Reconstruction of 3D CT Volume from 2D X-ray/DRR Image using Deep Learning

Final Presentation - Master Thesis

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[2] Institute for Biomedical Imaging, Hamburg University of Technology, Hamburg

Outline

- Introduction
- Project Goal
- Theory
- Experiments
- Results
- Conclusion
- Miscellaneous

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Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

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Types :

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Types :

- CT scan

Introduction - Medical Imaging

Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

Types :

- CT scan
- MRI

Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

Types :

- CT scan
- MRI
- Ultrasonography

Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

Types :

- CT scan
- MRI
- Ultrasonography
- Endoscopy

Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

Types :

- CT scan
- MRI
- Ultrasonography
- Endoscopy
- X-ray

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Types :

- CT scan
- MRI
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- Endoscopy
- X-ray
- Fluoroscopy

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Types of concern :

Introduction - Medical Imaging

Medical imaging is the mechanism of imaging the internal complicated structures of a human body for clinical diagnosis and treatment.

Types :

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- MRI
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Types of concern :

- CT scan

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Types :

- CT scan
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Types of concern :

- CT scan
- X-ray

Introduction - X-ray

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X-ray is an electromagnetic radiation, which travels from generator through human body to detector. Detector converts this radiation into raw X-ray image.

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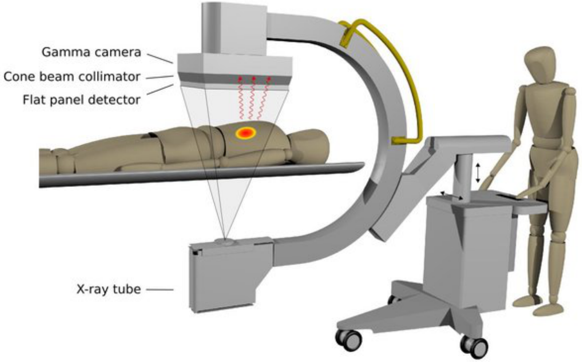

[2, 2019]

CT scan makes use of multiple X-ray images captured from several angles to produce cross-sectional images of human body.

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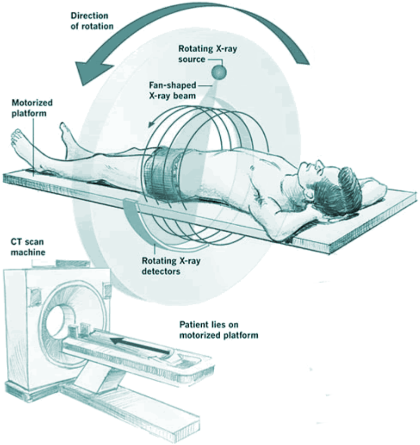

[4, 2018]

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Project Goal - Context

X-ray :

X-ray :

Advantages

X-ray :

Advantages

- Cheap

Project Goal - Context

X-ray :

Advantages

- Cheap
- Easily accessible

X-ray :

Advantages

- Cheap
- Easily accessible

Disadvantages

Project Goal - Context

X-ray :

Advantages

- Cheap
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Disadvantages

- Obscurity of relevant structures

Project Goal - Context

X-ray :

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Disadvantages

- Obscurity of relevant structures
- Loss of detail (2D)

X-ray :

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CT scan :

Project Goal - Context

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Project Goal - Context

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CT scan :

Advantages

- High resolution (3D)

Project Goal - Context

X-ray :

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Disadvantages

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- Loss of detail (2D)

CT scan :

Advantages

- High resolution (3D)
- Easy manipulation of data

Project Goal - Context

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CT scan :

Advantages

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Disadvantages

- Expensive

Project Goal - Context

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- High amount of radiation

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Motivation :

X-ray :

Advantages
- Cheap
- Easily accessible

Disadvantages
- Obscurity of relevant structures
- Loss of detail (2D)

CT scan :

Advantages
- High resolution (3D)
- Easy manipulation of data

Disadvantages
- Expensive
- High amount of radiation

Motivation : Reconstruction of 3D CT volume data with **high anatomic detailing** from **cheap** X-ray/DRR image using **deep learning**.

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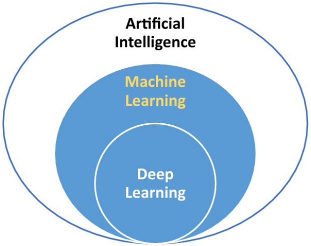
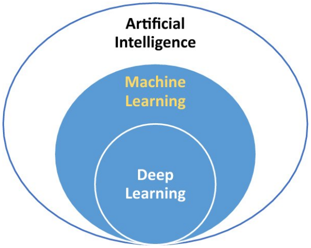
Theory - Artificial Intelligence, Machine Learning and Deep Learning

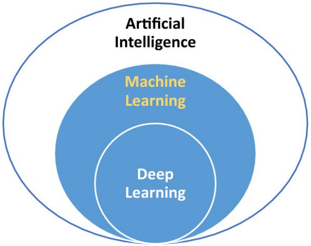


[1, 2020]



[1, 2020]

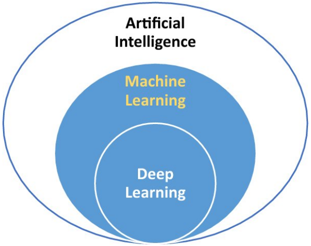
AI :



[1, 2020]

AI :

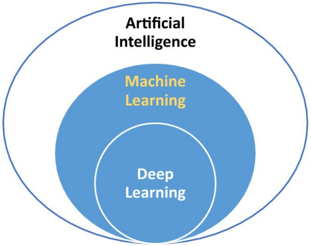
- Smart cities



[1, 2020]

AI :

- Smart cities
- Weather forecast



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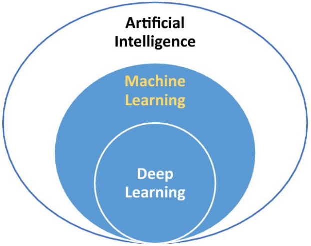

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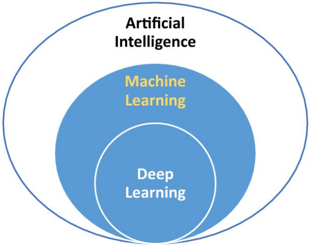

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AI :

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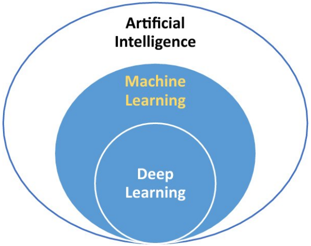
ML :

- Anomaly detection
- Sentiment analysis



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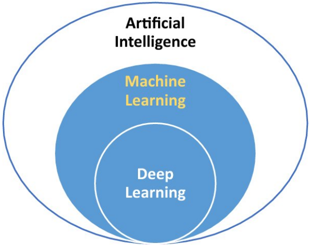
DL :



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AI :

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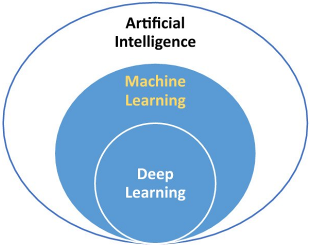

[1, 2020]

AI :

- Smart cities
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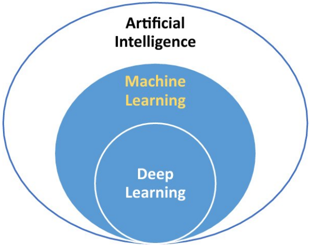
DL :

- Object detection
- Image segmentation



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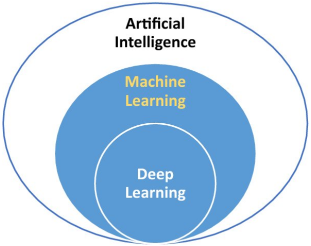
Deep Learning



[1, 2020]

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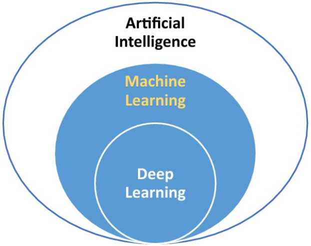
DL :

- Object detection
- Image segmentation

Deep Learning

- Made progress in computer vision



[1, 2020]

AI :

- Smart cities
- Weather forecast

ML :

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DL :

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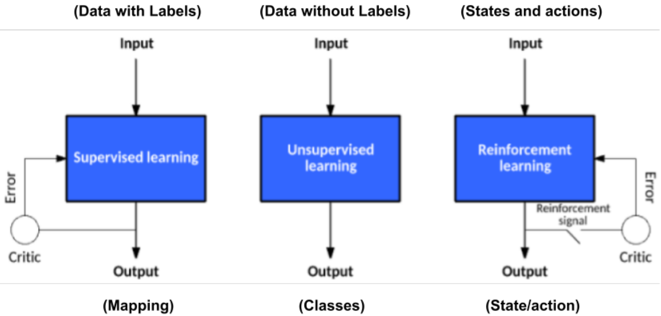
- Image segmentation

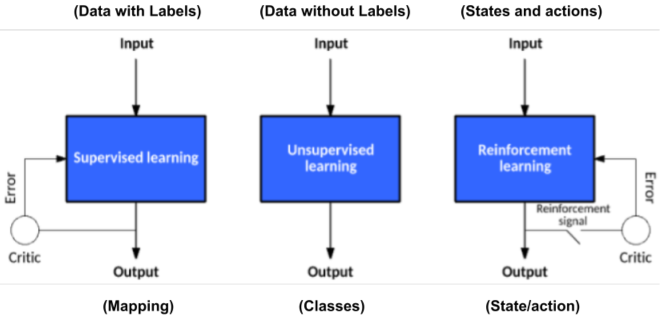
Deep Learning

- Made progress in computer vision
- Yet to make advancements in medical imaging

Theory - Learning Approaches

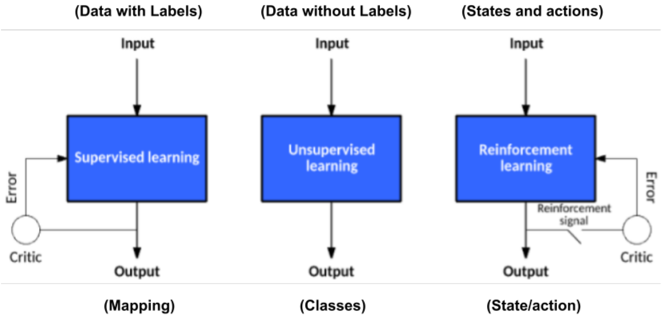


[3, 2019]



[3, 2019]

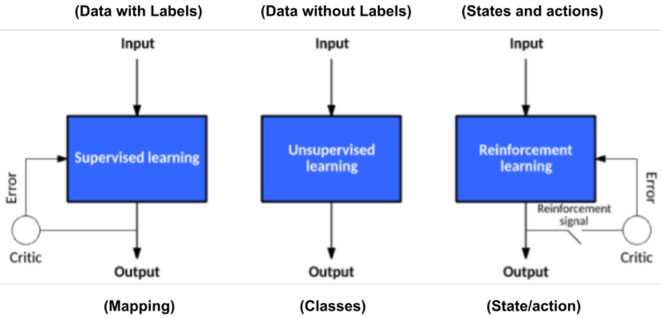
Types of Learning :



[3, 2019]

Types of Learning :

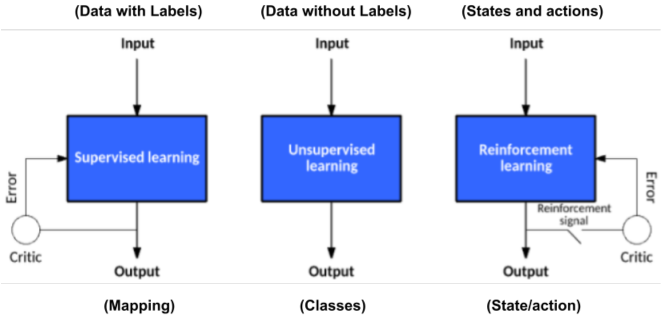
- Supervised



[3, 2019]

Types of Learning :

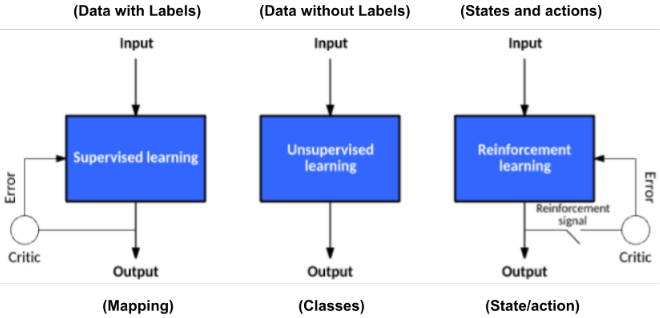
- Supervised
- Unsupervised



[3, 2019]

Types of Learning :

- Supervised
- Unsupervised
- Reinforcement



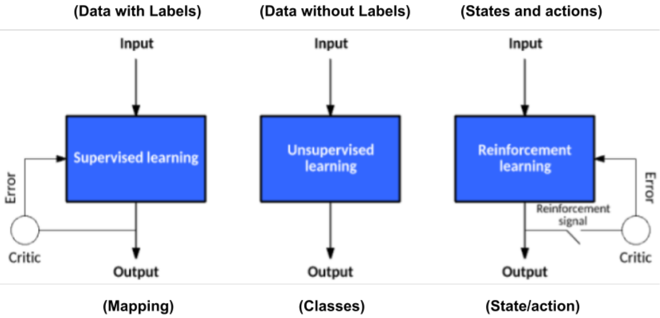
[3, 2019]

Types of Learning :

- Supervised
- Unsupervised
- Reinforcement

Approach of concern :

Theory - Learning Approaches



[3, 2019]

Types of Learning :

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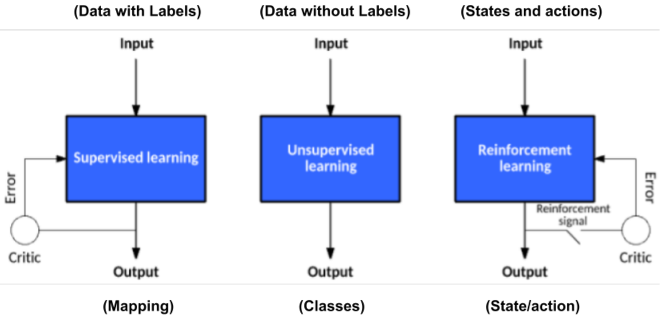
Approach of concern : Supervised



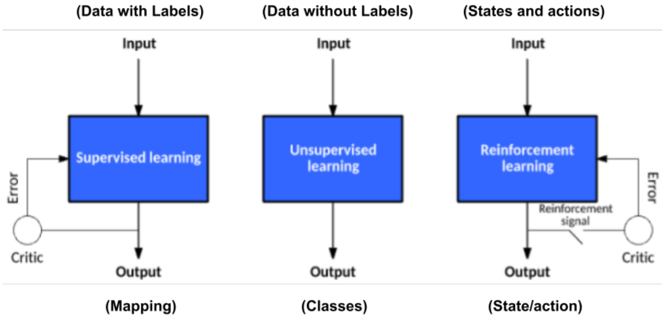
[3, 2019]

Types of Learning :

- Supervised
- Unsupervised
- Reinforcement

Approach of concern : Supervised

- Input (2D DRR)



[3, 2019]

Types of Learning :

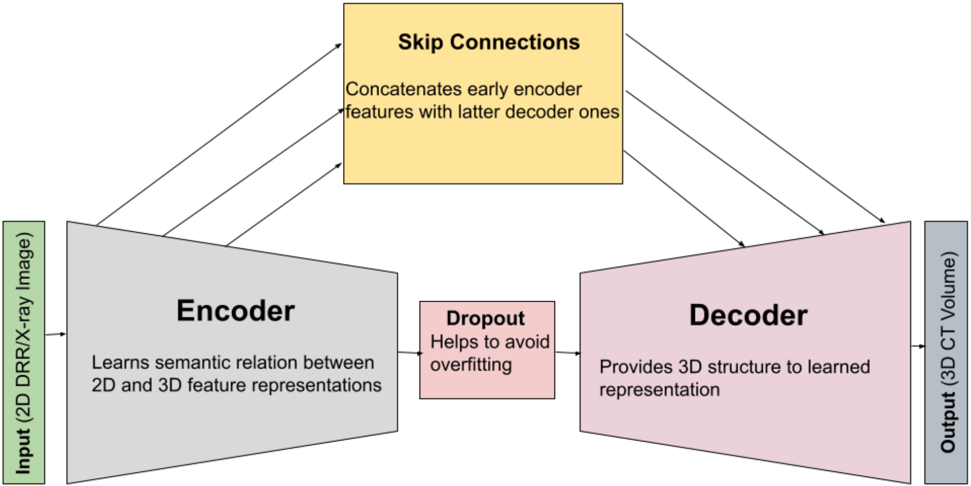
- Supervised
- Unsupervised
- Reinforcement

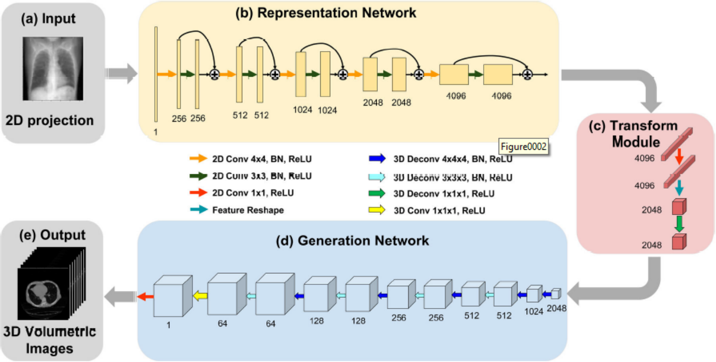
Approach of concern : Supervised

- Input (2D DRR)
- Label (3D CT scan)

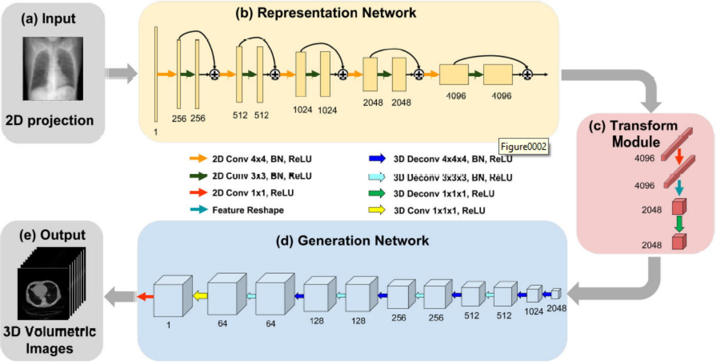
Theory - UNet Architecture

Theory - UNet Architecture



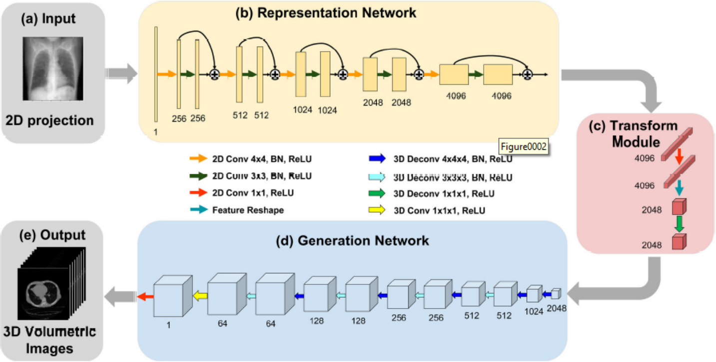

(a) Input
2D projection
(b) Representation Network
1
256 256
512 512
1024 1024
2048 2048
4096 4096
Figure0002
2D Conv 4x4, BN, ReLU
2D Conv 3x3, BN, ReLU
2D Conv 1x1, ReLU
Feature Reshape
3D Deconv 4x4x4, BN, ReLU
3D Deconv 3x3x3, BN, ReLU
3D Deconv 1x1x1, ReLU
3D Conv 1x1x1, ReLU
(c) Transform Module
4096
4096
2048
2048
(d) Generation Network
1
64
64
128
128
256
256
512
512
1024
2048
(e) Output
3D Volumetric Images

[5, 2019]



[5, 2019]

- **Drawback :**



[5, 2019]

- **Drawback :** Evaluation data was a part of training dataset.

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Experiments - General and Deep Learning Setup

General :

General :

Remote

General :

Remote

- AnyDesk

Experiments - General and Deep Learning Setup

General :

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- AnyDesk
- Chrome Remote

General :

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IDE

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General :

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System GPU

Experiments - General and Deep Learning Setup

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System GPU

- 2$\times$Nvidia Geforce GTX 1080 Ti

General :

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System GPU
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Deep Learning :

General :

Remote

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- Chrome Remote

IDE

- PyCharm
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System GPU

- $2\times$Nvidia Geforce GTX 1080 Ti
- $4\times$Nvidia V100 Tensor Core GPU

Deep Learning :

Batch Size

Experiments - General and Deep Learning Setup

General :

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- Chrome Remote

IDE
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- Google Colab

System GPU
- 2×Nvidia Geforce GTX 1080 Ti
- 4×Nvidia V100 Tensor Core GPU

Deep Learning :

Batch Size
- 1

Experiments - General and Deep Learning Setup

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System GPU

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Deep Learning :

Batch Size

- 1
- 4

General :

Remote

- AnyDesk
- Chrome Remote

IDE

- PyCharm
- Google Colab

System GPU

- 2$\times$Nvidia Geforce GTX 1080 Ti
- 4$\times$Nvidia V100 Tensor Core GPU

Deep Learning :

Batch Size

- 1
- 4

Regularisation

Experiments - General and Deep Learning Setup

General :

Remote

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- Chrome Remote

IDE

- PyCharm
- Google Colab

System GPU

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Deep Learning :

Batch Size

- 1
- 4

Regularisation

- L2

Experiments - General and Deep Learning Setup

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Deep Learning :

Batch Size

- 1
- 4

Regularisation

- L2
- Dropout

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Deep Learning :

Batch Size

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Regularisation

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Optimiser

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Deep Learning :

Batch Size

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- Adam

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- SGD

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Deep Learning :

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Loss

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Regularisation

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Loss

- L_D

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Regularisation

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Optimiser

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- SGD

Loss

- L_D
- L_D+L_R

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Metric

- SSIM

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Regularisation

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Optimiser

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- SGD

Loss

- L_D
- $L_D + L_R$

Metric

- SSIM
- PSNR

Experiments - Complete Workflow

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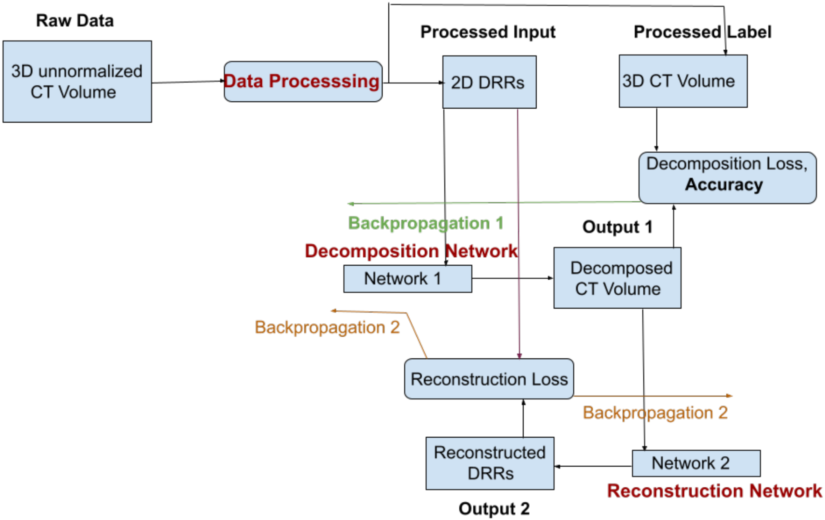
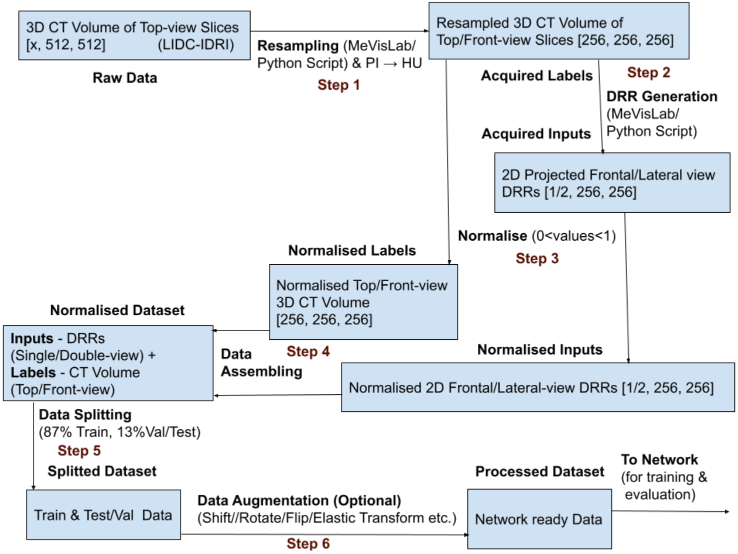
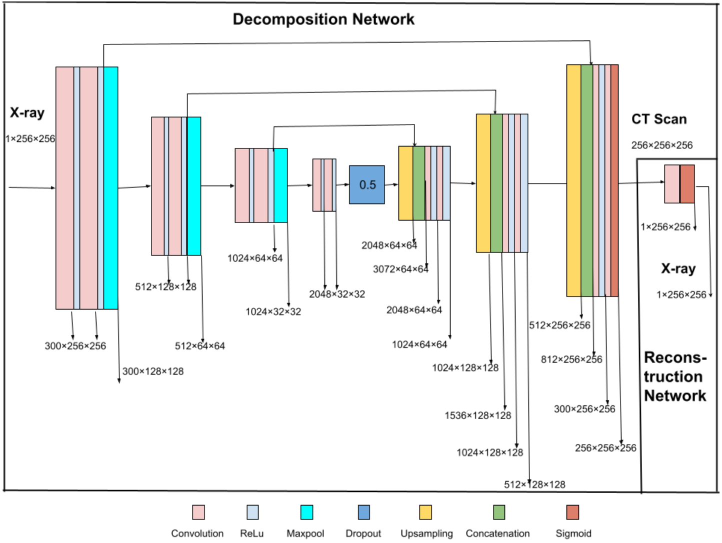


Experiments - Data Processing

Experiments - Data Processing



Experiments - Network Diagram



Decomposition Network
X-ray
1×256×256
300×256×256
300×128×128
512×128×128
512×64×64
1024×64×64
1024×32×32
2048×32×32
0.5
2048×64×64
3072×64×64
2048×64×64
1024×64×64
1024×128×128
1536×128×128
1024×128×128
512×128×128
512×256×256
812×256×256
300×256×256
256×256×256
CT Scan
256×256×256
1×256×256
X-ray
1×256×256
Recons-
truction
Network
Convolution
ReLu
Maxpool
Dropout
Upsampling
Concatenation
Sigmoid

1. **Baseline :**

1. **Baseline :** MeVisLab

Experiments - List of Experiments

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :**

Experiments - List of Experiments

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :**

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :**

Experiments - List of Experiments

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :** Decomposition+Reconstruction

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :** Decomposition+Reconstruction
5. **Dimension :**

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :** Decomposition+Reconstruction
5. **Dimension :** $512 \times 512 \times 512$ pixels

Experiments - List of Experiments

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :** Decomposition+Reconstruction
5. **Dimension :** $512 \times 512 \times 512$ pixels
6. **Viewpoint :**

Experiments - List of Experiments

1. **Baseline :** MeVisLab
2. **Dataset Pre-processing Method :** Python
3. **CT-DRR Combination :** Frontal
4. **Loss :** Decomposition+Reconstruction
5. **Dimension :** $512 \times 512 \times 512$ pixels
6. **Viewpoint :** Frontal+Lateral

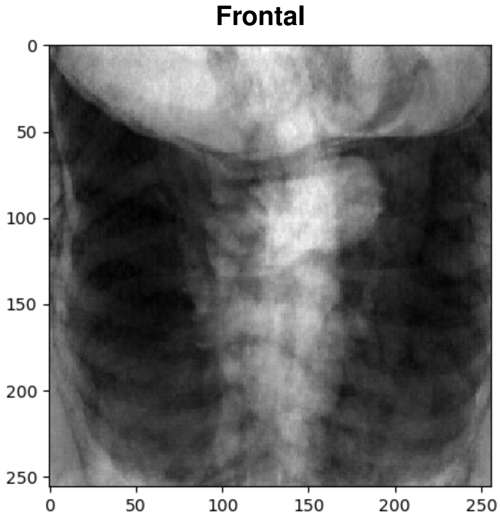
Outline

- Introduction
- Project Goal
- Theory
- Experiments
- Results
- Conclusion
- Miscellaneous

Results - Input DRR (MeVisLab) Patient 920 (LIDC - IDRI)

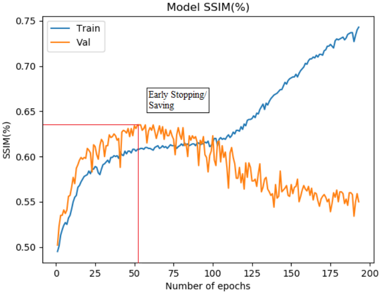
Results - Input DRR (MeVisLab) Patient 920 (LIDC - IDRI)

Frontal

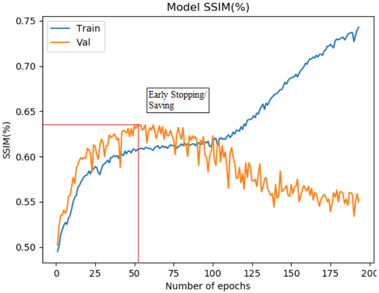

Frontal
0
50
100
150
200
250
0
50
100
150
200
250

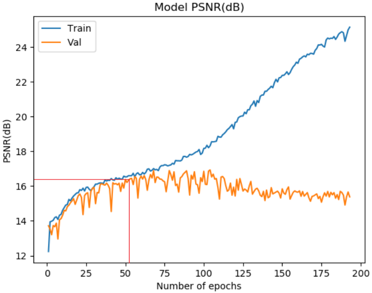
Results (Learning Curves) - Baseline

Results (Learning Curves) - Baseline

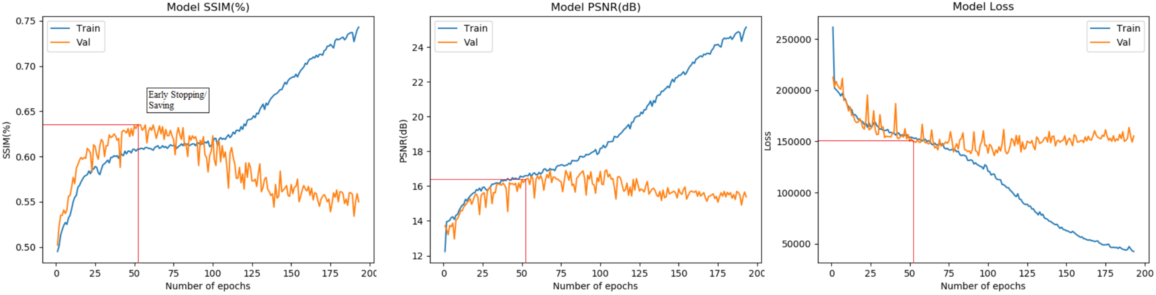


Results (Learning Curves) - Baseline

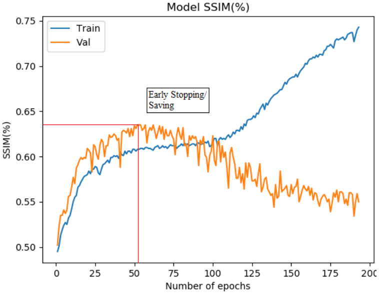


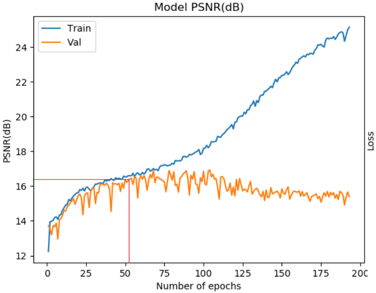


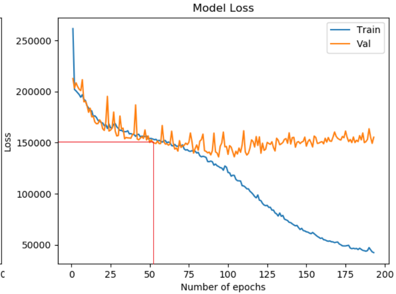
Results (Learning Curves) - Baseline



Results (Learning Curves) - Baseline

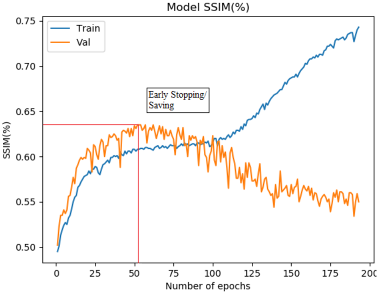


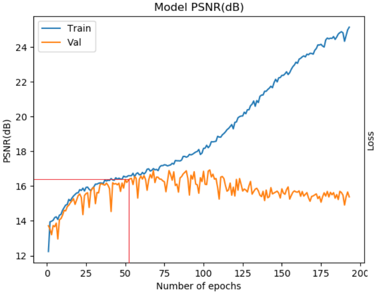


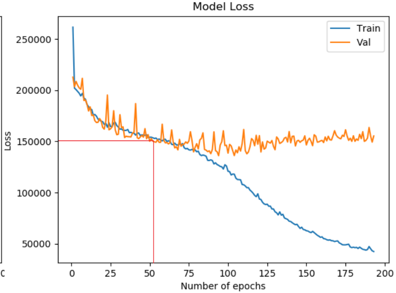


SSIM :

Results (Learning Curves) - Baseline

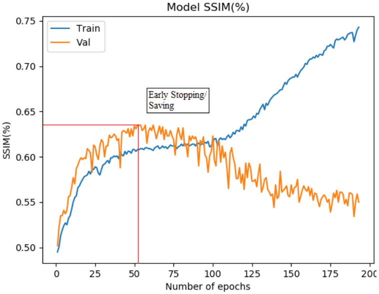


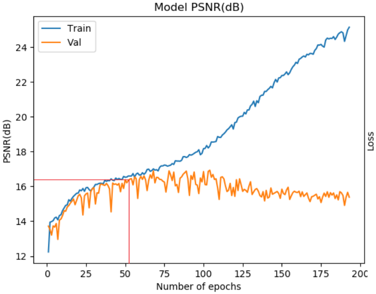


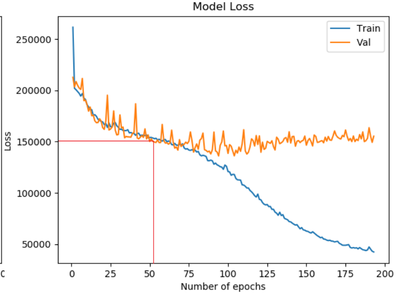


SSIM : 63.5%

Results (Learning Curves) - Baseline



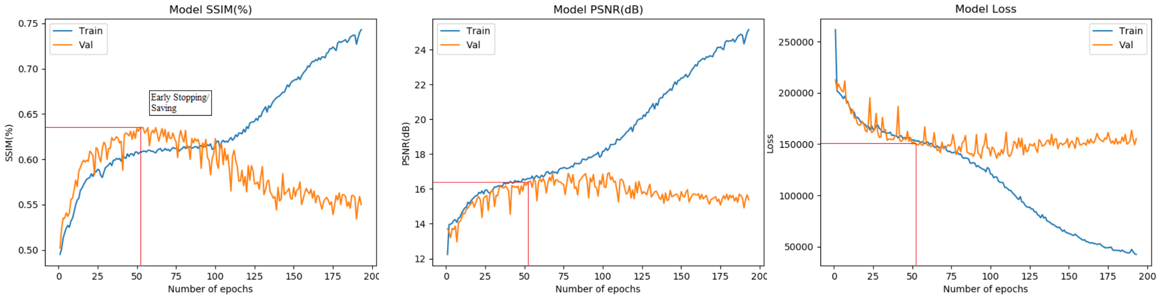




SSIM : 63.5%

PSNR:

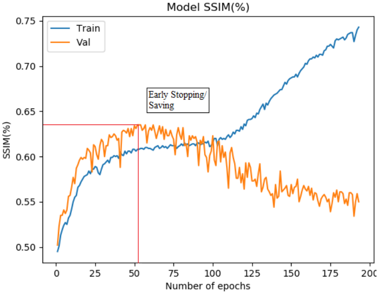
Results (Learning Curves) - Baseline

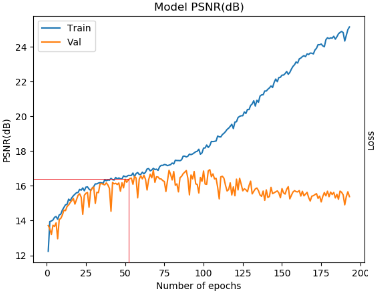


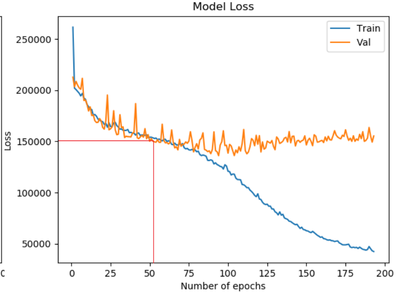
SSIM : 63.5%

PSNR: 16.339 dB

Results (Learning Curves) - Baseline





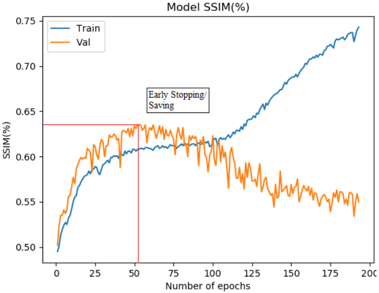


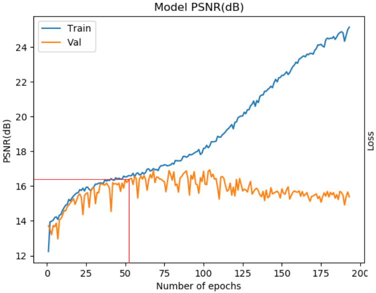
SSIM : 63.5%

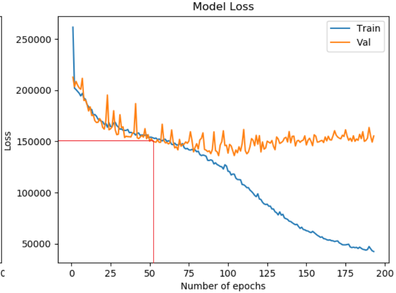
PSNR: 16.339 dB

Loss :

Results (Learning Curves) - Baseline







SSIM : 63.5%

PSNR: 16.339 dB

Loss : 150214.282

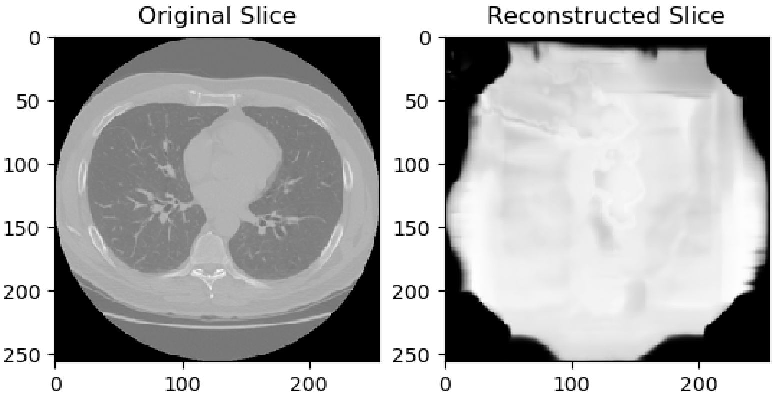
Results (CT Slices) - Baseline

SSIM :

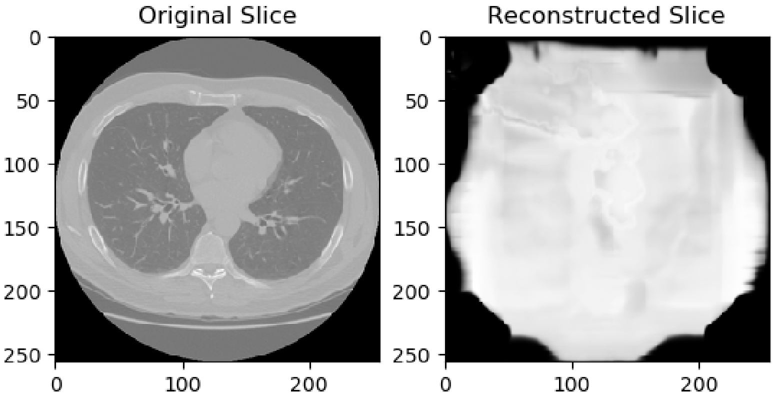
SSIM : 63.5%

Results (CT Slices) - Baseline

SSIM : 63.5%



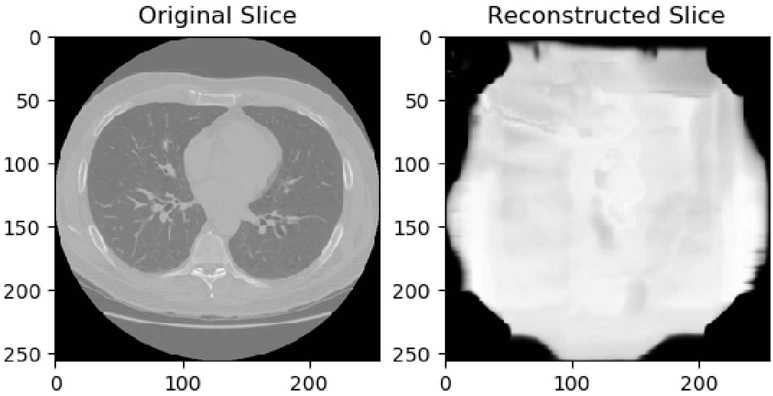
SSIM : 63.5%



Drawbacks :

Results (CT Slices) - Baseline

SSIM : 63.5%

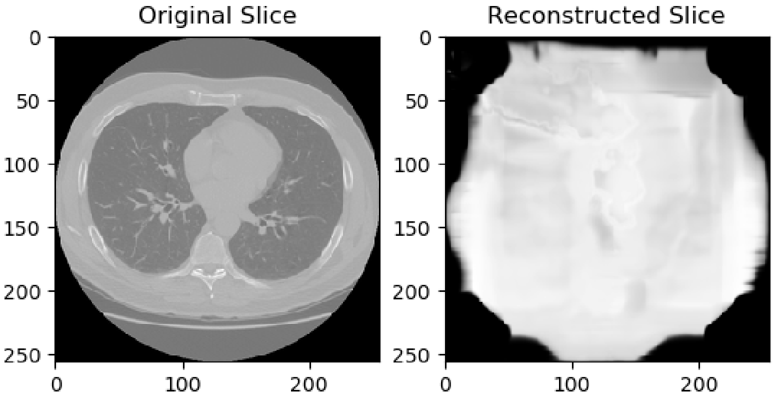


Drawbacks :

- Unrelated CT-DRR

Results (CT Slices) - Baseline

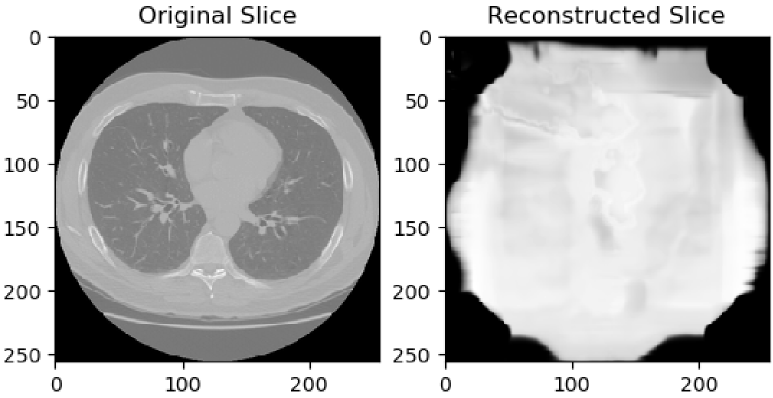
SSIM : 63.5%



Drawbacks :

- Unrelated CT-DRR
- Non-isotropic CT

SSIM : 63.5%



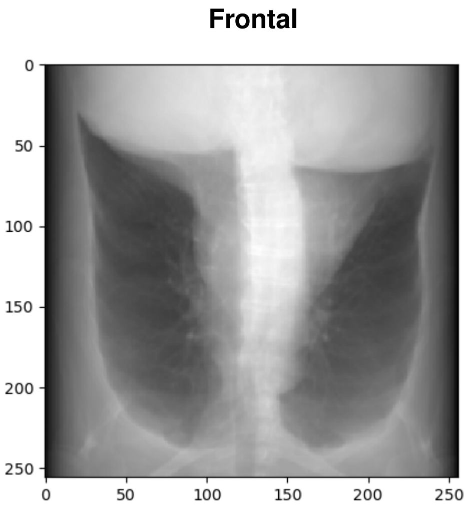
Drawbacks :

- Unrelated CT-DRR
- Non-isotropic CT
- Unrealistic DRR

Results - Input DRRs (Python) Patient 920 (LIDC-IDRI)

Frontal

Results - Input DRRs (Python) Patient 920 (LIDC-IDRI)



Results (CT Slices) - Dataset Pre-processing Method (Python)

SSIM :

SSIM : 65%

Results (CT Slices) - Dataset Pre-processing Method (Python)

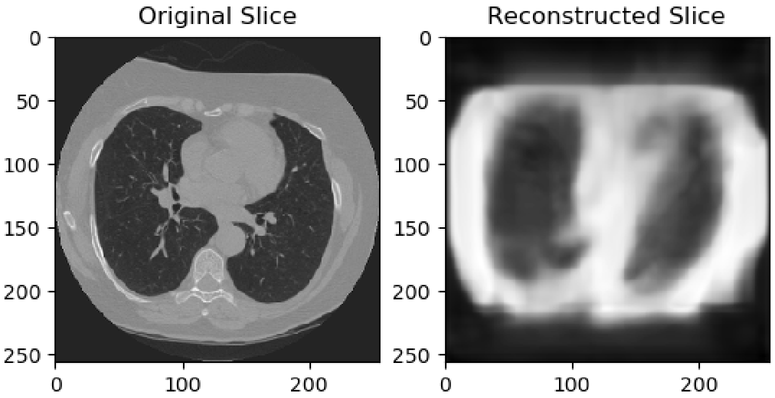
SSIM : 65%

Baseline :

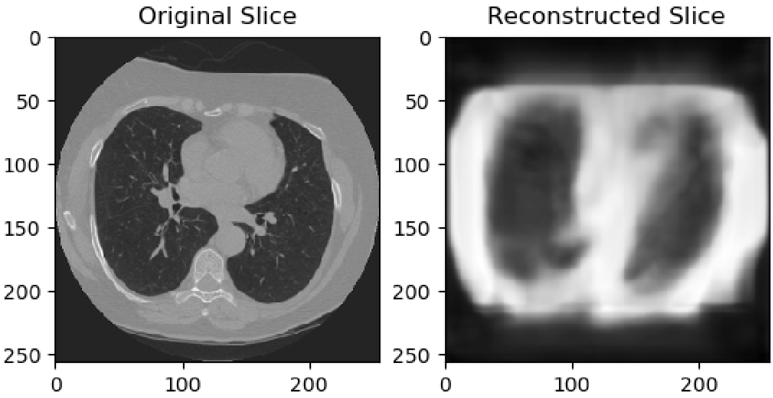
Results (CT Slices) - Dataset Pre-processing Method (Python)

SSIM : 65%
Baseline : 63.5%

SSIM : 65%
Baseline : 63.5%



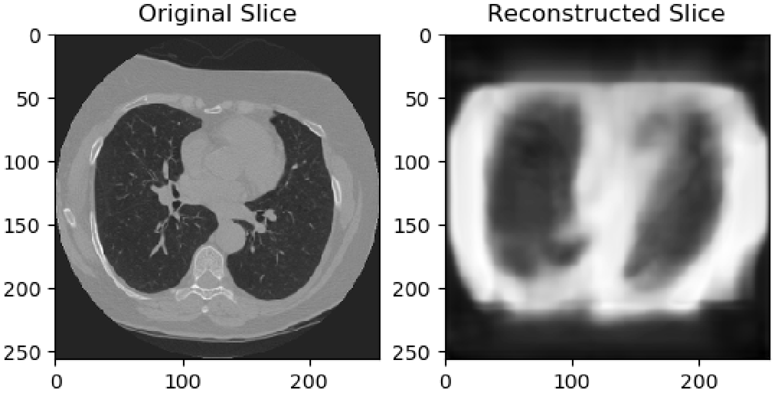
SSIM : 65%
Baseline : 63.5%



Drawback :

Results (CT Slices) - Dataset Pre-processing Method (Python)

SSIM : 65%
Baseline : 63.5%



Drawback :

- Unrelated semantics between CT and DRR

Results (CT Slices) - CT-DRR Combination (Frontal)

SSIM :

Results (CT Slices) - CT-DRR Combination (Frontal)

SSIM : 72.5%

Results (CT Slices) - CT-DRR Combination (Frontal)

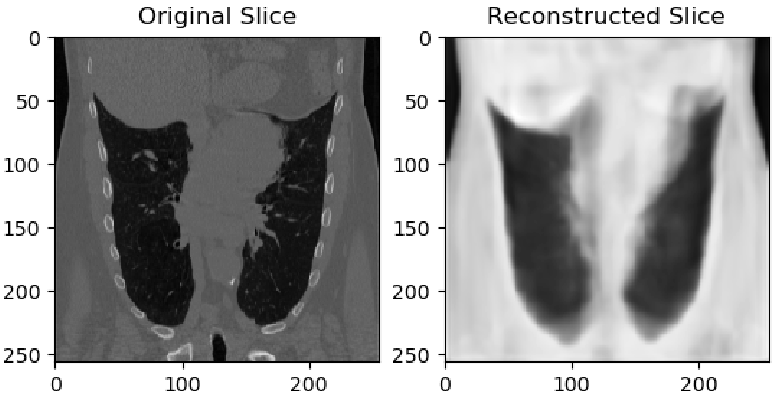
SSIM : 72.5%

Baseline :

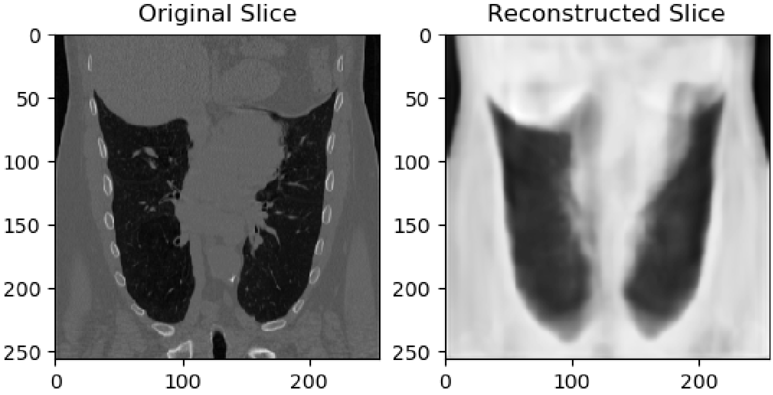
Results (CT Slices) - CT-DRR Combination (Frontal)

SSIM : 72.5%
Baseline : 63.5%

SSIM : 72.5%
Baseline : 63.5%



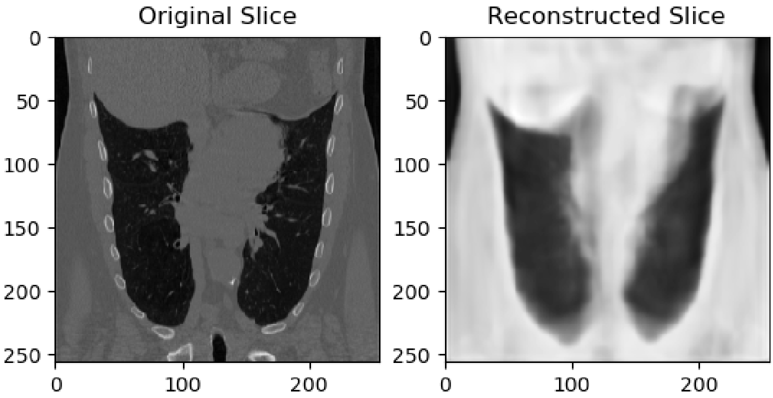
SSIM : 72.5%
Baseline : 63.5%



Improvement :

Results (CT Slices) - CT-DRR Combination (Frontal)

SSIM : 72.5%
Baseline : 63.5%



Improvement :

- Better optimisation with advanced loss factor

Results (CT Slices) - Loss (Decomposition+Reconstruction)

Results (CT Slices) - Loss (Decomposition+Reconstruction)

SSIM :

SSIM : 72.9%

Results (CT Slices) - Loss (Decomposition+Reconstruction)

SSIM : 72.9%

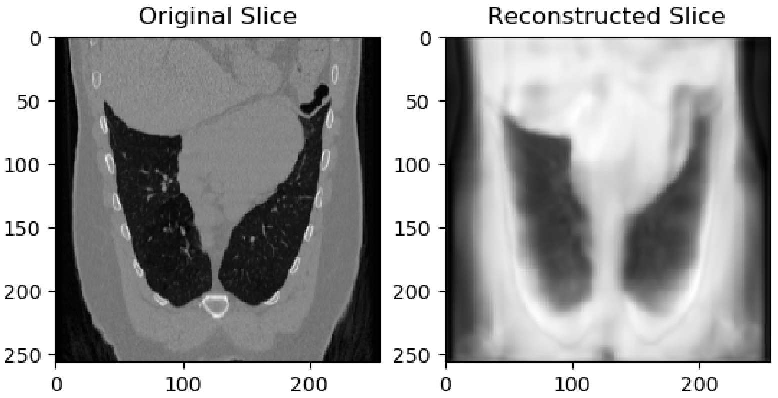
Baseline :

Results (CT Slices) - Loss (Decomposition+Reconstruction)

SSIM : 72.9%
Baseline : 63.5%

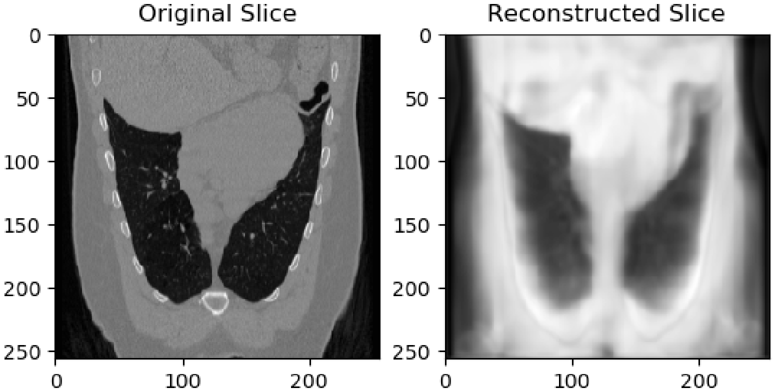
Results (CT Slices) - Loss (Decomposition+Reconstruction)

SSIM : 72.9%
Baseline : 63.5%



Results (CT Slices) - Loss (Decomposition+Reconstruction)

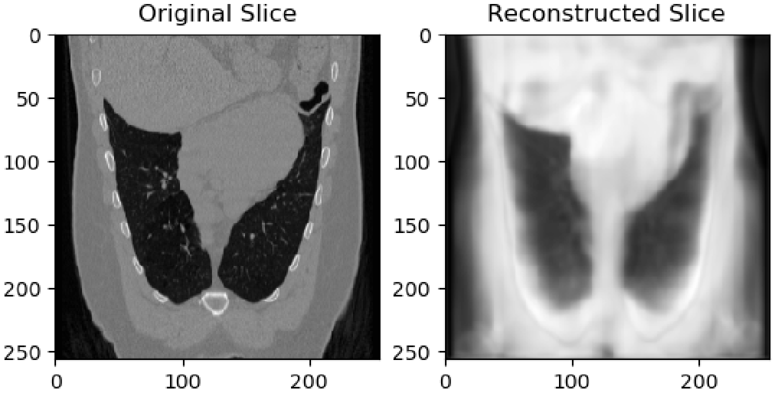
SSIM : 72.9%
Baseline : 63.5%



Improvement :

Results (CT Slices) - Loss (Decomposition+Reconstruction)

SSIM : 72.9%
Baseline : 63.5%



Improvement :

- More information with increased resolution

Results (CT Slices) - Dimension ($512 \times 512 \times 512$ pixels)

Results (CT Slices) - Dimension ($512 \times 512 \times 512$ pixels)

SSIM :

SSIM : 80.2%

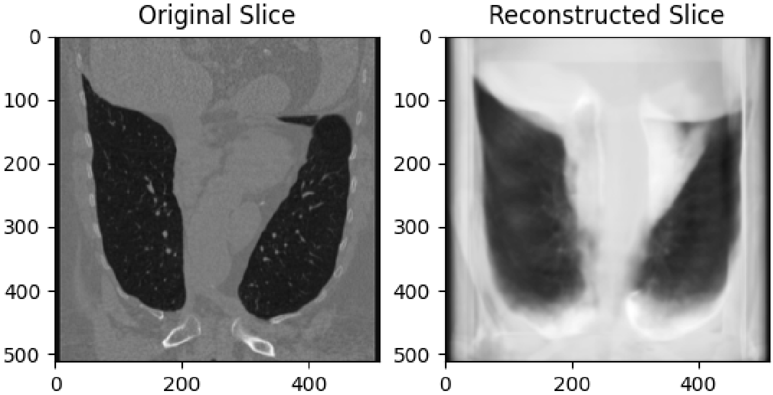
SSIM : 80.2%

Baseline :

Results (CT Slices) - Dimension ($512 \times 512 \times 512$ pixels)

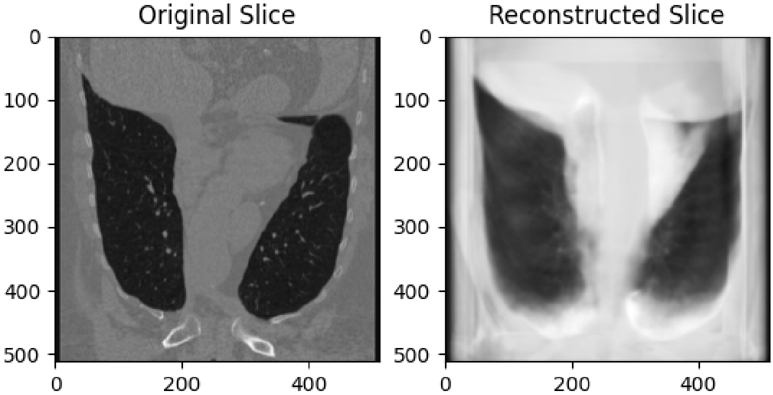
SSIM : 80.2%
Baseline : 63.5%

SSIM : 80.2%
Baseline : 63.5%



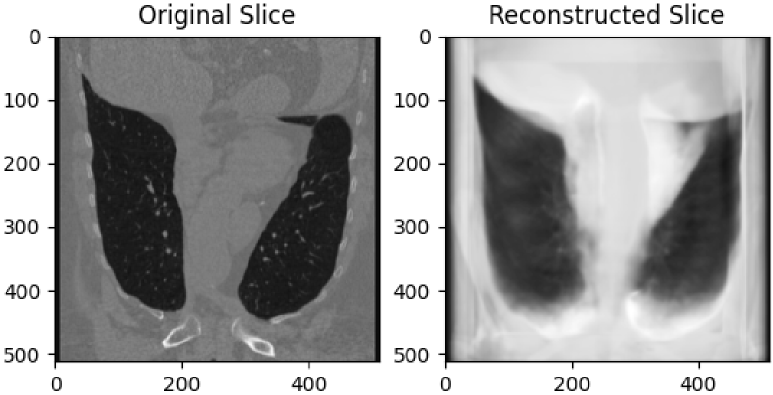
Results (CT Slices) - Dimension ($512 \times 512 \times 512$ pixels)

SSIM : 80.2%
Baseline : 63.5%



Improvement :

SSIM : 80.2%
Baseline : 63.5%



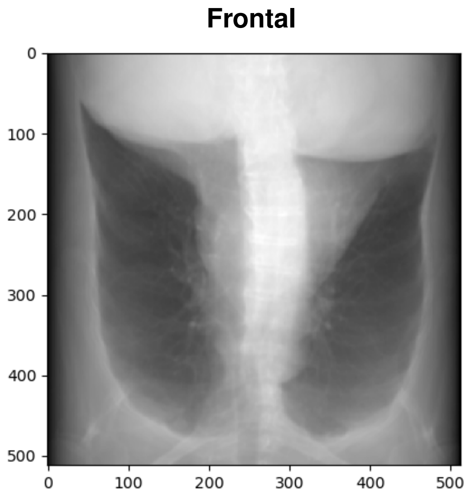
Improvement :

- More perspective with additional view points

Results - Double-view Input DRRs (Python) Patient 920 (LIDC-IDRI)

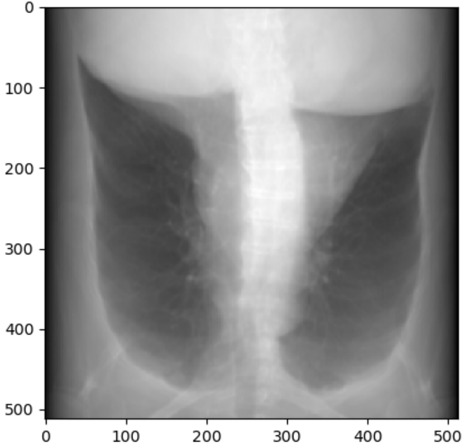
Frontal

Results - Double-view Input DRRs (Python) Patient 920 (LIDC-IDRI)



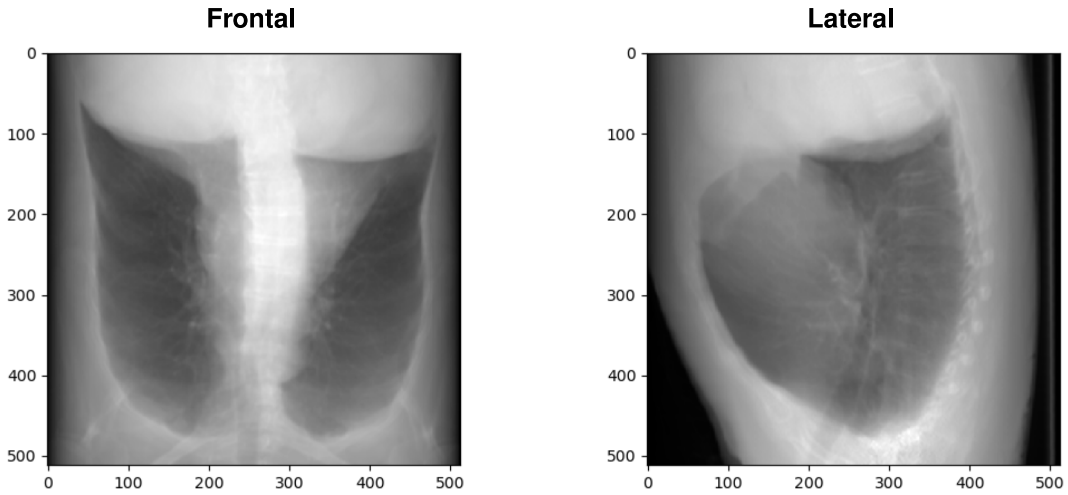
Results - Double-view Input DRRs (Python) Patient 920 (LIDC-IDRI)

Frontal



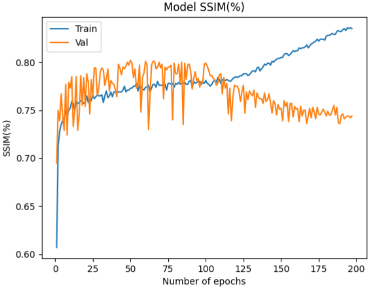
Lateral

Results - Double-view Input DRRs (Python) Patient 920 (LIDC-IDRI)

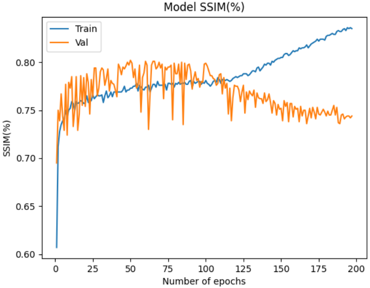


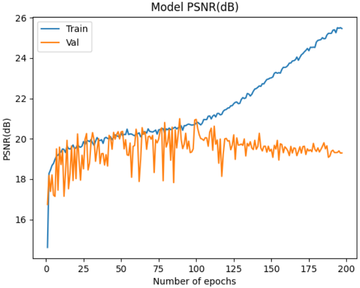
Results (Learning Curves) - Viewpoint (Frontal+Lateral)

Results (Learning Curves) - Viewpoint (Frontal+Lateral)

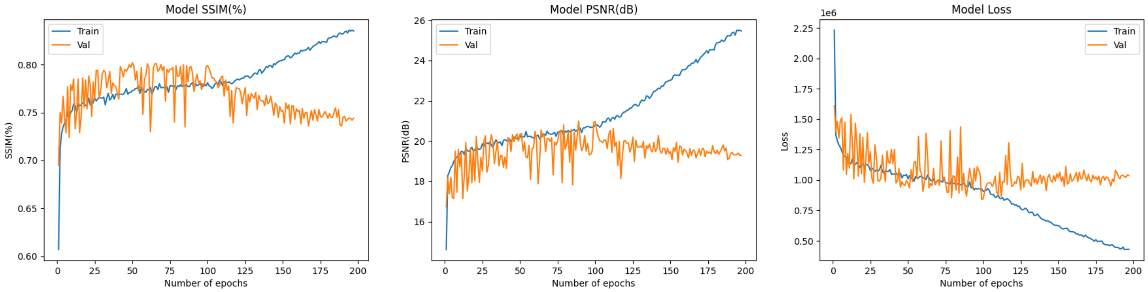


Results (Learning Curves) - Viewpoint (Frontal+Lateral)

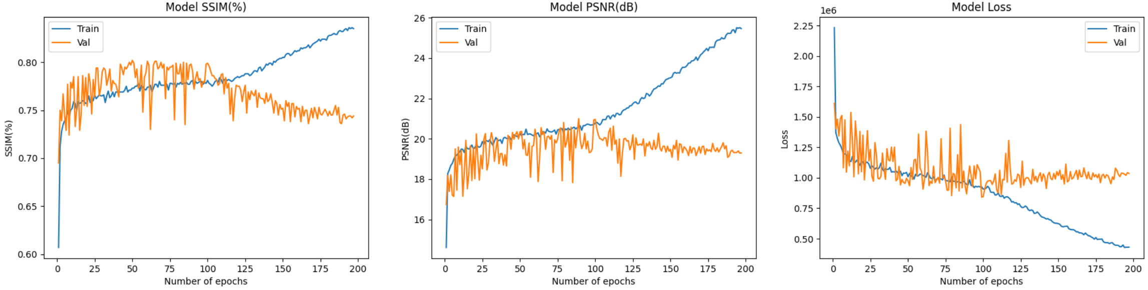




Results (Learning Curves) - Viewpoint (Frontal+Lateral)

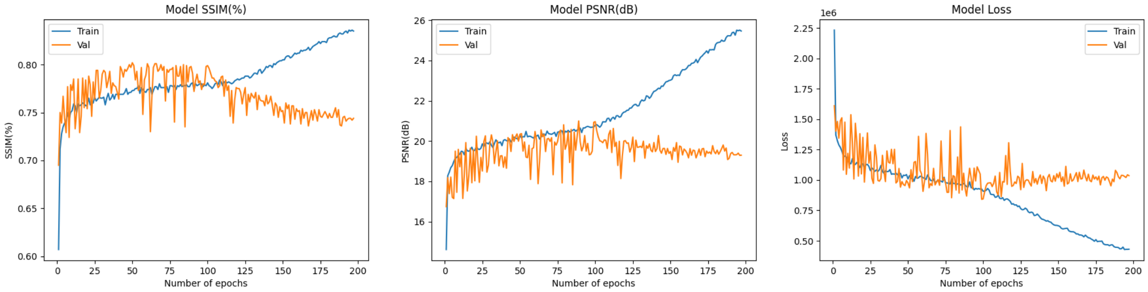


Results (Learning Curves) - Viewpoint (Frontal+Lateral)



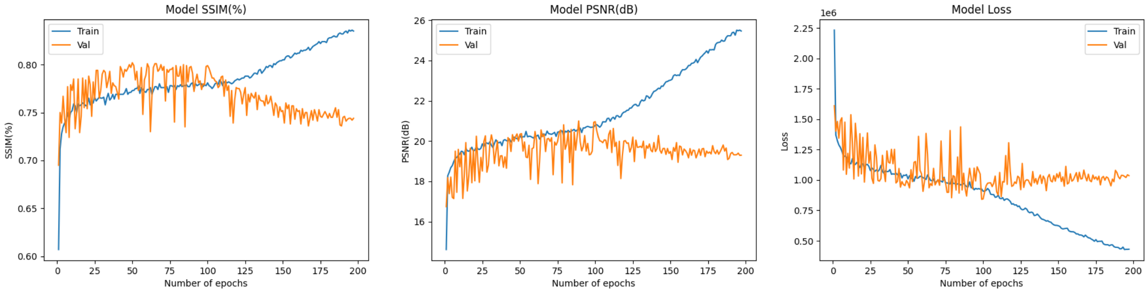
SSIM :

Results (Learning Curves) - Viewpoint (Frontal+Lateral)



SSIM : 80.2%

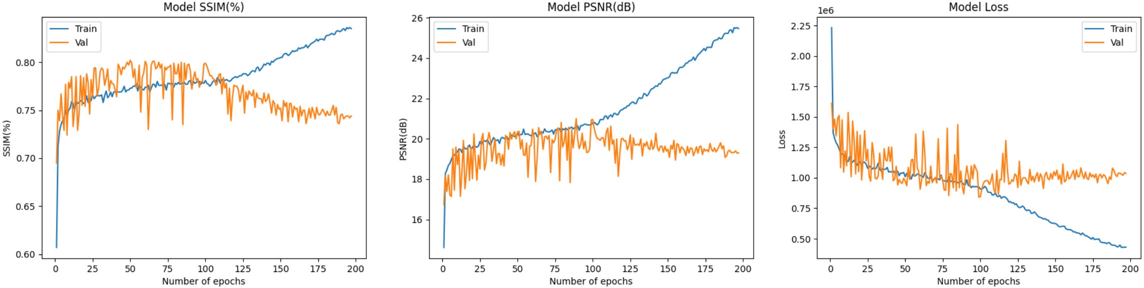
Results (Learning Curves) - Viewpoint (Frontal+Lateral)



SSIM : 80.2%

PSNR :

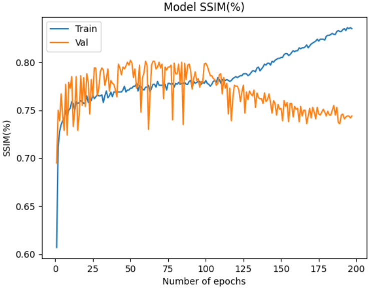
Results (Learning Curves) - Viewpoint (Frontal+Lateral)

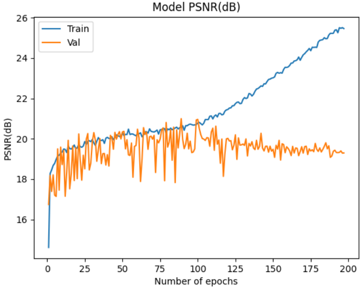


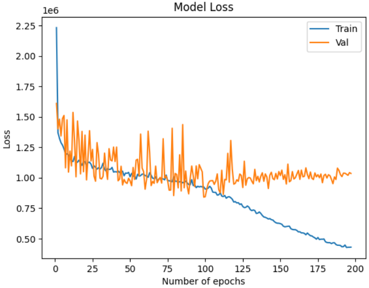
SSIM : 80.2%

PSNR : 22.714 dB

Results (Learning Curves) - Viewpoint (Frontal+Lateral)





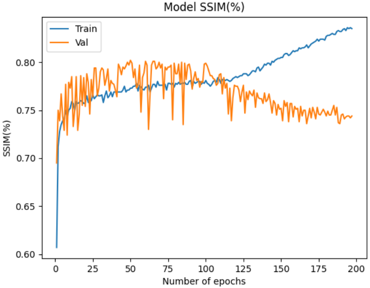


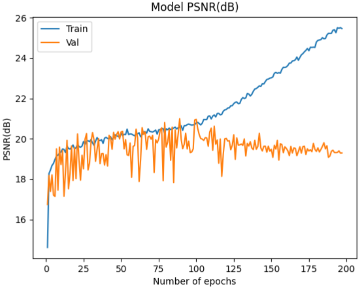
SSIM : 80.2%

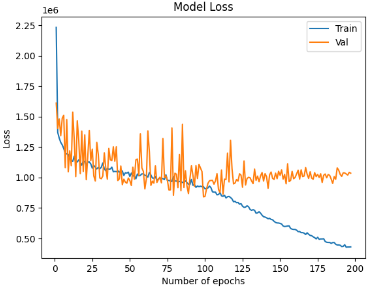
PSNR : 22.714 dB

Loss :

Results (Learning Curves) - Viewpoint (Frontal+Lateral)



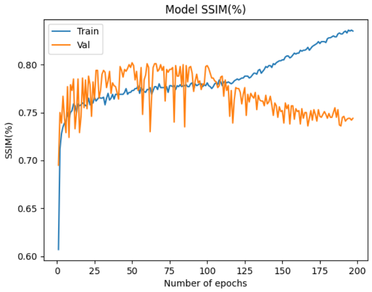


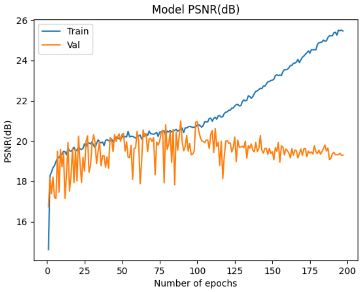


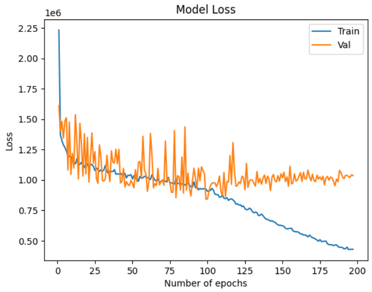
SSIM : 80.2% **PSNR :** 22.714 dB **Loss :** 86451.029

Baseline :

Results (Learning Curves) - Viewpoint (Frontal+Lateral)







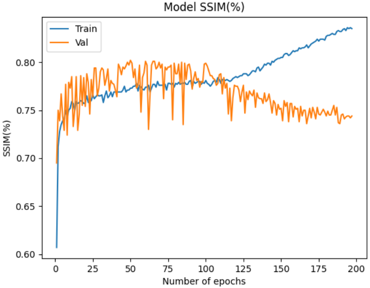
SSIM : 80.2%

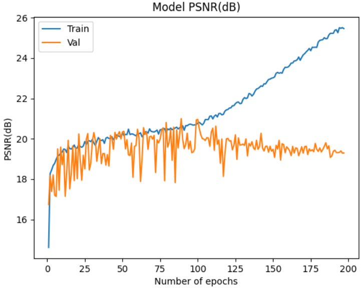
Baseline : 63.5%

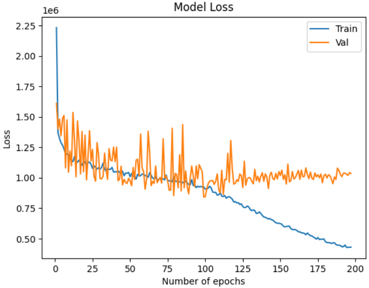
PSNR : 22.714 dB

Loss : 86451.029

Results (Learning Curves) - Viewpoint (Frontal+Lateral)





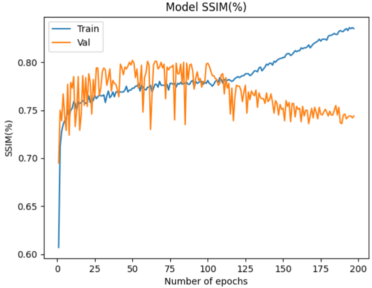


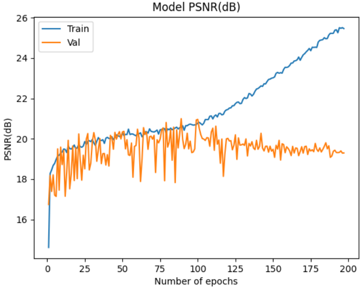
SSIM : 80.2%
Baseline : 63.5%

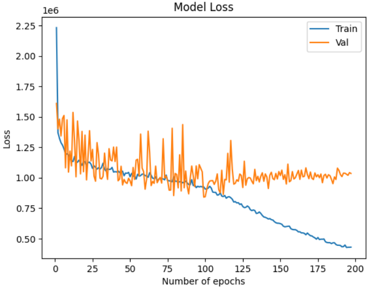
PSNR : 22.714 dB
:

Loss : 86451.029

Results (Learning Curves) - Viewpoint (Frontal+Lateral)





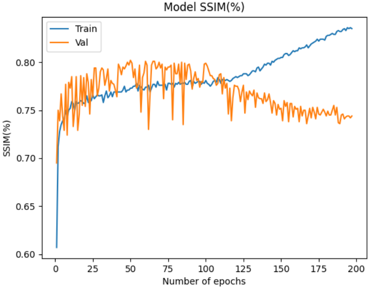


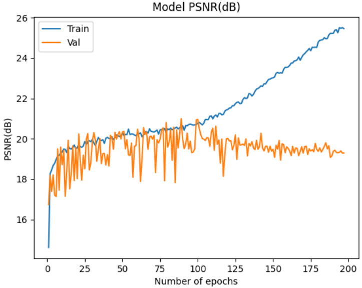
SSIM : 80.2%
Baseline : 63.5%

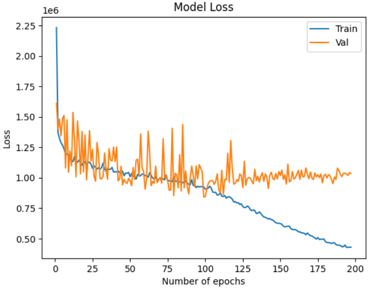
PSNR : 22.714 dB
: 16.339 dB

Loss : 86451.029

Results (Learning Curves) - Viewpoint (Frontal+Lateral)



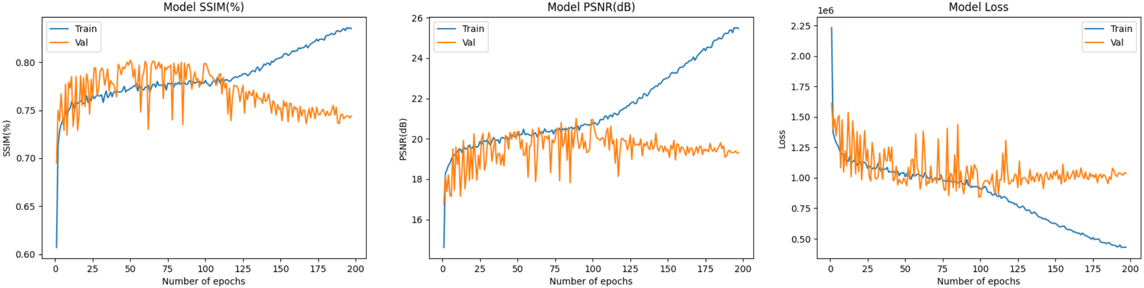




SSIM : 80.2% **PSNR :** 22.714 dB **Loss :** 86451.029

Baseline : 63.5% : 16.339 dB :

Results (Learning Curves) - Viewpoint (Frontal+Lateral)



SSIM : 80.2%
Baseline : 63.5%

PSNR : 22.714 dB
: 16.339 dB

Loss : 86451.029
: 150214.282

Results (CT Slices) - Viewpoint (Frontal+Lateral)

SSIM :

SSIM : 80.2%

SSIM : 80.2%

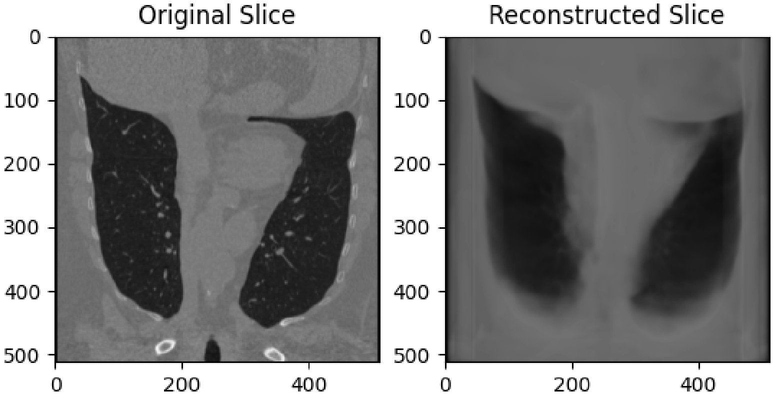
Baseline :

Results (CT Slices) - Viewpoint (Frontal+Lateral)

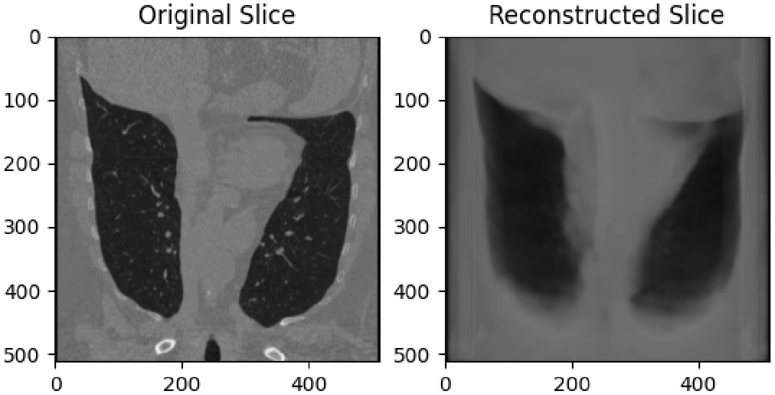
SSIM : 80.2%
Baseline : 63.5%

Results (CT Slices) - Viewpoint (Frontal+Lateral)

SSIM : 80.2%
Baseline : 63.5%

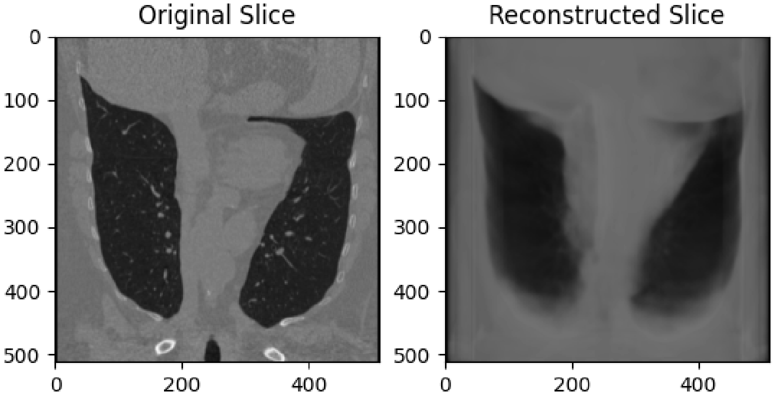


SSIM : 80.2%
Baseline : 63.5%



Improvement :

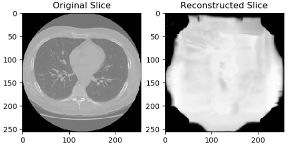
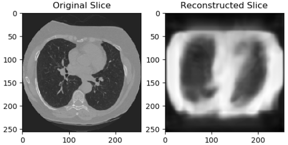
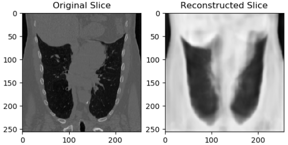
SSIM : 80.2%
Baseline : 63.5%



Improvement :

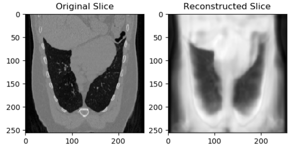
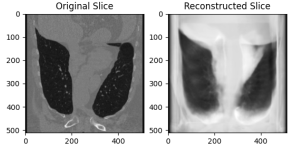
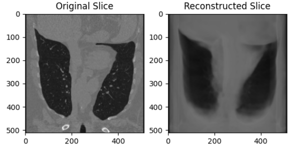
- Advanced network architecture

Results - Overview

Stage	Option	CT Slices	SSIM
Baseline	MeVisLab		63.5%
Data Proc.	Python		65%
CT-DRR	Frontal		72.5%

Results - Overview (Extended)

Results - Overview (Extended)

Stage	Option	CT Slices	SSIM
Loss	Dec.+Rec.		72.9%
Dimension	512 pixels		80.2%
Viewpoint	Double		80.2%

Outline

- Introduction
- Project Goal
- Theory
- Experiments
- Results
- Conclusion
- Miscellaneous

Conclusion - Summary

Conclusion - Summary

- Test SSIM value of 80.2% achieved

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- Test SSIM value of 80.2% achieved
- Not a substantial improvement with additional viewpoint

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- Test SSIM value of 80.2% achieved
- Not a substantial improvement with additional viewpoint
- Easy dataset pre-processing method devised

Conclusion - Summary

- Test SSIM value of 80.2% achieved
- Not a substantial improvement with additional viewpoint
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- Multiple network weights saved as per requirement

Conclusion - Summary

- Test SSIM value of 80.2% achieved
- Not a substantial improvement with additional viewpoint
- Easy dataset pre-processing method devised
- Multiple network weights saved as per requirement
- Satisfying output CT slices generated during evaluation

Conclusion - Future Work

- Training a wider 2D-3D UNet

Conclusion - Future Work

- Training a wider 2D-3D UNet
- Use of 3D-GANs (3D-GAN)

Conclusion - Future Work

- Training a wider 2D-3D UNet
- Use of 3D-GANs (3D-GAN)
- 3D-R2N2 network architecture

Conclusion - Future Work

- Training a wider 2D-3D UNet
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Conclusion - Future Work

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- Generation of other imaging modalities from X-ray

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- Building an UI for the application **(in process)**

Conclusion - Future Work

- Training a wider 2D-3D UNet
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- 3D-R2N2 network architecture
- A cleaner dataset
- Style transfer from X-ray to DRR
- Generation of other imaging modalities from X-ray
- Building an UI for the application **(in process)**
- Hosting the same

Conclusion - Thank You

Conclusion - Thank You

Thanks for your time!

Thanks for your time!

Additional Thanks to Ivo, Professor Knopp and UKE.

Thanks for your time!

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Any Question or Suggestion?

- Ashraf Darwish, Aboul Ella Hassanien, and Swagatam Das. "A survey of swarm and evolutionary computing approaches for deep learning". In: *Artificial Intelligence Review* 53 (Mar. 2020). DOI: 10.1007/s10462-019-09719-2.
- Wilco Koppert et al. "A comparative study of NaI(Tl), CeBr3, and CZT for use in a real-time simultaneous nuclear and fluoroscopic dual-layer detector". In: *Physics in Medicine and Biology* 64 (June 2019). DOI: 10.1088/1361-6560/ab267c.
- Ying Siu Liang. "End-user Robot Programming in Cobotic Environments". PhD thesis. June 2019.
- Cyber Physics. *CT Scan Imaging Diagram*. https://www.cyberphysics.co.uk/topics/medical/CTScanner.htm. 2018.
- Liyue Shen, Wei Zhao, and Lei Xing. "Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning". In: *Nature Biomedical Engineering* 3 (Nov. 2019). DOI: 10.1038/s41551-019-0466-4.

Outline

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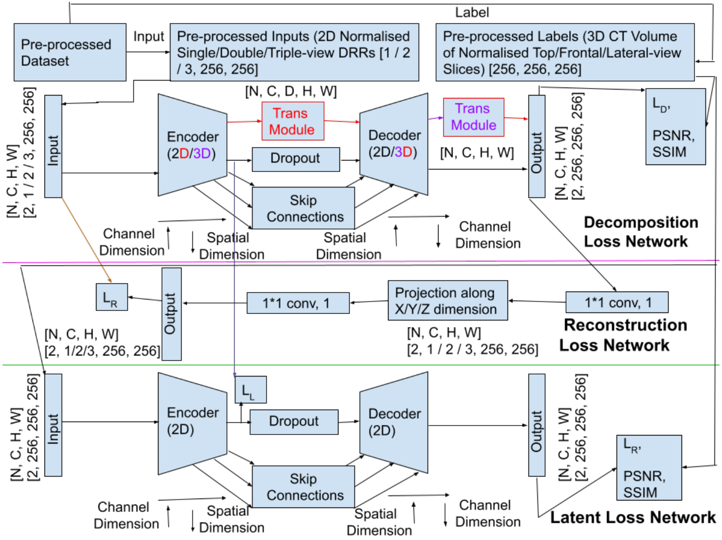
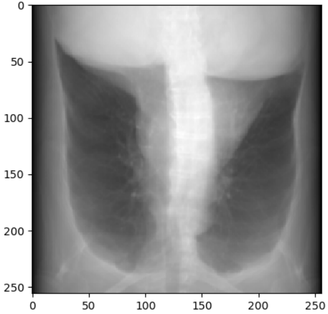
Miscellaneous - Network Architecture

Miscellaneous - Network Architecture

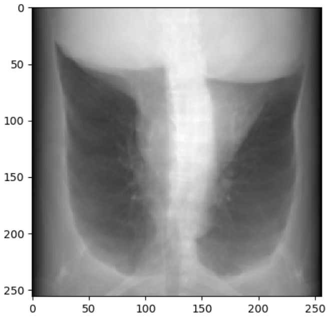


Frontal

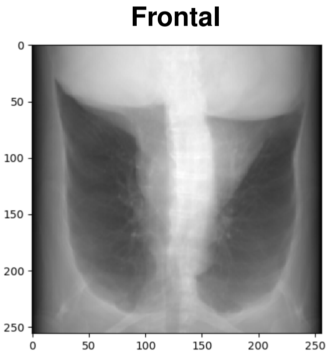
Frontal

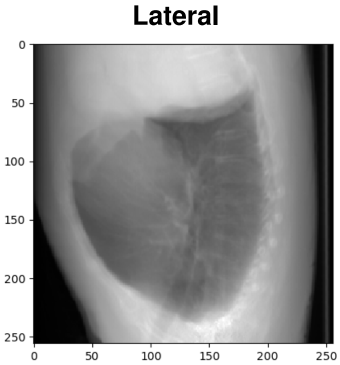


Frontal

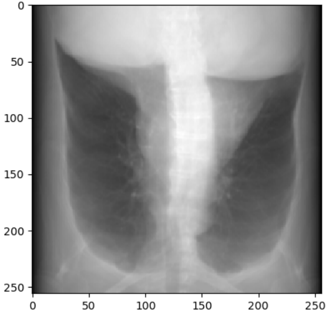


Lateral

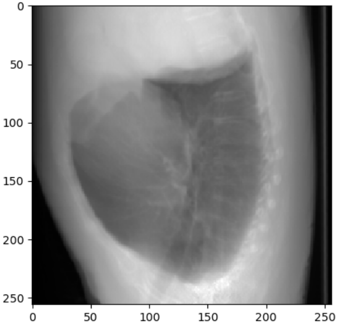

Frontal
0
50
100
150
200
250
0 50 100 150 200 250


Lateral
0
50
100
150
200
250
0 50 100 150 200 250

Frontal

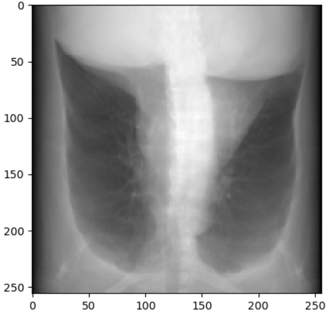


Lateral

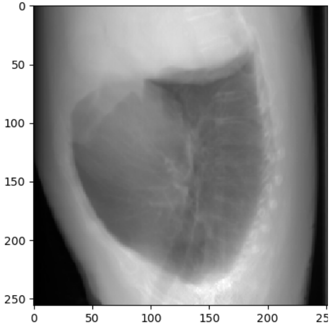


Top

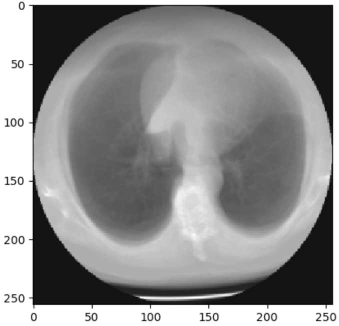
Frontal



Lateral



Top



SSIM :

SSIM : 72.7%

SSIM : 72.7%

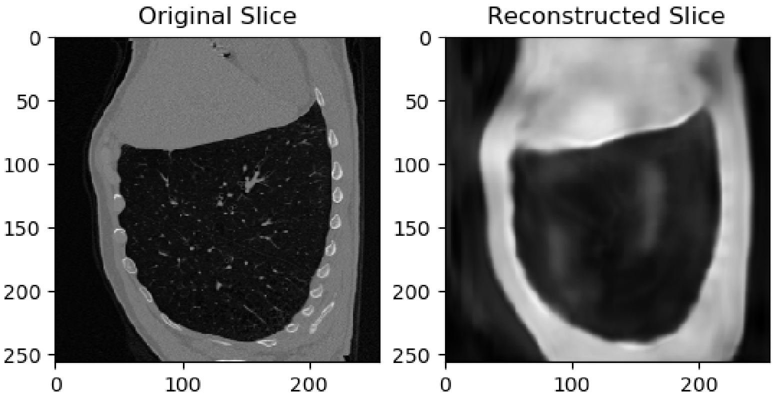
Baseline :

SSIM : 72.7%

Baseline : 63.5%

Miscellaneous - CT (Lateral) - DRR (Triple) - Dimension 256

SSIM : 72.7%
Baseline : 63.5%



Miscellaneous - CT (Top) - DRR (Triple) - Dimension 256

SSIM :

Miscellaneous - CT (Top) - DRR (Triple) - Dimension 256

SSIM : 74%

Miscellaneous - CT (Top) - DRR (Triple) - Dimension 256

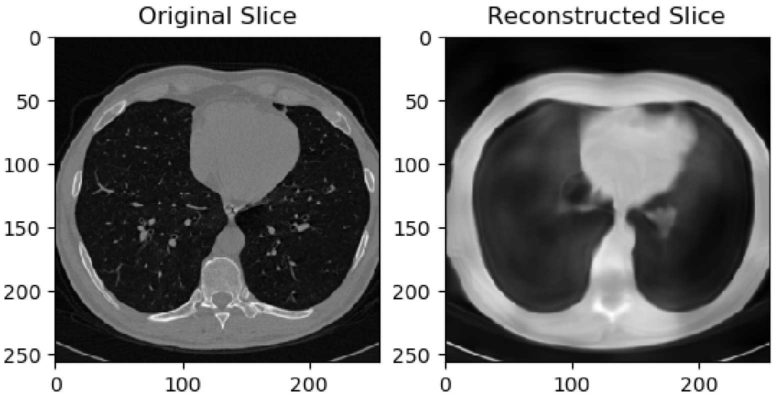
SSIM : 74%

Baseline :

Miscellaneous - CT (Top) - DRR (Triple) - Dimension 256

SSIM : 74%
Baseline : 63.5%

SSIM : 74%
Baseline : 63.5%



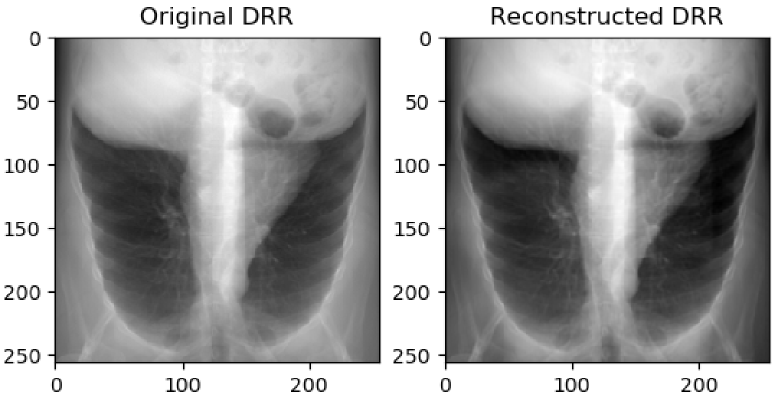
Miscellaneous - 3D CT –> 2D DRR

SSIM :

Miscellaneous - 3D CT –> 2D DRR

SSIM : 98.1%

SSIM : 98.1%


Original DRR
Reconstructed DRR
0
50
100
150
200
250
0
100
200
0
50
100
150
200
250
0
100
200

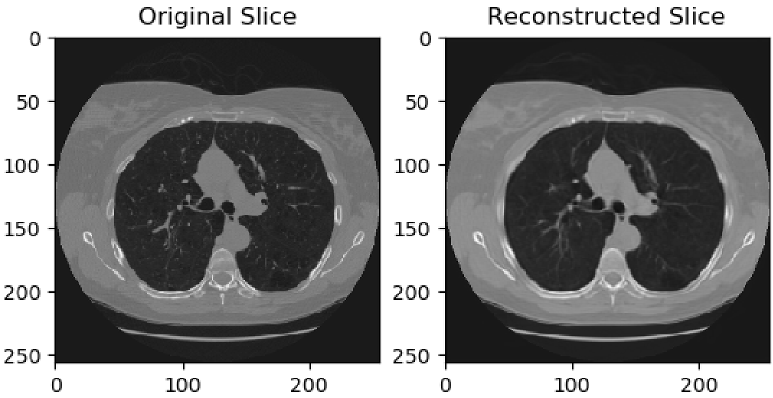
Miscellaneous - 3D CT –> 3D CT

SSIM :

SSIM : 91.9%

Miscellaneous - 3D CT –> 3D CT

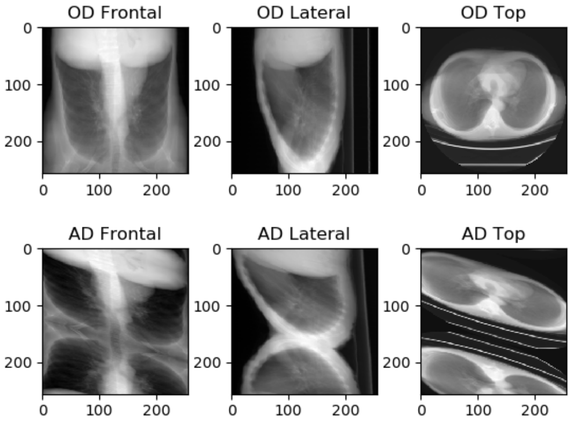
SSIM : 91.9%



Miscellaneous - Data Augmentation (Elastic Transform ($\alpha = 1, \beta = 50$)

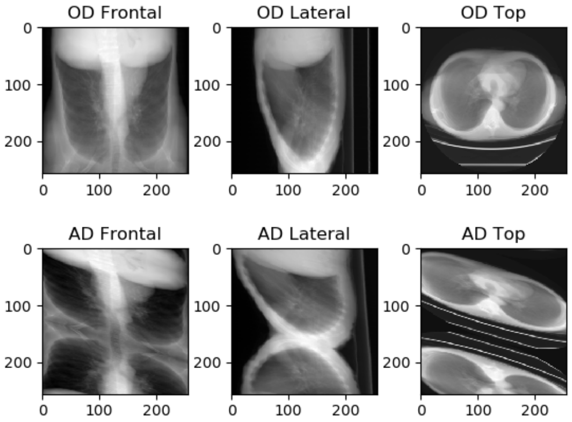
DRRs

DRRs


OD Frontal
OD Lateral
OD Top
AD Frontal
AD Lateral
AD Top
0
100
200

Miscellaneous - Data Augmentation (Elastic Transform ($\alpha = 1, \beta = 50$))

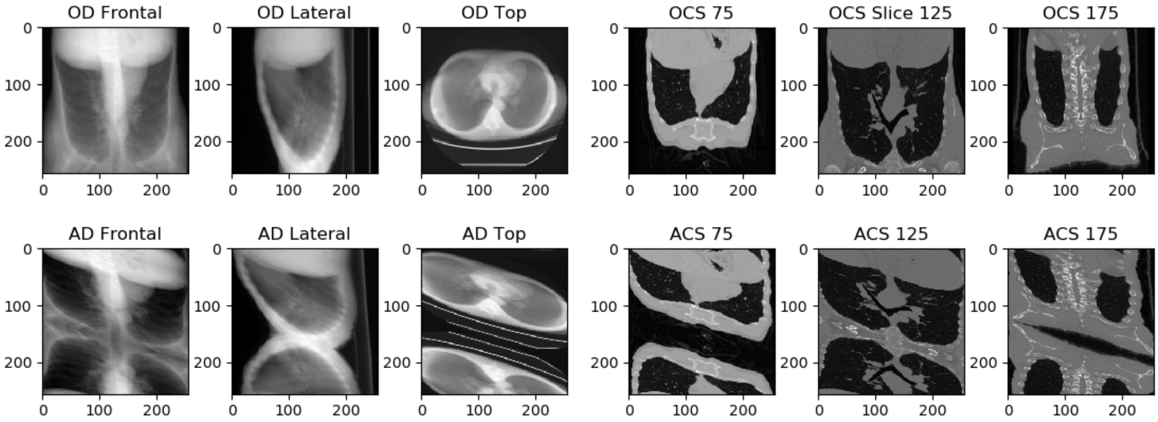
DRRs



CT Slices

Miscellaneous - Data Augmentation (Elastic Transform ($\alpha = 1, \beta = 50$))

DRRs **CT Slices**



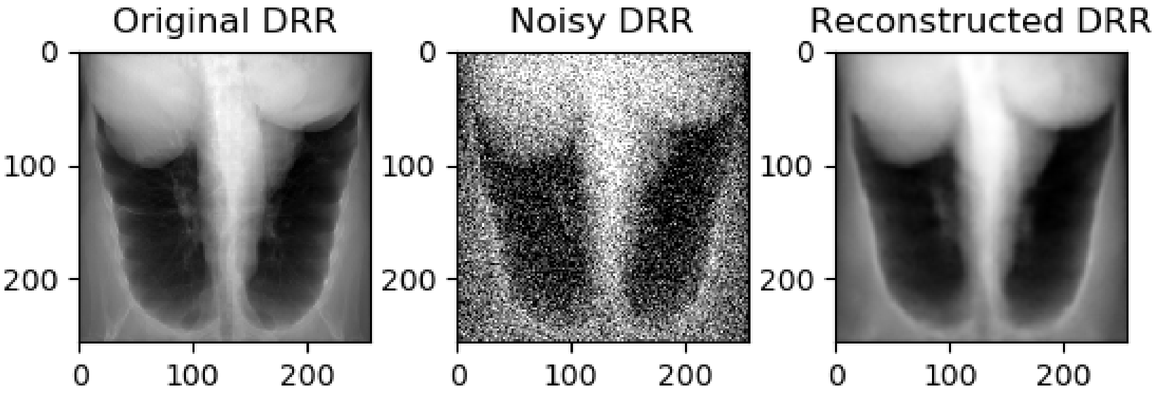
SSIM :

Miscellaneous - Denoising

SSIM : 94%

Miscellaneous - Denoising

SSIM : 94%



Miscellaneous - UI (in process)

Miscellaneous - UI (in process)