Imperial College London

BioMedIA

Deep Learning in Medical Imaging: To Integrate more Knowledge

Speaker: **Zeju Li**

Mar 6th 2019

Overview

About Me

- Who am I?
- Where do I come from?
- What did I do?

Ways to integrate more knowledge in deep learning

- To Integrate **Task-Specific** knowledge
  - DeepVolume: Thin-section MR image reconstruction
- To integrate **Cross-Domain** knowledge
  - DecGAN: Chest X-ray image decomposition
- To integrate **Inter-Process** knowledge
  - DLR: Image based biomarker prediction

About me

Who am I?

- First year PhD student
  - My first supervisor is Ben
- Family name:
  - Li
  - It is the most common family name in China.
  - There are about **100 million** people in China named “Li”
- Given name:
  - Zeju
  - Every Chinese name has a meaning
  - Zeju is “watering the beech”

李

泽榉

About me

Where do I come from?

- I spent 7 years in **Shanghai**, the largest city in China (> 40 million people).
- I got B.S (EE) and M.S. (BME) both from Fudan University.
  - One of our alumni, **Wenzhe Shi** came from the same university.
- I came from the lab named "the Key laboratory of Medical Imaging Computing and Computer Assisted Intervention (MICCAI) of Shanghai"

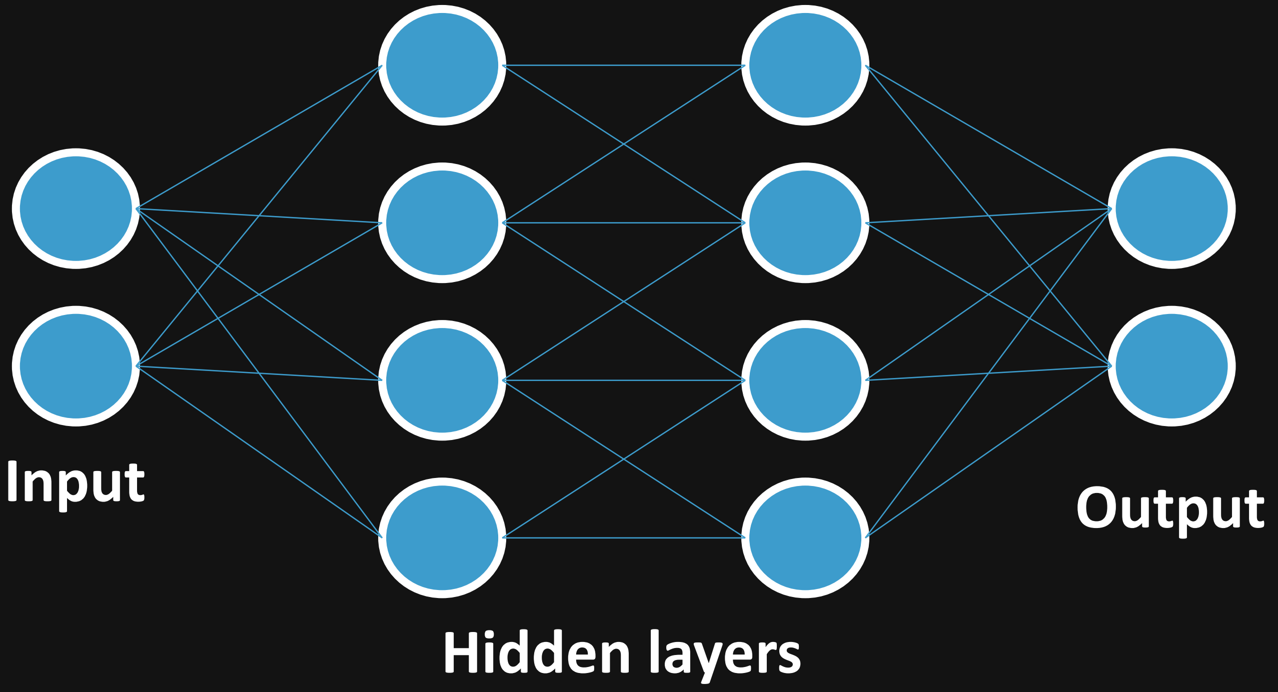
What did I do?

- Research focus of undergraduate study
  - Ultrasound beamforming
- Research focus of master study
  - MR Image analysis of glioma
  - Brain tumor segmentation

Task-Specific knowledge

How to integrate more knowledge into the network?

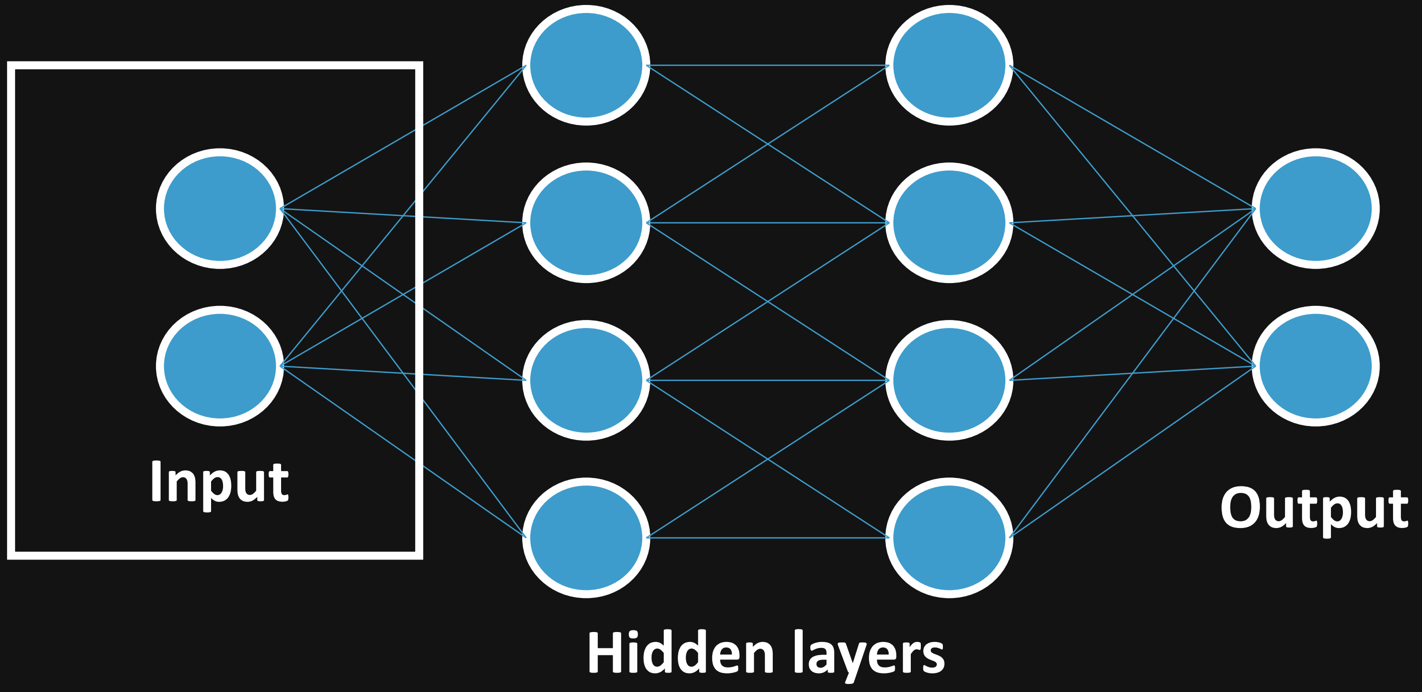
- If it is possible to integrate more **paired** information?



Task-Specific knowledge

How to integrate more knowledge into the network?

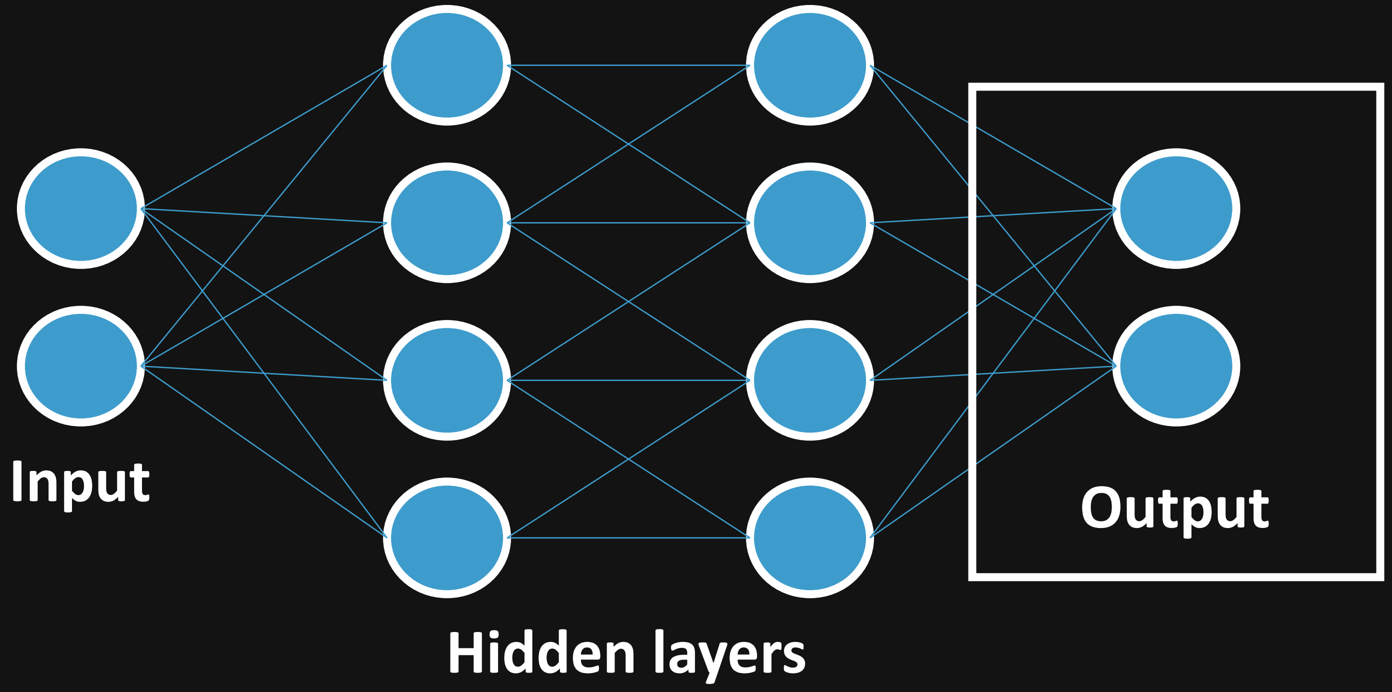
- If it is possible to integrate more **paired** information?
  - Input space (multiple modalities..)



Task-Specific knowledge

How to integrate more knowledge into the network?

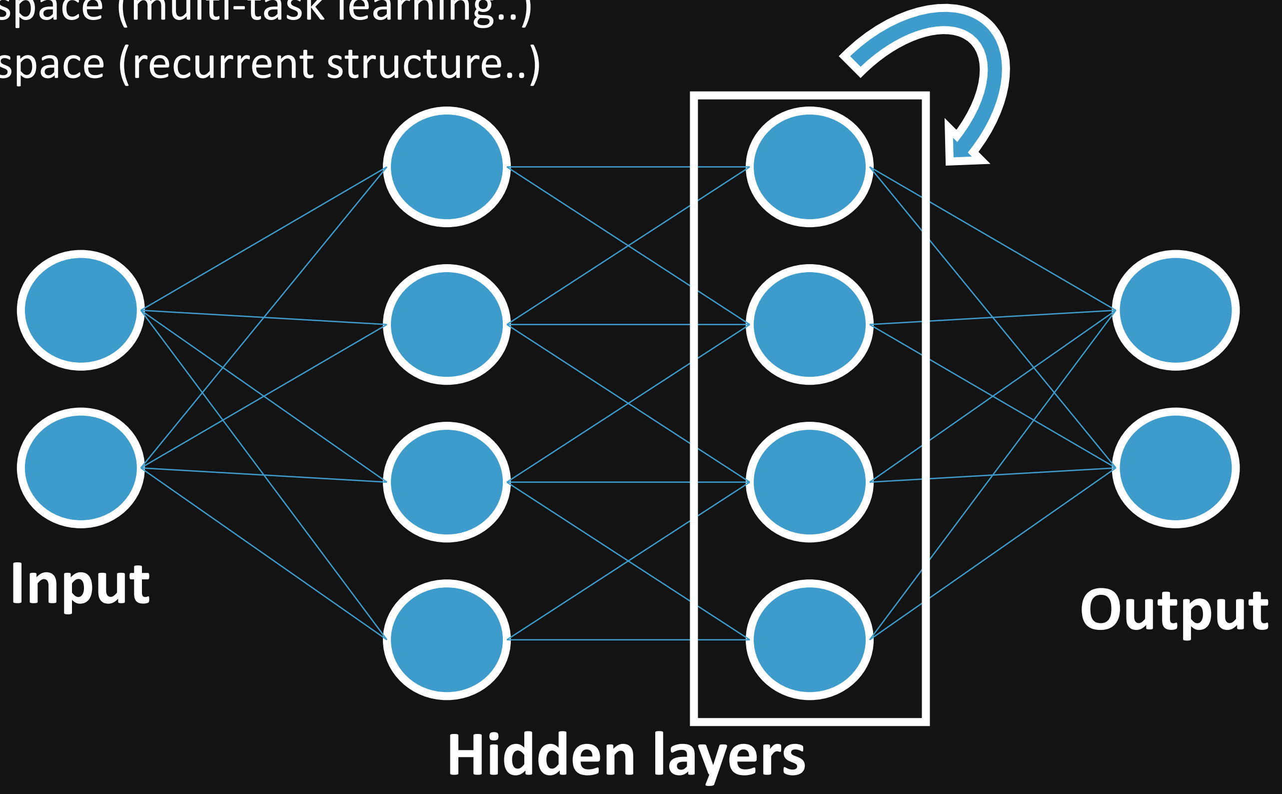
- If it is possible to integrate more **paired** information?
  - Input space (multiple modalities..)
  - Output space (multi-task learning..)



Task-Specific knowledge

How to integrate more knowledge into the network?

- If it is possible to integrate more **paired** information?
  - Input space (multiple modalities..)
  - Output space (multi-task learning..)
  - Hidden space (recurrent structure..)

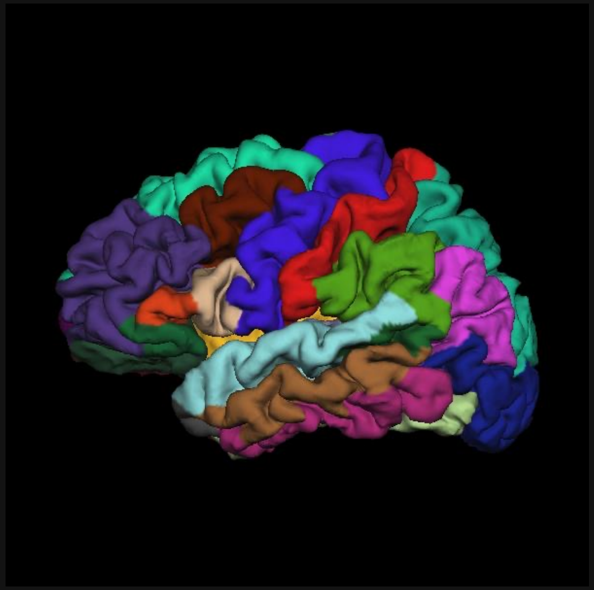


DeepVolume: Thin-section MR image reconstruction

Brain MR images

- Until 2010, **5 billion** medical imaging studies had been conducted worldwide
- However, much of the information available in medical data is untapped because of the gap between research and hospital imaging setting
- For example, automated neuroimaging analysis is mostly based on thin-section MR images, however most of brain MRI is thick-section in hospitals

Only thin-section images

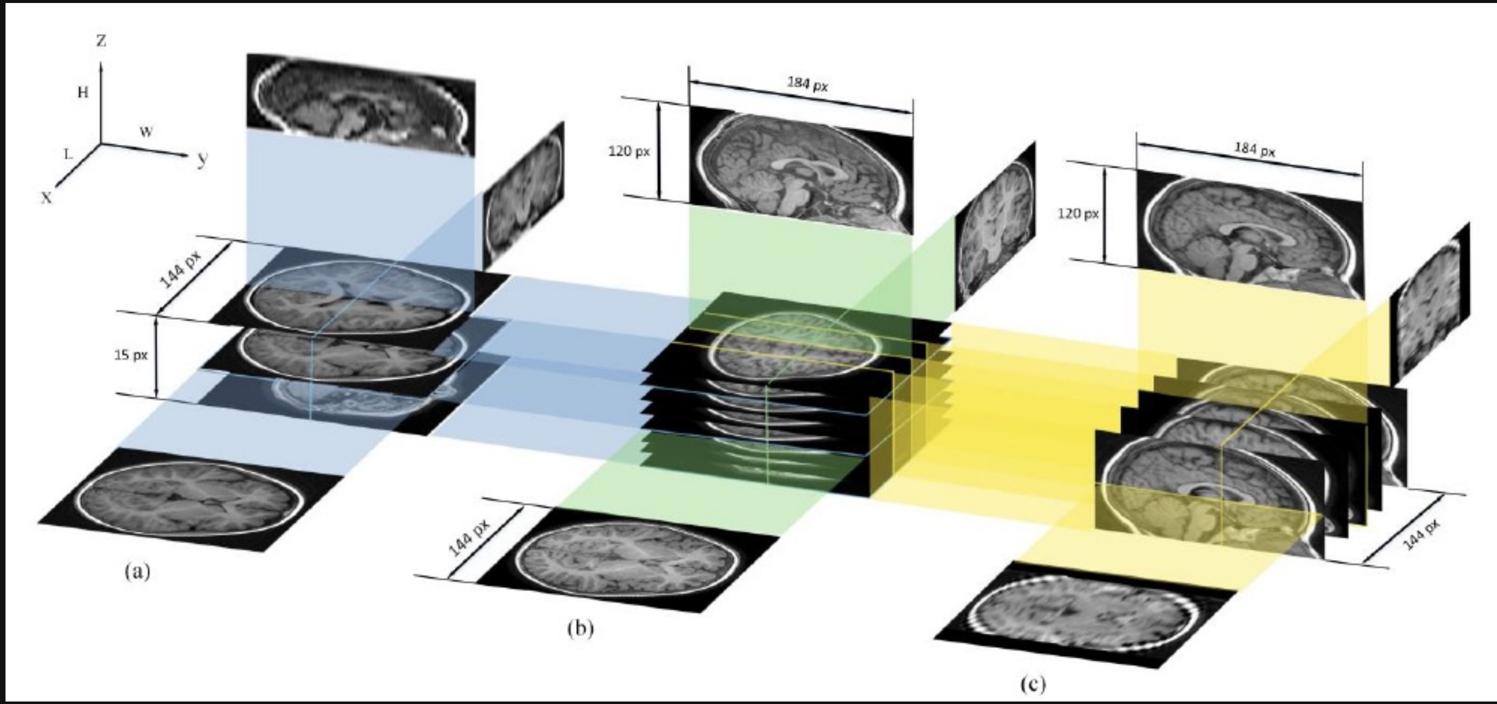


Z. Li et al. DeepVolume: Brain Structure and Spatial Connection-Aware Network for Thin-Section Brain MRI Reconstruction. Under Revision

DeepVolume: Thin-section MR image reconstruction

Brain MR images

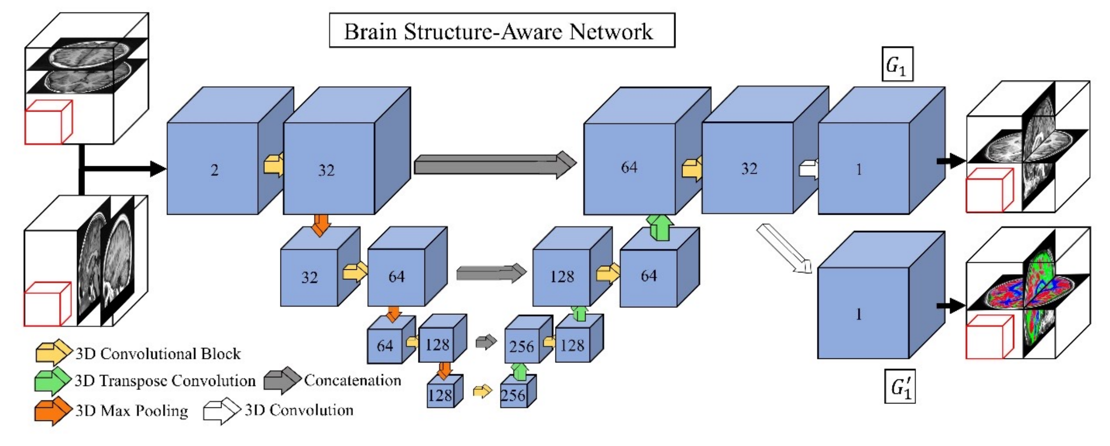
- We want to reconstruct thin-section MR images based on thick-section MR images from different planes
- What **paired task-specific** knowledge can we integrate?
  - **Input space**: images from different planes
  - **Output space**: brain structure segmentation
  - **Hidden space**: high-resolution sagittal information



DeepVolume: Thin-section MR image reconstruction

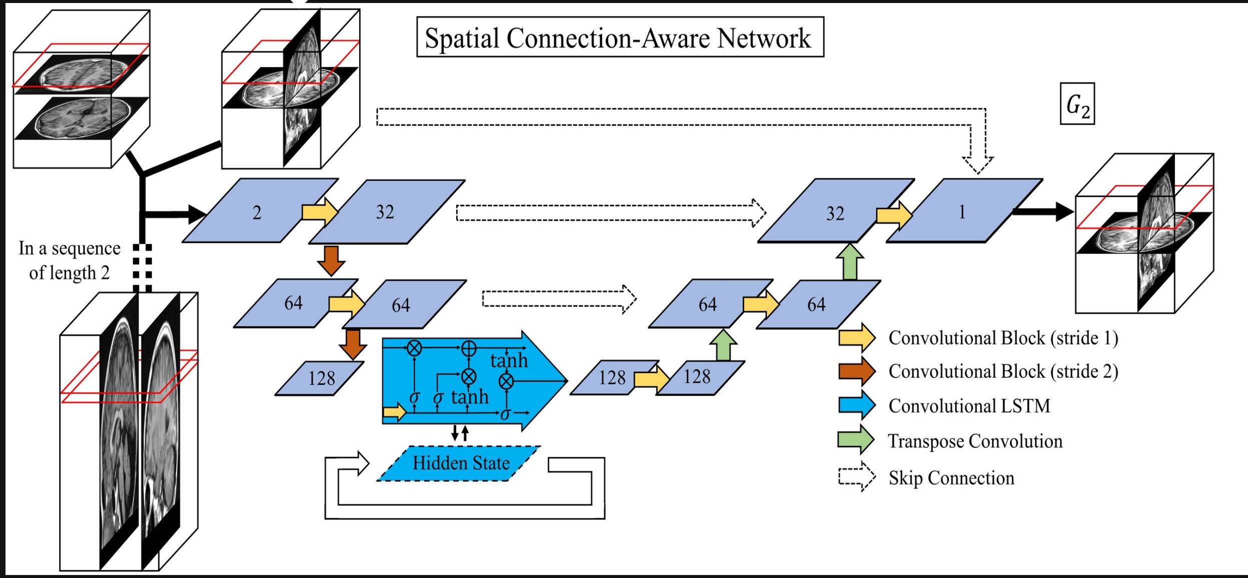
Method

- DeepVolume: Two cascade neural networks



- Network 1:
  - Based on 3D U-net
  - Thick-section images in two planes are inputted (**input space**)
  - Brain structure supervision is added (**output space**)

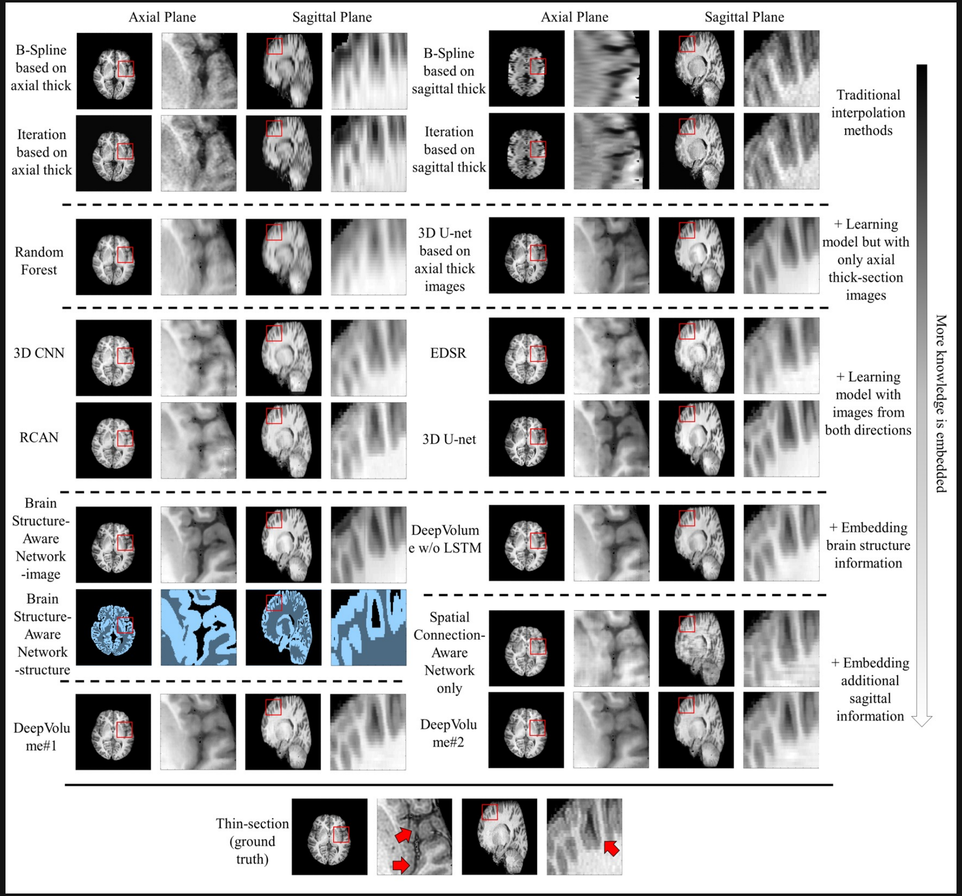
- Network 2:
  - Preliminary results are modified
  - Additional sagittal information is embedded with Conv-LSTM (**hidden space**)

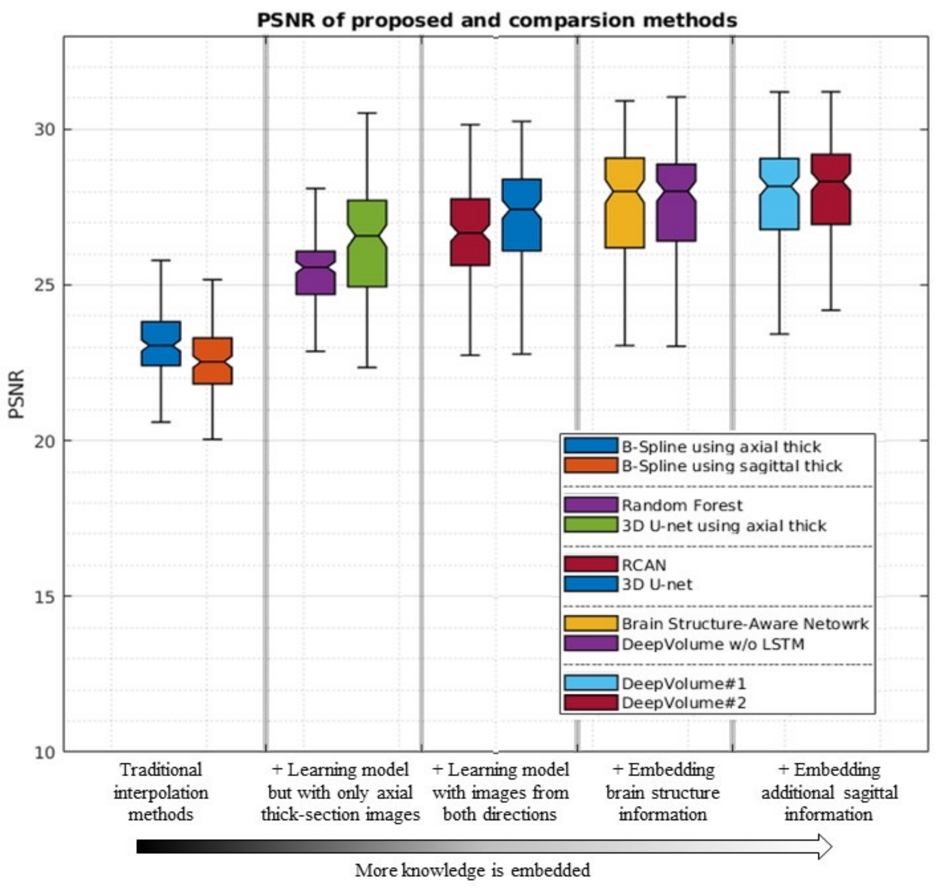


DeepVolume: Thin-section MR image reconstruction

Results: Reconstruction

- The more knowledge, the better.



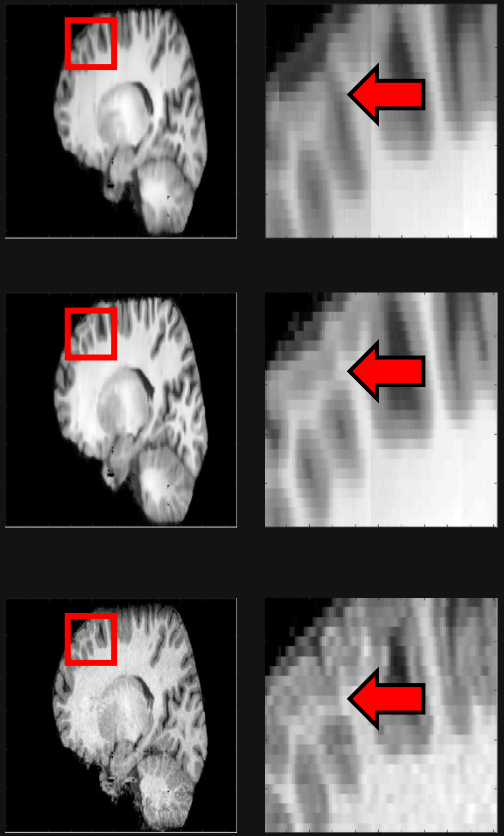


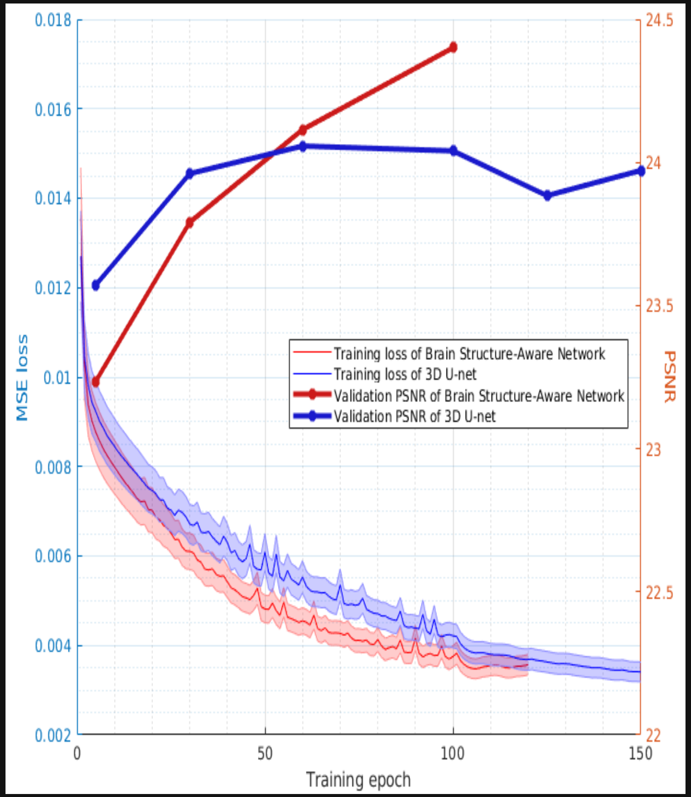
DeepVolume: Thin-section MR image reconstruction

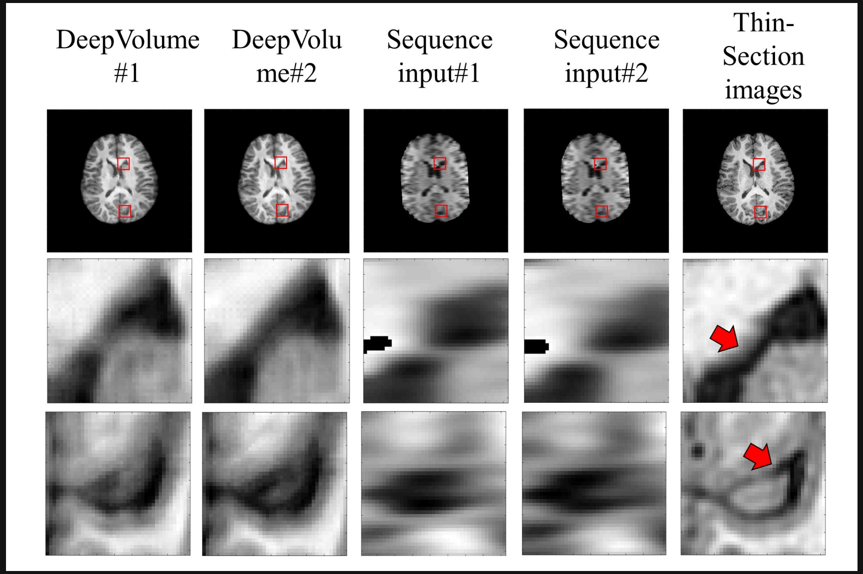
Results: Reconstruction

- Both plane input: correct structure
- Brain structure supervision: prevent overfitting
- More sagittal information: enhance spatial continuity

- 3D U-net based on axial thick images
- 3D U-net
- Thin-section (ground truth)



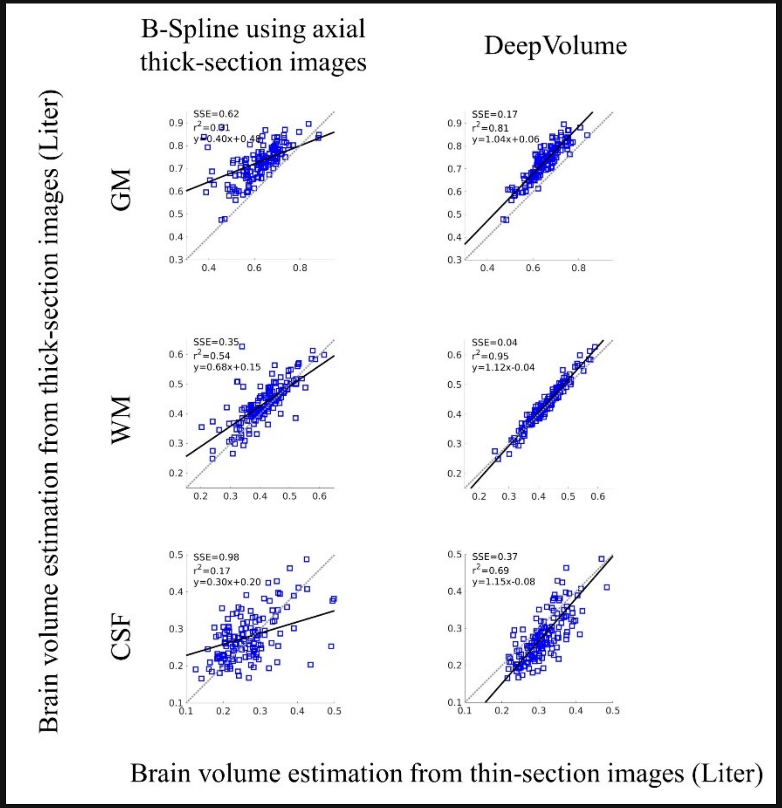


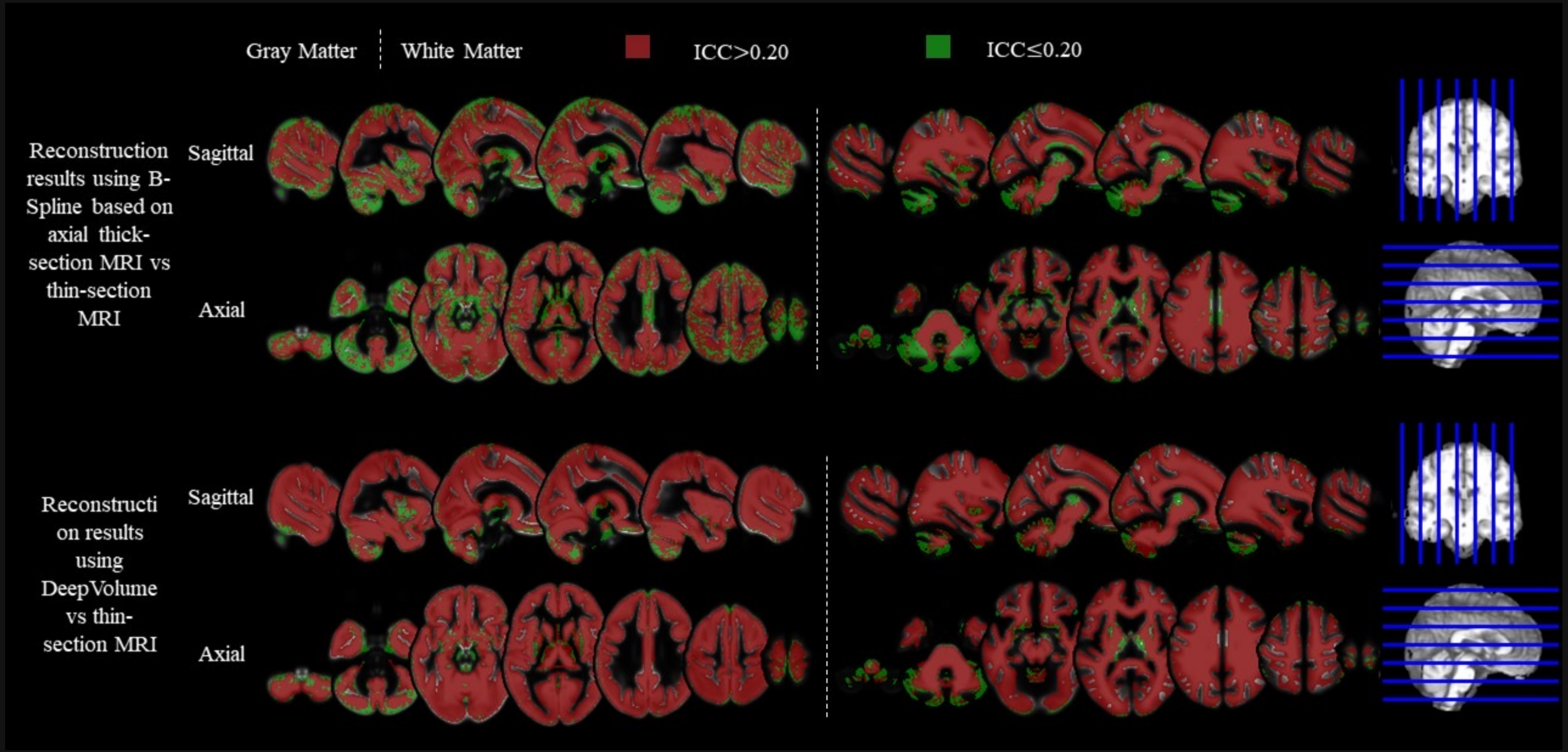


DeepVolume: Thin-section MR image reconstruction

Results: Brain Volumetry

- Based on DeepVolume, the brain estimation could be more reliable (consistent with thin-section MRI)

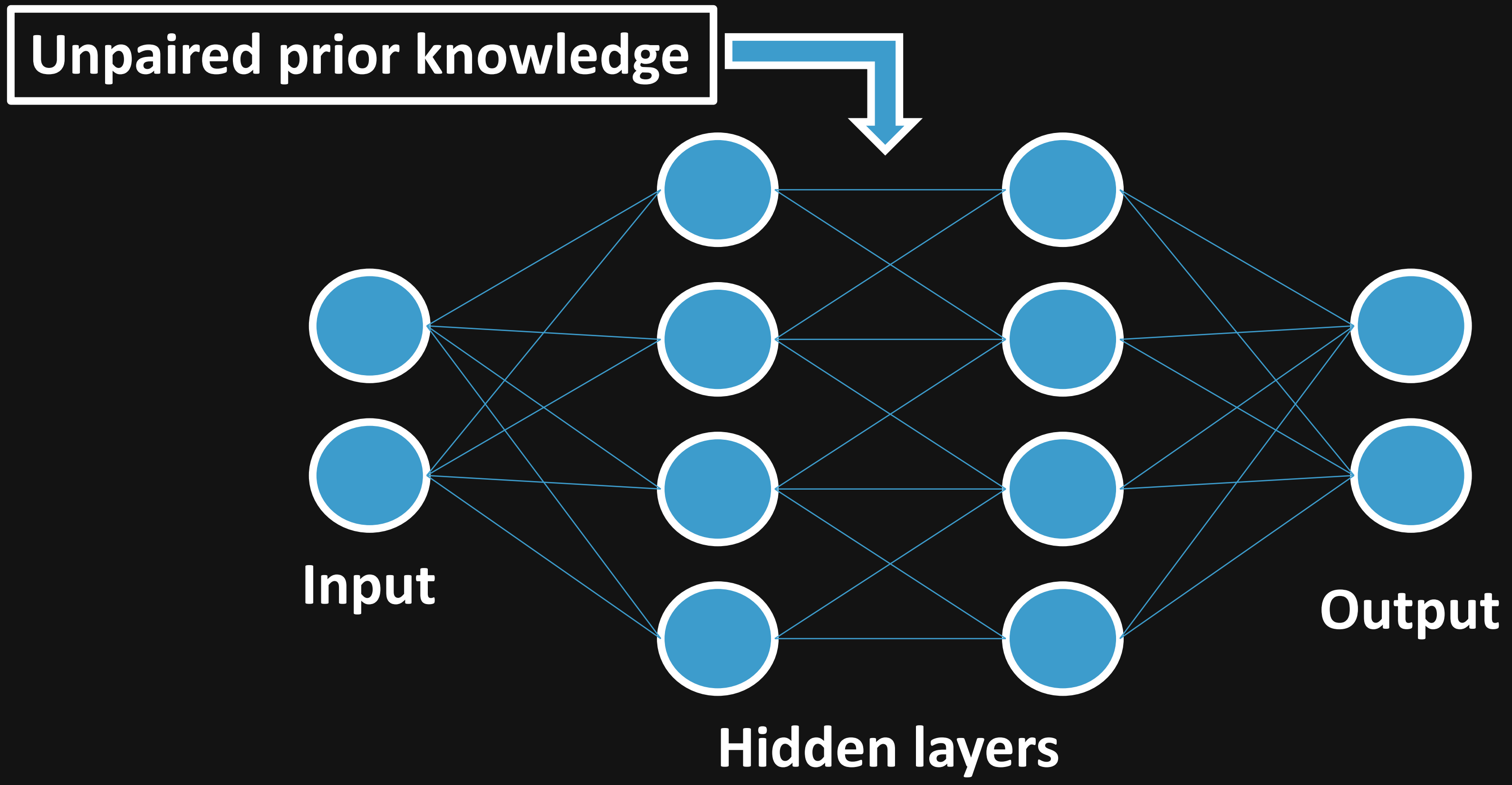




Cross-Domain knowledge

How to integrate more knowledge into the network?

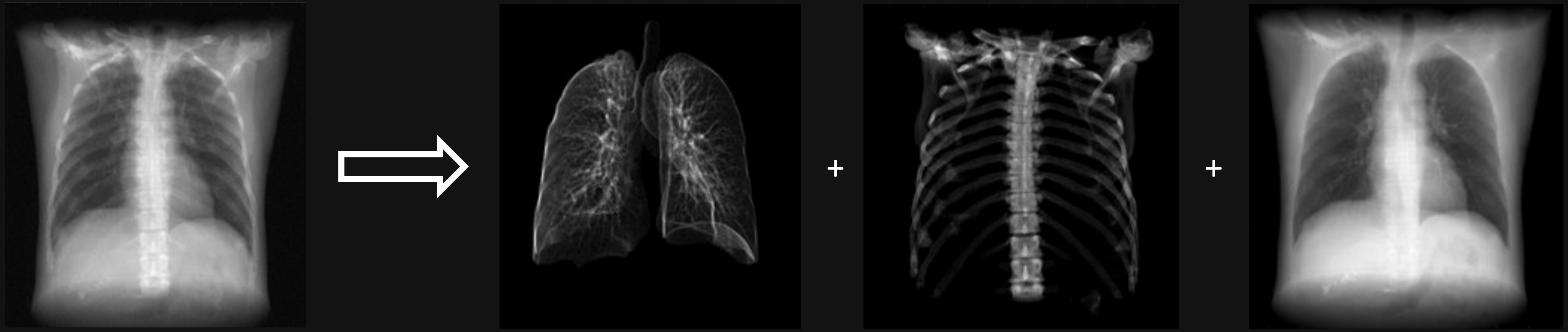
- If it is possible to utilize **unpaired cross-domain** knowledge in neural network?



DecGAN: Chest X-ray image decomposition

Chest X-ray

- Chest X-ray (CXR) is the most common type of diagnostic image
- CXR is only a 2D projection image which contains overlapped anatomies.
- There is clinical evidence supporting that decomposing an X-ray image into **different components** (e.g., bone, lung and soft tissue) improves diagnostic value.
- CXR and CT are two closely **related medical imaging modalities** given that a 3D CT is reconstructed from a set of X-ray projections.

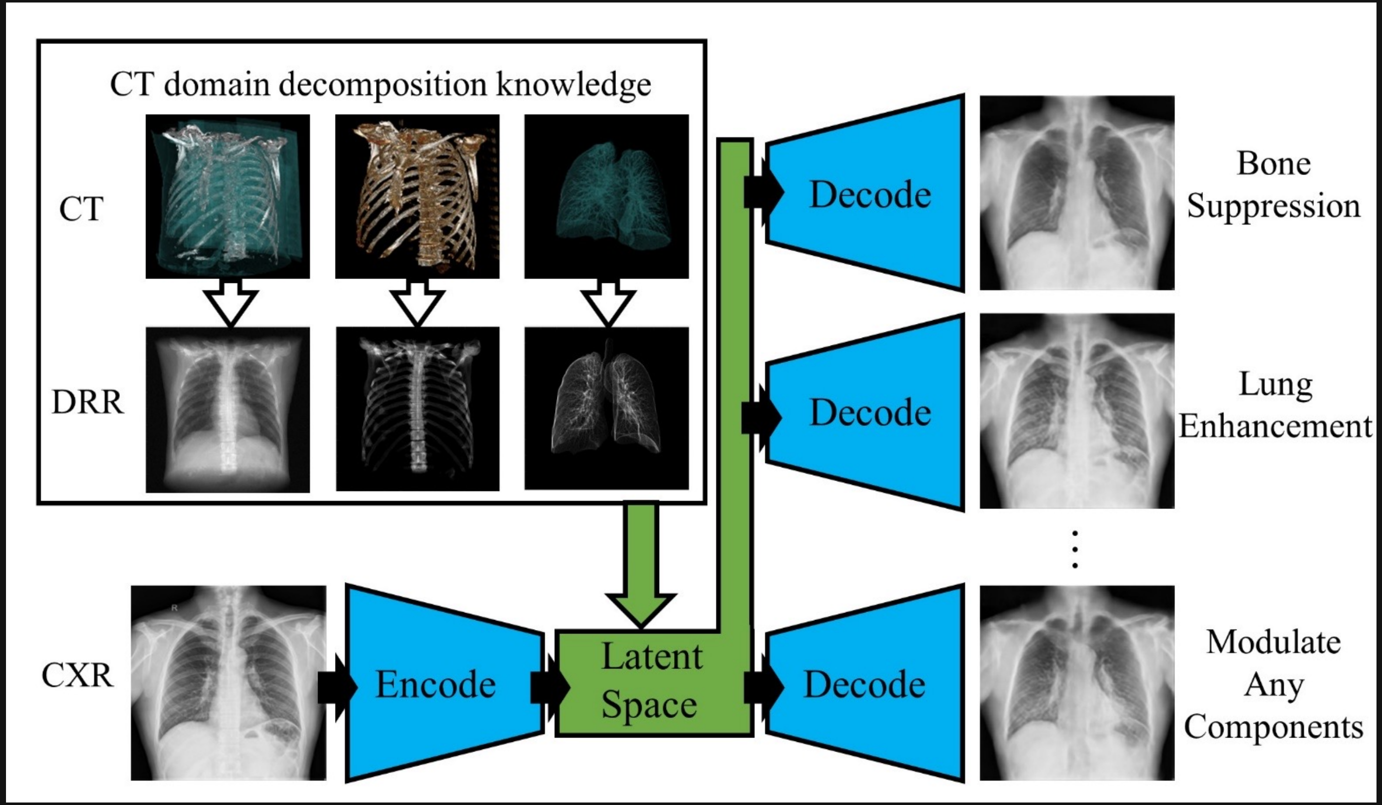


Z. Li et al. Encoding CT Anatomy Knowledge for Unpaired Chest X-ray Image Decomposition. In preparation

DecGAN: Chest X-ray image decomposition

Chest X-ray

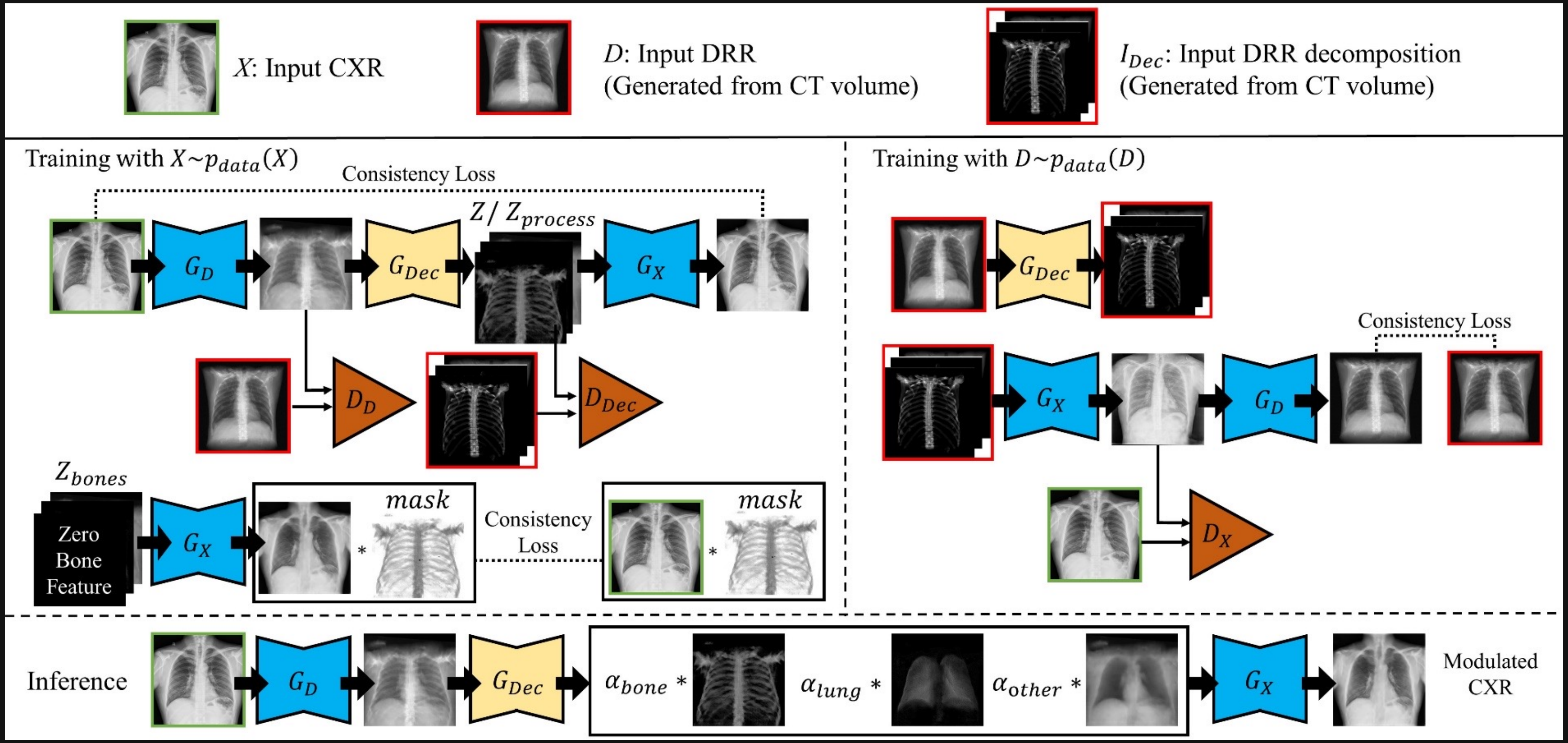
- We want to integrate the **cross-domain** CT knowledge for CXR decomposition.
- The key idea is to embed DRR priori decomposition into the latent space of unpaired CXR autoencoder.



DecGAN: Chest X-ray image decomposition

Method

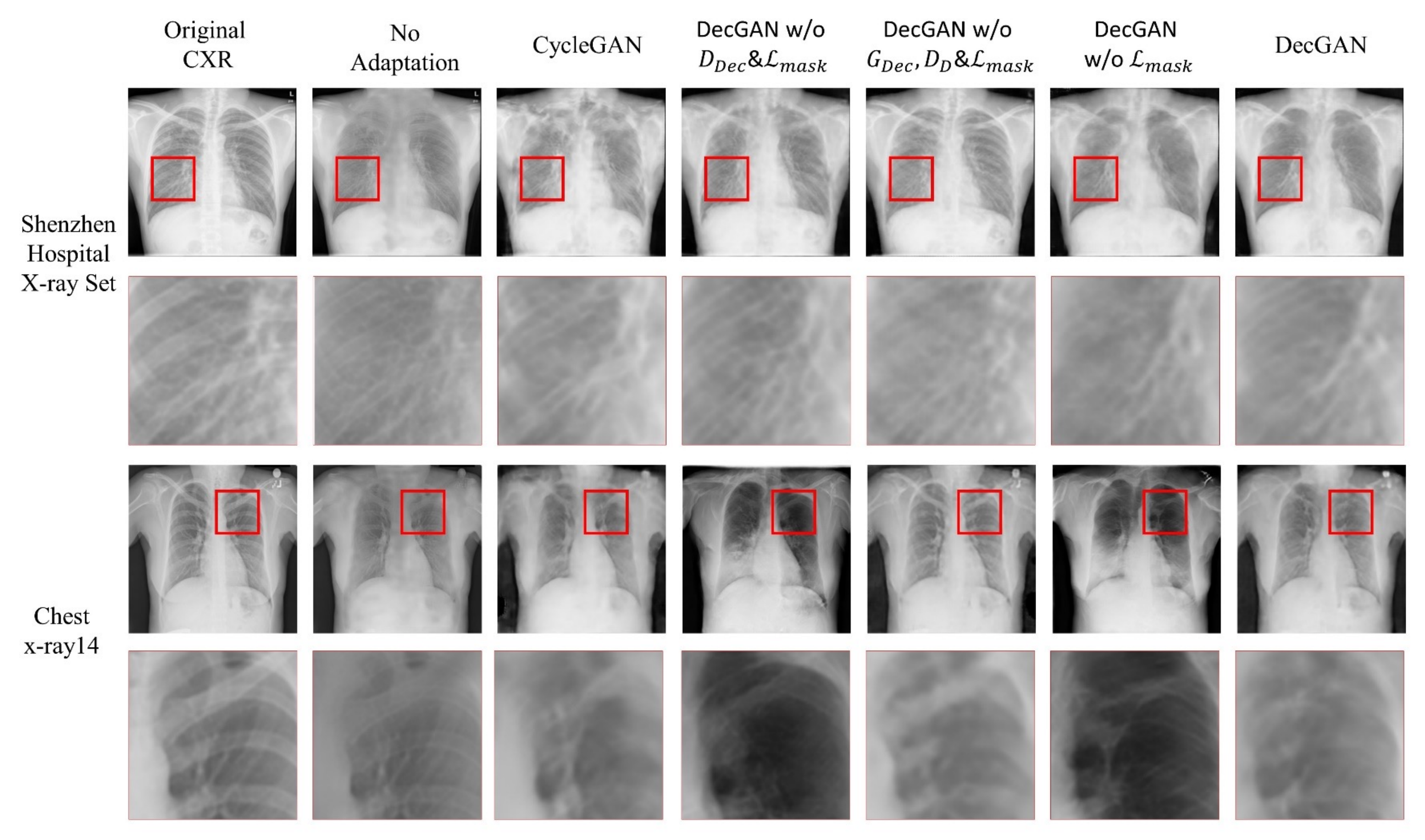
- Base on the backbone of CycleGAN
- Insect the **decomposition process** inside the DRR domain
- More constrains base on the structure of CXR



DecGAN: Chest X-ray image decomposition

Results: Bone suppression

- We can get the superior unsupervised bone suppression results

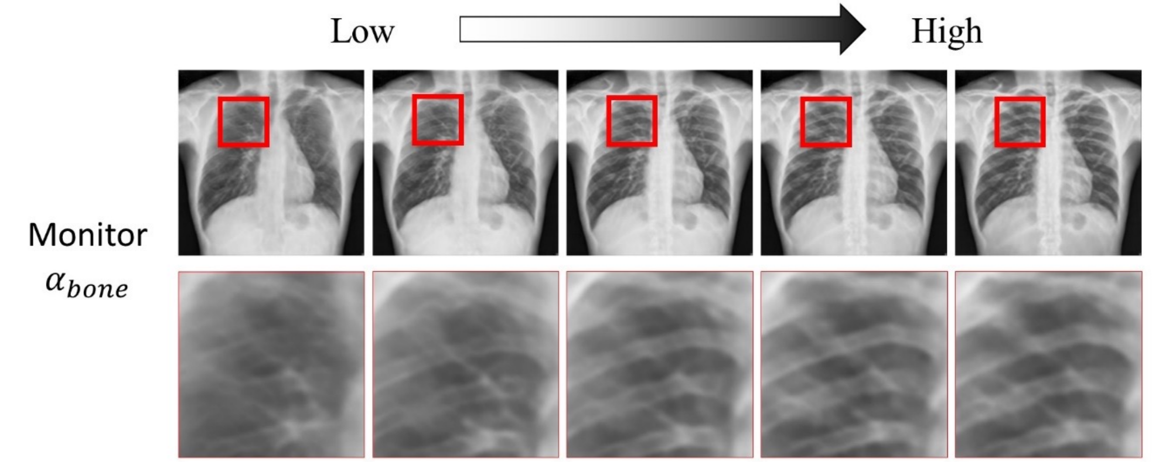


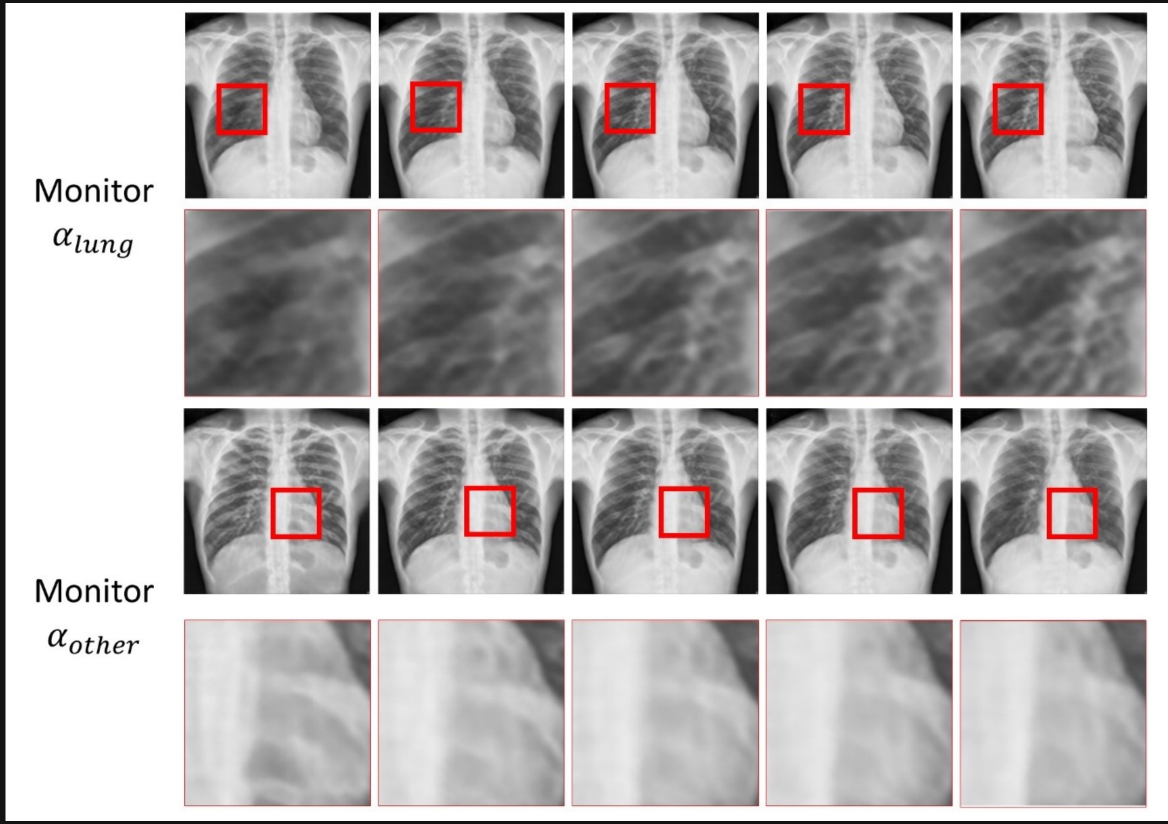
Method	$r_l(10^4)$	PSNRs
CXR	3.82	——
Blind Signal Separation	2.47	29.7
No Adaptation	1.41	26.7
CycleGAN	1.50	27.1
DecGAN w/o G_{Dec} or $\mathcal{L}_{mask}$	1.03	27.5
DecGAN w/o G_{Dec}, D_D or $\mathcal{L}_{mask}$	1.60	29.7
DecGAN w/o $\mathcal{L}_{mask}$	0.549	26.4
DecGAN	**0.854**	**29.6**

DecGAN: Chest X-ray image decomposition

Results: Components modulation

- We can modulate CXR components by changing the latent factors

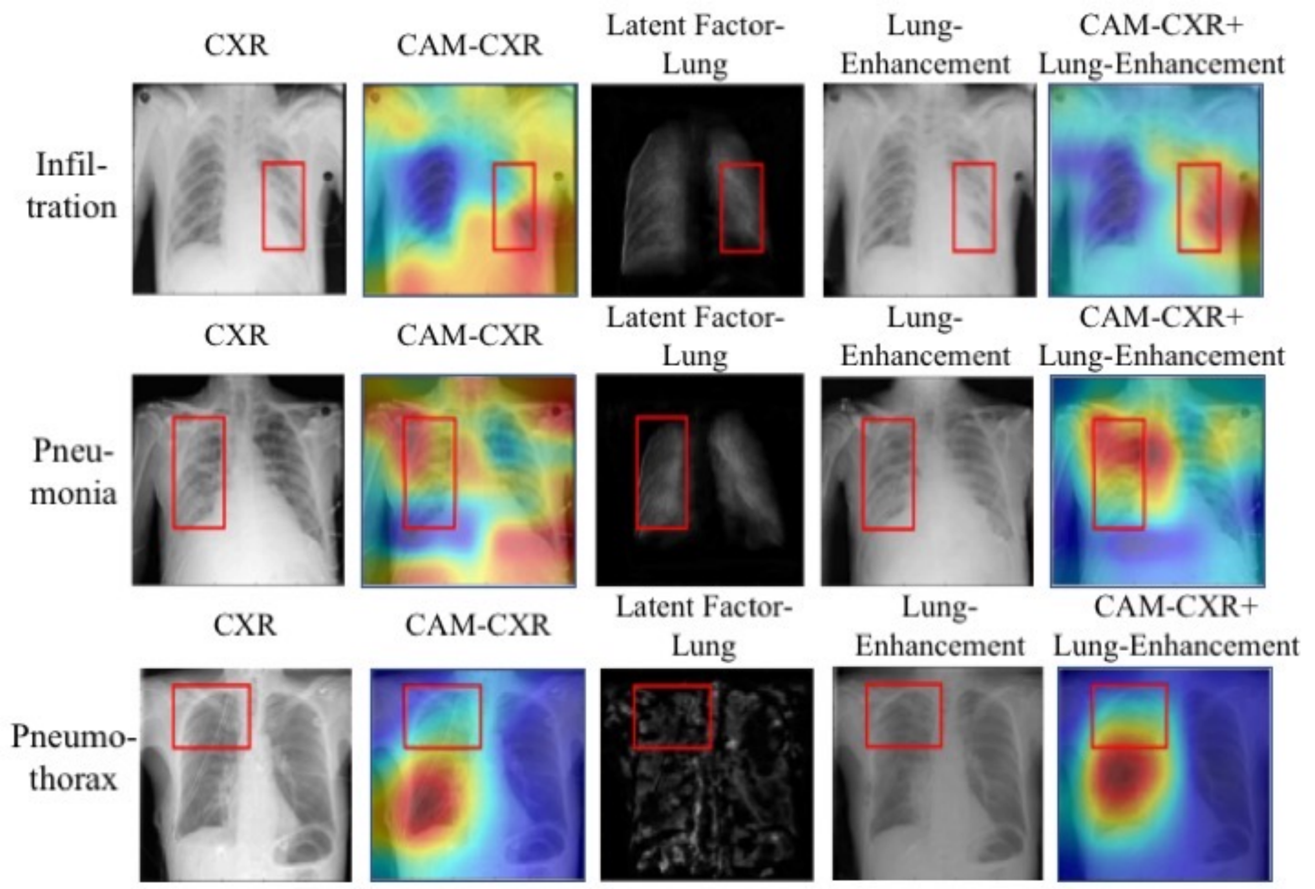




DecGAN: Chest X-ray image decomposition

Results: CXR Diagnosis

- By including the CT knowledge, we can get the state-of-the-art lung disease diagnosis results

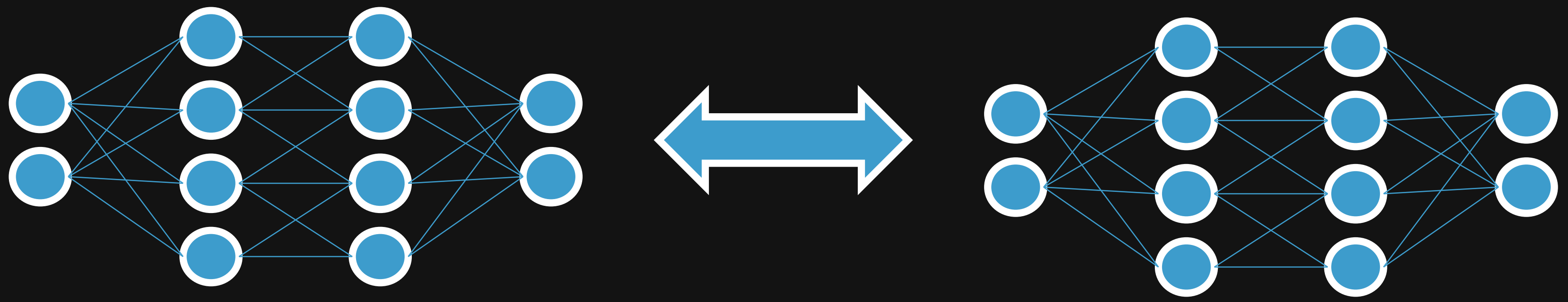


Method	Wang et al [33]	Yao et al [35]	DenseNet-121 [15] [27]	DenseNet-121 +Lung-Enhancement
Atelectasis	0.700	0.733	0.777	**0.781**
Cardiomegaly	0.810	0.858	0.879	**0.881**
Effusion	0.759	0.806	0.825	**0.827**
Infiltration	0.661	0.675	0.696	**0.703**
Mass	0.693	0.727	**0.836**	0.835
Nodule	0.669	**0.778**	0.773	**0.778**
Pneumonia	0.658	0.690	0.730	**0.737**
Pneumothorax	0.799	0.805	0.842	**0.843**
Consolidation	0.703	0.717	0.761	**0.762**
Edema	0.805	0.806	0.847	**0.851**
Emphysema	0.833	0.842	**0.920**	0.917
Fibrosis	0.786	0.757	0.823	**0.837**
Pleura Thicken	0.684	0.724	0.779	**0.783**
Hernia	0.872	0.824	**0.938**	0.929
Average	0.745	0.767	0.816	**0.819**

Inter-Process knowledge

How to integrate more knowledge into the network?

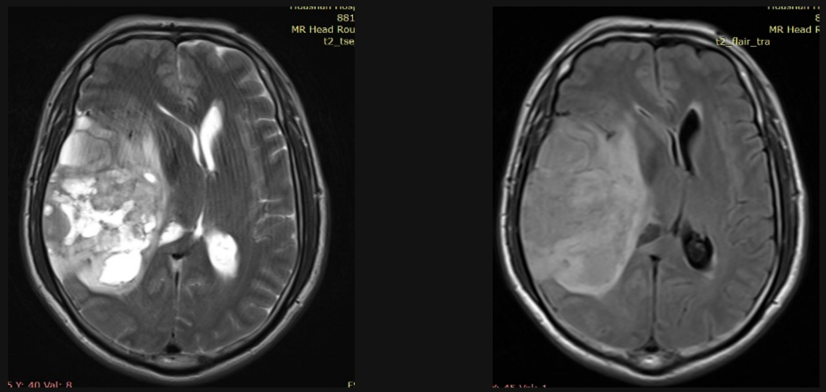
- There are usually many processes in an full application of medical imaging (reconstruction, segmentation and classification…)
- If it is possible to connect them and grep **inter-process** knowledge?



DLR: Image based biomarker prediction

Glioma biomarker

- Biomarker proved to be of clinical significance of glioma
- IDH1 mutation (*a kind of **biomarker***) is suggested as **key events** in the formation of brain tumors.
- High grade glioma with a wild-type IDH1 gene have a median overall survival of only 1 year, whereas IDH1-mutated glioblastoma patients have a median overall survival of over 2 years
- However, **clinical dissection is required** to obtain those information

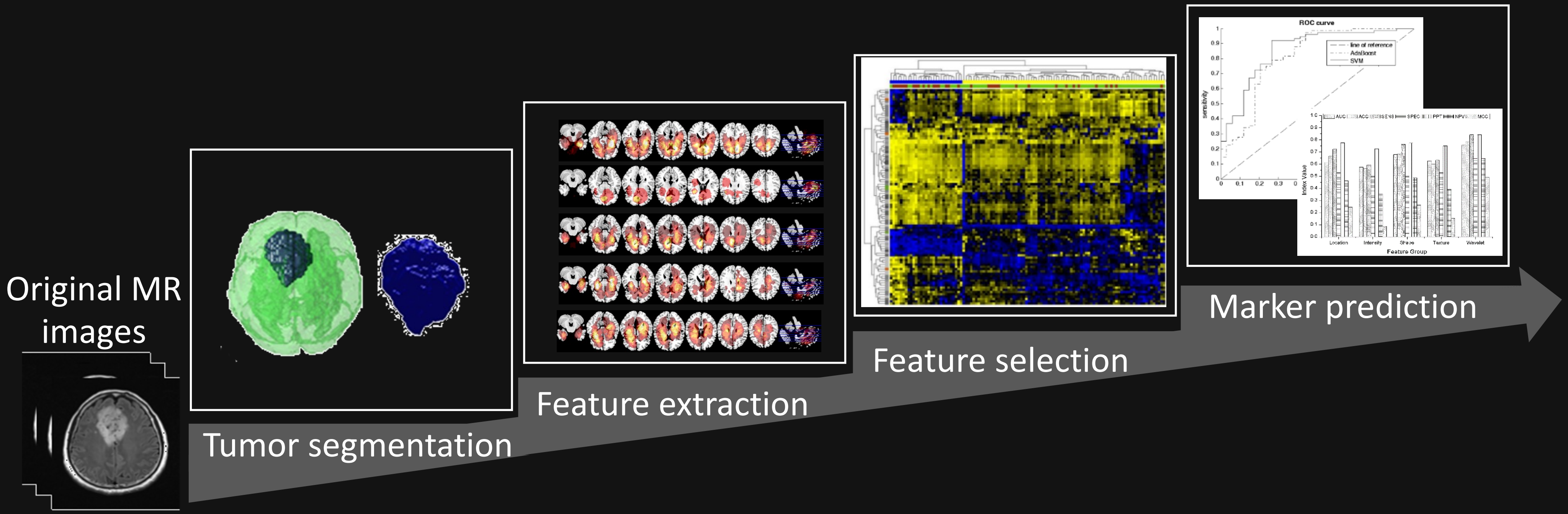


Z. Li et al. Deep Learning based Radiomics (DLR) and its usage in noninvasive IDH1 prediction for low grade glioma. *Sci. Rep.* 2017.

DLR: Image based biomarker prediction

Glioma biomarker

- Normally, the process (Radiomics) contains several cascade steps
- However, we think there are some errors between the processes.



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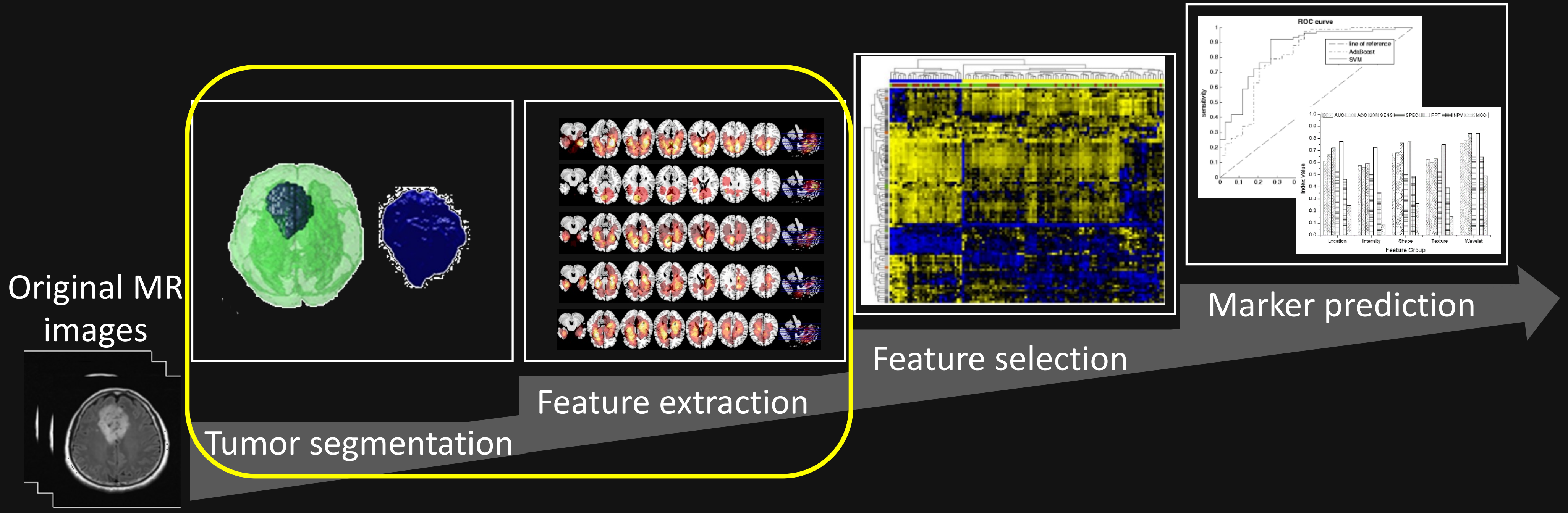
DLR: Image based biomarker prediction

Glioma biomarker

- Normally, the process (Radiomics) contains several cascade steps
- However, we think there are some errors between the processes.
- If it is possible to reduce the errors and integrate **inter-process** knowledge in neural network?



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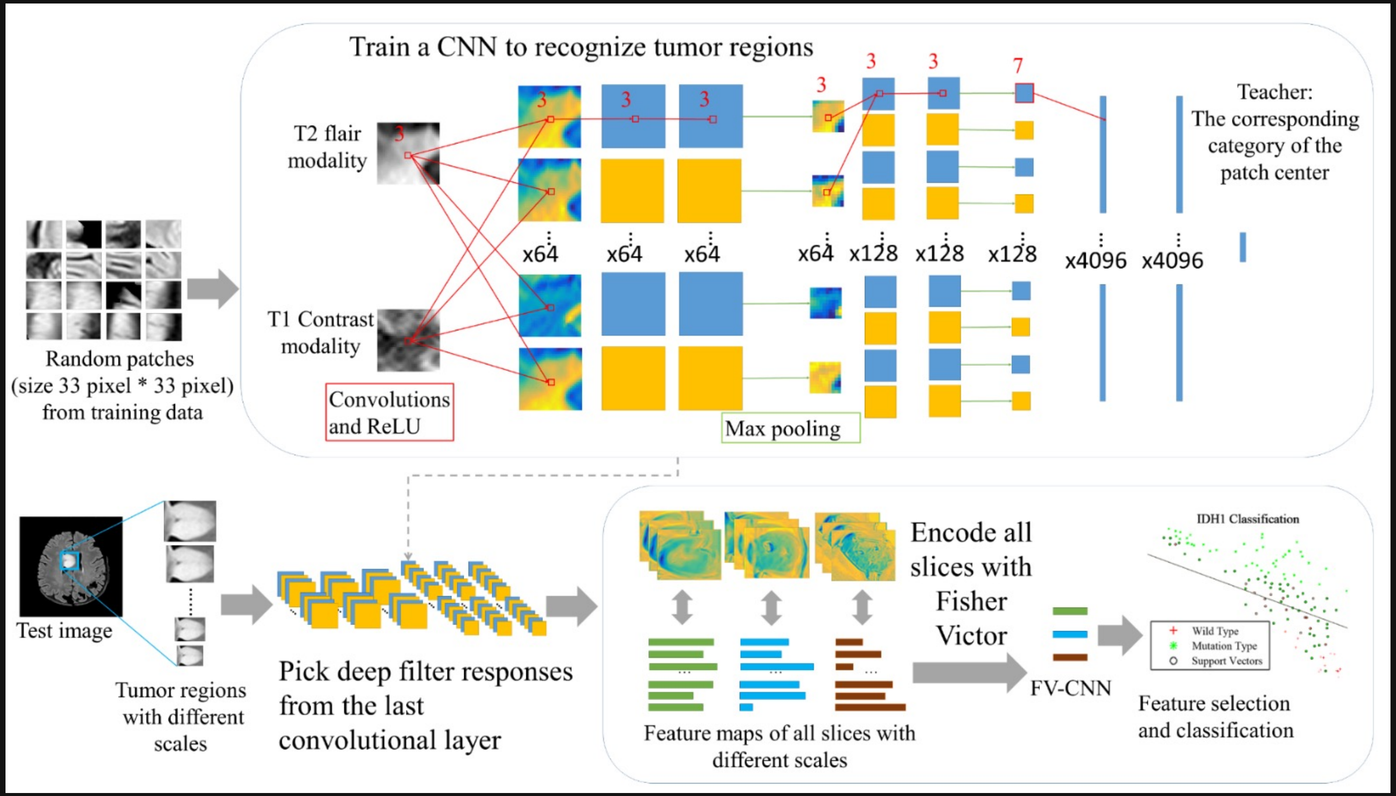
DLR: Image based biomarker prediction

Method

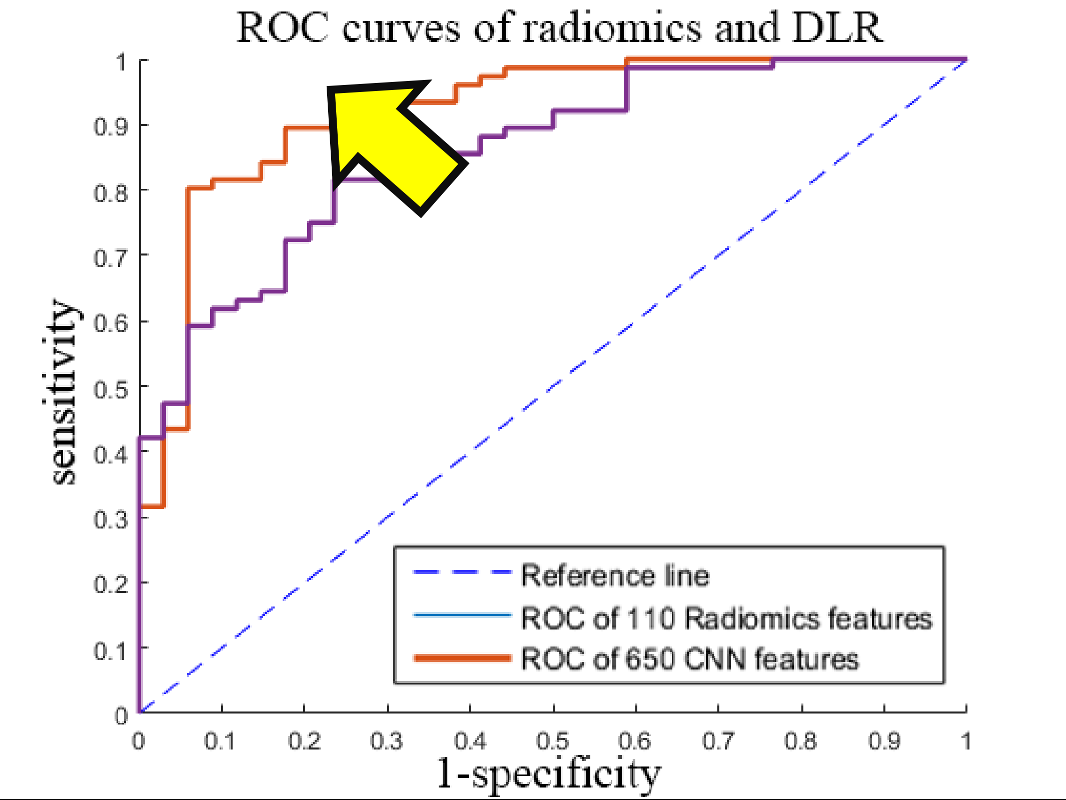
- DLR use CNN to identify the **characteristics** of glioma by obtaining effective information directly from the CNN network for tumor segmentation
- The three dimensions of the tumor area are reduced to the same dimension by **Fisher Vector**



DLR: Image based biomarker prediction

Results

- DLR is able to improve **6%** prediction accuracy in IDH1 prediction of grade II gliomas compared with traditional radiomics framework



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DLR: Image based biomarker prediction

Results

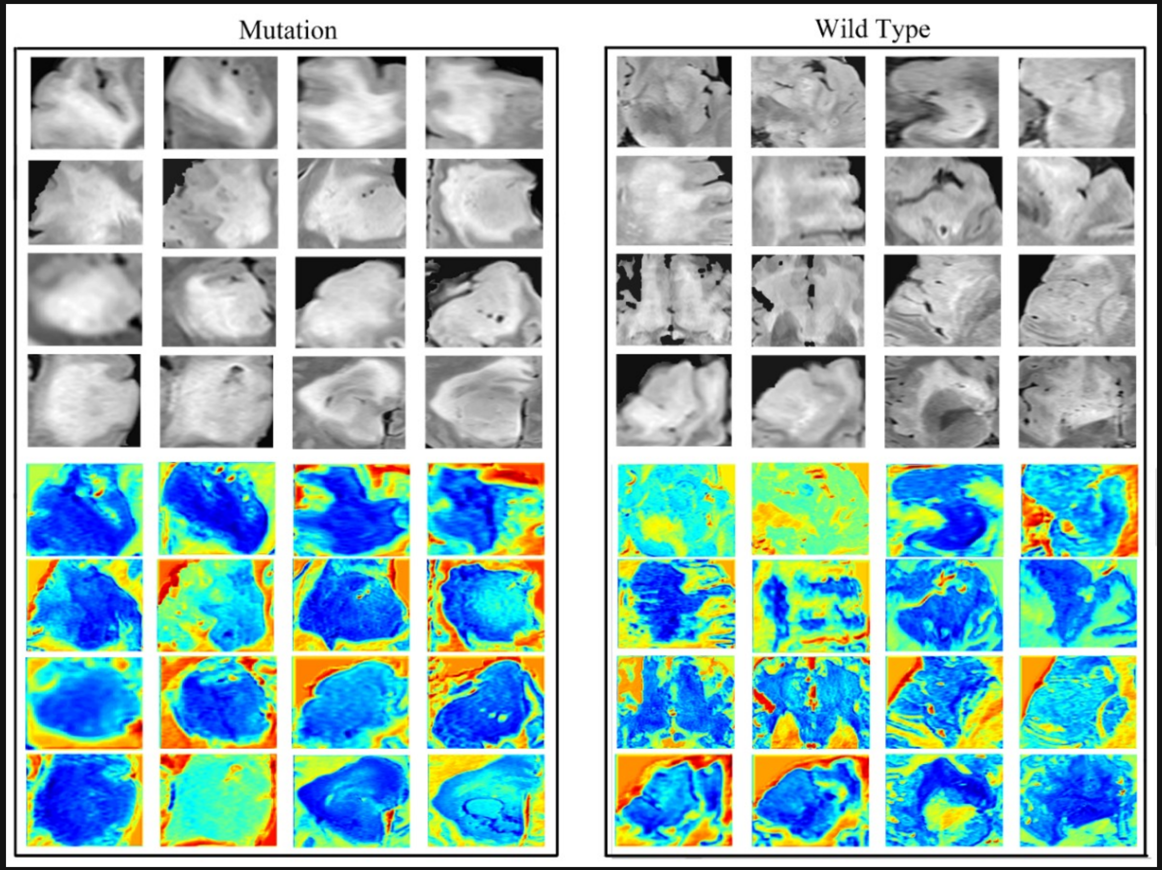
- The best performance can be obtained based on the last convolutional layer
- Deeper layers have more information about the details and internal textures

Methods	AUC	ACC	SENS	SPEC	PPV	NPV	MCC
Conv.1	0.6165	0.5630	0.5393	0.6333	0.8136	0.3167	0.1499
Conv.2	0.7109	0.6387	0.6404	0.6333	0.8382	0.3725	0.2402
Conv.3	0.8858	0.8403	0.9213	0.6000	0.8723	0.7200	0.5557
Conv.4	0.8734	0.7899	0.8876	0.5000	0.8404	0.6000	0.4132
Conv.5	0.9004	0.8571	0.9101	**0.7000**	**0.9000**	0.7241	0.6171
Fc.7	0.8614	0.8319	0.9326	0.5333	0.8557	0.7273	0.5212
Fc.8	0.7524	0.7647	0.8876	0.4000	0.8144	0.5455	0.3217
Conv.6	**0.9157**	**0.8655**	**0.9438**	0.6333	0.8842	**0.7917**	**0.6246**

DLR: Image based biomarker prediction

Results

- Some of the information obtained in the feature layer is related to the biomarker information of the tumor

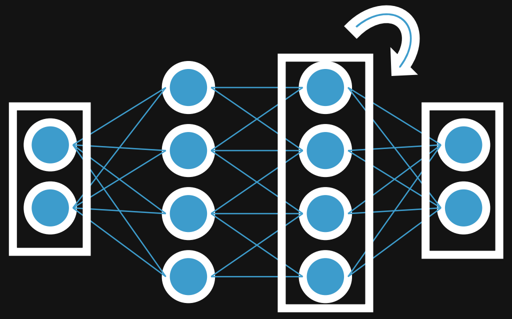


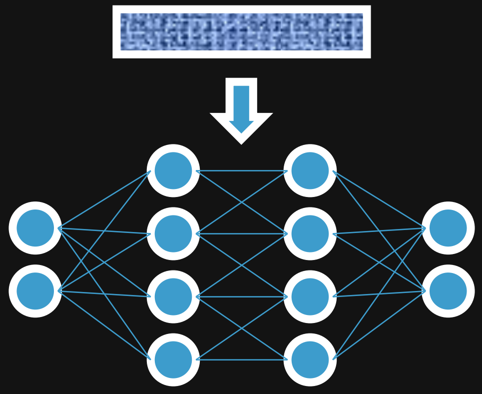
Take home message

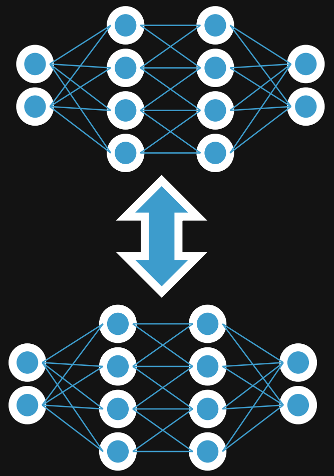
Conclusion

- To boost the performance of deep neural network for medical imaging, it is usefully to consider integrating more knowledge into the network.

- To integrate **task-specific** knowledge in an obvious way
- To integrate **cross-domain** knowledge in the latent space
- To integrate **inter-process** knowledge by combining them







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Thank you!

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