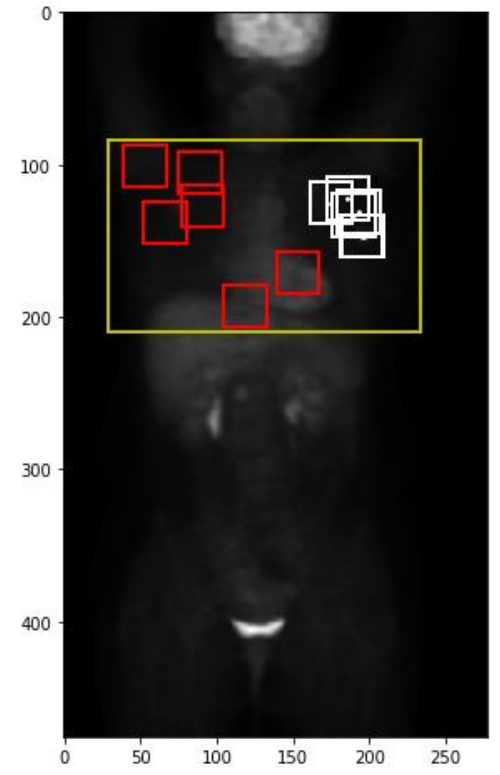
Ground-truth mask
Slice coronal view



Ground-truth mask
Slice coronal view



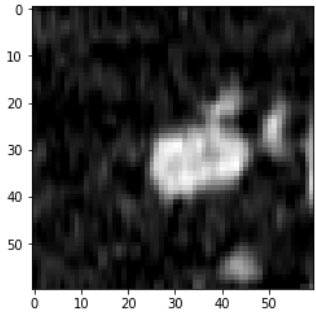
CT
Slice coronal view



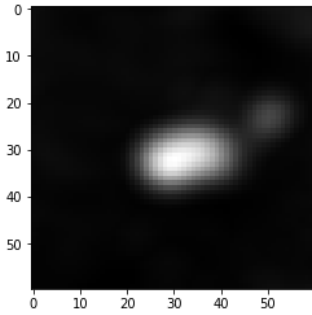
PET
MIP coronal view



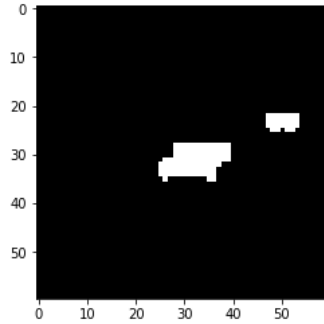
Automatic axillary lymph node segmentation in PET/CT volumes – Patch Extraction for CNN – Positive patches



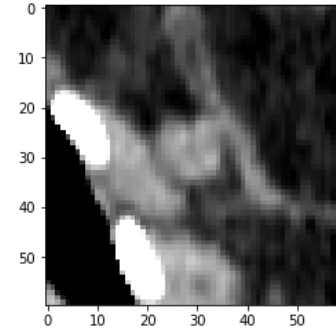
CT



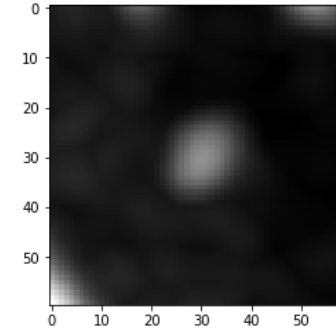
PET



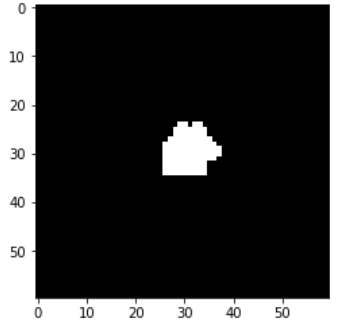
Ground truth
binary mask



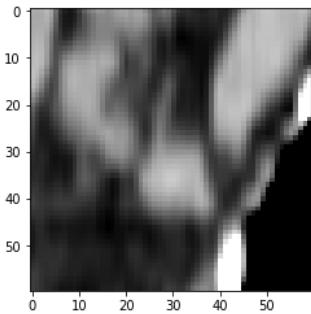
CT



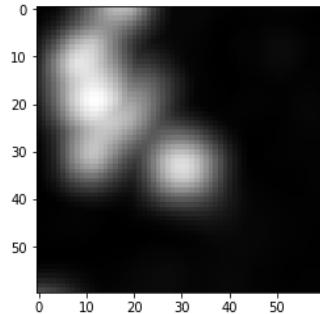
PET



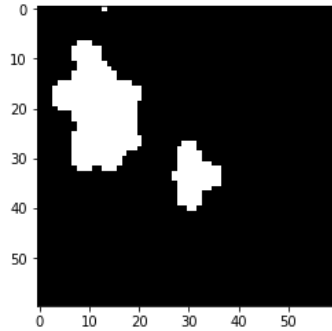
Ground truth
binary mask



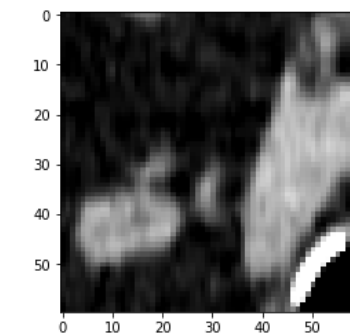
CT



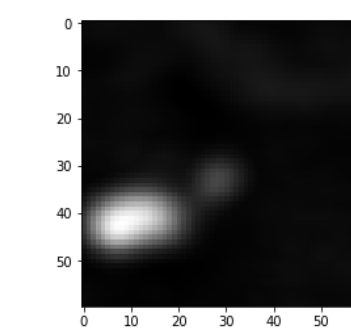
PET



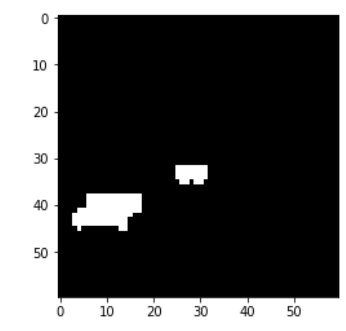
Ground truth
binary mask



CT



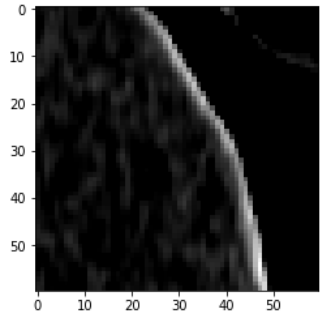
PET



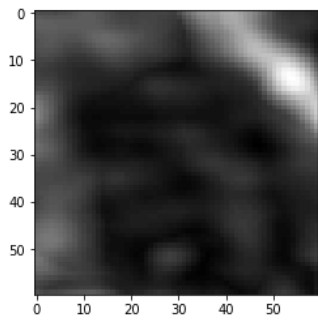
Ground truth
binary mask



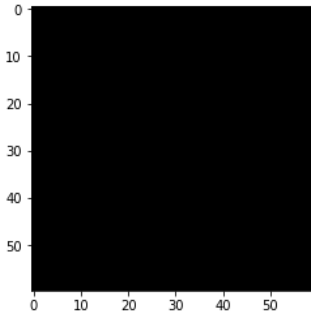
Automatic axillary lymph node segmentation in PET/CT volumes – Patch Extraction for CNN – Negative patches



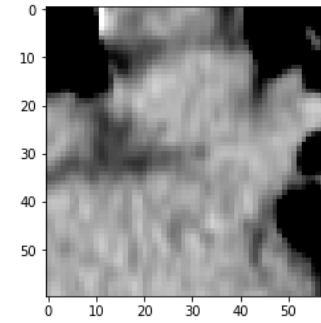
CT



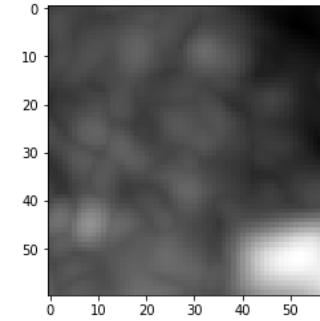
PET



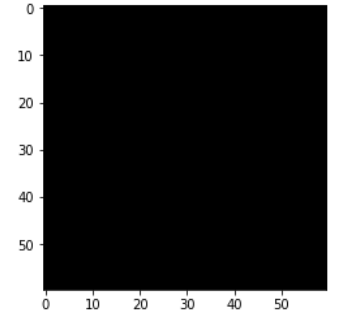
Ground truth
binary mask



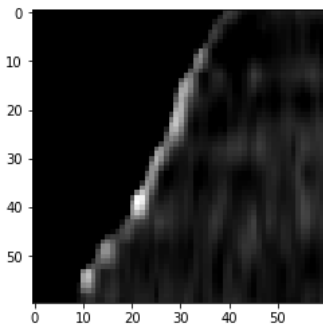
CT



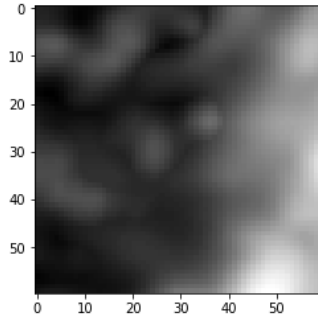
PET



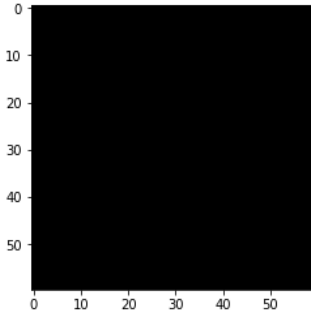
Ground truth
binary mask



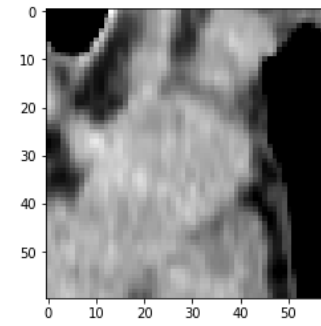
CT



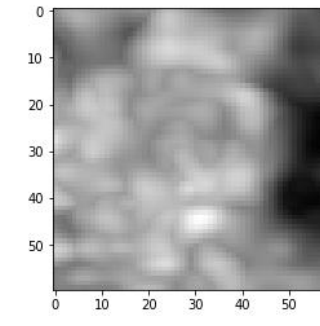
PET



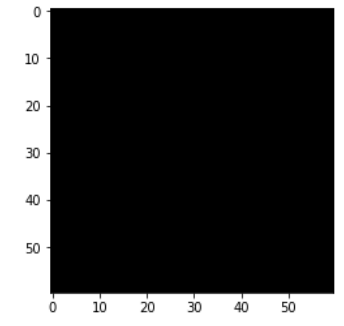
Ground truth
binary mask



CT



PET



Ground truth
binary mask

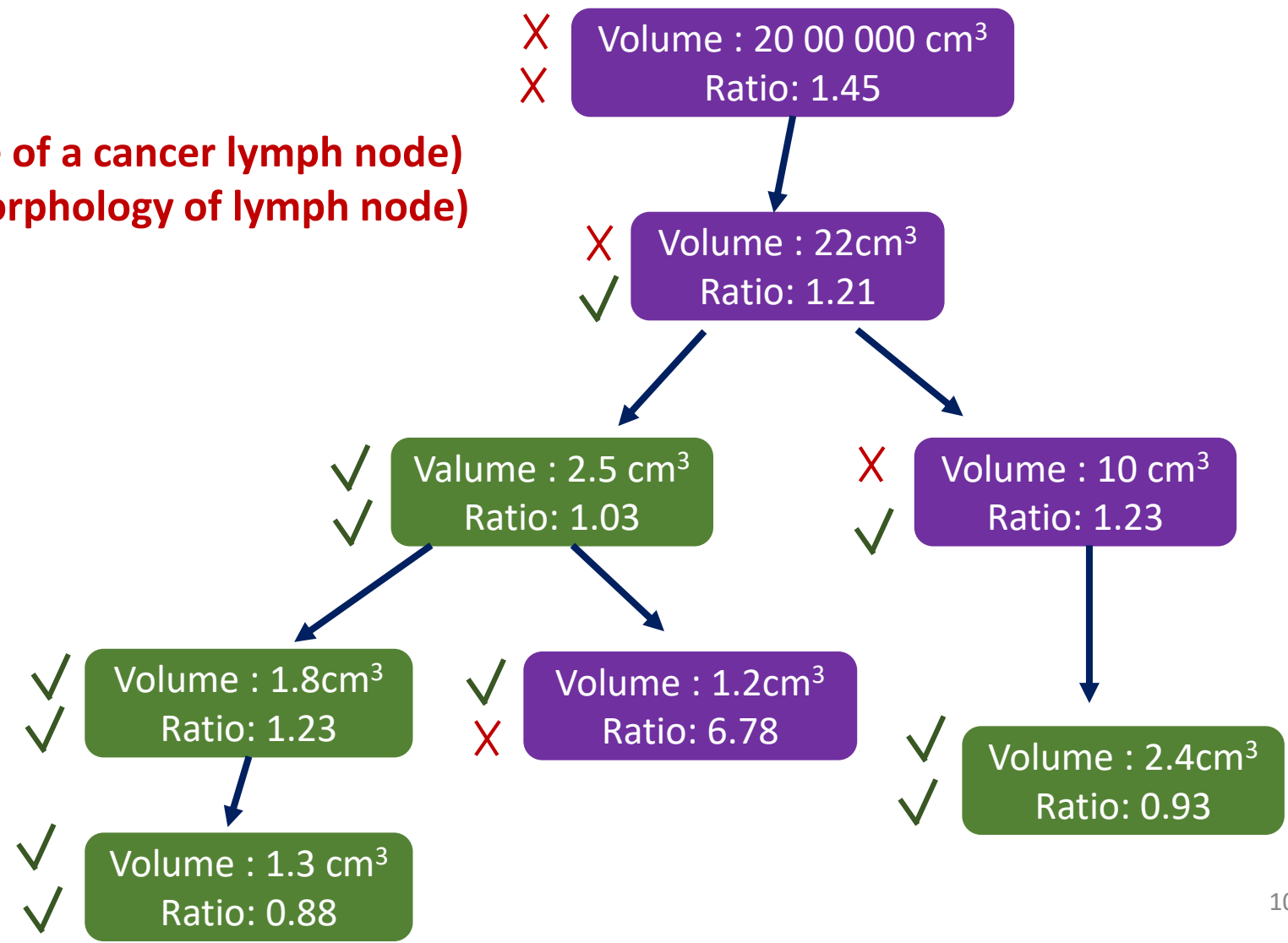


Automatic axillary lymph node segmentation in PET/CT volumes – Methodology – 3D Component trees

Valid volume: $0.5\text{cm}^3 - 4\text{cm}^3$ (volume of a cancer lymph node)
Valid ratio: $0.7 - 1.3$ (squared morphology of lymph node)

We attribute to each node:
The ratio of its nearest ancestor with valid ratio and volume

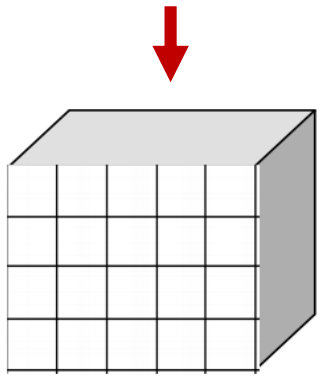
- Valid nodes
- Invalid nodes





Automatic axillary lymph node segmentation in PET/CT volumes – Methodology – 3D Component trees

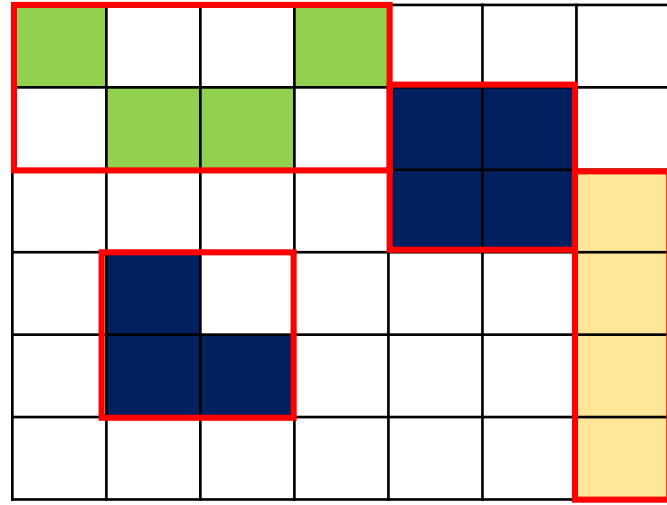
- For a given voxel v , it is assigned:
- The **valid ratio value** of its nearest ancestor node
 - **-1** if itself or none of its ancestors has a valid ratio and volume



V1

Descriptor (area and ratio)

Goal: Keep the connected components that describe the best a cancer lymph node



Volume descriptor

(blue voxels represent cancer lymph nodes)



-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	1	1	-1
-1	-1	-1	-1	1	1	-1
-1	1	-1	-1	-1	-1	-1
-1	1	1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1

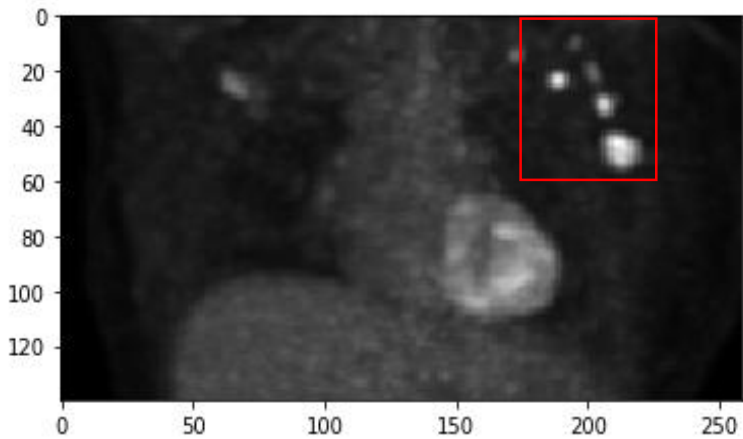
Ideal Result

-1 (all the voxels that do not intersect a lymph node)
Ratio value (voxels that intersect a lymph node)

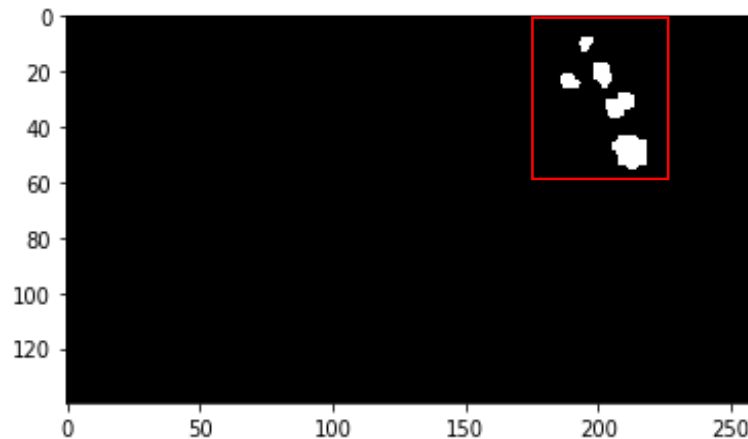


Automatic axillary lymph node segmentation in PET/CT volumes – Methodology – 3D Component trees

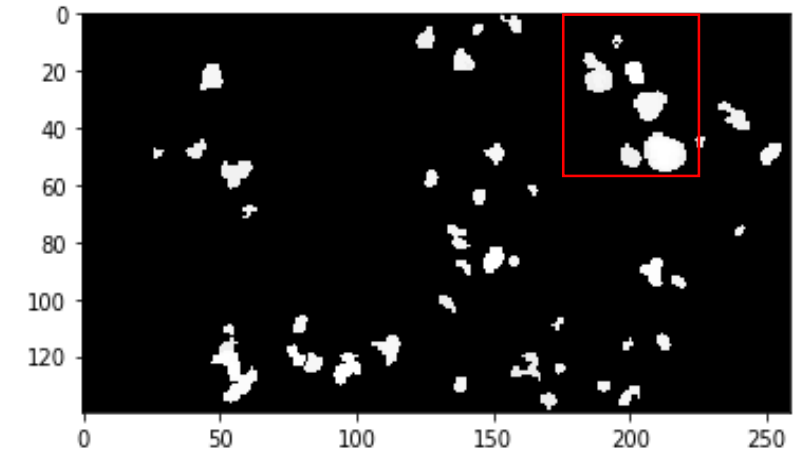
- A 3D component tree is extracted from a PET volume
- Total number of nodes: **1863**
- Grays values quantification: **0-63**
- **Results** : Based on meaningful descriptors **area and ratio**



Axillary PET image



Ground-truth-mask

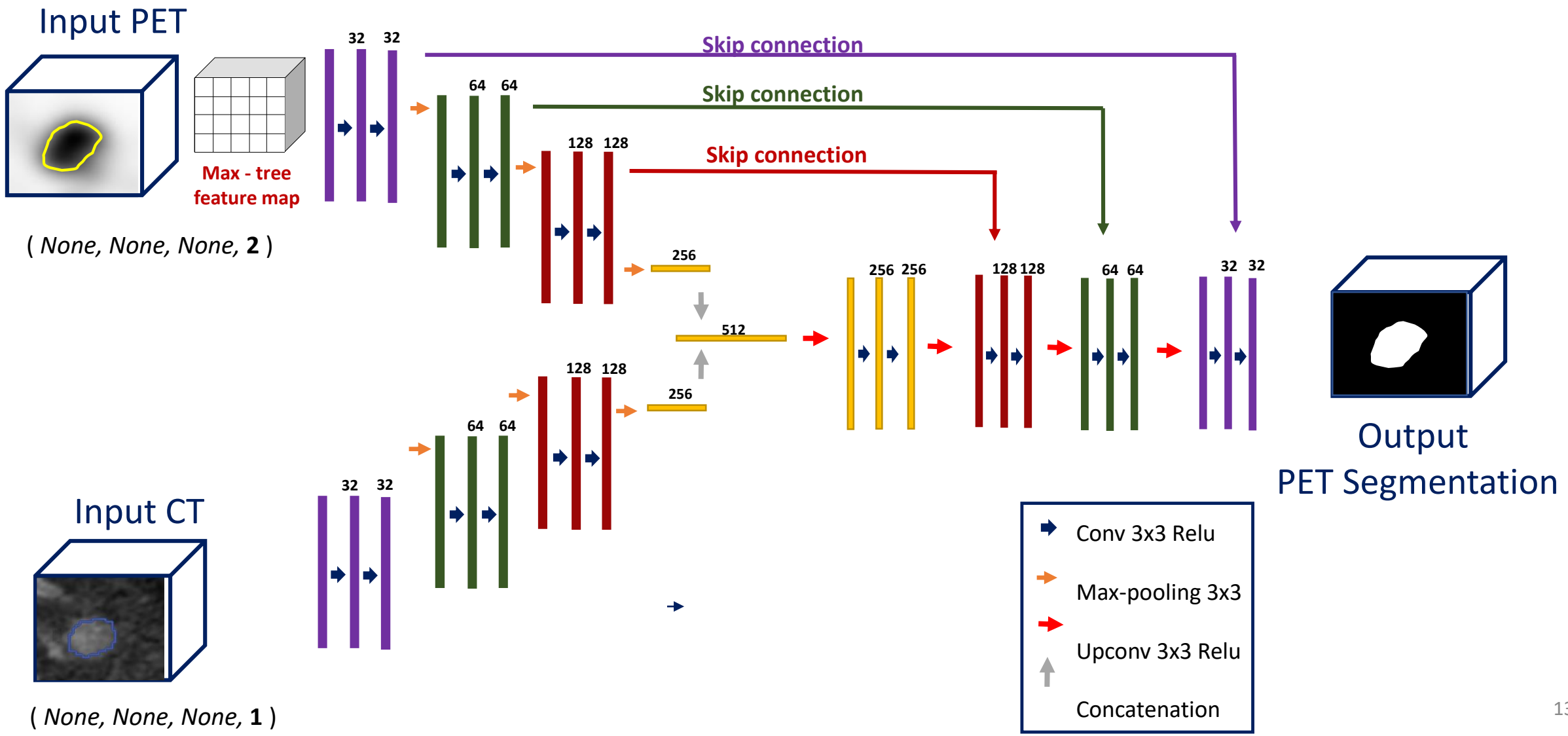


Results of lymph nodes candidates

All lymph nodes are preserved
however false positives remain



Automatic axillary lymph node segmentation in PET/CT volumes – Methodology – Neural Network





Automatic axillary lymph node segmentation in PET/CT volumes – Methodology – Neural Network

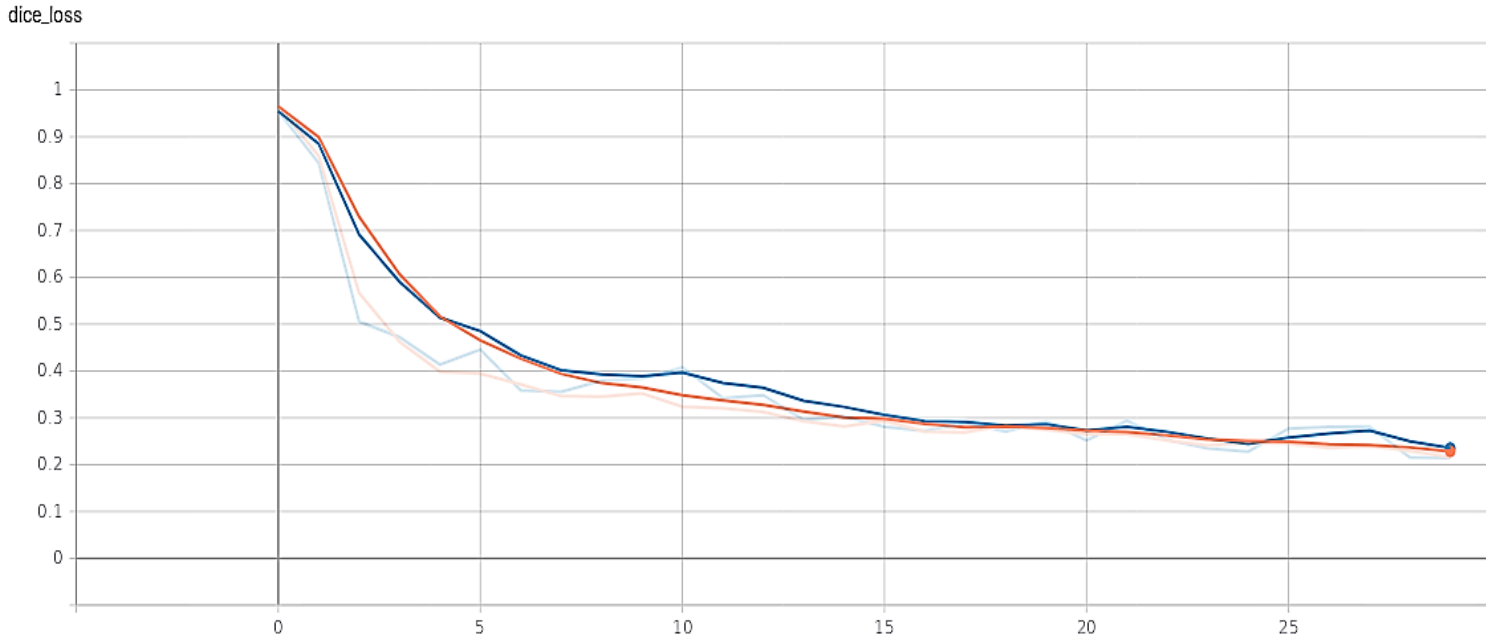
Total nb of patches: **640**
Patches for training: **448 (70%)**
Patches for validation: **192 (30%)**
Loss Function: **1 - Dice Score**
Iterations: **30**

Type of CNN: **U-NET**
Number of layers: **3**
Batch normalization: **YES**
Dropout: **NO**

Image resolution:
1 voxel=1.5mm
3D Patch size:
60 mm x 60 mm x 60 mm

■ Training set
■ Validation set

Validation set converges at around **0.28**
Training set converges at around **0.29**



Small structures → Dice Loss is very sensitive

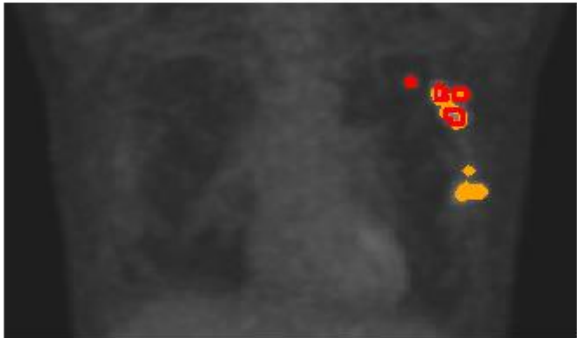


Automatic axillary lymph node segmentation in PET/CT volumes – Results – Using only neural network

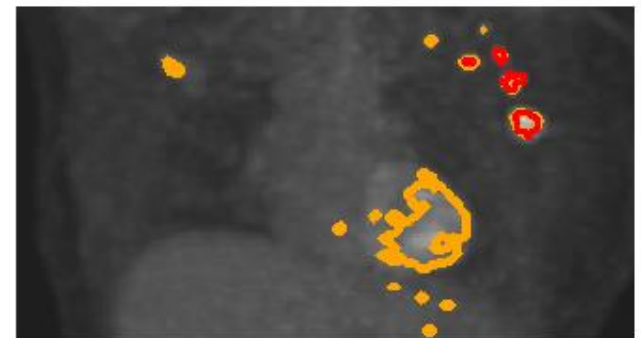
 **Ground-truth**
 **Prediction**

Mean dice score (10 datasets) :
53.76/100

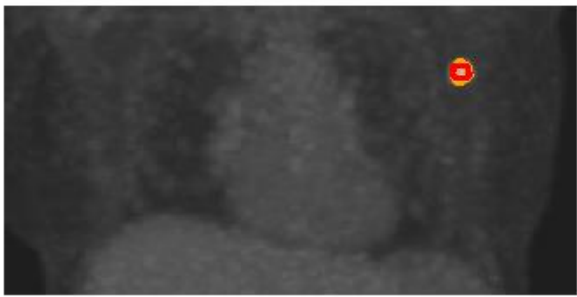
- ✓ Model is able to recognize the axillary area
- ✓ Model is able to keep most of true positive
- Model presents a lot of false positives
- Dice score is sensitive to small structures



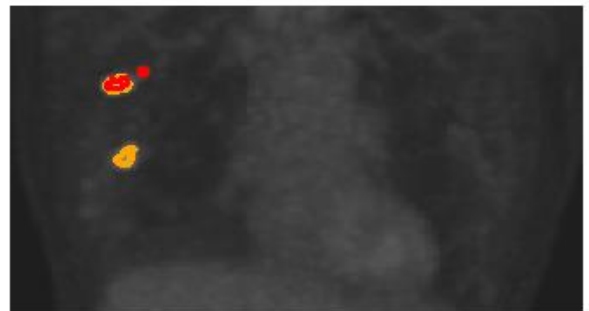
Dice score : 46.21/100



Dice score : 29.73/100



Dice score : 83.22/100



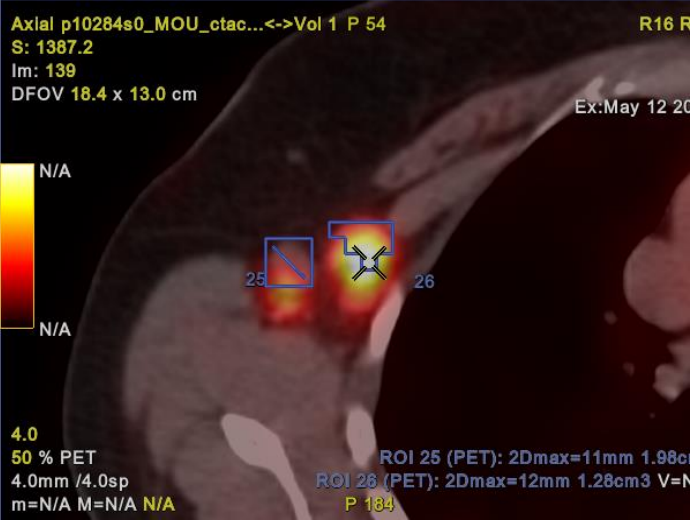
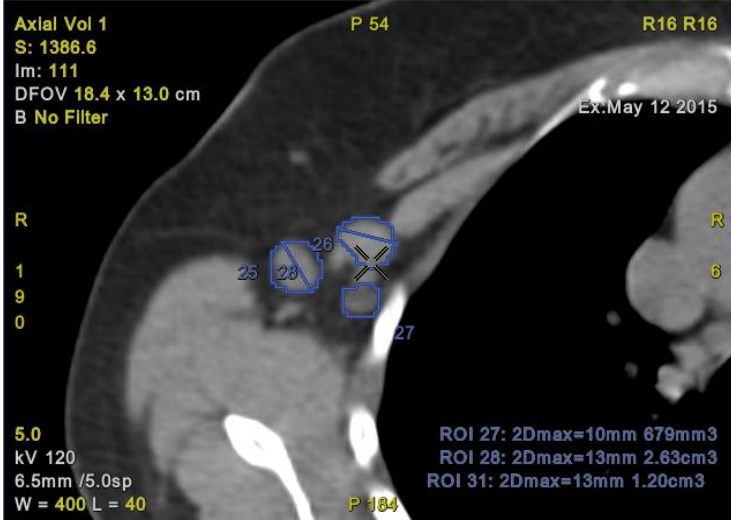
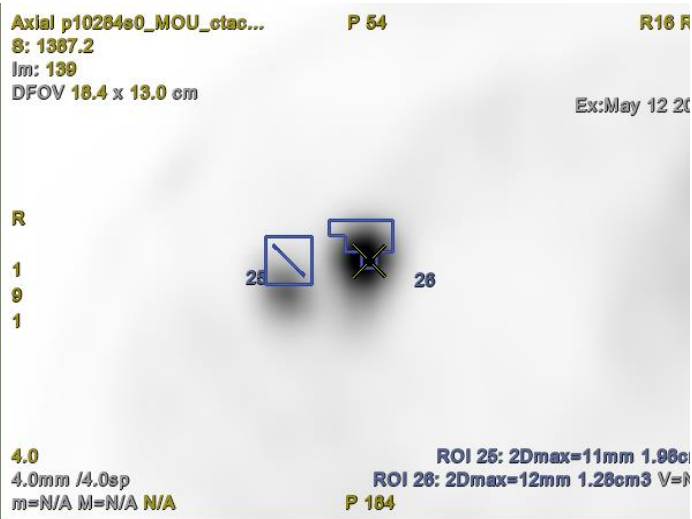
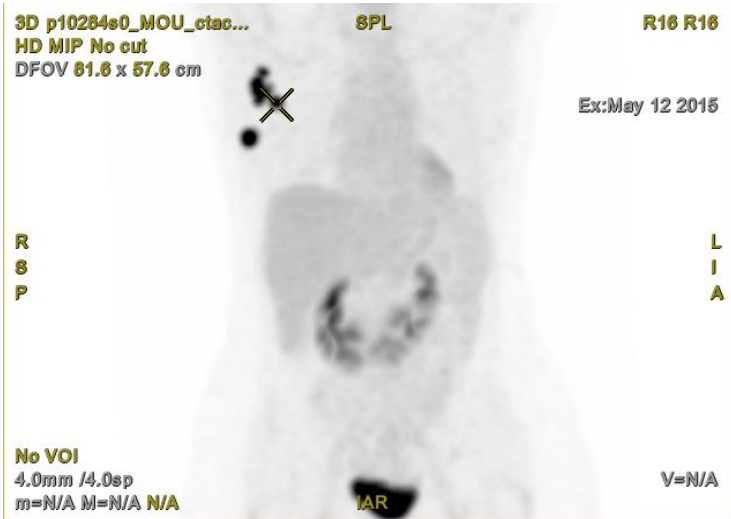
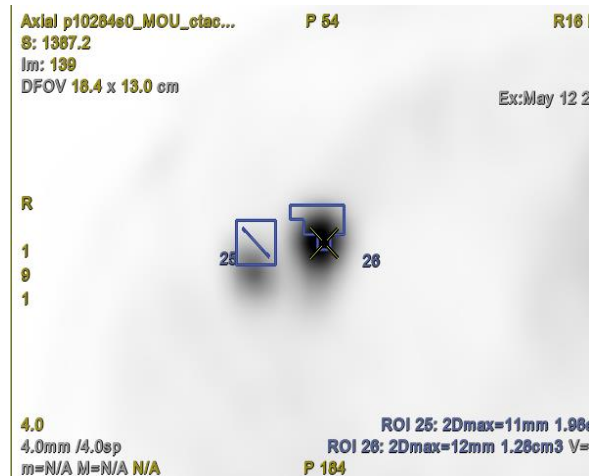
Dice score : 47.96/100



Automatic axillary lymph node segmentation in PET/CT volumes – Challenges

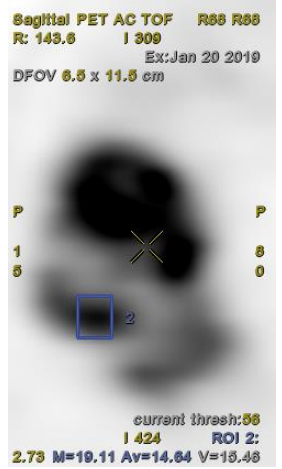
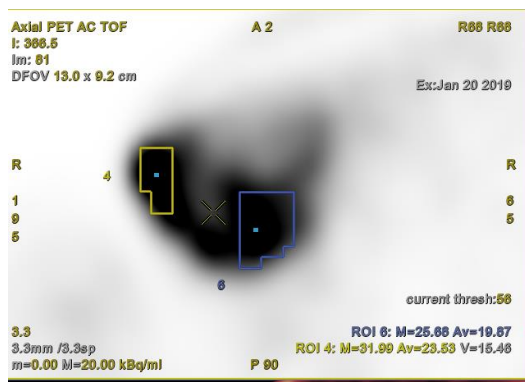
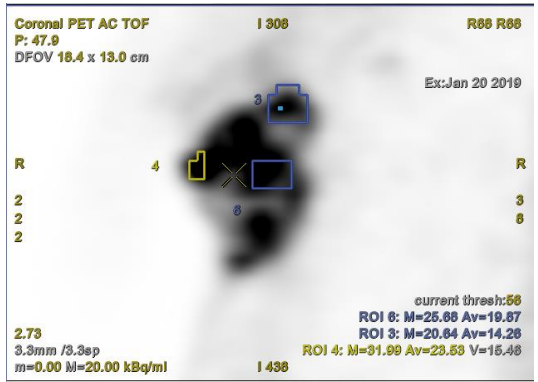
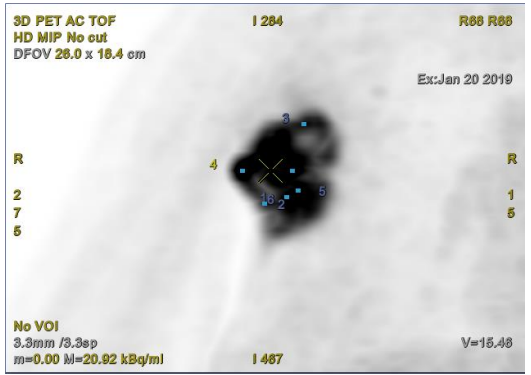
PET and CT shifting due to patient movement since axillary area is sensitive to breathing

Non rigid transformation can hardly correct this matching mistake since patient movement does not follow a continuous elastic deformation





Automatic axillary lymph node segmentation in PET/CT volumes – Challenges



In some advanced cancer cases lymph nodes become joint and are difficult to separate (even for medical experts) because of PET resolution limitations

In CT scans, joint lymph nodes appear to be one single lymph node having a huge area

