KU LEUVEN

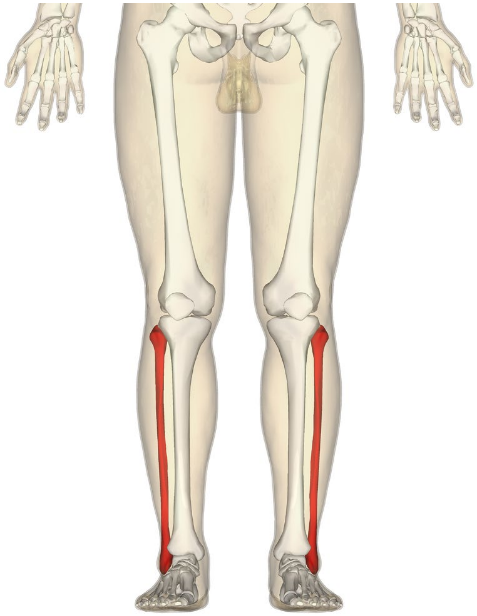
Automatic segmentation of fibula bone by using deep learning

Promotor: Prof. Bart Vanrumste
Co-supervisor: Dr. Yi Sun

Beiyang Li r0735133
Zechun Wang r0736595

Subject of master thesis

- Proposes an **automatic fibula segmentation** approach in CT scans



KU LEUVEN

Outline

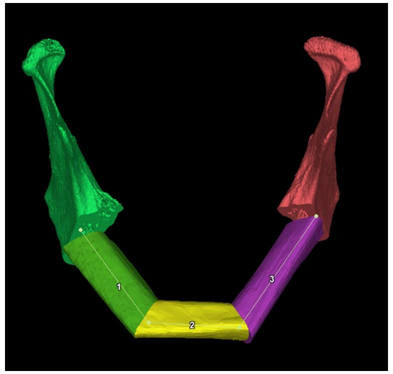
1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
4. Conclusion

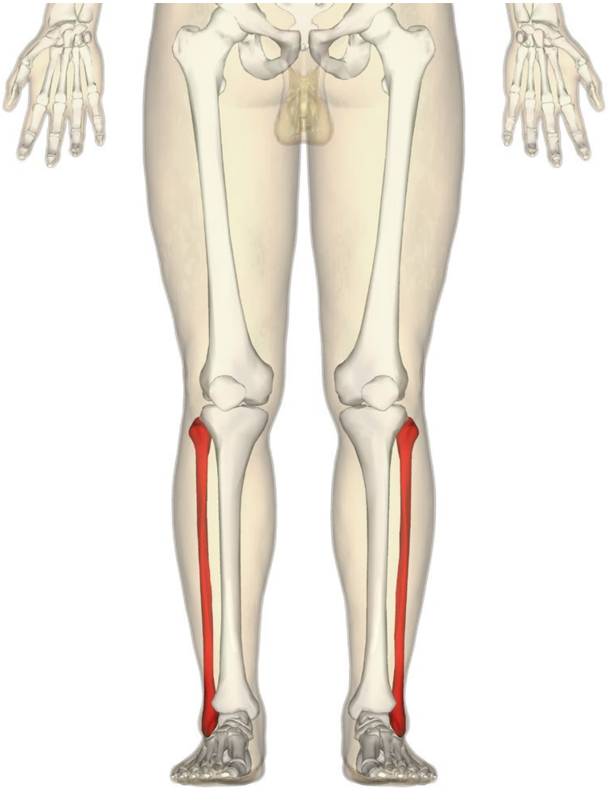
Outline

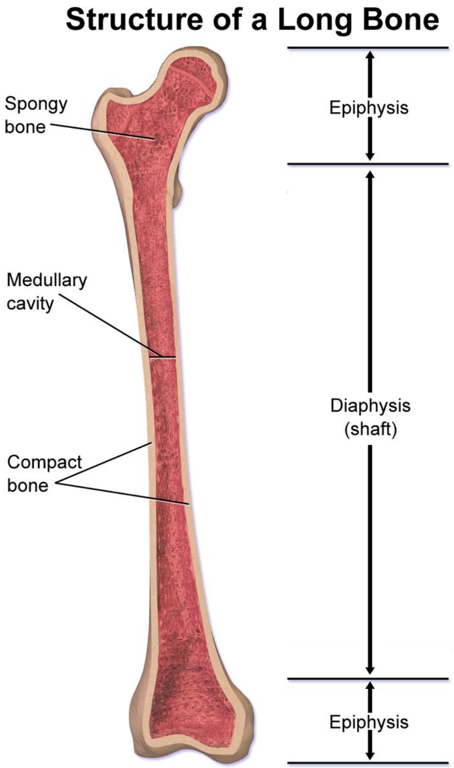
1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
4. Conclusion

Concept of Fibula

- The fibula is a leg bone on the lateral side of the tibia.
- Segmentation of fibula is commonly used in the mandibular reconstruction.



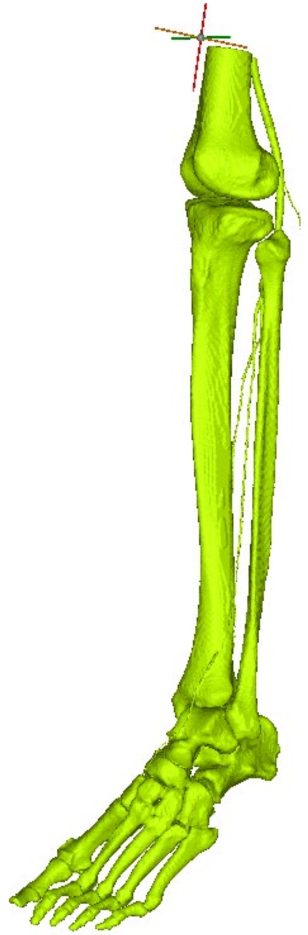




The traditiontal fibula segmentation method

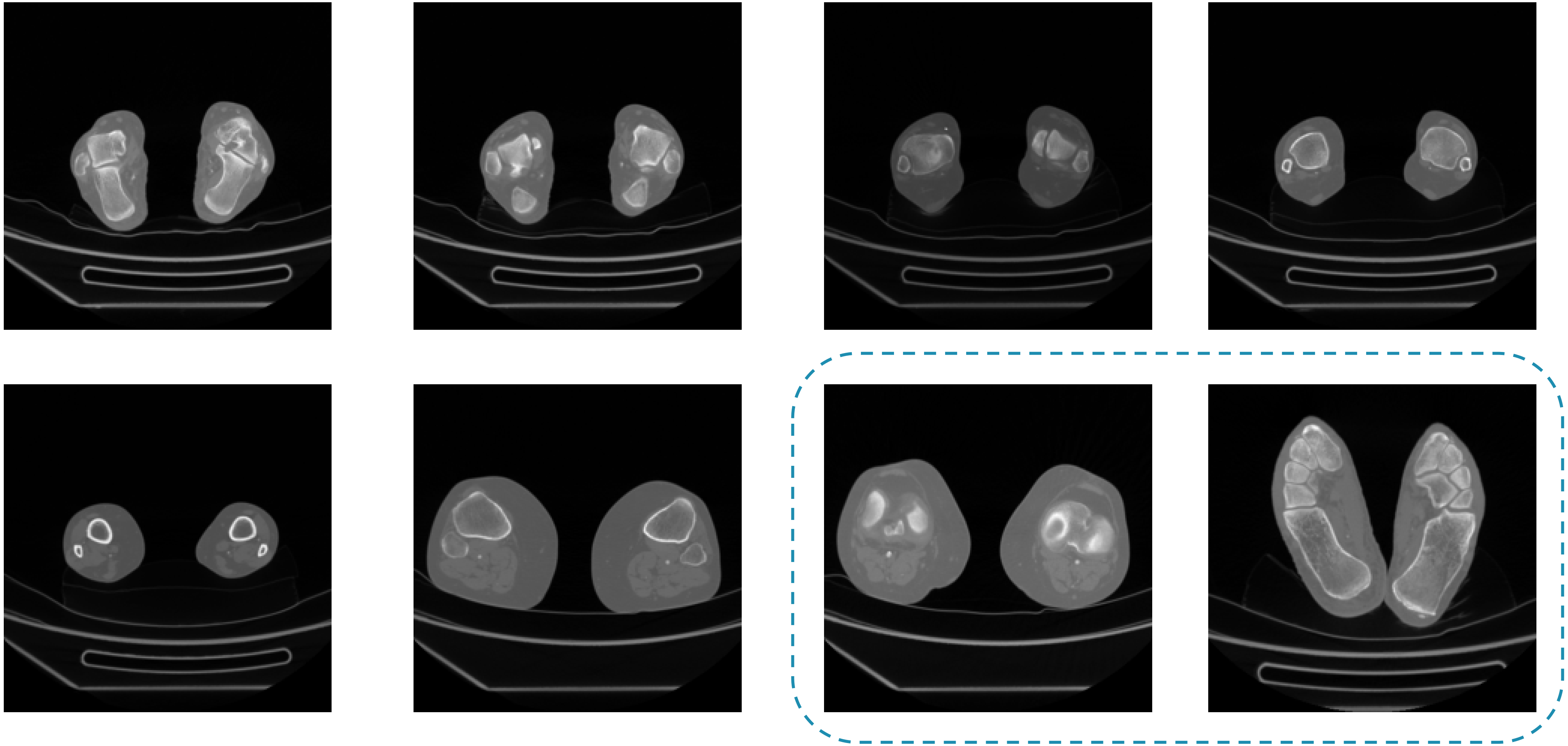
- Traditional medical segmentation adopts thresholding algorithm method with the assistant of manual annotations.

- The segmentation results of thresholding algorithm cannot be directly adopted in clinical applications, experts are still required to spend lots of time to further manually improve on the results' quality. Zhou et al. (2019)

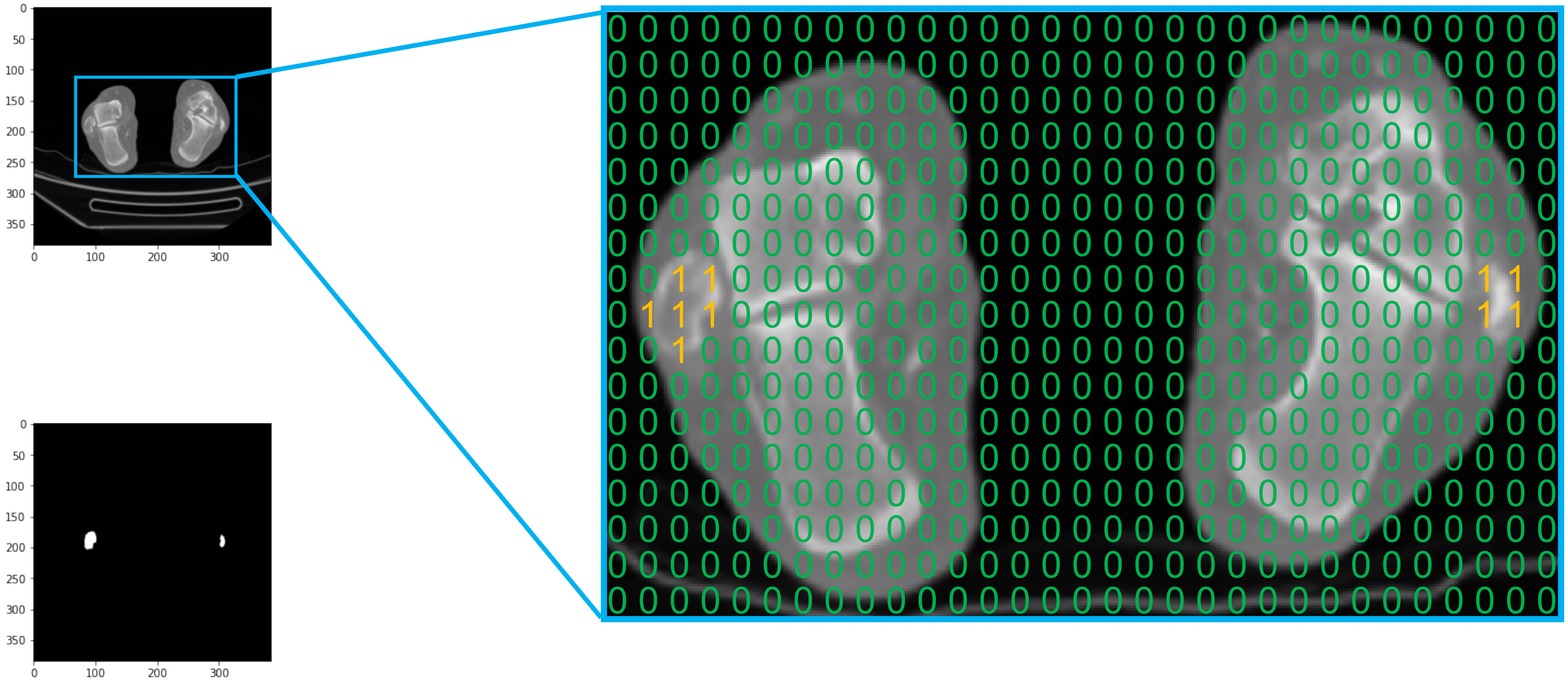


Zhou, Chen, L., & Wang, Z. (2019). Interactive Deep Editing Framework for Medical Image Segmentation. In *Medical Image Computing and Computer Assisted Intervention – MICCAI 2019* (Vol. 11766, pp. 329–337). Springer International Publishing. https://doi.org/10.1007/978-3-030-32248-9_37

Challenge



What is segmentation



Outline

1. Motivation
2. Dataset & Data preprocessing
    a. Data Preparation
    b. Data Preprocessing
3. Methodology & Experiments
4. Conclusion

Dataset

- Source: Sint-Rafael hospital
- Image Dimension: 512 x 512

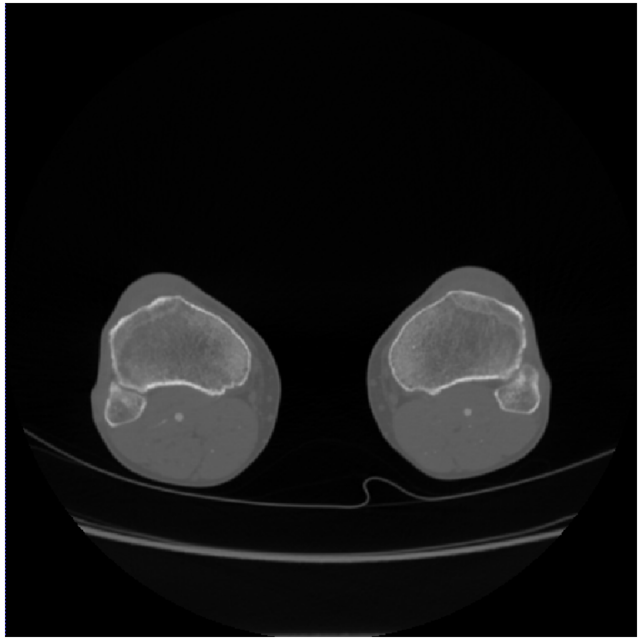
- Dataset description
  - 19 CT scans
  - 409 to 1543 CT slices
  - 15830 images
  - 20.4 GB

- Data distribution

	Train set	Validation set	Test set
Number of CT scans	16	1	2
Number of images	13636	790	1404

- Limitation： Only one validation set

Dataset



Original CT slice

Experts' manual annotations

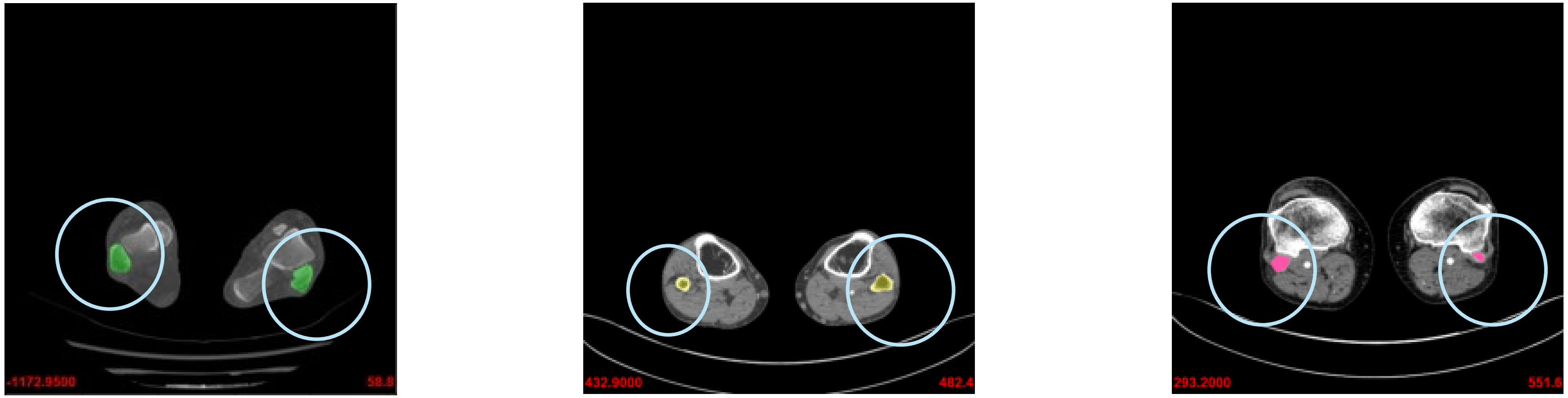
Examples in the data set

Serial number	Number of CT slices in one scan	Distance between each slice (mm)
1	734	0.6
2	670	0.6
3	790	0.6
4	786	0.6
5	794	0.6
6	799	0.6
7	810	0.6
8	951	0.6
9	803	0.7
10	767	0.8
11	761	0.8
12	999	0.625
13	1543	0.4
14	901	0.7
15	759	0.7
16	797	0.7
17	774	0.8
18	409	1.5
19	983	0.6

Outline

1. Motivation
2. Dataset & Data preprocessing
   a. Data Preparation
   b. Data Preprocessing
3. Methodology & Experiments
4. Conclusion

Data preprocessing



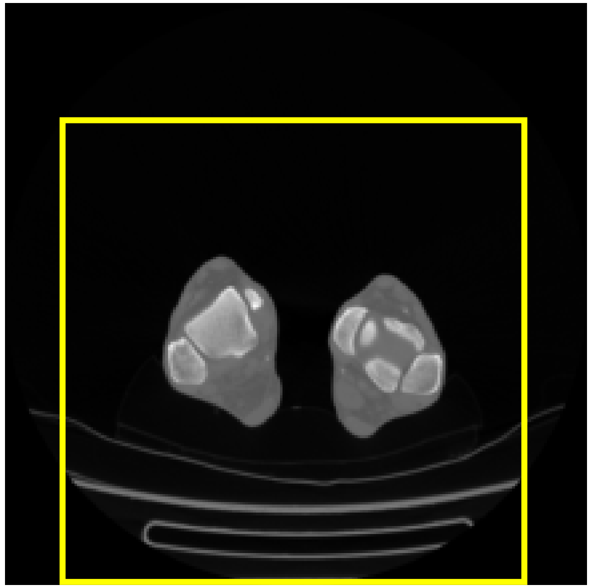
The original data of the manual annotations

the ground truth after HSV processing

Data preprocessing

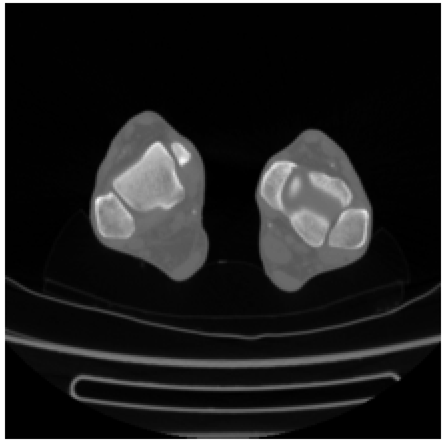
Convolution kernel

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 10 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$



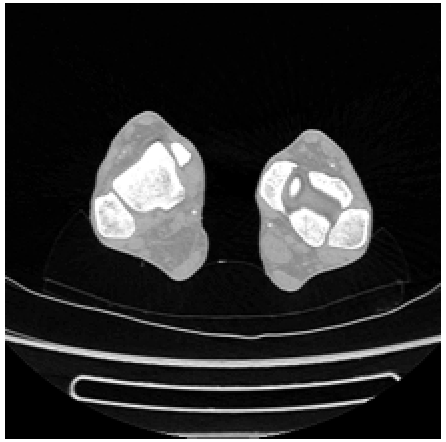
512 x 512

Crop



384 x 384

Convolution enhancement



384 x 384

For boundary enhancement

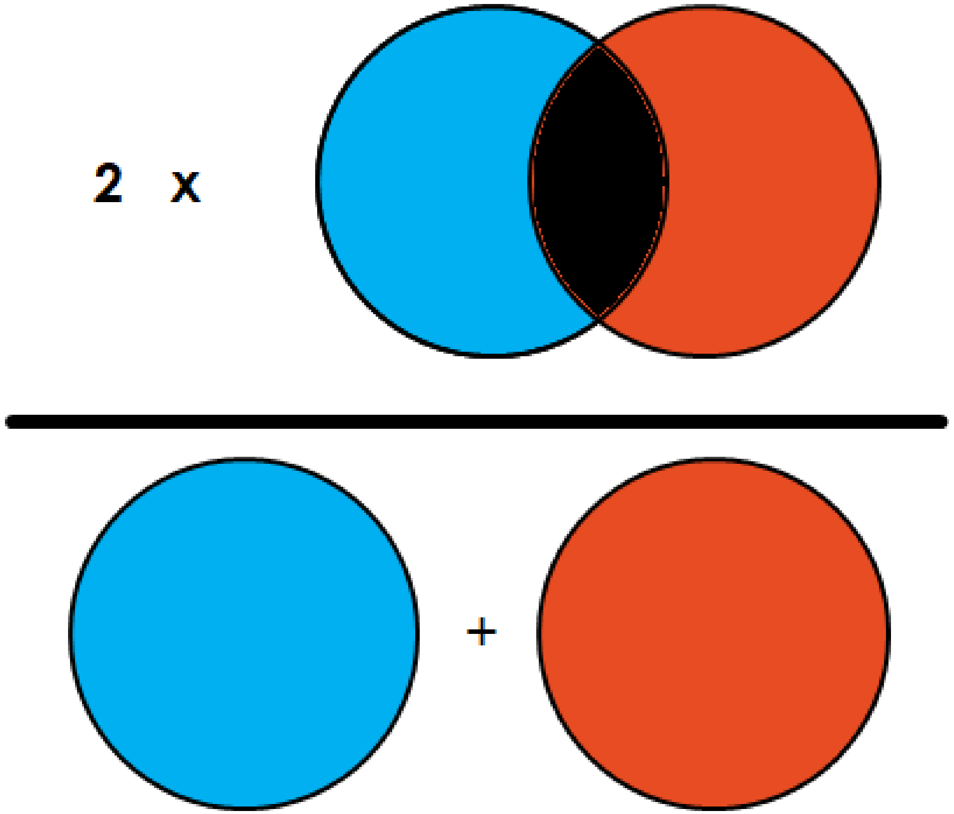
Outline

1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
    a. Evaluation criterion
    b. Single-planar segmentation model
    c. Multi-planar segmentation model
    d. Multi-planar segmentation model with data augmentation
4. Conclusion

Dice Score

- $D(X,Y) = \frac{2*|X \cap Y|}{|X|+|Y|}$

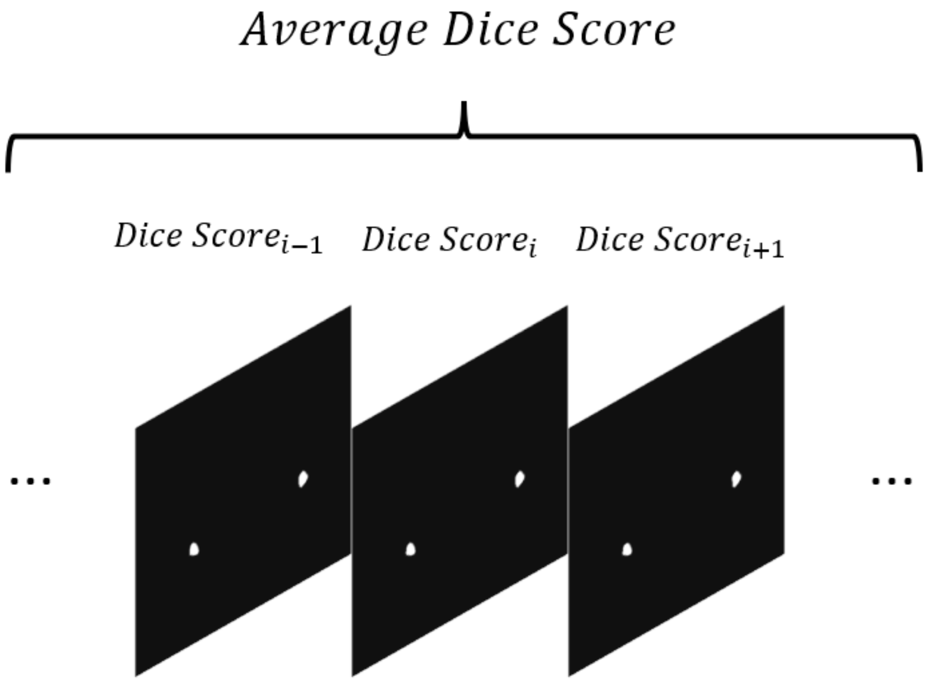
- By using this method, a score between 0 and 1 can be computed.



Two method of Dice Score

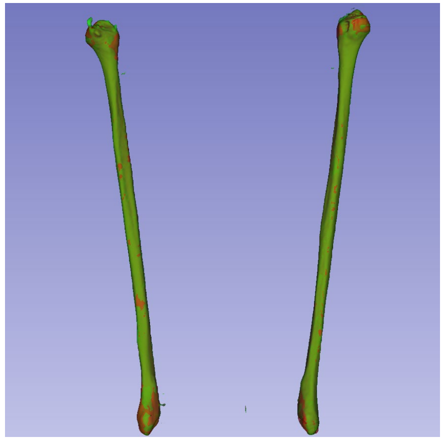
Average Dice score

- Average of each dice score in one CT scan.
- Focus more on evaluating the whole output



Volumetric Dice score

- Overlap voxel area
- Pay more attention to the evaluation of fibula.



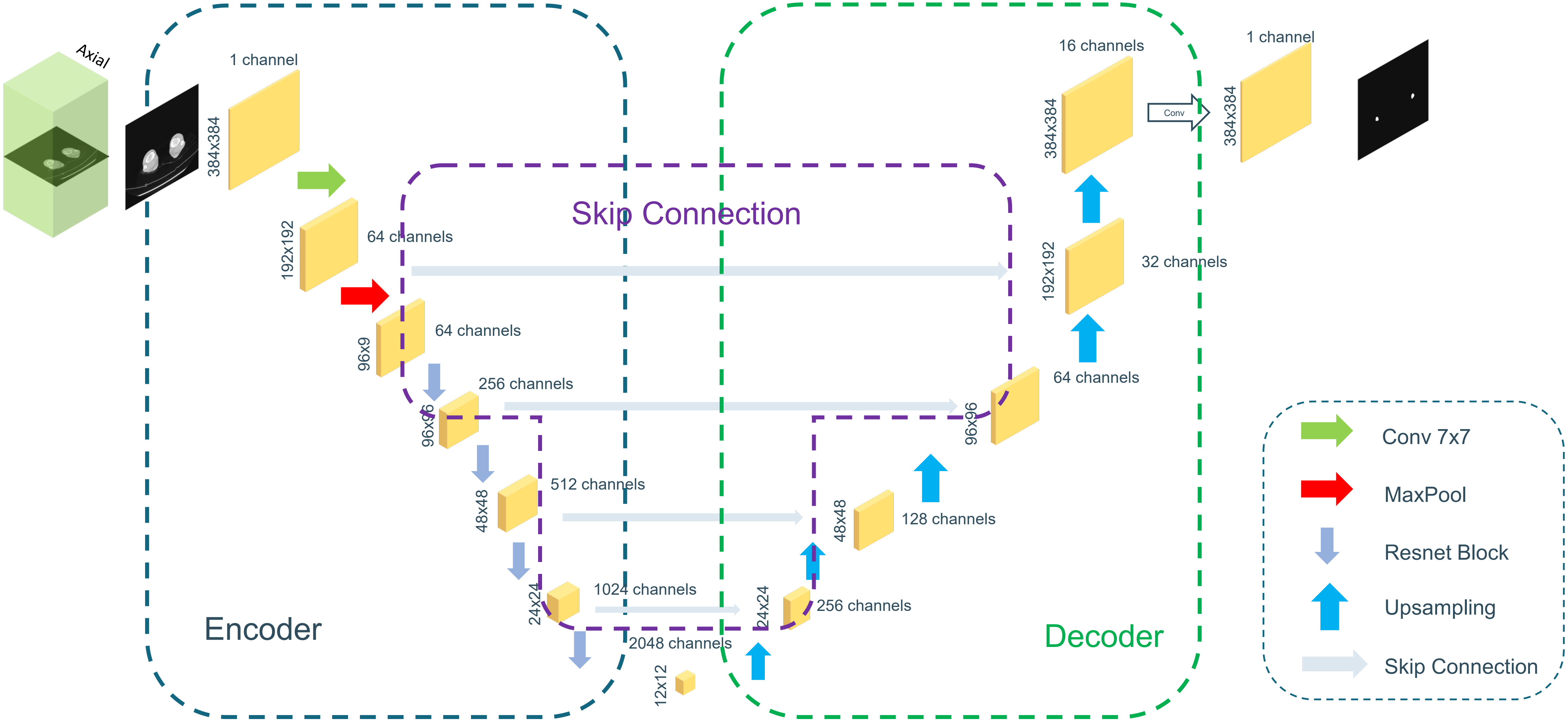
$$\text{Volumetric Dice Score} = \frac{2*|X \cap Y|}{|X|+|Y|}$$

KU LEUVEN

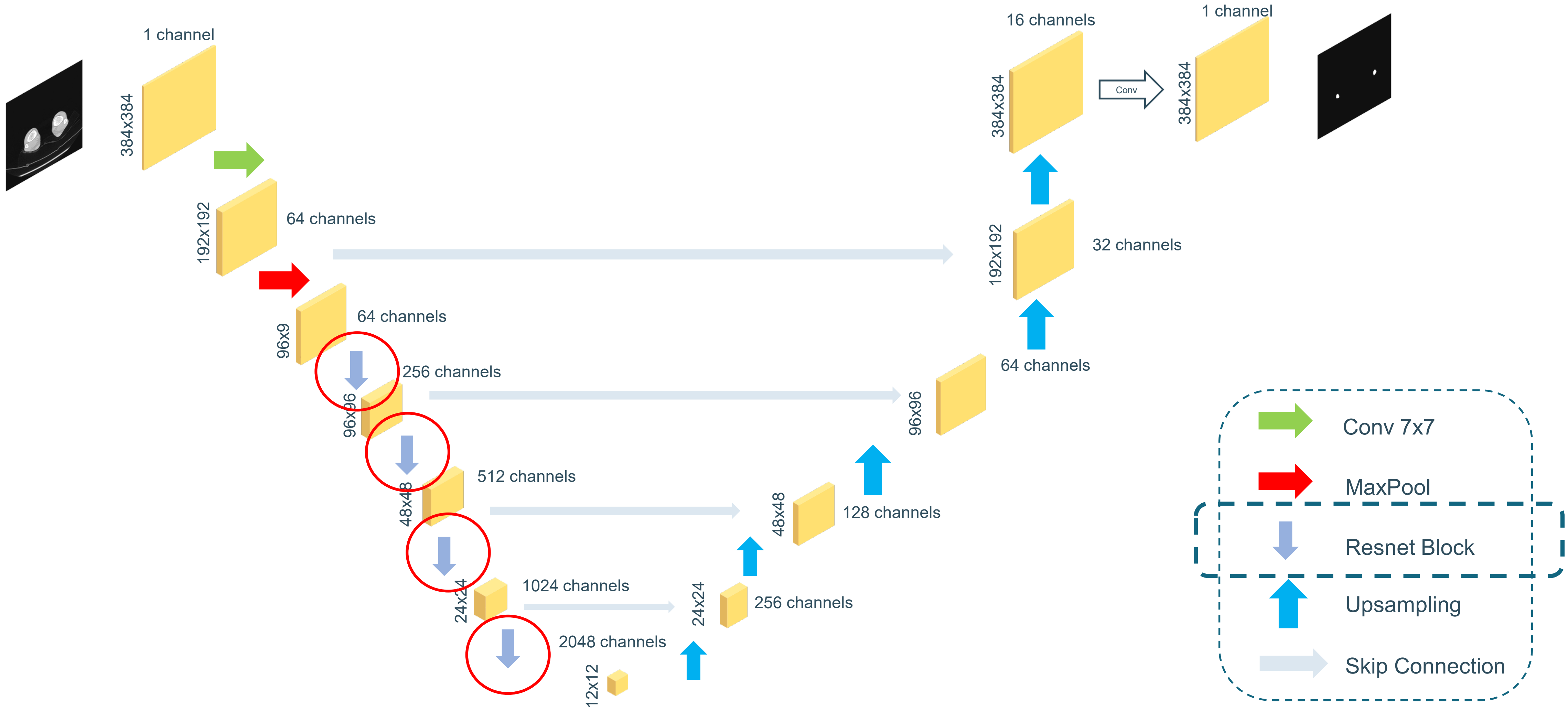
Outline

1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
   a. Evaluation criterion
   b. Single-planar segmentation model
   c. Multi-planar segmentation model
   d. Multi-planar segmentation model with data augmentation
4. Conclusion

Single-planar segmentation model

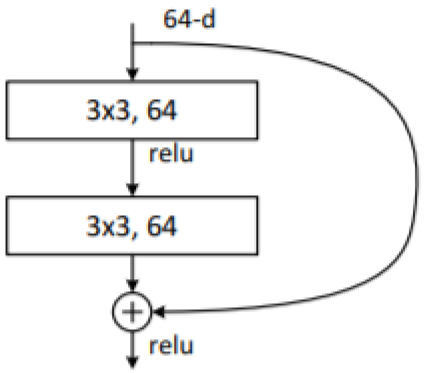


Single-planar segmentation model: Res-Net block

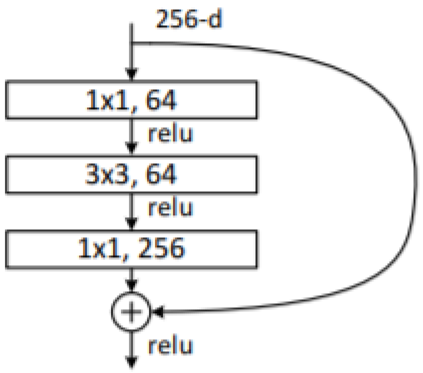


Res-Net block

- Traditional Res-Net consists of building blocks or bottlenecks



The structure of the building block for ResNet-18 and ResNet-34

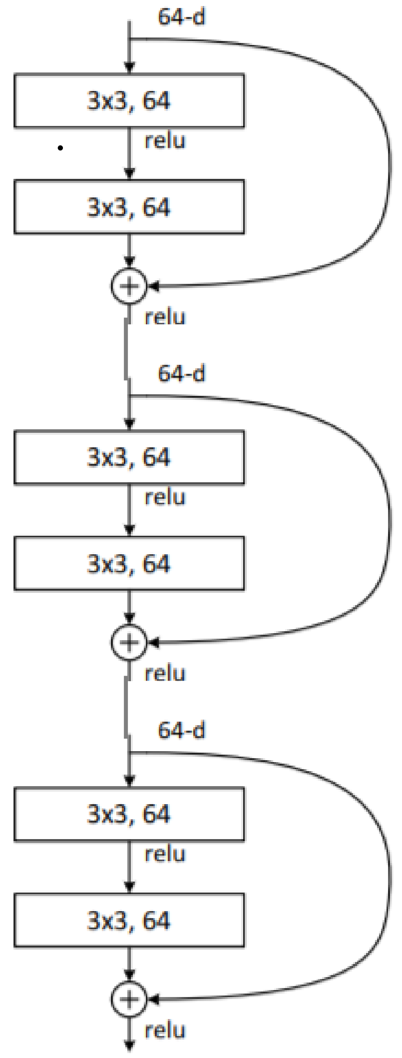


The structure of the bottleneck block for ResNet-50 and higher Res-Net

Res-Net architecutre

- The Architectures for 34 layers and 50 layers Res-Net

Layer Name	34-layer	50-layer
Conv1	7×7, 64, stride 2	
Conv2-x	3×3 max pool, stride 2	
	$\begin{bmatrix}3\times3, & 64\\3\times3, & 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, & 64\\3\times3, & 64\\1\times1 & 256\end{bmatrix}\times3$
Conv3-x	$\begin{bmatrix}3\times3, & 128\\3\times3, & 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, & 128\\3\times3, & 128\\1\times1 & 512\end{bmatrix}\times4$
Conv4-x	$\begin{bmatrix}3\times3, & 256\\3\times3, & 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, & 256\\3\times3, & 256\\1\times1 & 1024\end{bmatrix}\times6$
Conv5-x	$\begin{bmatrix}3\times3, & 512\\3\times3, & 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, & 512\\3\times3, & 512\\1\times1 & 2048\end{bmatrix}\times3$



KU LEUVEN

Upsampling

10	4	22
2	18	7
9	14	25

3 x 3

10		4		22	
2		18		7	
9		14		25	

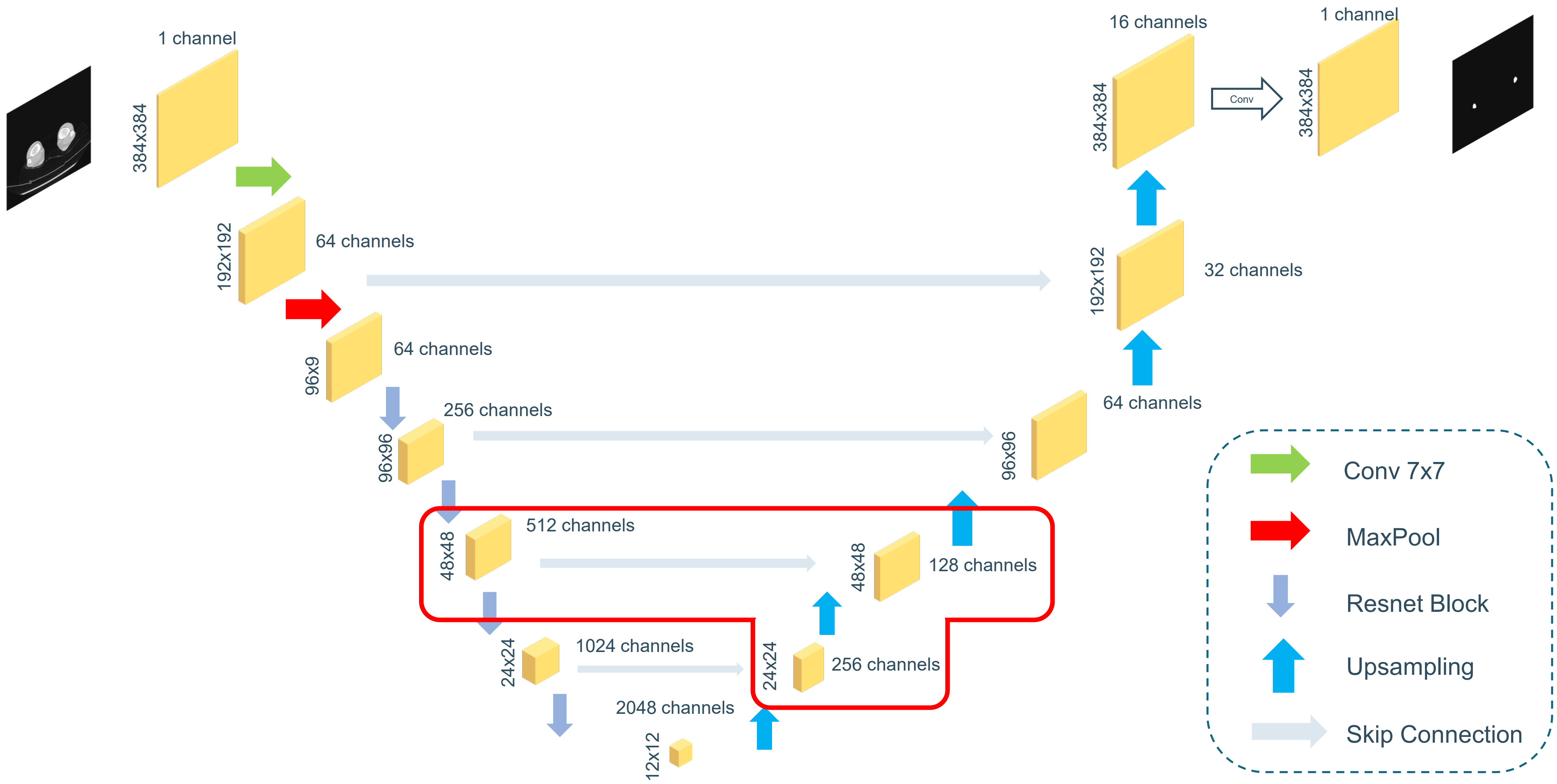
6 x 6

10	10	4	4	22	22
10	10	4	4	22	22
2	2	18	18	7	7
2	2	18	18	7	7
9	9	14	14	25	25
9	9	14	14	25	25

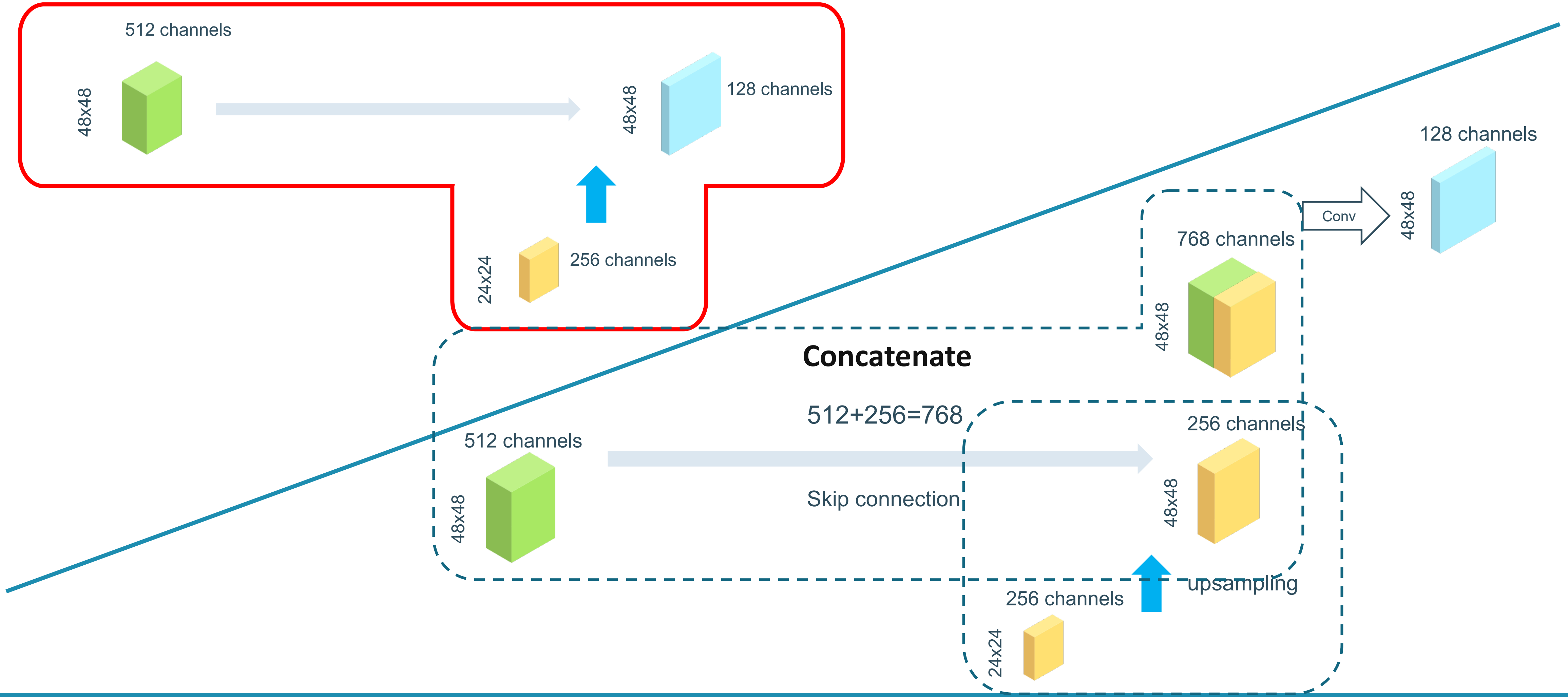
6 x 6

Nearest Neighbor Interpolation

Skip connection

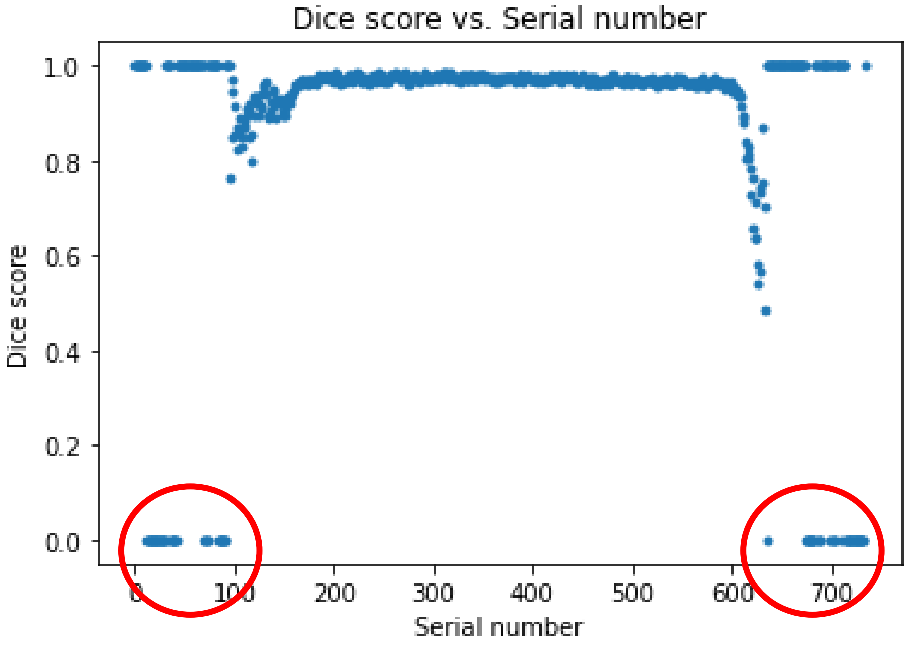


Skip connection

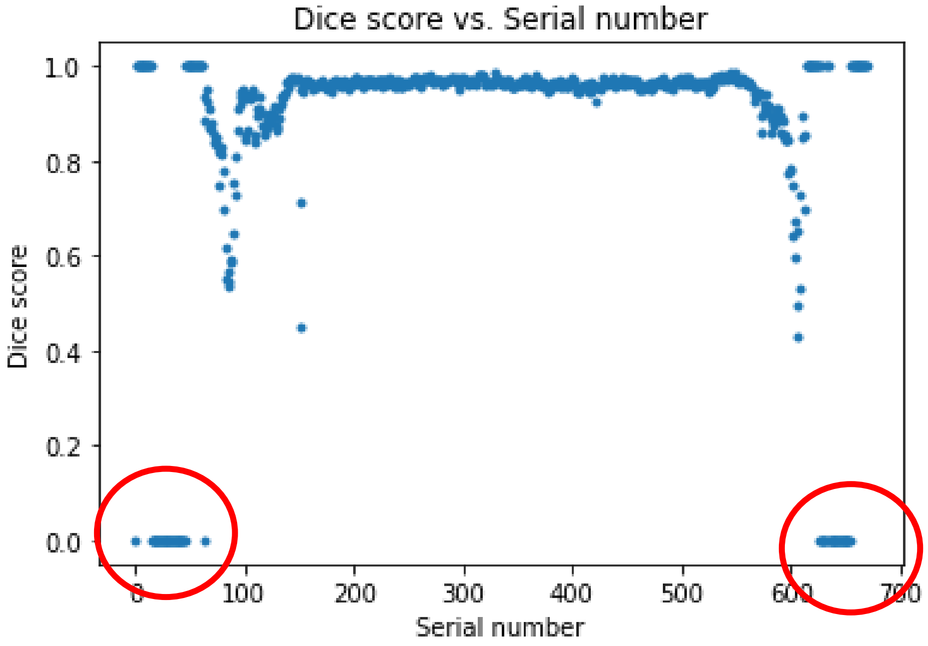


KU LEUVEN

Experiment 1: 34-layer Res-Net in signle-planar model



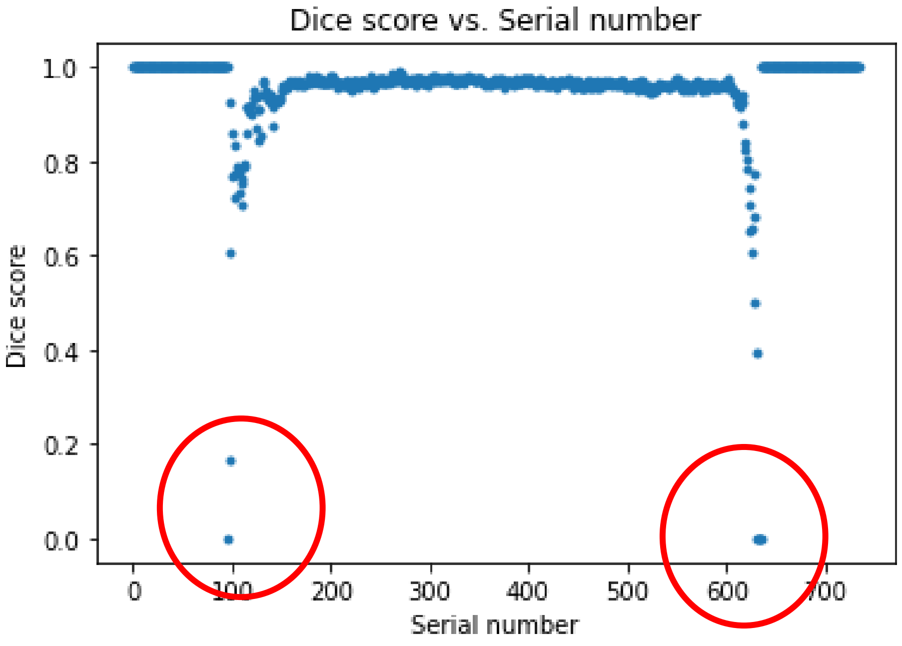
Test set 1



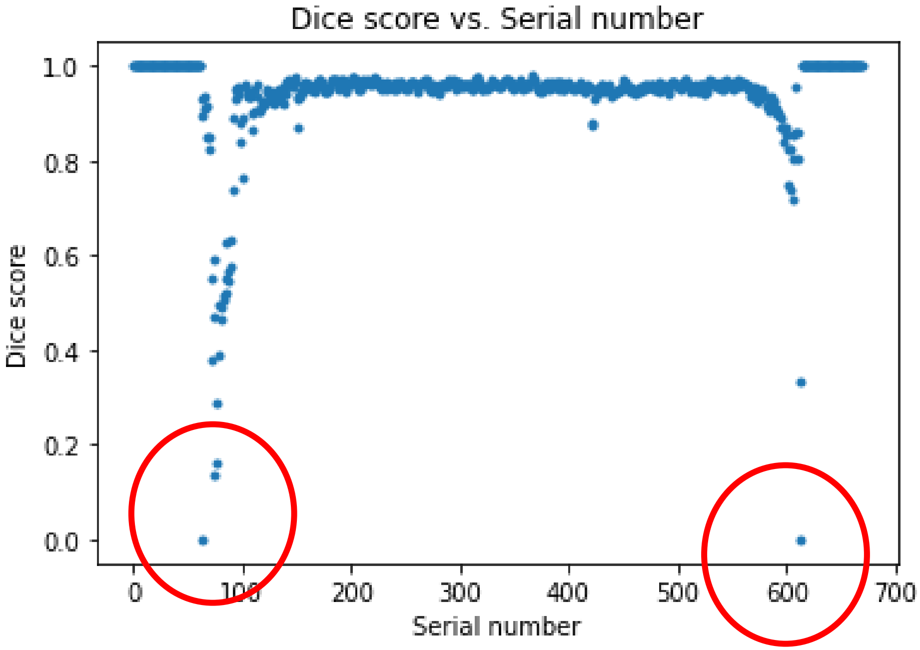
Test set 2

	Average Dice Score	Volumetric Dice Score
Test set 1	0.863	0.920
Test set 2	0.859	0.917

Experiment 2: 50-layer Res-Net in single-planar model



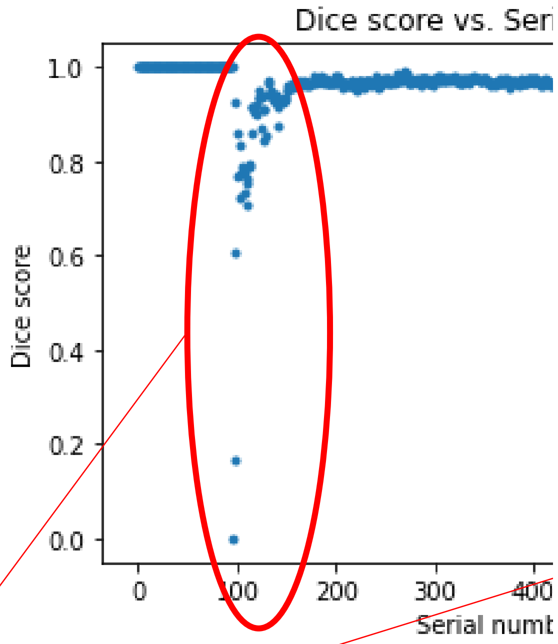
Test set 1



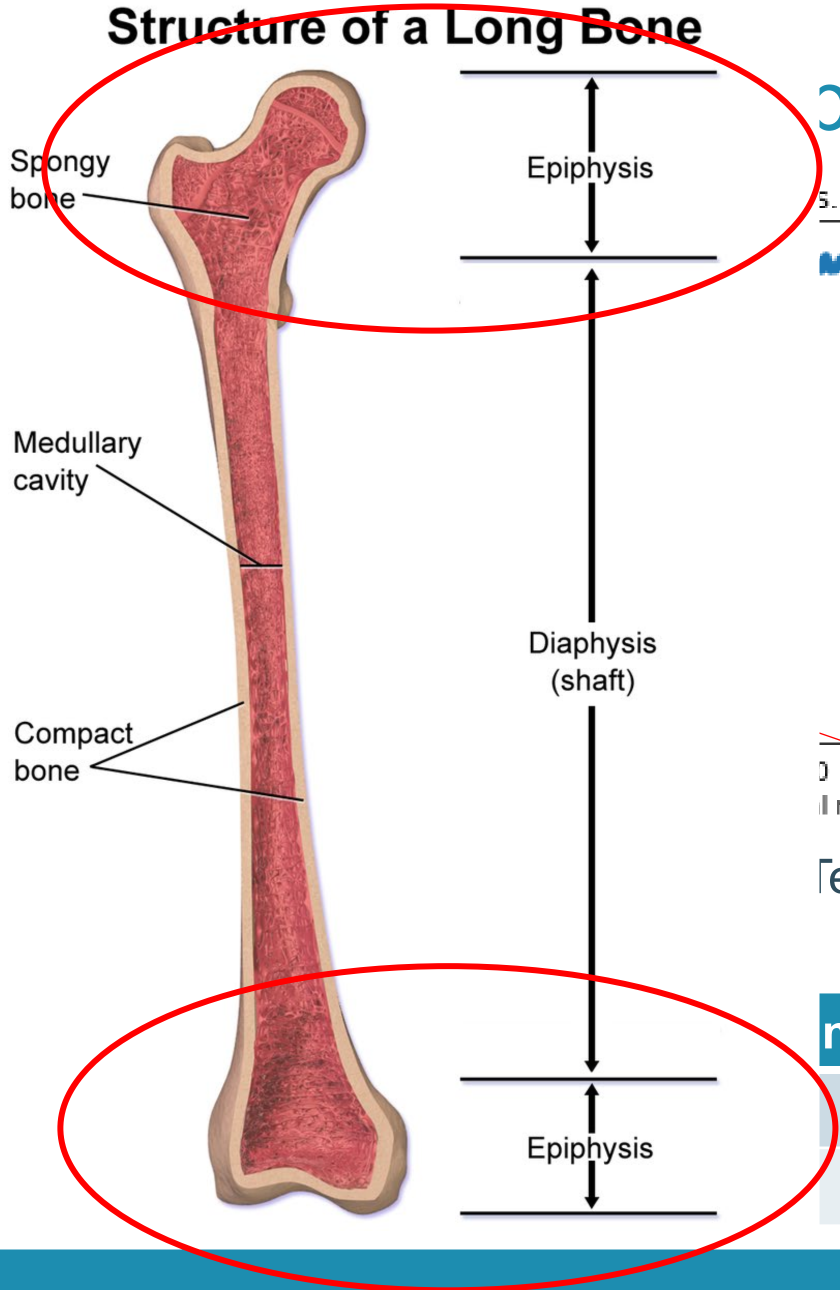
Test set 2

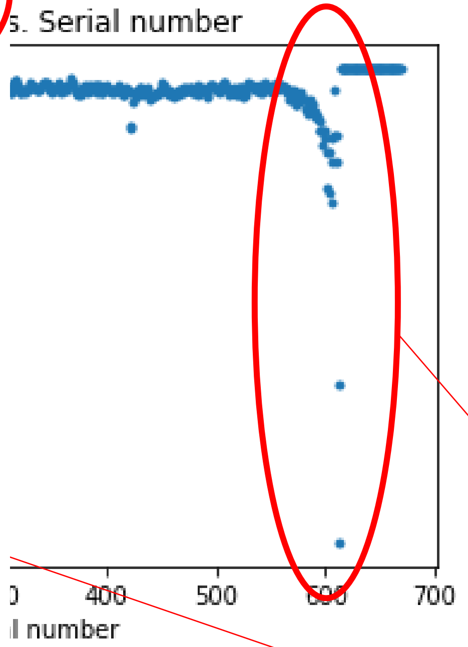
	Average Dice Score	Volumetric Dice Score
Test set 1	0.952	0.946
Test set 2	0.884	0.906

Experiment 2: 50-la… …planar model



Test s





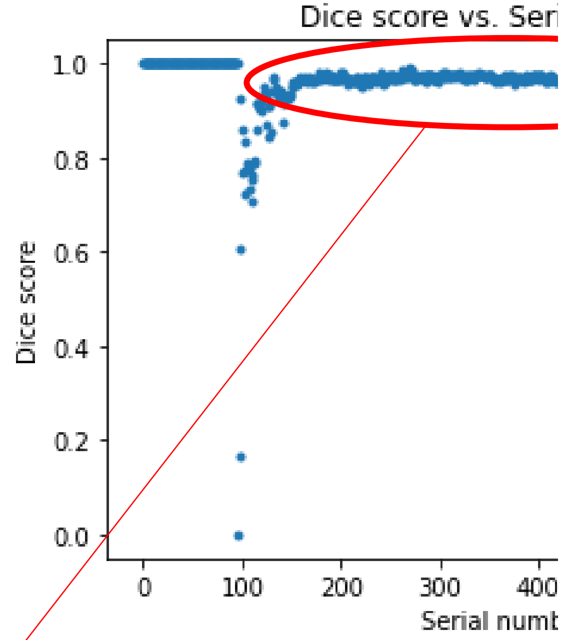
Test set 2

Epiphysis part

Epiphysis part

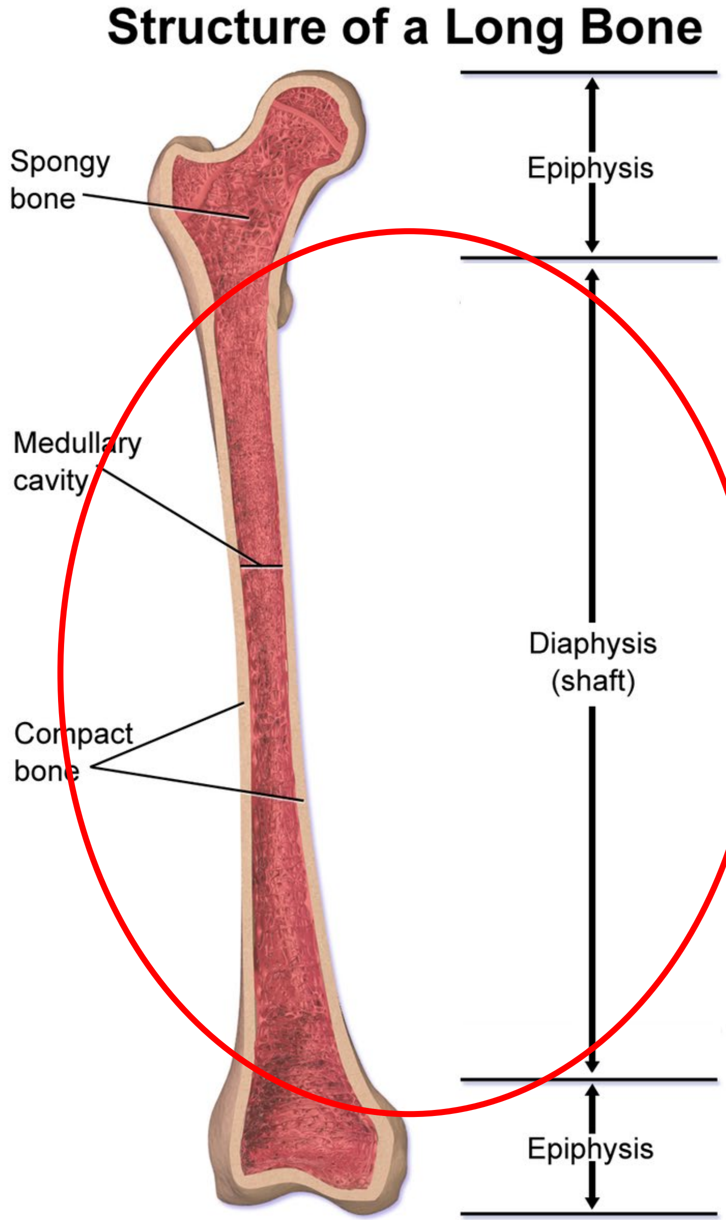
	…metric Dice Score
Test set 1	0.946
Test set 2	0.906

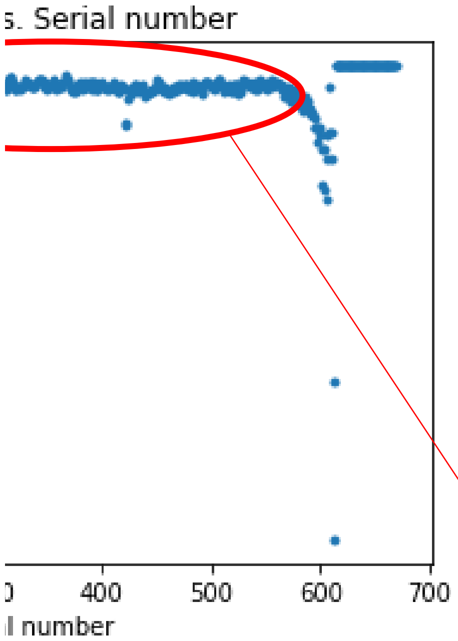
Experiment 2: 50-la… …planar model



Diaphysis part

Test s





Test set 2

Diaphysis part

	metric Dice Score
Test set 1	0.946
Test set 2	0.906

KU LEUVEN

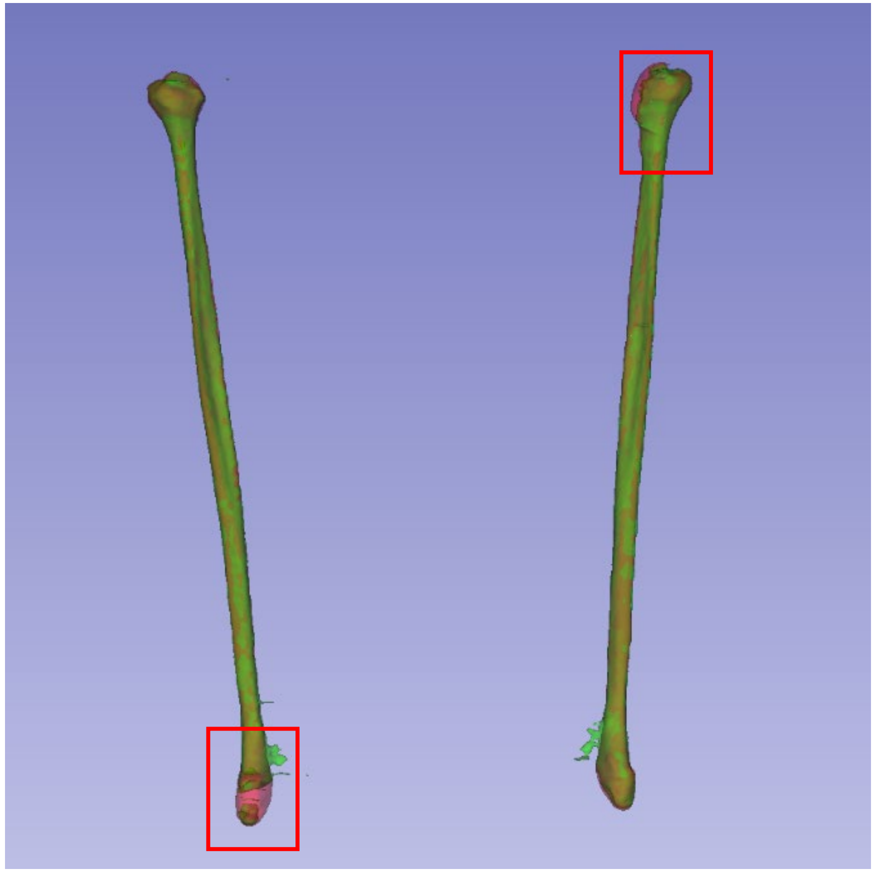
Comparison of Experiment 1 and 2

	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
34-layer Res-Net	0.863	0.859	0.920	0.917
50-layer Res-Net	0.952 ↑	0.884 ↑	0.946 ↑	0.906 ↓

→ Adopt 50-layer Res-Net structure for single –planar segmentation model

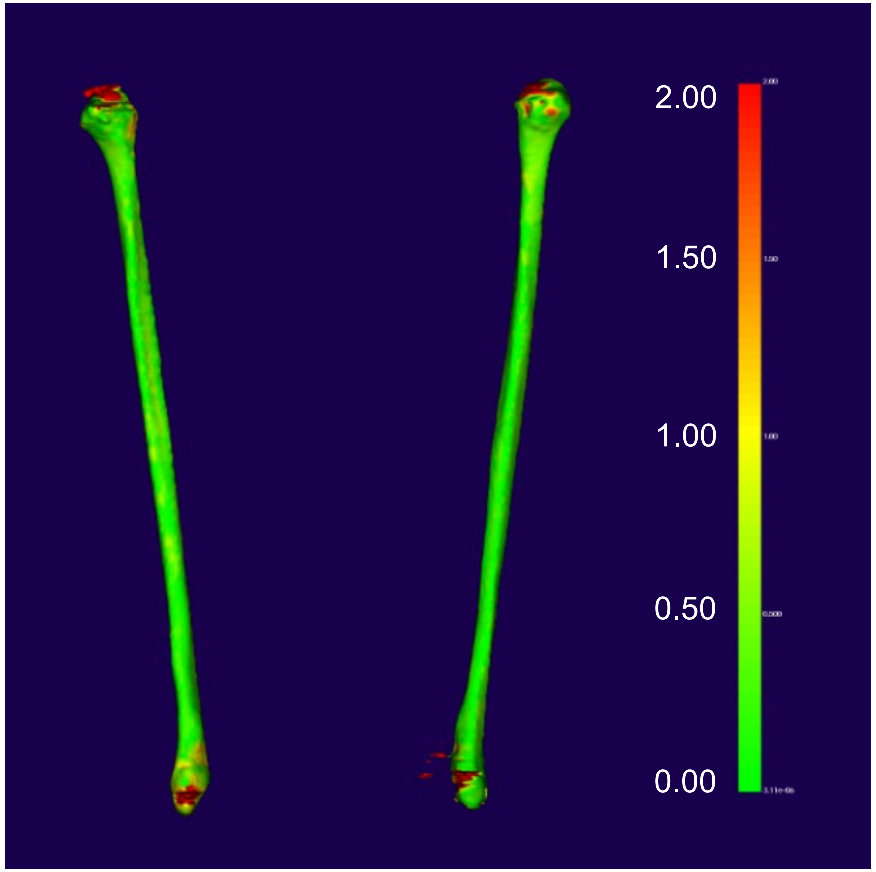
Discussion for Experiment 2:
50-layer Res-Net in single-planar model

Test set 1

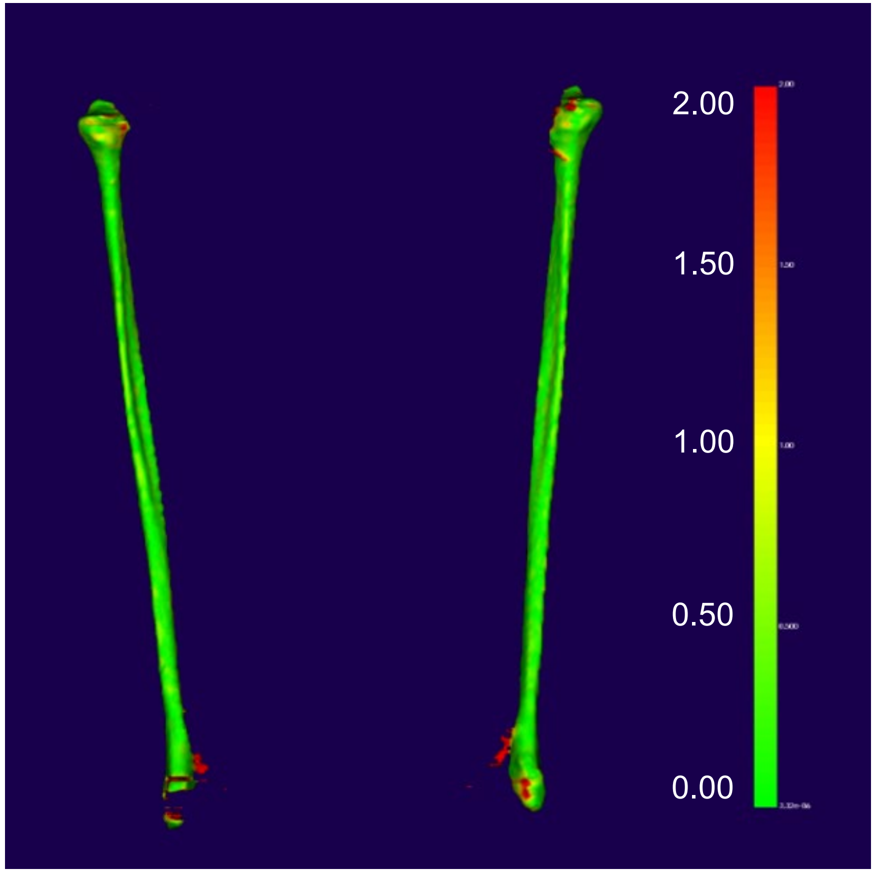


Test set 2

Discussion for Experiment 2

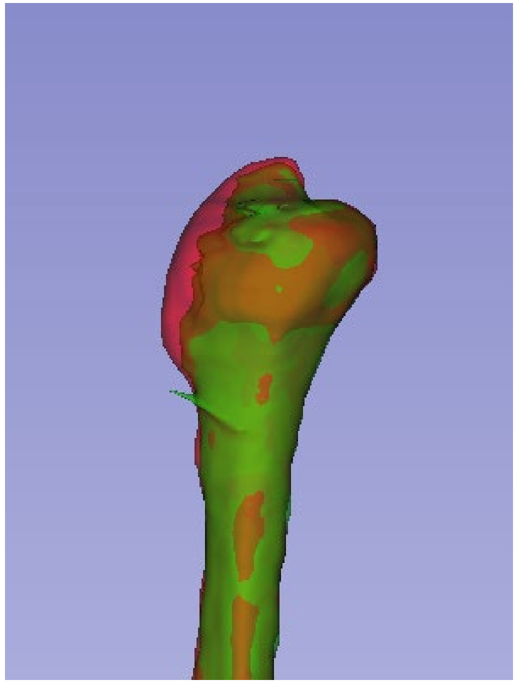


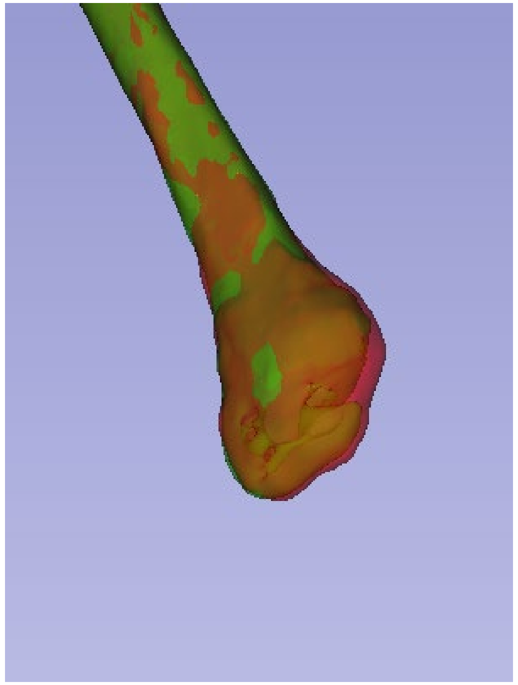
Test set 1



Test set 2

Two method to improve epiphysis segmentation





- Information combination
- Data augmentation

KU LEUVEN

3D Network to 2.5D Network

3D network (3D Unet)

(Regardless of computing and VRAM)

- Combine the information between image slices
- Ensure the continuity
- Better than 2D network

Drawbacks for fibula segmentation

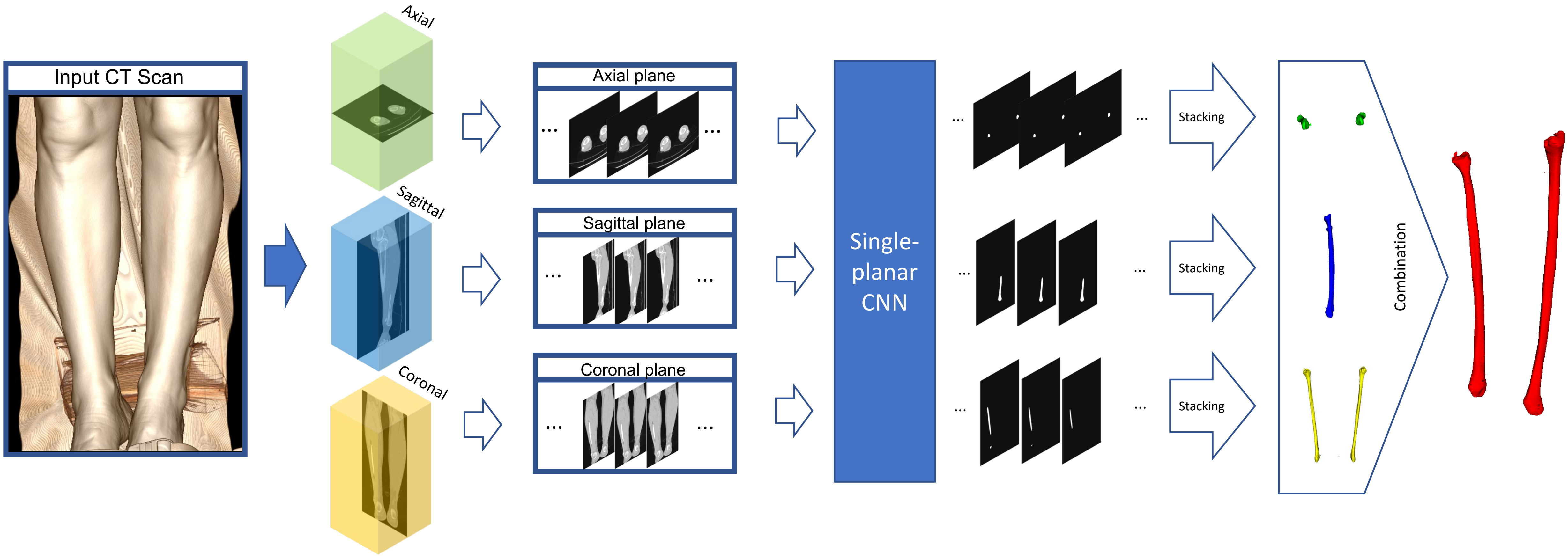
- **limitation of the VRAM** (800x384x384)
- Cannot take the entire 3D metric as input
- Crop to **a series of 3D patches**
- Network is difficult to learning the **overall structure**

Multi-planar combination (2.5D Network)

Outline

1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
    a. Evaluation criterion
    b. Single-planar segmentation model
    c. Multi-planar segmentation model
    d. Multi-planar segmentation model with data augmentation
4. Conclusion

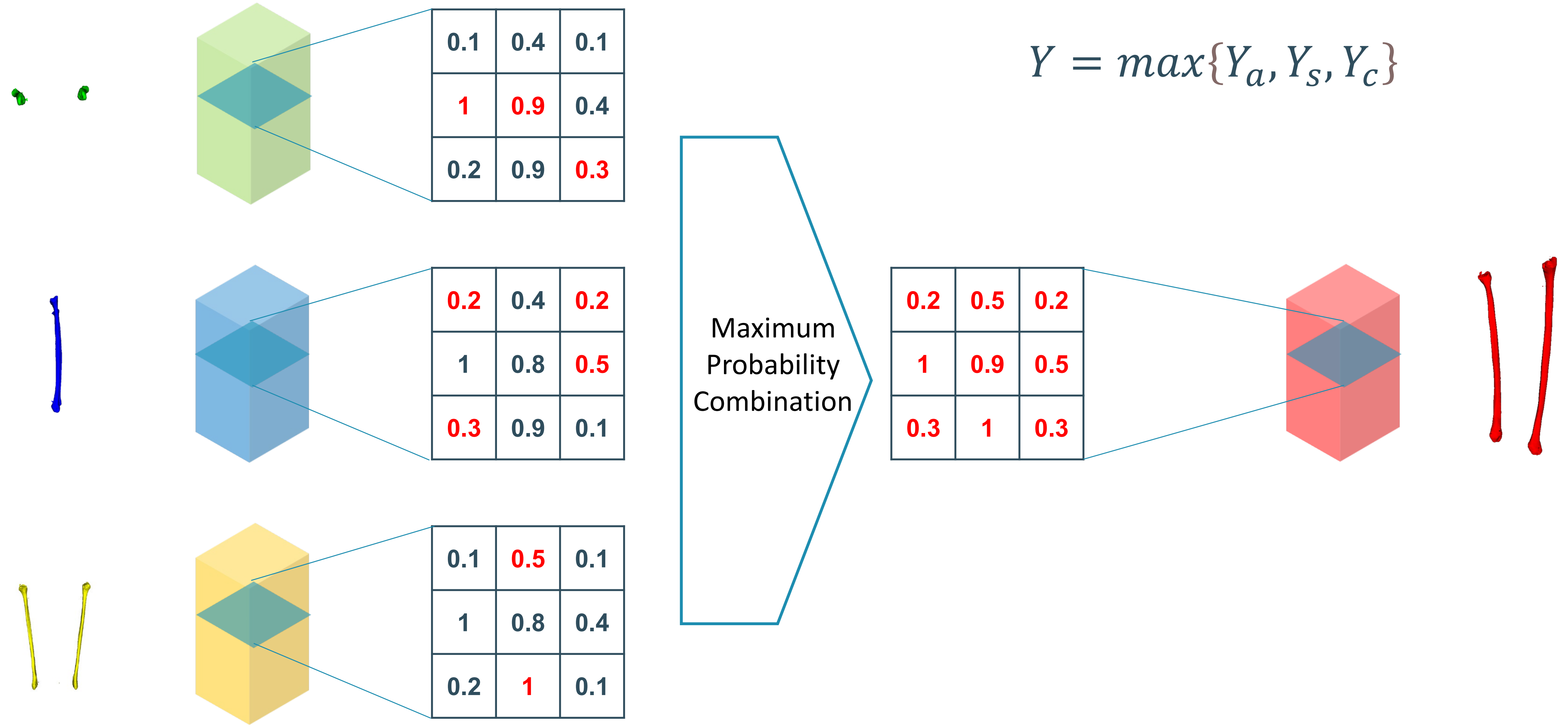
Multi-planar segmentation model



KU LEUVEN

Maximum Probability Combination

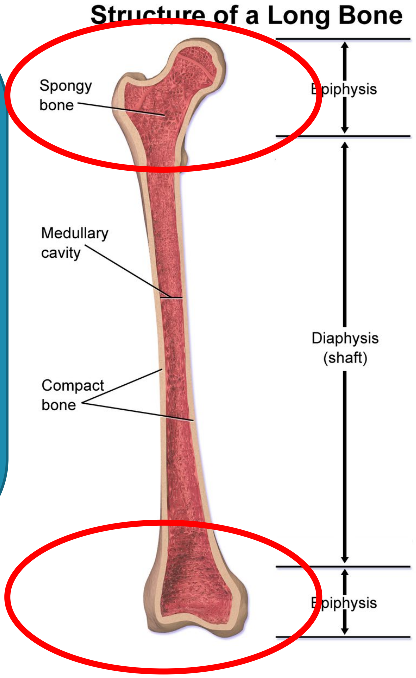
$$Y = max\{Y_a, Y_s, Y_c\}$$



Cropping the region of interest (CROI) method

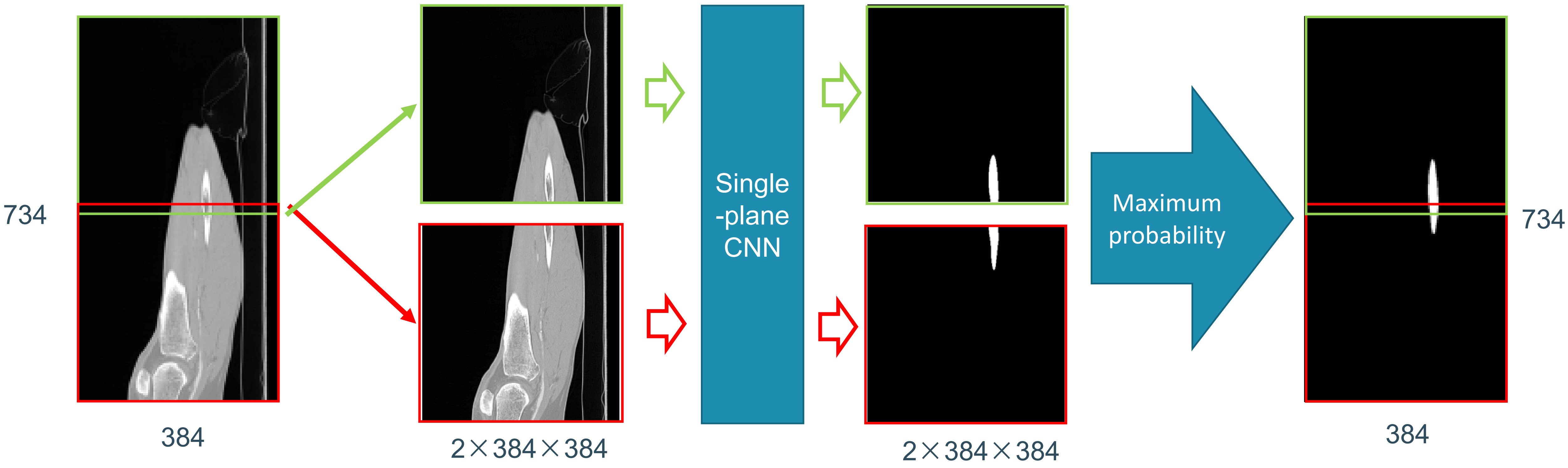
- The input image for single-planar segmentation model is 384x384
- Different resolution (384x734,384x670…)

- Predicted performance of **epiphysis part** is worse than the diaphysis part
- Focus on data at **epiphysis part**

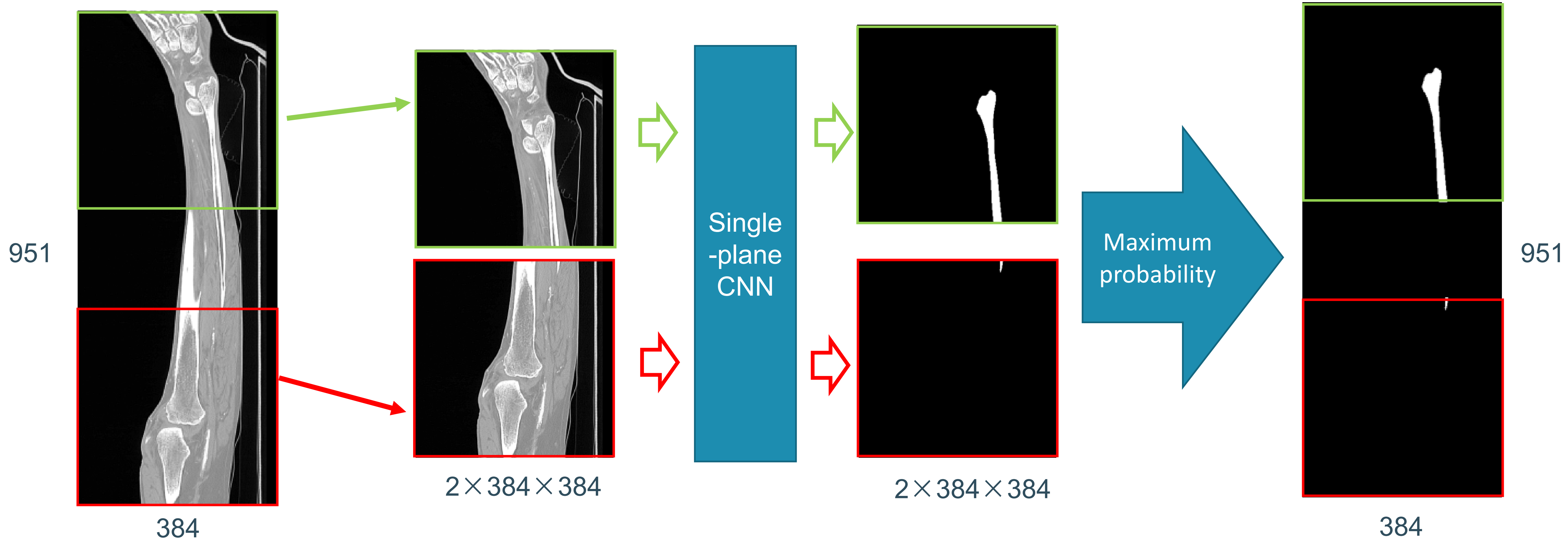


Cropping the region of interest (CROI)

Cropping the region of interest (CROI) method (For sagittal and coronal)



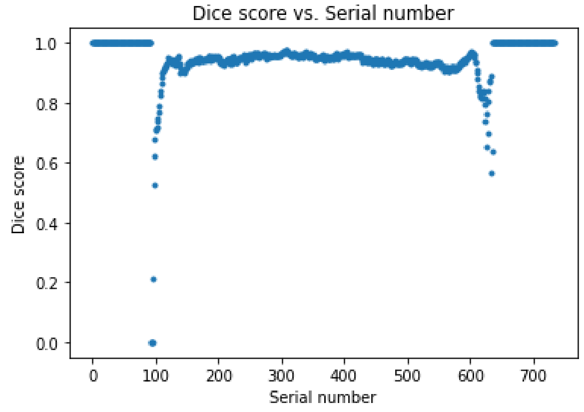
Cropping the region of interest (CROI) method (For sagittal and coronal)

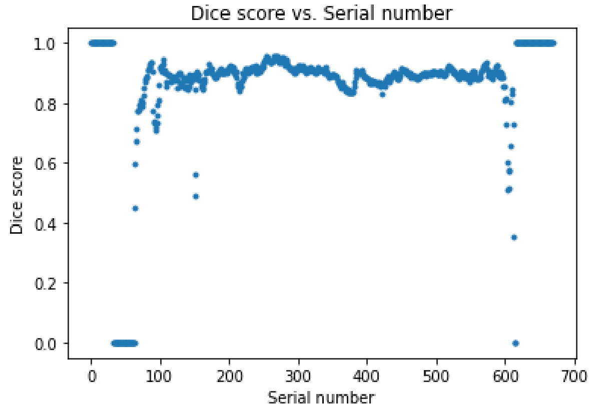


KU LEUVEN

Experiment 3：Multi-planar segmentation model

Combination result



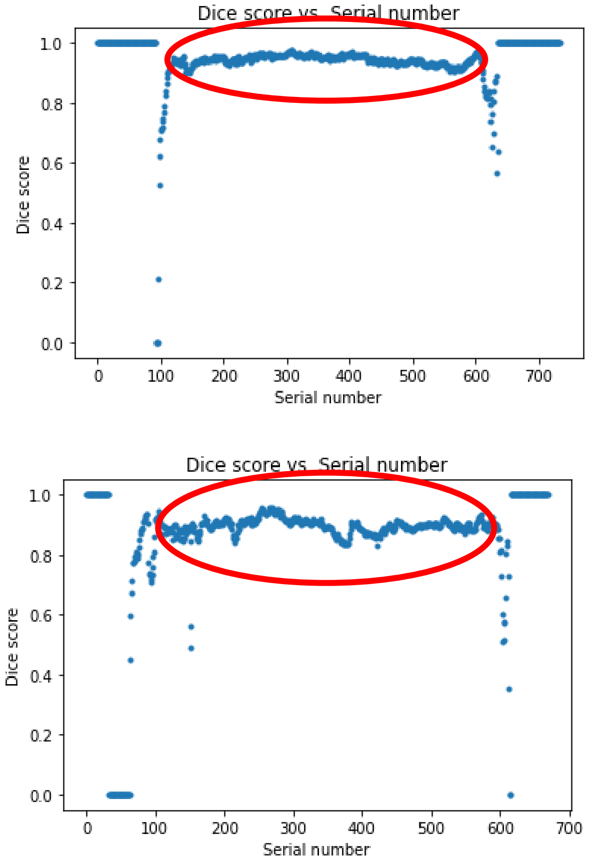


	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
Axial plane	0.956	0.938	0.947	0.923
Sagittal plane	0.942	0.938	0.908	0.909
Coronal plane	0.946	0.945	0.918	0.896
Combination result	0.945 ▼	0.856 ▼	0.932 ▼	0.883 ▼

KU LEUVEN

Experiment 3： Multi-planar segmentation model

Combination result

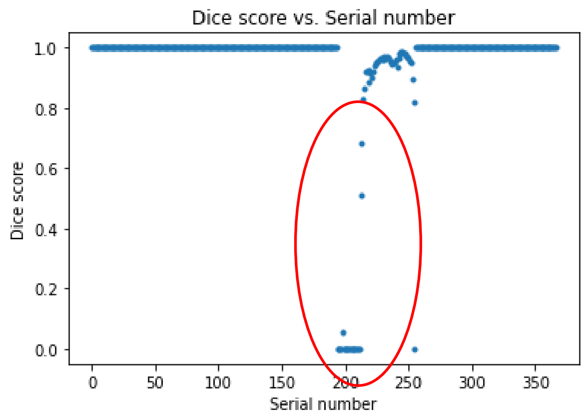


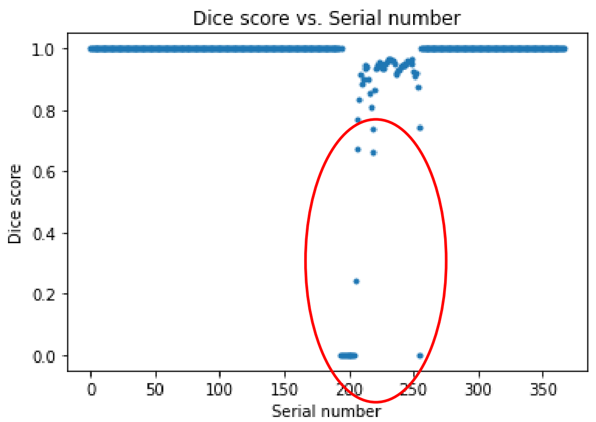
	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
Axial plane	0.956	0.938	0.947	0.923
Sagittal plane	0.942	0.938	0.908	0.909
Coronal plane	0.946	0.945	0.918	0.896
Combination result	0.945 ▼	0.856 ▼	0.932 ▼	0.883 ▼

KU LEUVEN

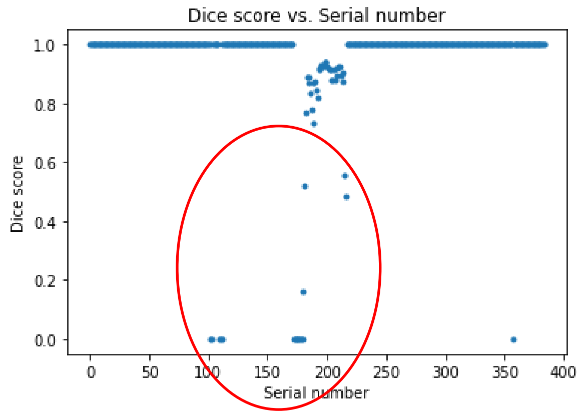
Experiment 3： Multi-planar segmentation model

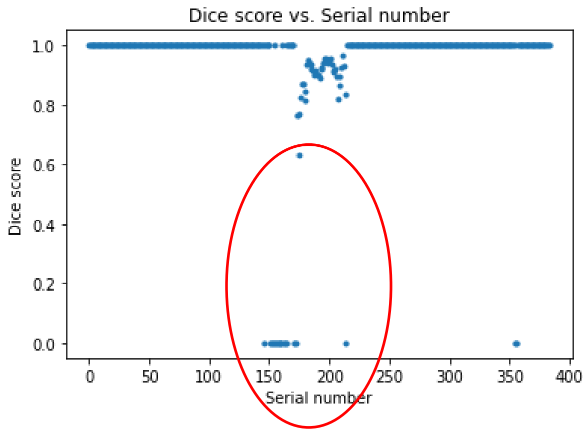
Coronal plane subnetwork





Test set 1



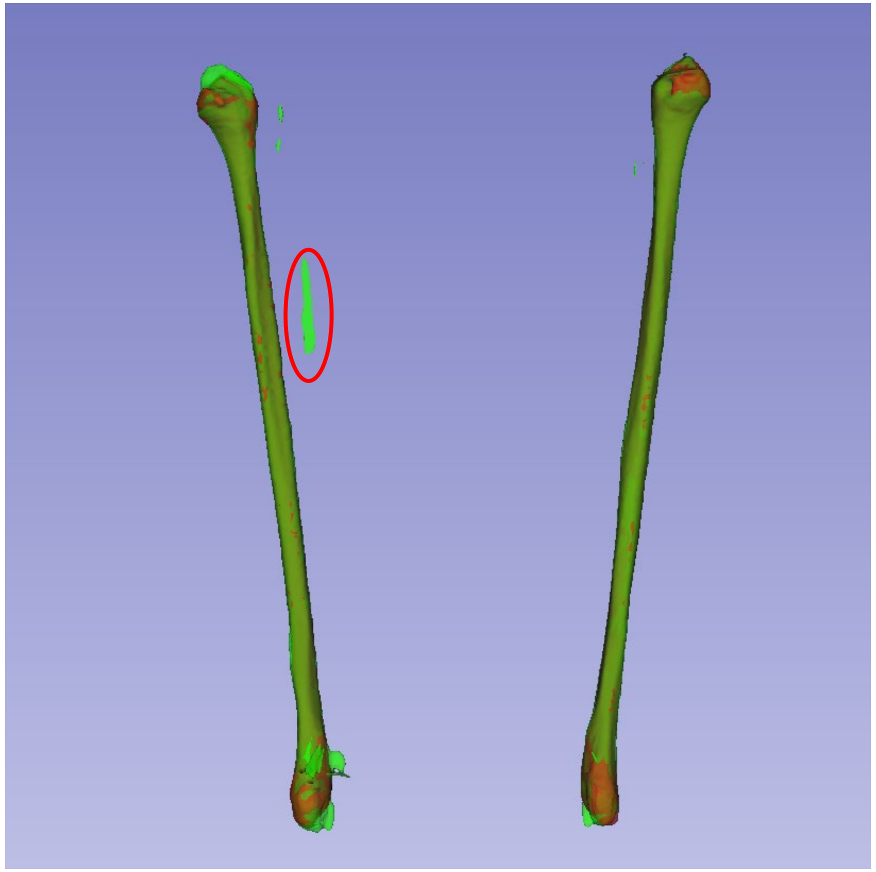


Test set 2

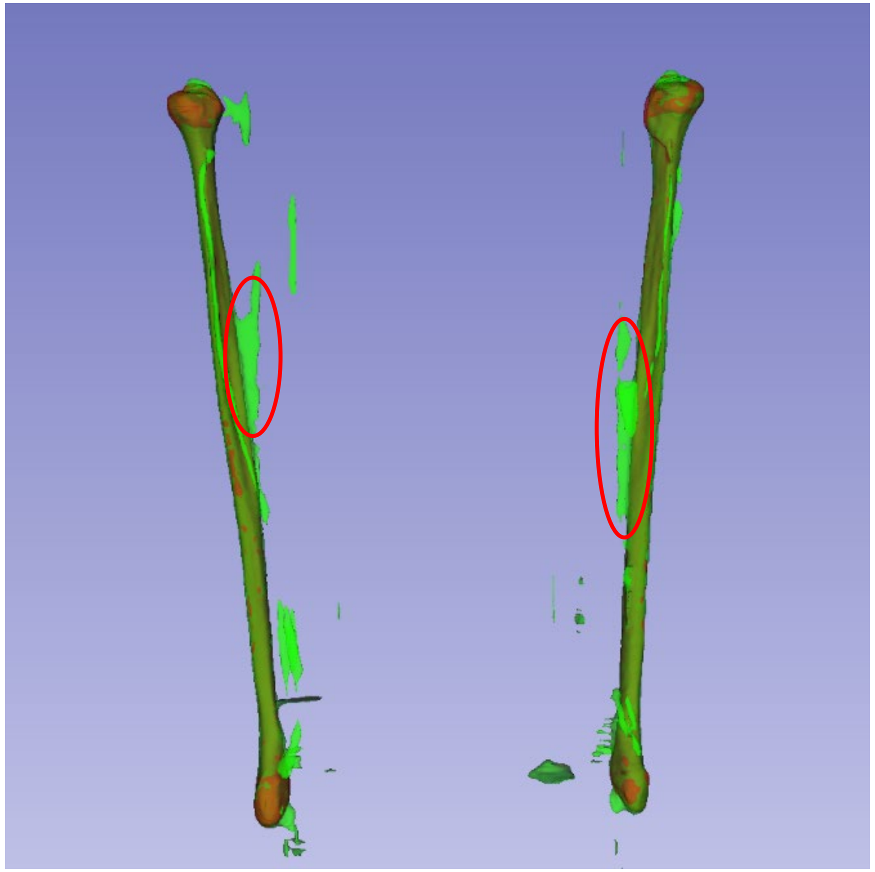
- Too few useful parts
- Result is poor

KU LEUVEN

Discussion for Experiment 3: Multi-planar segmentation model

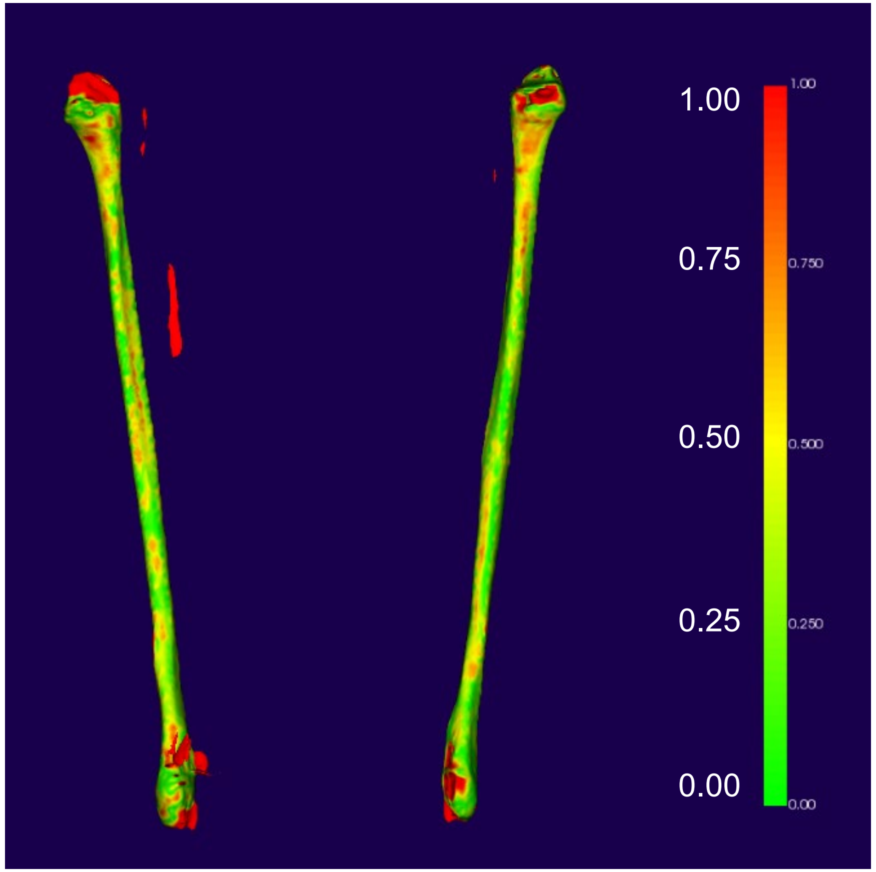


Test set 1

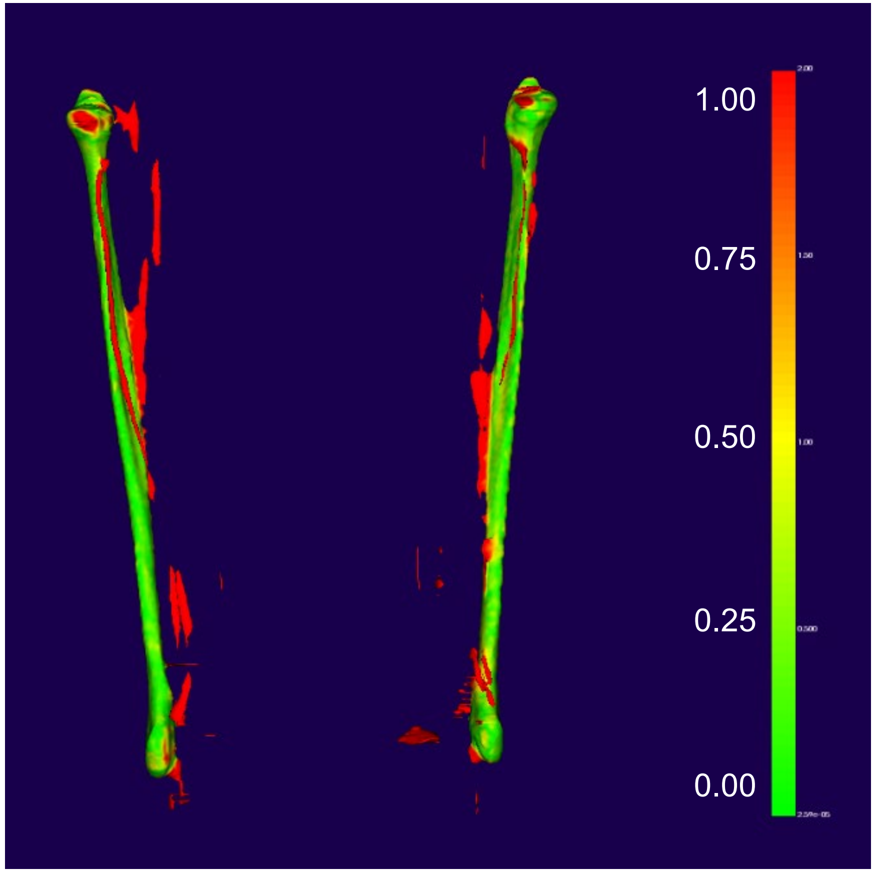


Test set 2

Discussion for Experiment 3



Test set 1



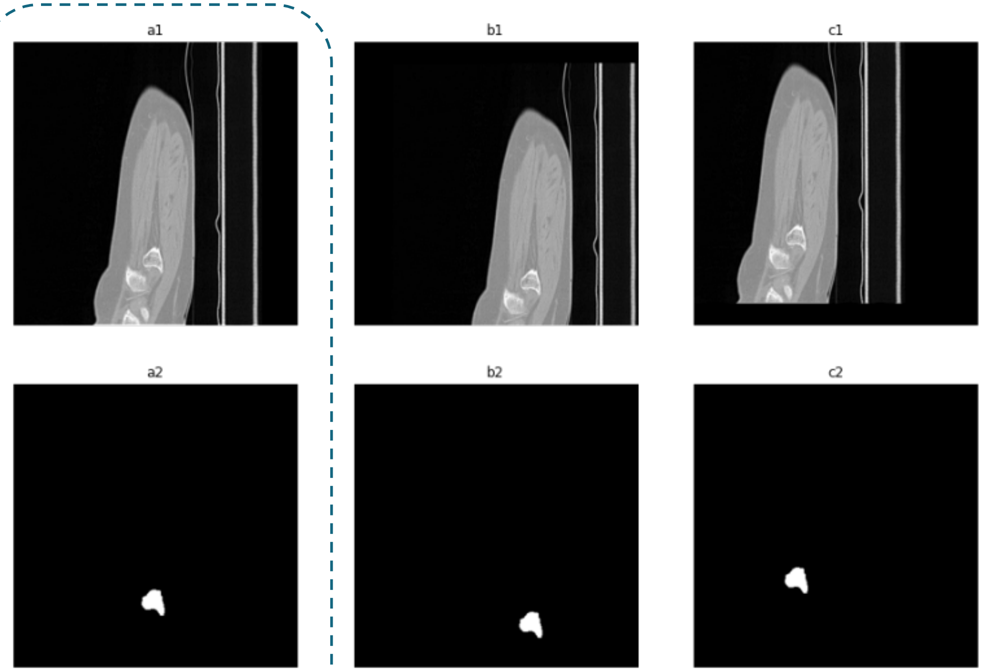
Test set 2

Outline

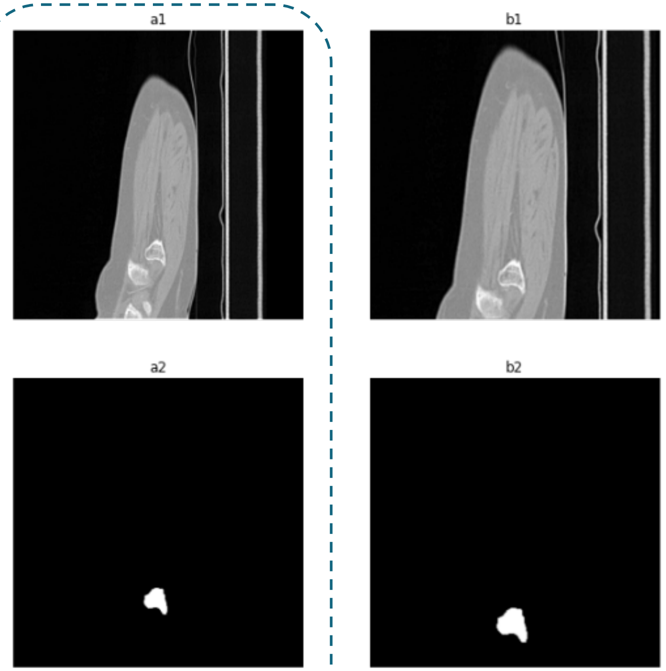
Data Augmentation

Images

Ground Truth



Original b c



Original

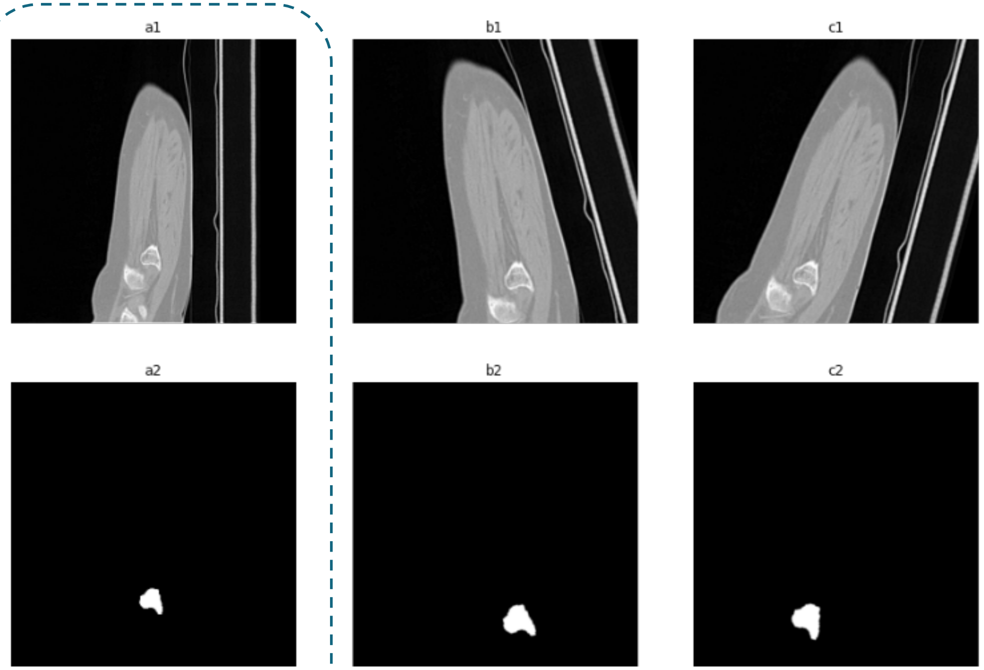
- **Translation:** b. 50 to the right and 30 downwards
  c. 50 to the left and 30 upwards

- **Scale:** 1.3 times.

Data Augmentation

Images

Ground Truth

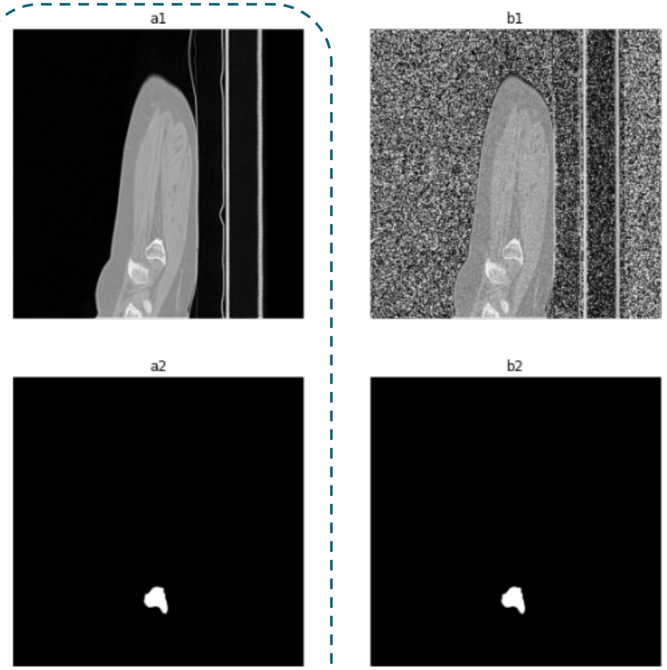


Original

Counter clockwise

Clockwise

- **Rotate:** 15 degrees rotate, and 1.3 times enlarged

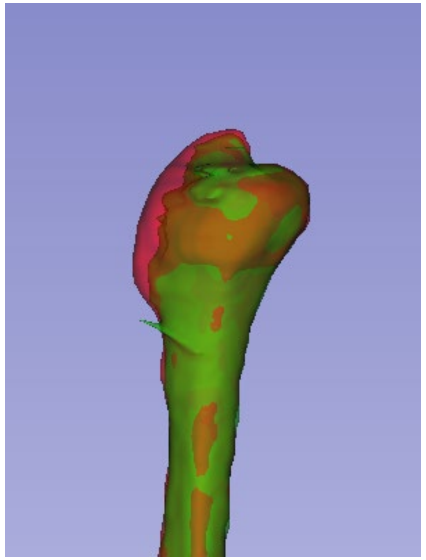


Original

- **Gaussian noise:** an average of zero and a standard deviation of 1

KU LEUVEN

Data Augmentation

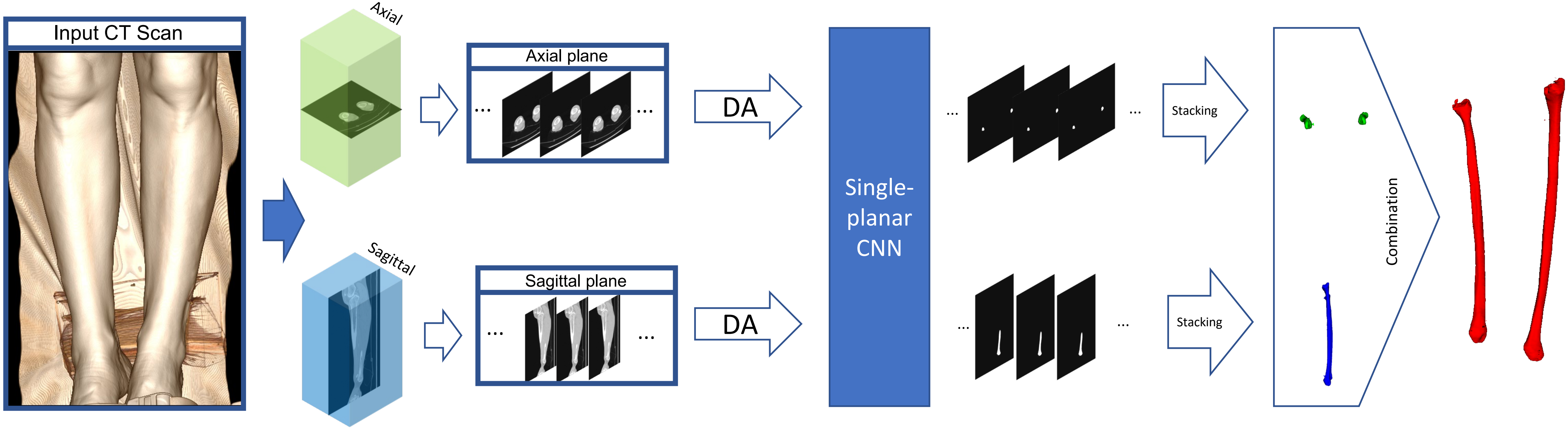


- Axial:
  - Select **epiphysis part manually** from train set
  - 2160 to 10,800
- Sagittal:
  - Select slices included the **fibula bone**
  - 2830 to 14,150

- Add to original train set

KU LEUVEN

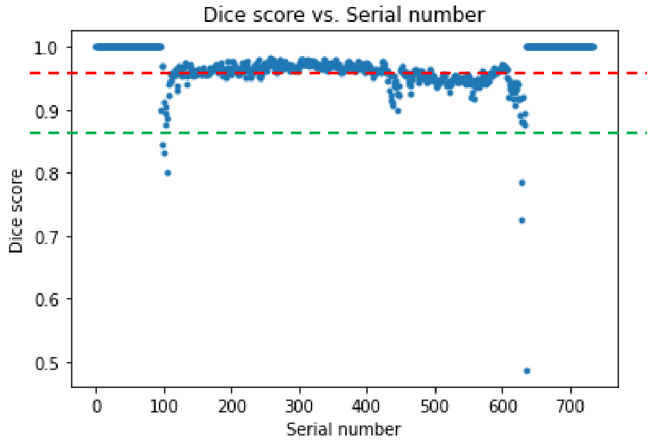
Final segmentation model



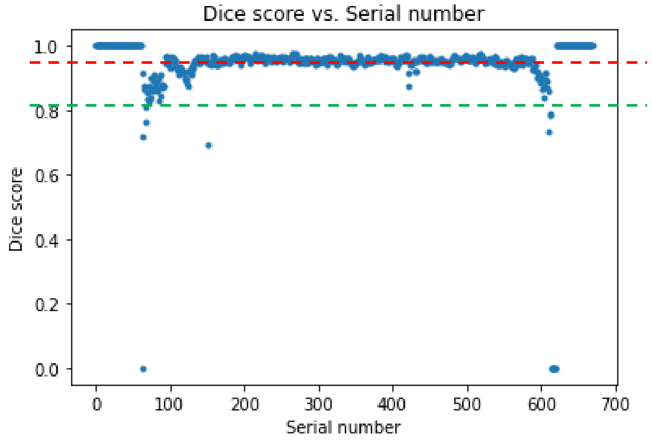
- Data augmentation
- Multi-planar segmentation only with axial plane and sagittal plane.

Experiment 4

Axial segmentation result on axial slices after data augmentation



Test set 1



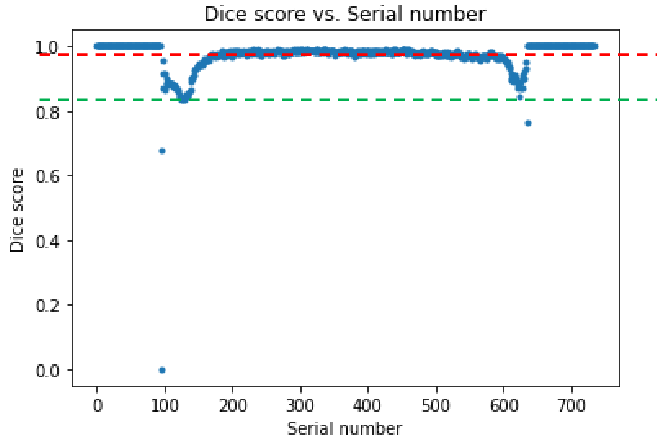
Test set 2

	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
Axial plane	0.956	0.938	0.947	0.923
Axial plane After Data Augmentation	0.967	0.943	0.957	0.944
Sagittal plane	0.942	0.938	0.908	0.909
Sagittal plane After Data Augmentation	0.961	0.972	0.955	0.964
Data Augmentation Combination	0.967	0.944	0.957	0.946

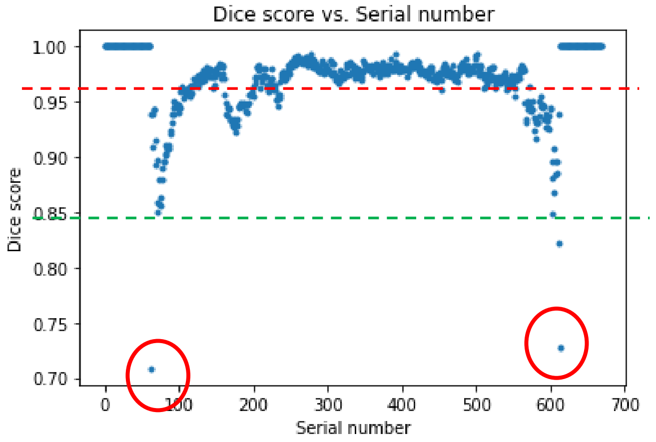
KU LEUVEN

Experiment 4

Sagittal segmentation result on axial slices after data augmentation



Test set 1



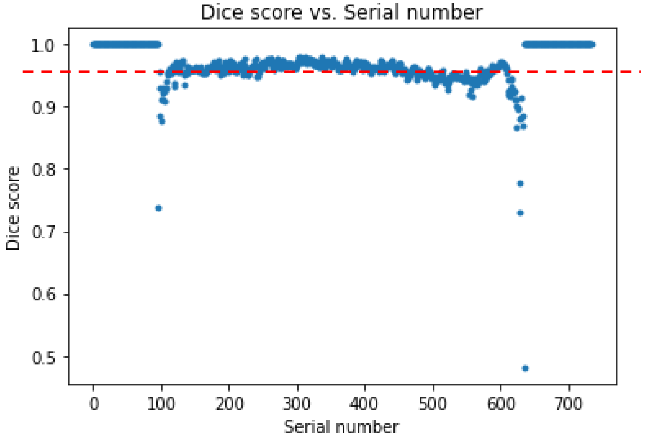
Test set 2

	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
Axial plane	0.956	0.938	0.947	0.923
Axial plane After Data Augmentation	0.967	0.943	0.957	0.944
Sagittal plane	0.942	0.938	0.908	0.909
Sagittal plane After Data Augmentation	0.961	0.972	0.955	0.964
Data Augmentation Combination	0.967	0.944	0.957	0.946

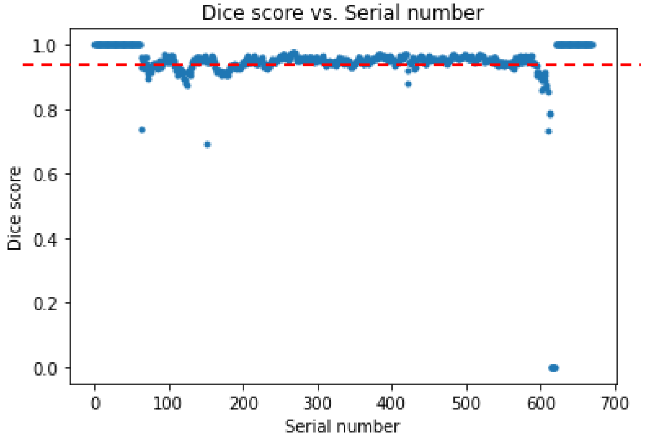
KU LEUVEN

Experiment 4

Combination segmentation result on axial slices after data augmentation



Test set 1



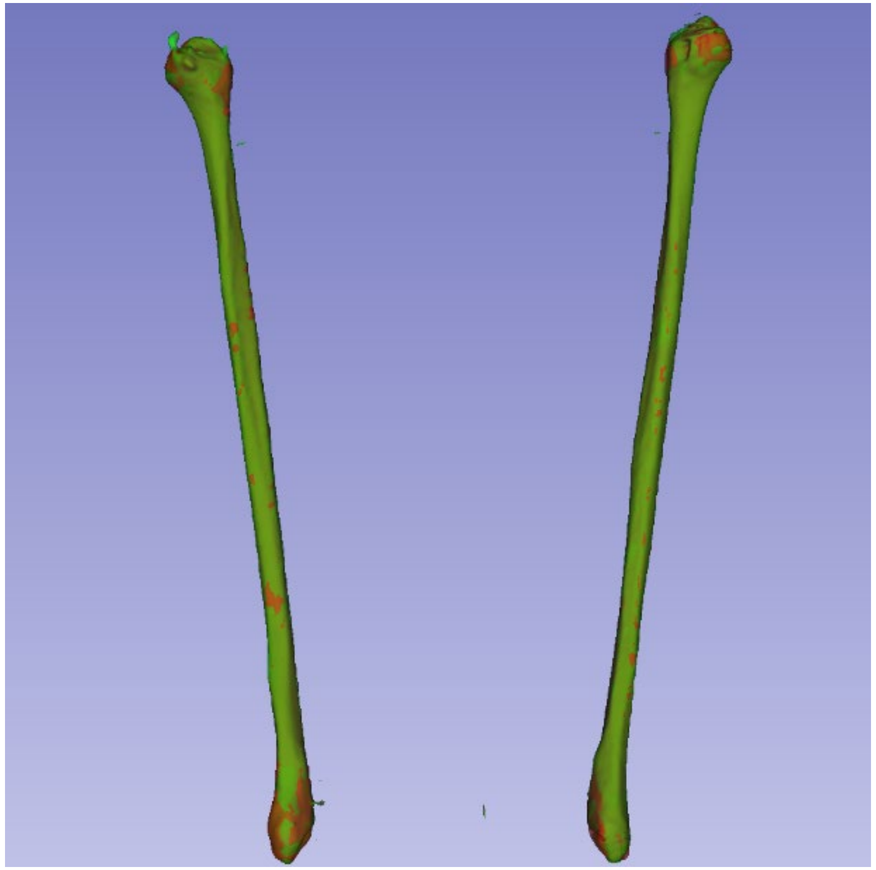
Test set 2

	Test set 1 average Dice score	Test set 2 average Dice score	Test set 1 volume Dice Score	Test set 2 volume Dice Score
Axial plane	0.956	0.938	0.947	0.923
Axial plane After Data Augmentation	0.967	0.943	0.957	0.944
Sagittal plane	0.942	0.938	0.908	0.909
Sagittal plane After Data Augmentation	0.961	0.972	0.955	0.964
Data Augmentation Combination	0.967	0.944	0.957	0.946

KU LEUVEN

Discussion for Experiment 4:

Multi-planar segmentation model with data augmentation



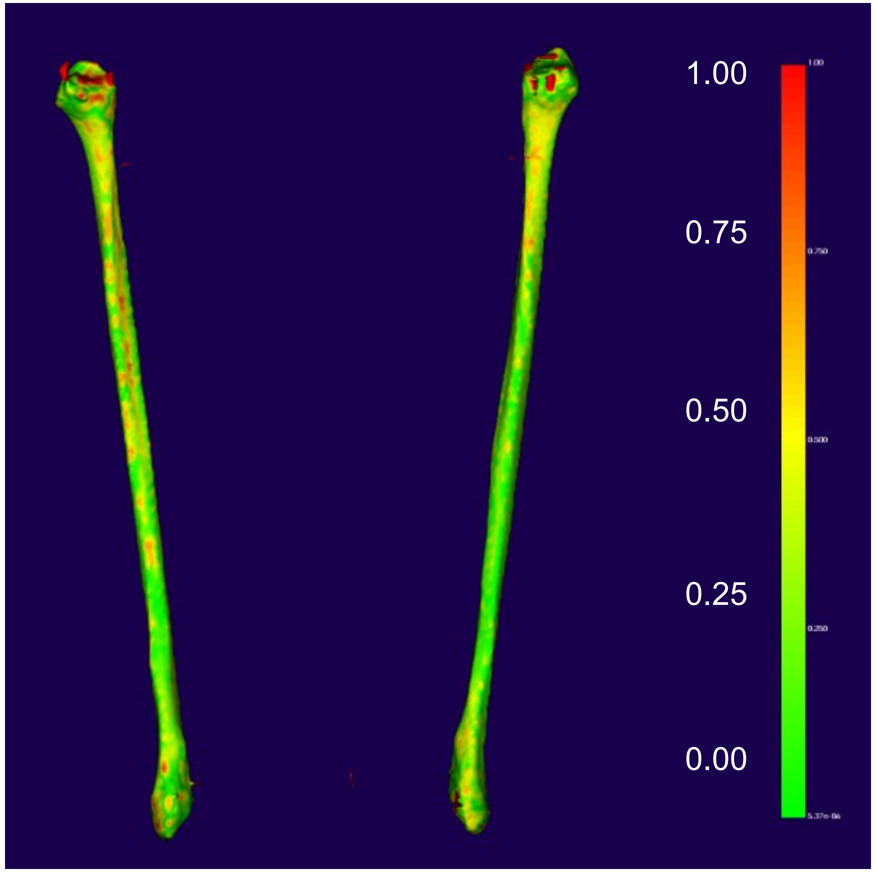
Test set 1

Test set 2

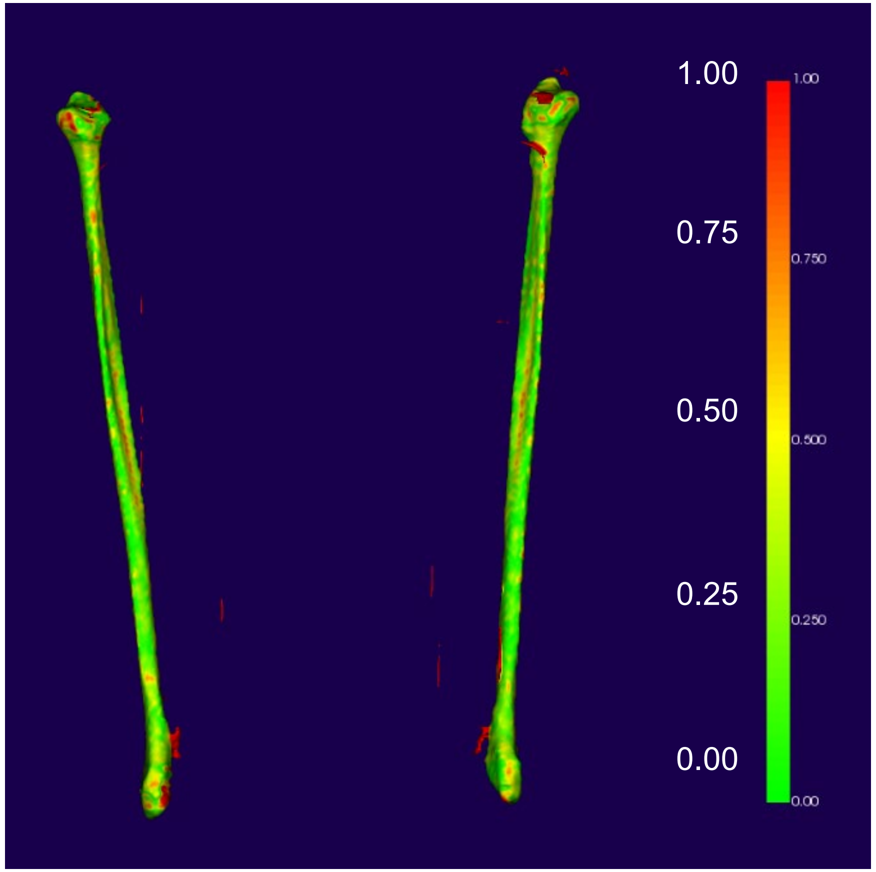
KU LEUVEN

Discussion for Experiment 4:

Multi-planar segmentation model with data augmentation



Test set 1



Test set 2

KU LEUVEN

Outline

1. Motivation
2. Dataset & Data preprocessing
3. Methodology & Experiments
4. Conclusion

Conclusion

- An automatic fibula segmentation neural network

→ proven to be accurate and efficient

- The multi-planar segmentation model

→ increased the segmentation accuracy of epiphysis
→ decreased the segmentation accuracy of diaphysis

- The data augmentation

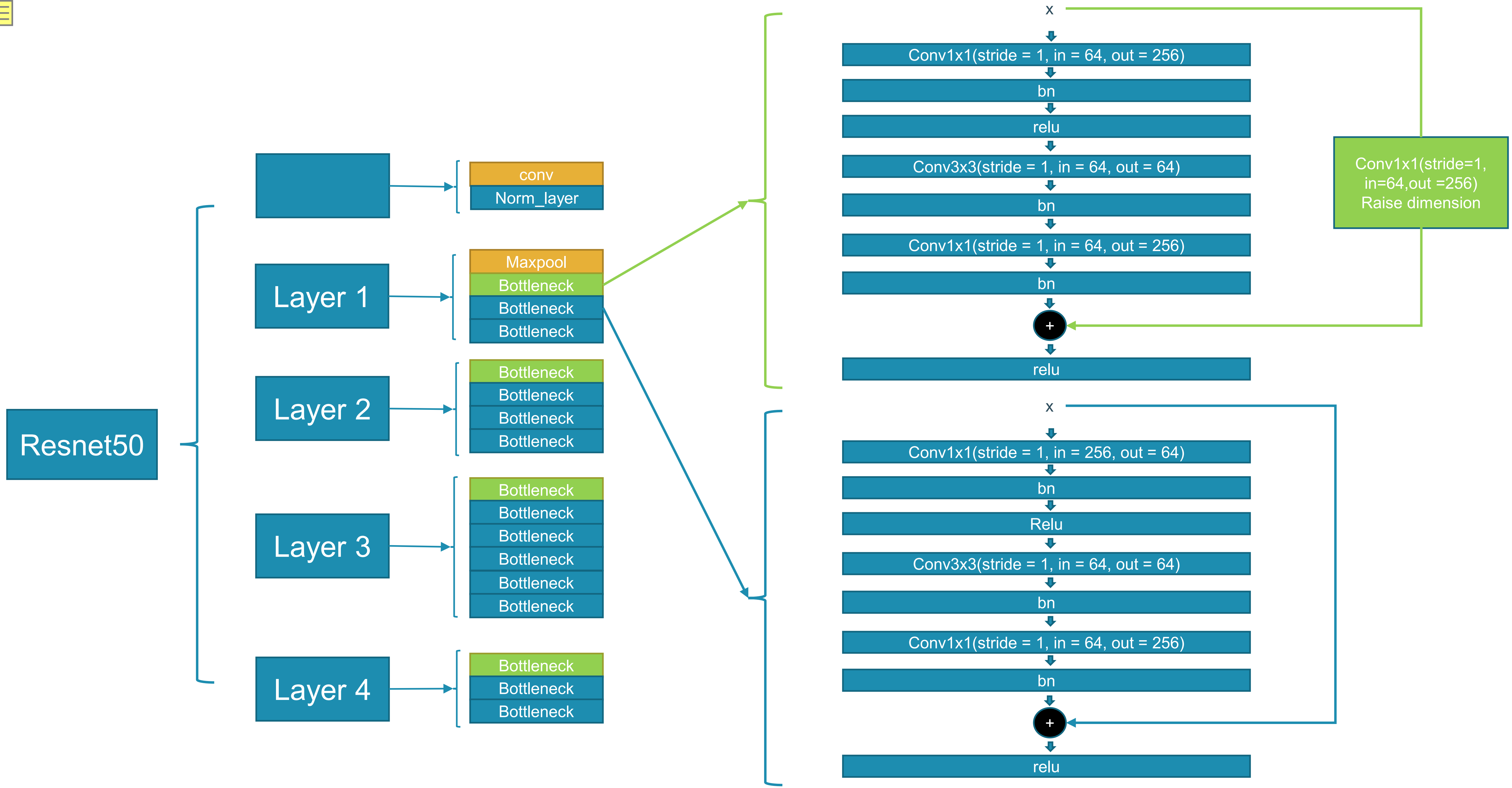
→ increased segmentation accuracy for single-planar segmentation and multi-planar segmentation

- Applicable for clinical medical fibula segmentation

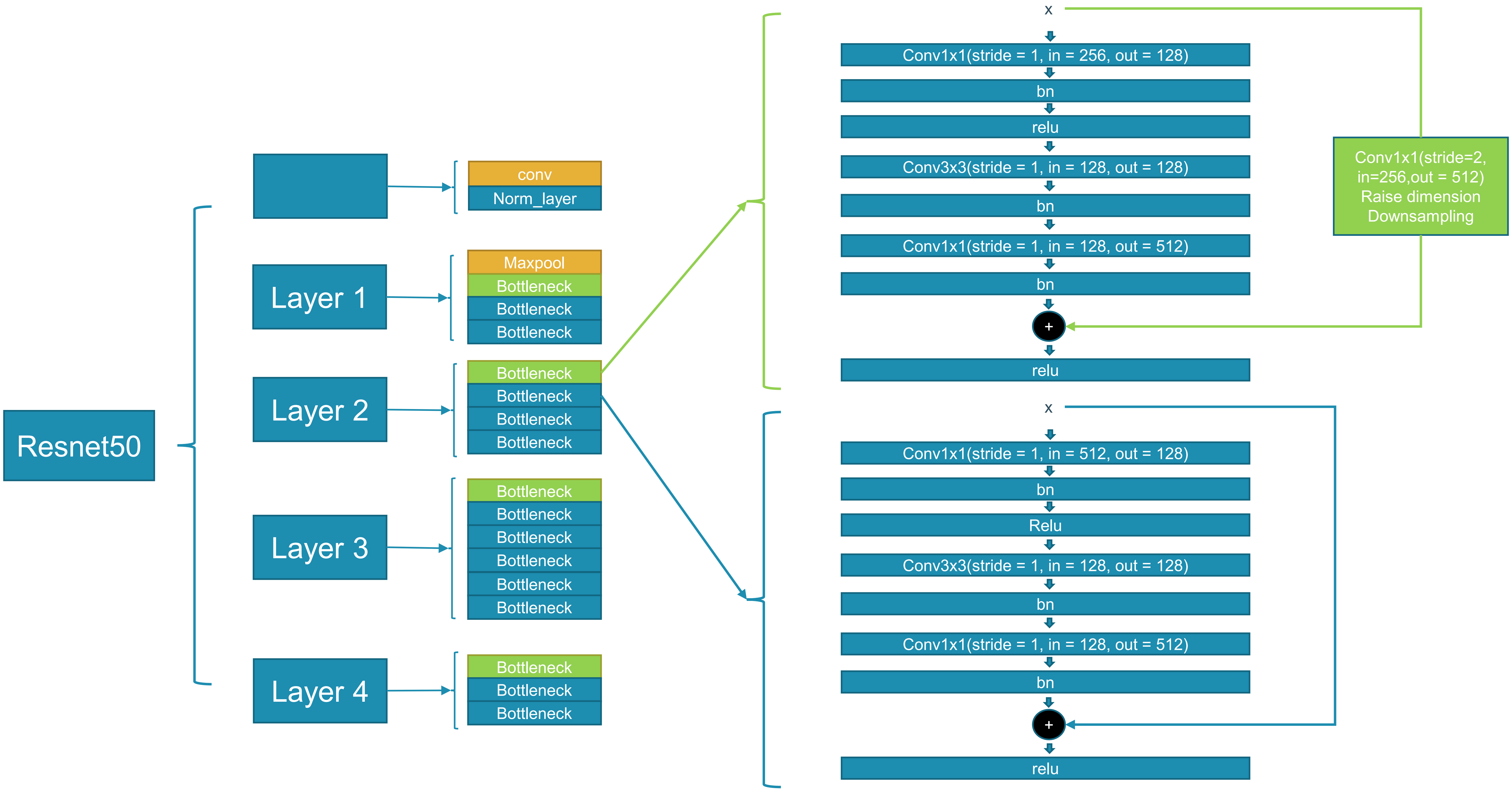
→ Dice score higher than 0.95

Thank You

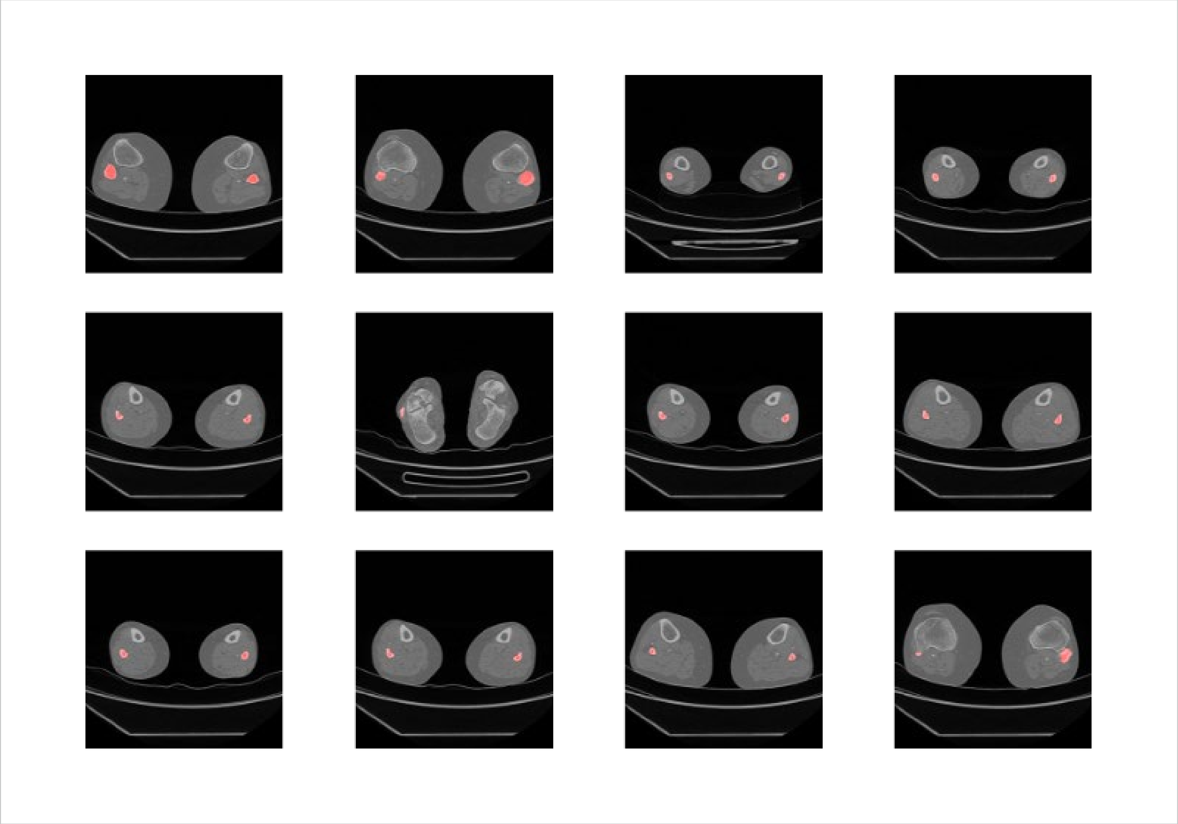
For Your Attention

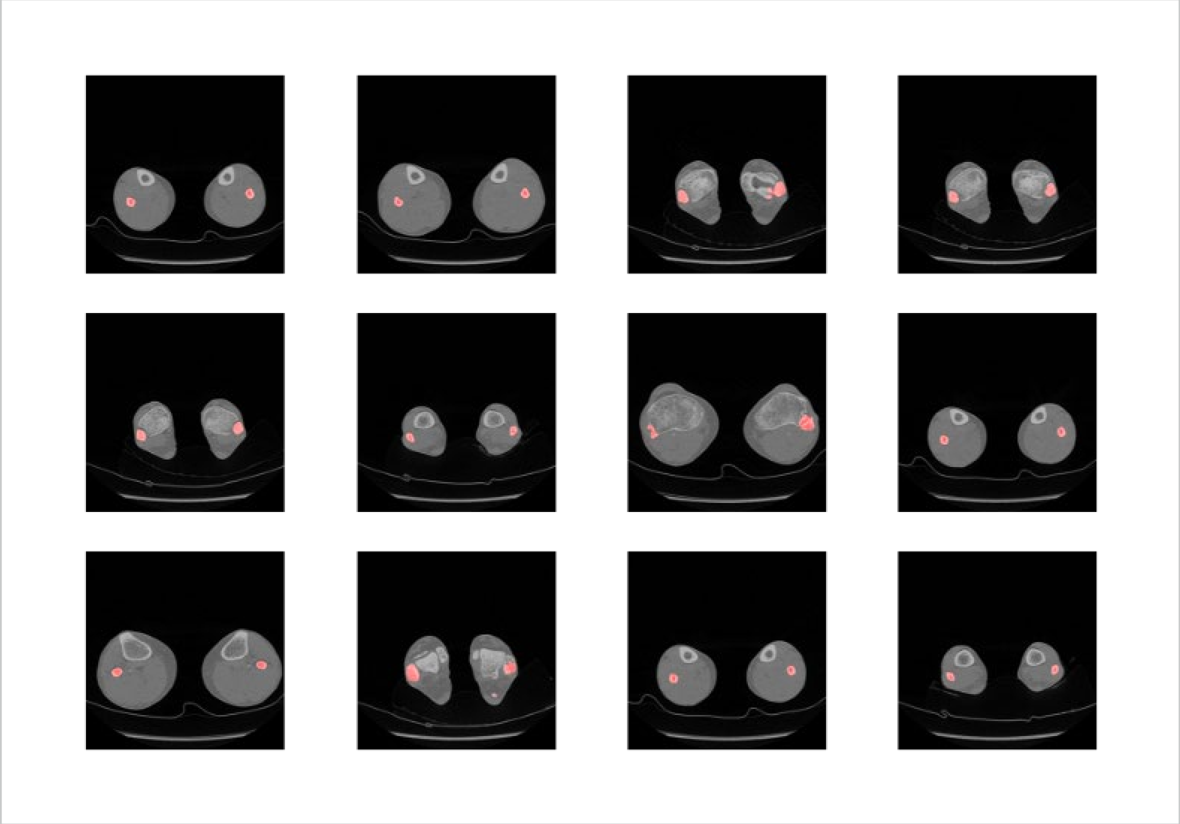

Resnet50
conv
Norm_layer
Layer 1
Maxpool
Bottleneck
Bottleneck
Bottleneck
Layer 2
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Layer 3
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Layer 4
Bottleneck
Bottleneck
Bottleneck
x
Conv1x1(stride = 1, in = 64, out = 256)
bn
relu
Conv3x3(stride = 1, in = 64, out = 64)
bn
Conv1x1(stride = 1, in = 64, out = 256)
bn
+
relu
Conv1x1(stride=1, in=64,out =256) Raise dimension
x
Conv1x1(stride = 1, in = 256, out = 64)
bn
Relu
Conv3x3(stride = 1, in = 64, out = 64)
bn
Conv1x1(stride = 1, in = 64, out = 256)
bn
+
relu

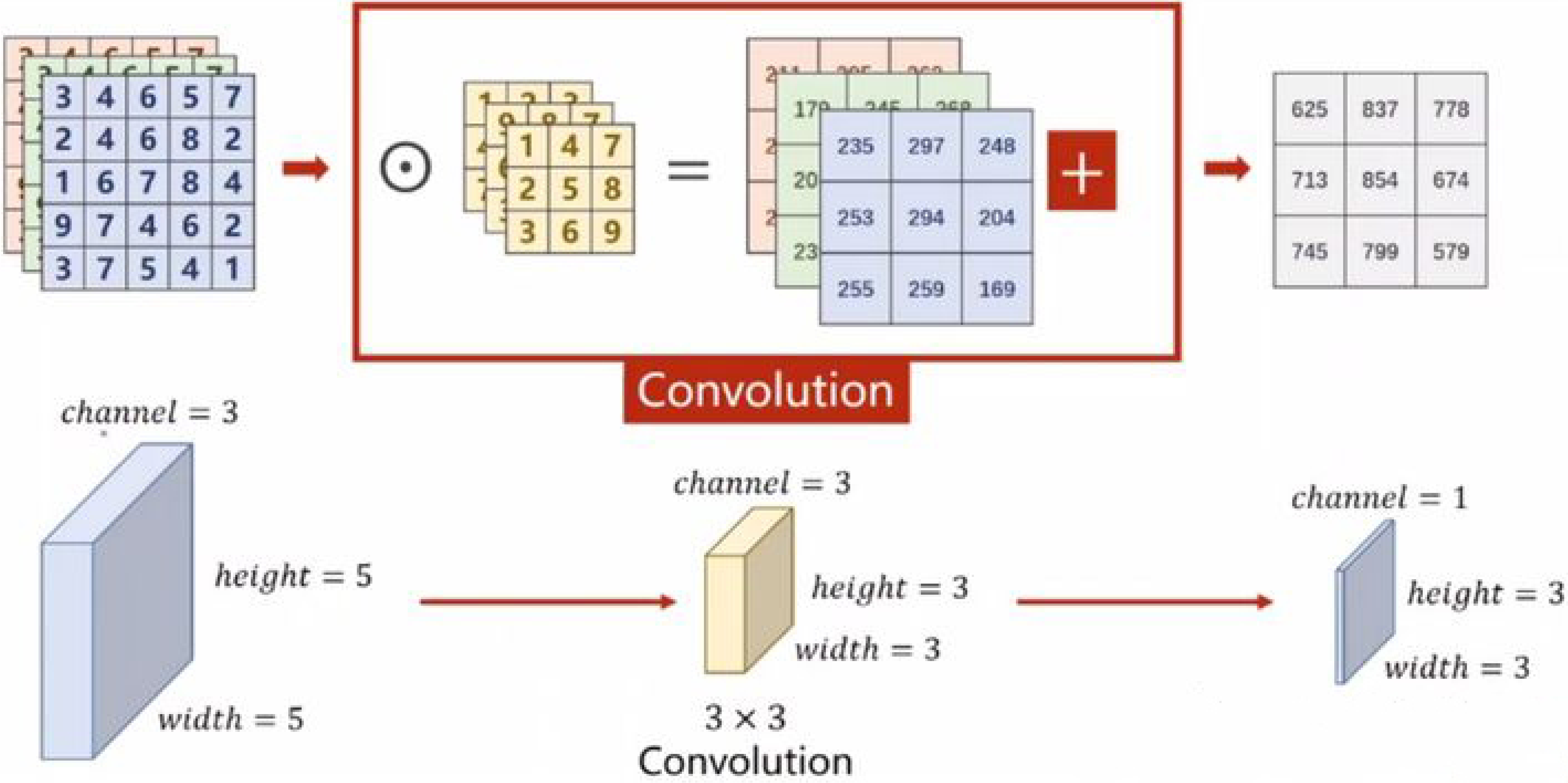
KU LEUVEN

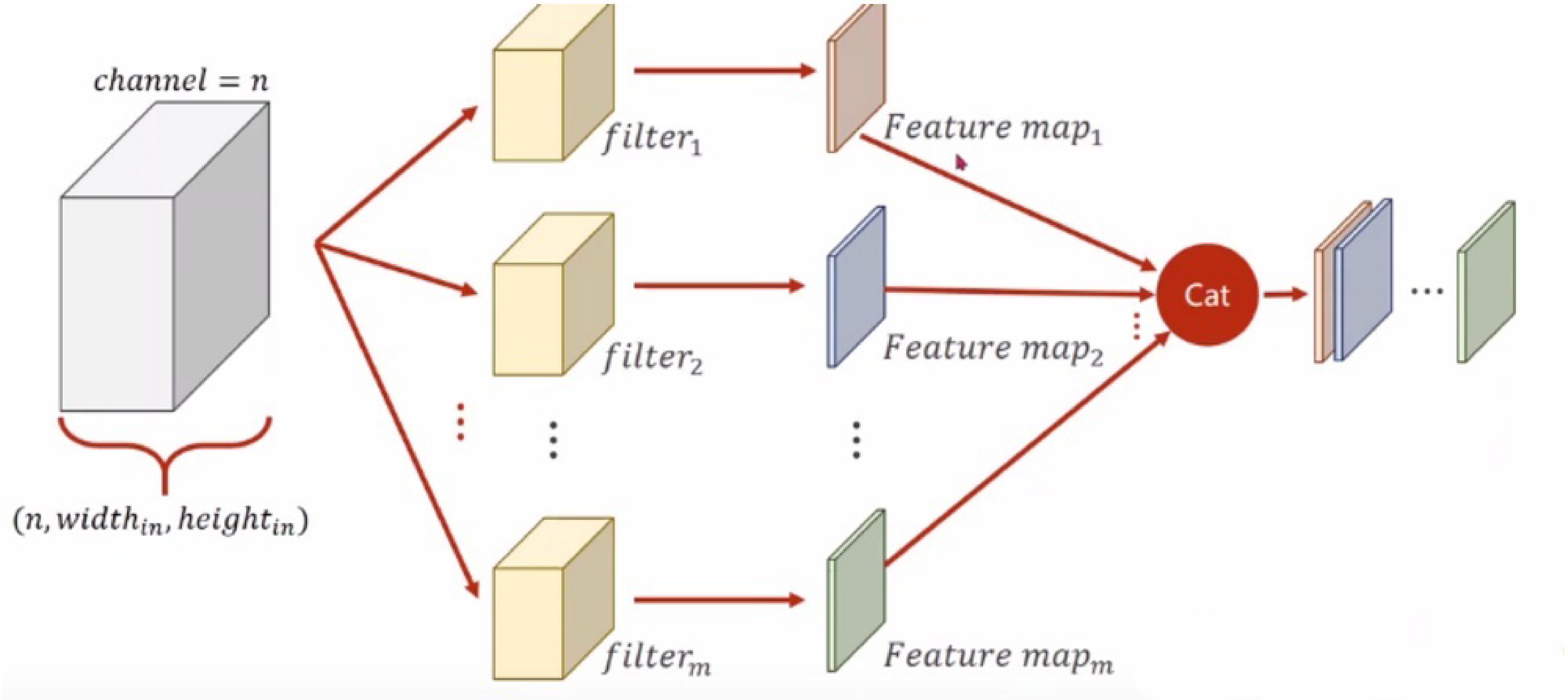

Resnet50
conv
Norm_layer
Layer 1
Maxpool
Bottleneck
Bottleneck
Bottleneck
Layer 2
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Layer 3
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Bottleneck
Layer 4
Bottleneck
Bottleneck
Bottleneck
x
Conv1x1(stride = 1, in = 256, out = 128)
bn
relu
Conv3x3(stride = 1, in = 128, out = 128)
bn
Conv1x1(stride = 1, in = 128, out = 512)
bn
+
relu
Conv1x1(stride=2, in=256,out = 512) Raise dimension Downsampling
x
Conv1x1(stride = 1, in = 512, out = 128)
bn
Relu
Conv3x3(stride = 1, in = 128, out = 128)
bn
Conv1x1(stride = 1, in = 128, out = 512)
bn
+
relu

Results of Experiment 2





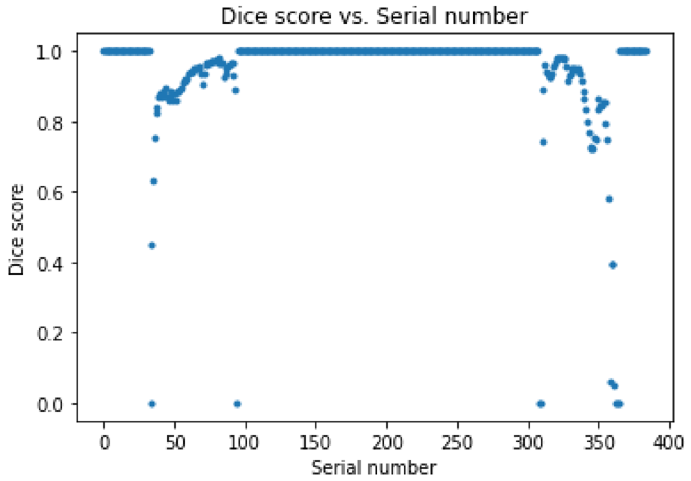

3 4 6 5 7
2 4 6 8 2
1 6 7 8 4
9 7 4 6 2
3 7 5 4 1
1 4 7
2 5 8
3 6 9
235 297 248
253 294 204
255 259 169
625 837 778
713 854 674
745 799 579
Convolution
$channel = 3$
$height = 5$
$width = 5$
$channel = 3$
$height = 3$
$width = 3$
3×3
Convolution
$channel = 1$
$height = 3$
$width = 3$

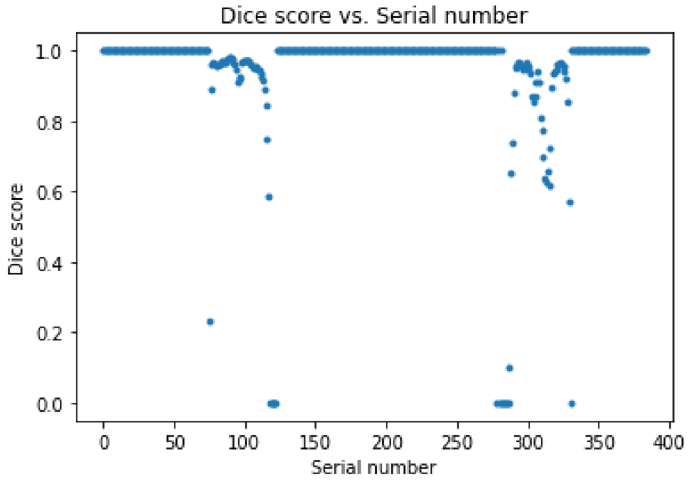

channel = n
filter1
filter2
filterm
Feature map1
Feature map2
Feature mapm
Cat
(n, widthin, heightin)

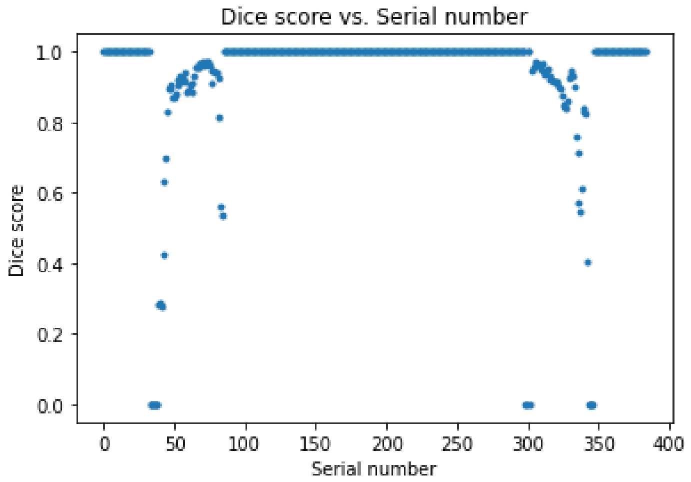
KU LEUVEN

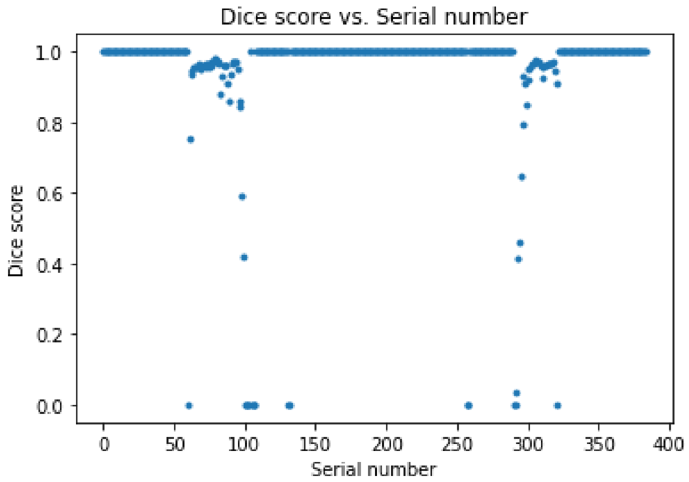
Experiment 3

Sagittal plane subnetwork





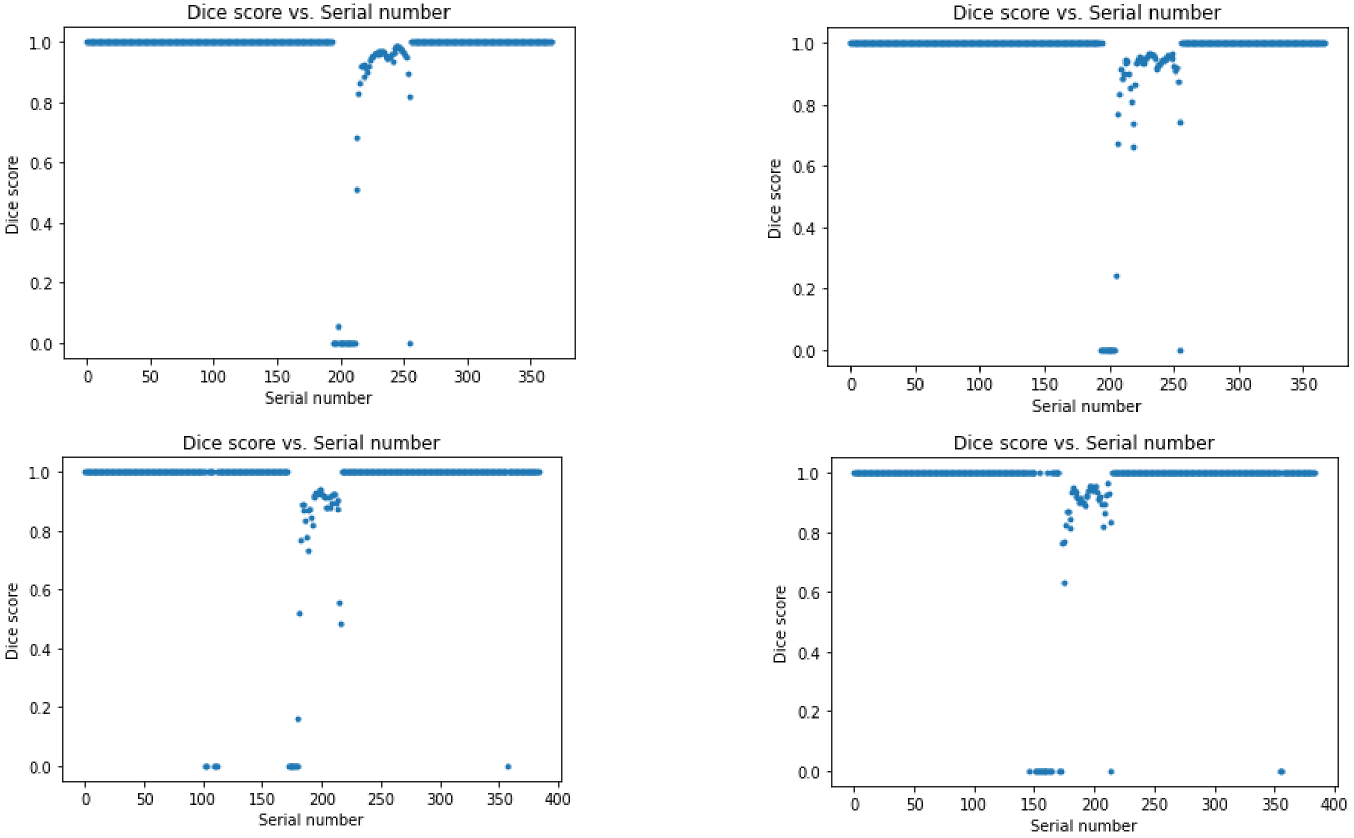




KU LEUVEN

Experiment 3

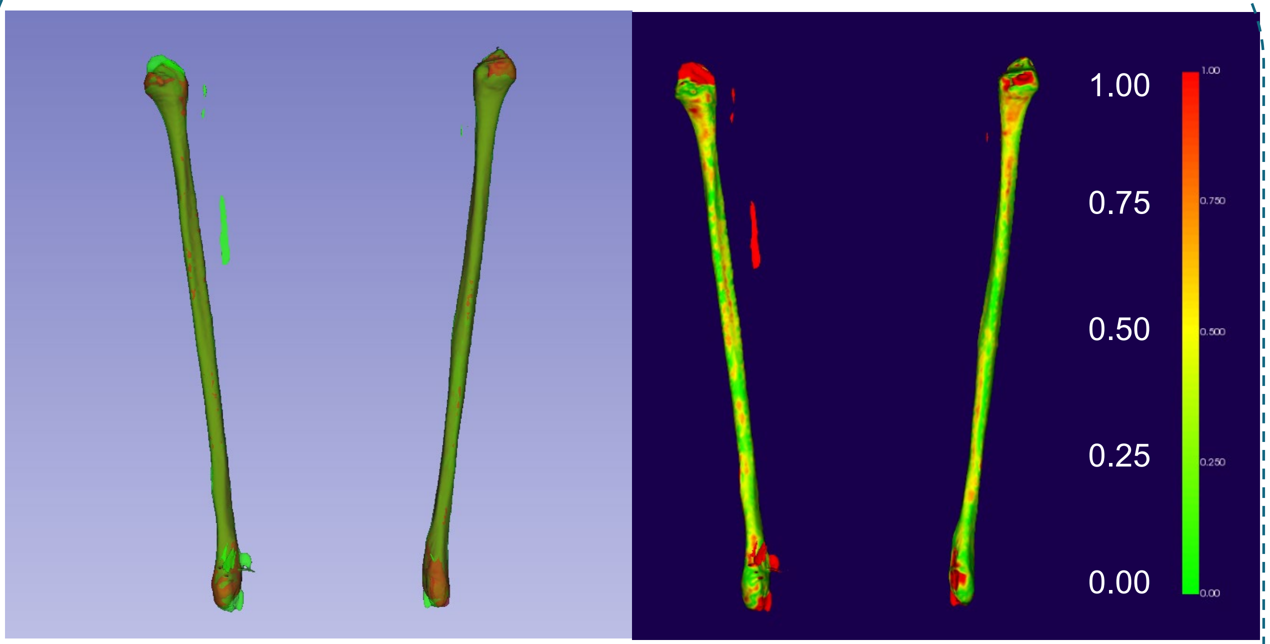
Coronal plane subnetwork



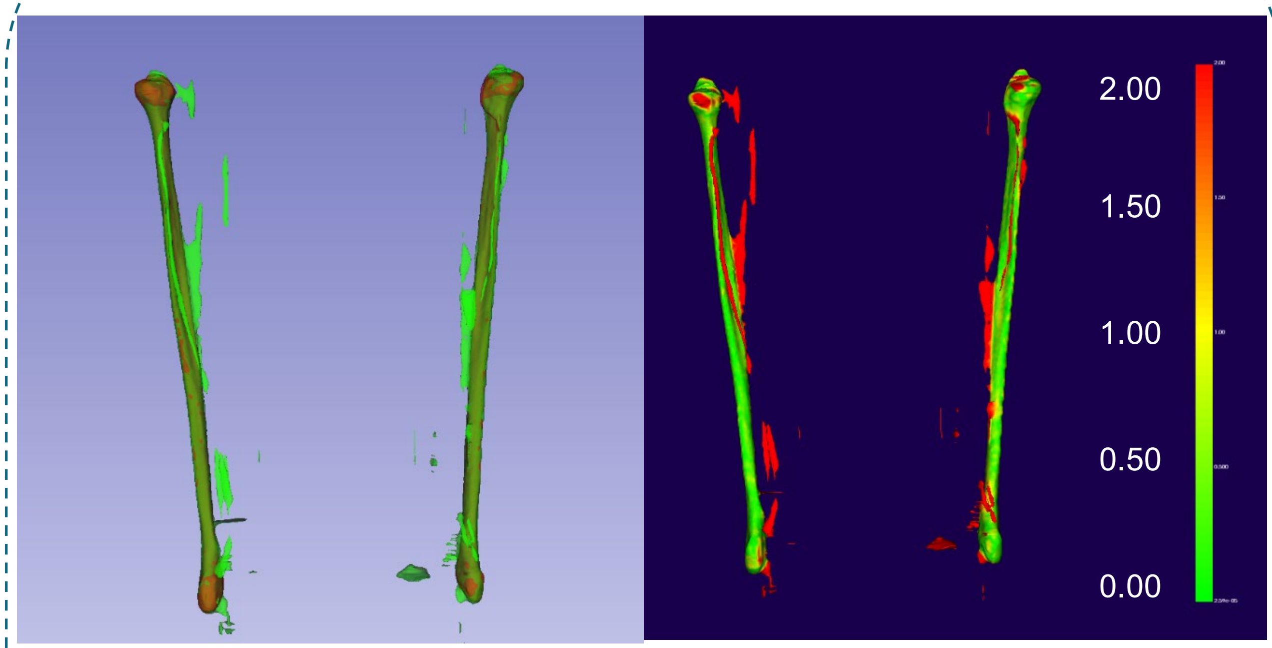
1. Too few useful parts
2. Result is poor

KU LEUVEN

Discussion for Experiment 3

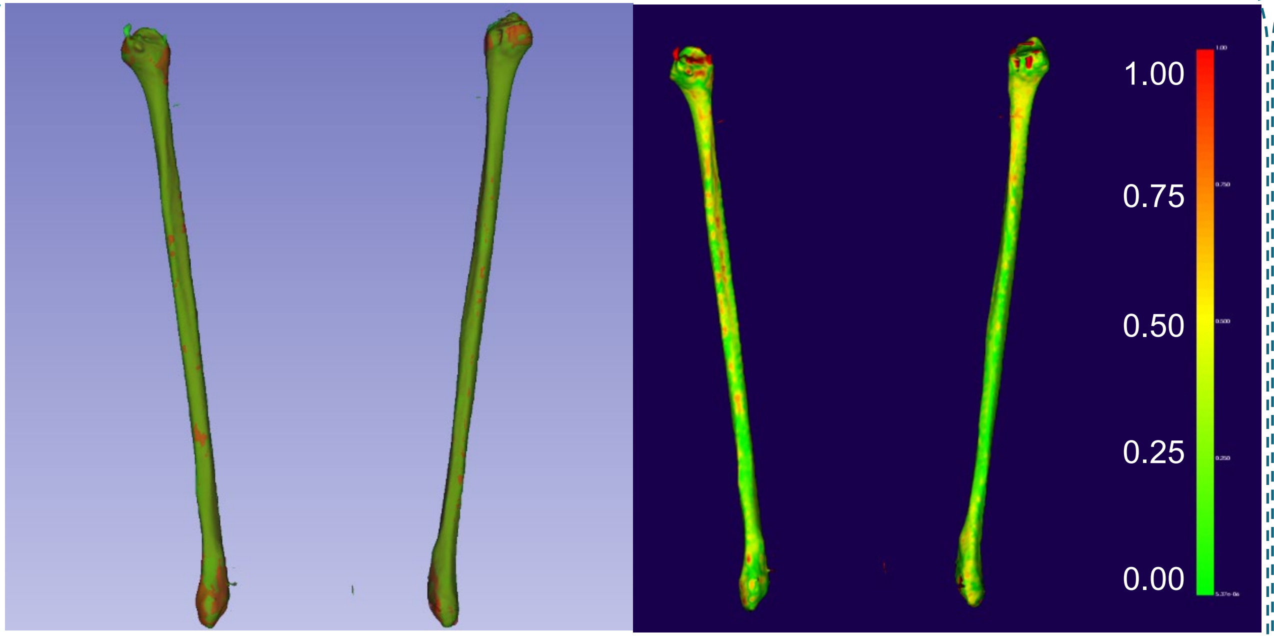


Test set 1

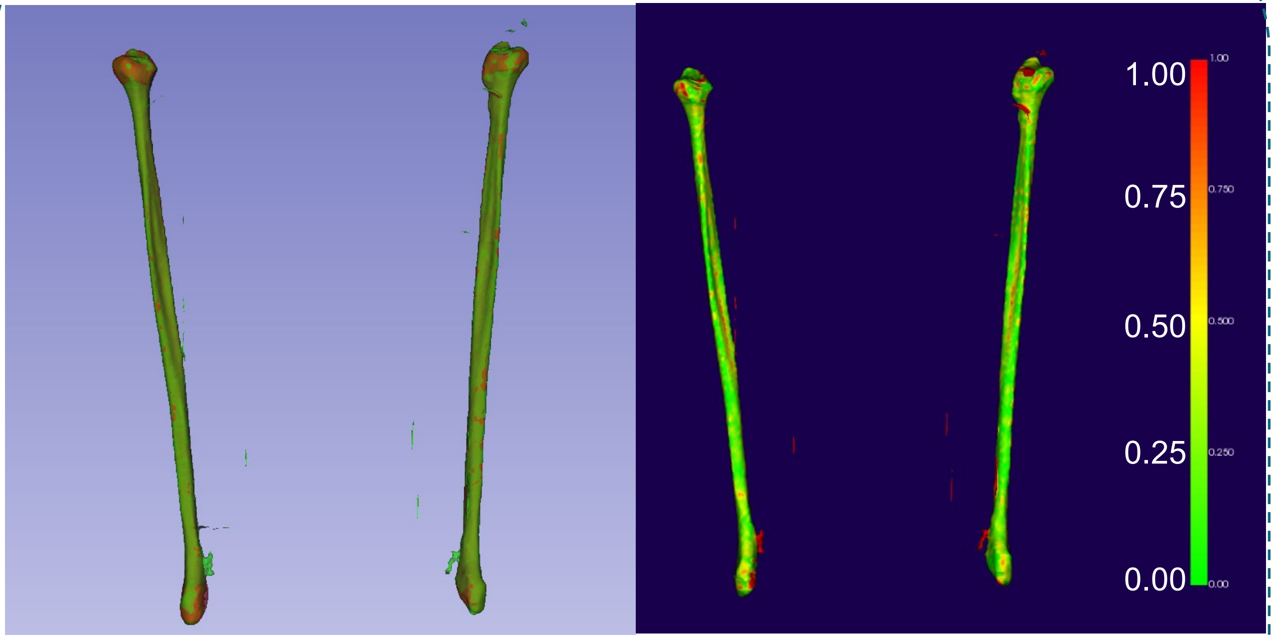


Test set 2

Discussion for Experiment 4



Test set 1



Test set 2