AI for Image Reconstruction

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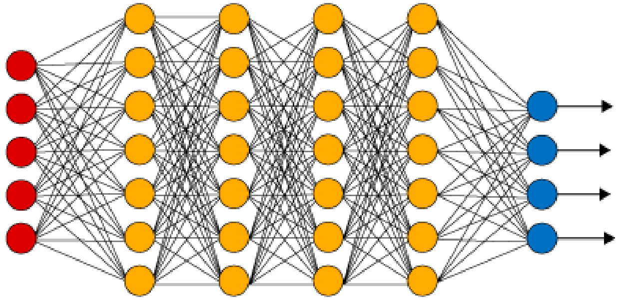
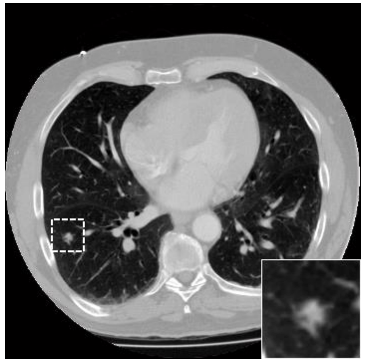
Introduction - Deep Neural Networks



- **Strong expression power**
  - **Good approximation of most complicated functions**
- Easy Realization
  - Composed of simple operations such as convolution
  - Training by backpropagation (chain rule of derivative)
  - High performance toolkit (Tensorflow, Caffe, etc.)

Applications of deep learning in medical imaging

- Detection

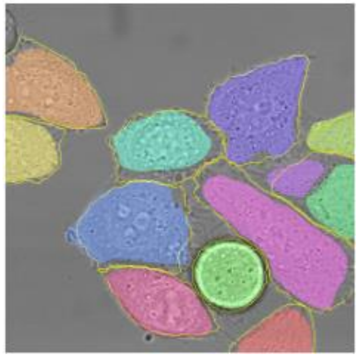


Wu, Dufan, et al. "End-to-End Abnormality Detection in Medical Imaging." *arXiv preprint arXiv:1711.02074* (2017).

- Classification

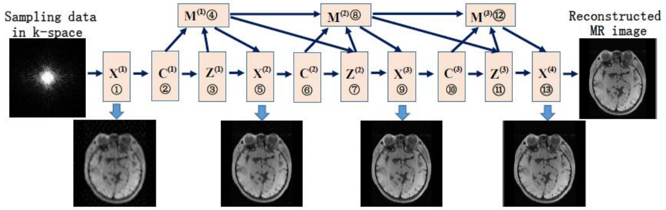
Esteva, Andre, et al. "Dermatologist-level classification of skin cancer with deep neural networks." *Nature* 542.7639 (2017): 115-118.

- Segmentation



Ronneberger, Olaf, et al. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2015.

- Reconstruction



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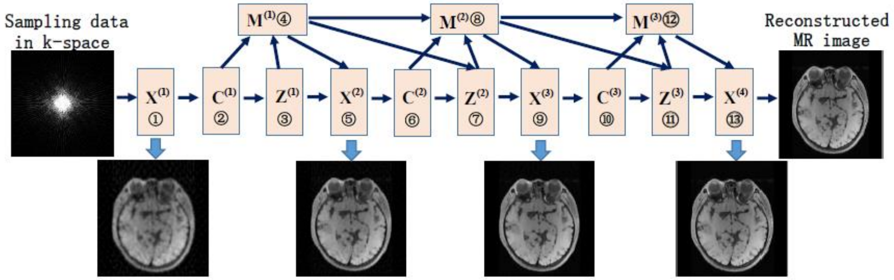

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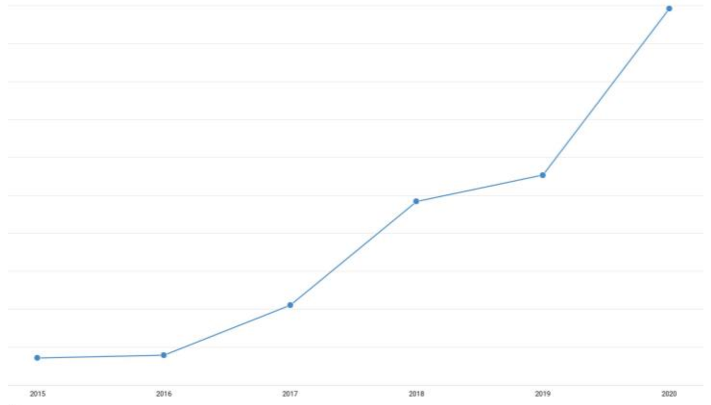


2015 2020

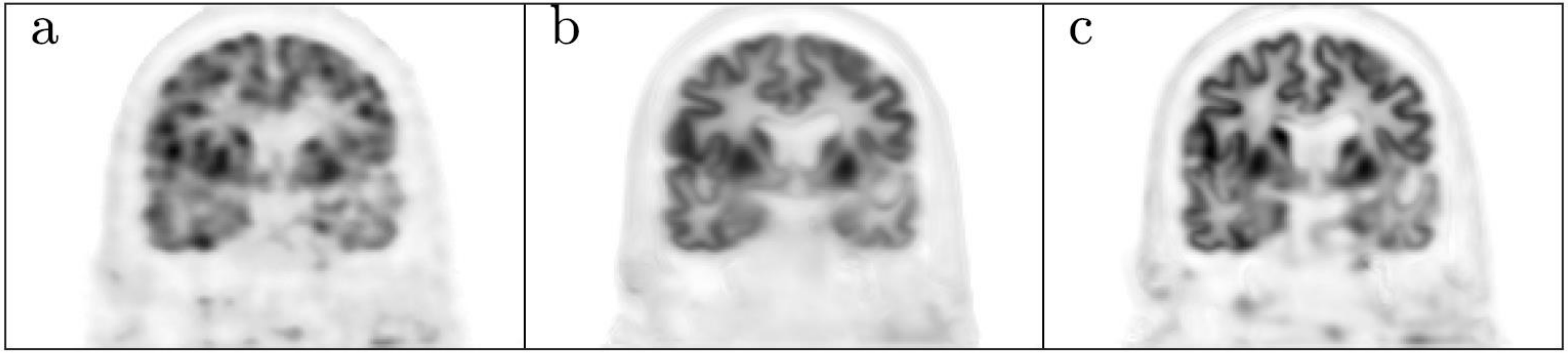
- Supervised Learning
  - Large Training Data with Labels
  - Annotation is bottle neck
- Unsupervised Learning
  - Large Training Data without Label
  - Single Training Data (same subject) w/o Label
- Semi-supervised Learning

- Structure
  - ResNet
  - U-NET
  - ……

- Not Covered
  - MRI
  - PET corrections (Attn, Scatters)
  - Denoising

Method: Deep Image Prior

- Unlike natural images, *prior images of the same subject*, instead of random noise, can be employed as network input, which should further improve the results.
- Instead of using the corrupted image as training labels, *sinogram data can be utilized* as training labels and training function can be formulated based on maximum likelihood *(Gong et al 2018).*



(a) Denoising with random noise as network input

(b) Denoising with MR prior as network input

(c) Reconstruction with MR prior as network input

K. Gong, ... Q. Li, IEEE Transactions on Medical Imaging, Dec, 2018

Introduction – Image Reconstruction

$$L(y\,|\,x)=\sum_{i=1}^{N} y_i \log([Px]_i + r_i + s_i) - ([Px]_i + r_i + s_i)$$

Data Model

$$P(x)=\frac{1}{Z}e^{-\beta U(x)}$$

Image Model

Cost Function MAP

$$\Phi(x,y)=L(y\,|\,x)-\beta U(x)$$

System Model

$$y=\mathbf{P}x$$

$$\mathbf{P}=\mathbf{P}_{norm}\mathbf{P}_{blur}\mathbf{P}_{attn}\mathbf{P}_{geom}\mathbf{P}_{range}$$

Optimization Algorithms

- ❑ OSEM
- ❑ Modified BSREM
- ❑ Relax OS-SPS
- ❑ PCG

Statistical PET Reconstruction

Outline

- DL in Penalty Function in Recon
  - PET & CT
- DL in Image Model in Recon (PET)
  - Kernel Based Method
  - Deep Image Prior on Static Recon
- Unroll Type Network in Recon
  - PET EM-NET
  - CT – single energy & dual energy
- Parametric (kinetic) Imaging
- Opportunity and Challenge

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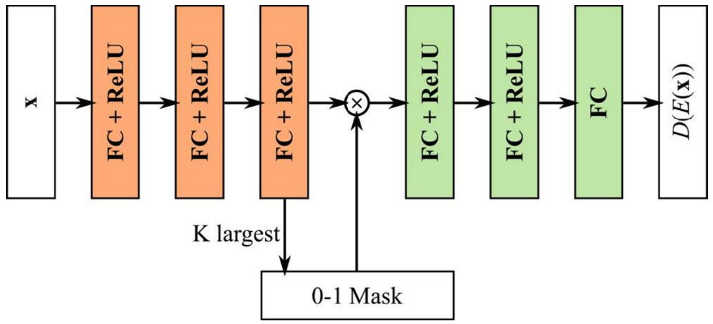
- Parametric (kinetic) Imaging
  - Indirect
  - Direct
  - Hybrid

- Opportunity and Challenge

DL based CT Reconstruction algorithm

- K-sparse autoencoder (KSAE)

$$E, D = \arg\min \sum_k ||\mathbf{x}_k - D(E(\mathbf{x}_k))||_2$$
$$s.t.\ ||E(\mathbf{x}_k)||_0 \leq K$$



KSAE trained on local patches with fully connected network.

  - K – sparsity level, approximately 10% of the length of encoded data.
  - Greatly enforced the details compare to normal autoencoder.

- After KSAE is trained, we can use standard penalized loss function

$$\mathbf{x}, \mathbf{y} = \arg\min ||\mathbf{A}\mathbf{x} - \mathbf{b}||_{\mathbf{w}}^2 + \beta \sum_m^M ||\mathbf{P}_m \mathbf{x} - D(E(\mathbf{y}_m))||_2^2$$
$$s.t.\ ||E(\mathbf{y}_m)||_0 \leq K, \quad m = 1, 2, \ldots, M \qquad (3)$$

  - $\mathbf{x}$ – image to be reconstructed; $\mathbf{y}_m$ - latent image for mth patch; $\mathbf{P}_m$ - patch operator.

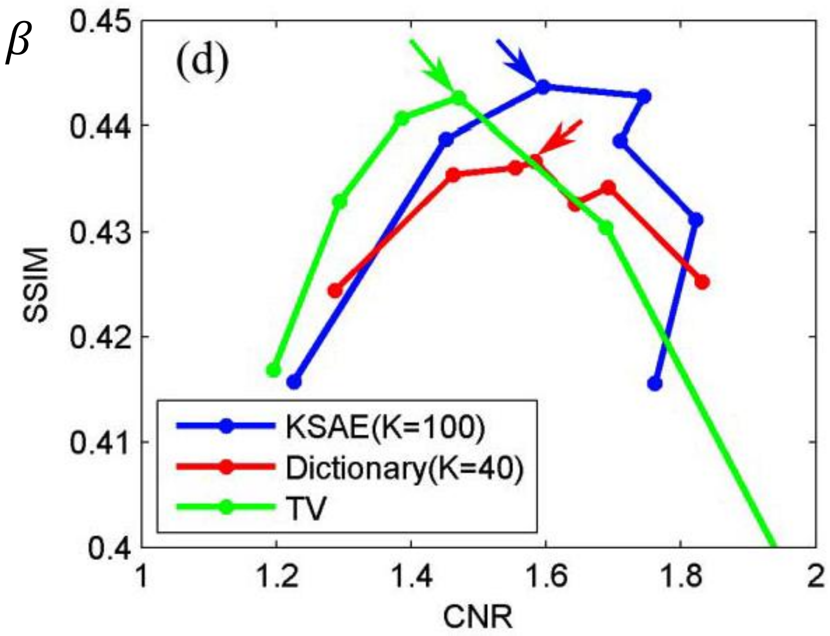
- The problem can be solved via alternative optimization
  - Monotonic; $\mathbf{x}$ part can be optimized via SQS;
  - $\mathbf{y}$ part can be optimized via gradient descent. L0 constraint was enforced via greedy method.

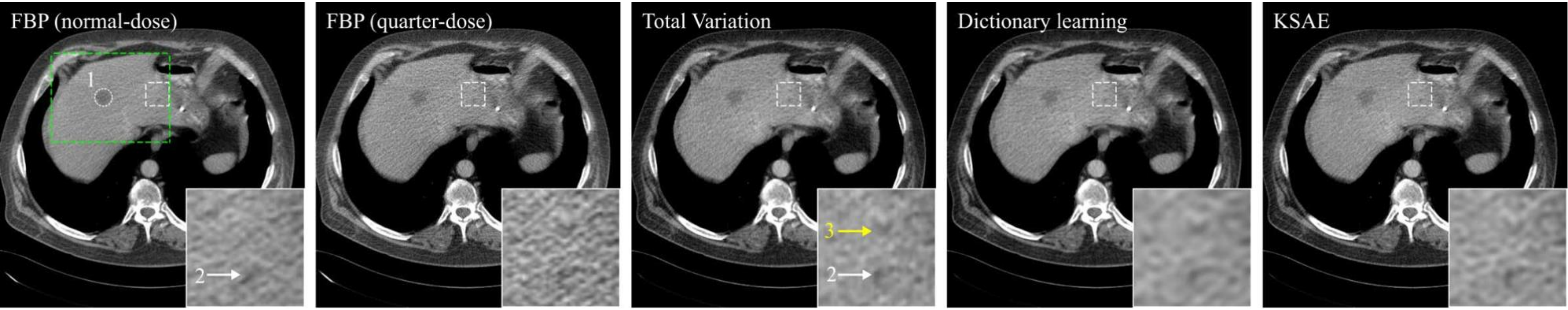
D. Wu, …, Q. Li, IEEE transactions on medical imaging 36 (12), 2479-2486

DL based CT Recon

- KSAE had improved SSIM-CNR compared to TV and dictionary learning.
- It also gave improved lesion visibility and lower false positivity in the images.

SSIM-CNR trade-offs with β





KSAE kept the true lesion (white arrow 2) and reduced the false lesion (yellow arrow 3) compared to other low-dose results.

D. Wu, …, Q. Li, IEEE transactions on medical imaging 36 (12), 2479-2486

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Image Model

- For image reconstruction inverse problems,

$$\boldsymbol{y} = \boldsymbol{P}\boldsymbol{x} + \boldsymbol{r}$$

- Change $\boldsymbol{x}$ to be the output of a network $f(\boldsymbol{z}|\boldsymbol{\theta})$

$$\boldsymbol{y} = \boldsymbol{P}f(\boldsymbol{z}|\boldsymbol{\theta}) + \boldsymbol{r}$$

  - $\boldsymbol{z}$ is the input to the network, *unknown parameters*.
  - $\boldsymbol{\theta} = [\boldsymbol{w}, \boldsymbol{b}]$ are the parameters of the network, pre-trained using low-dose and high-does pairs.

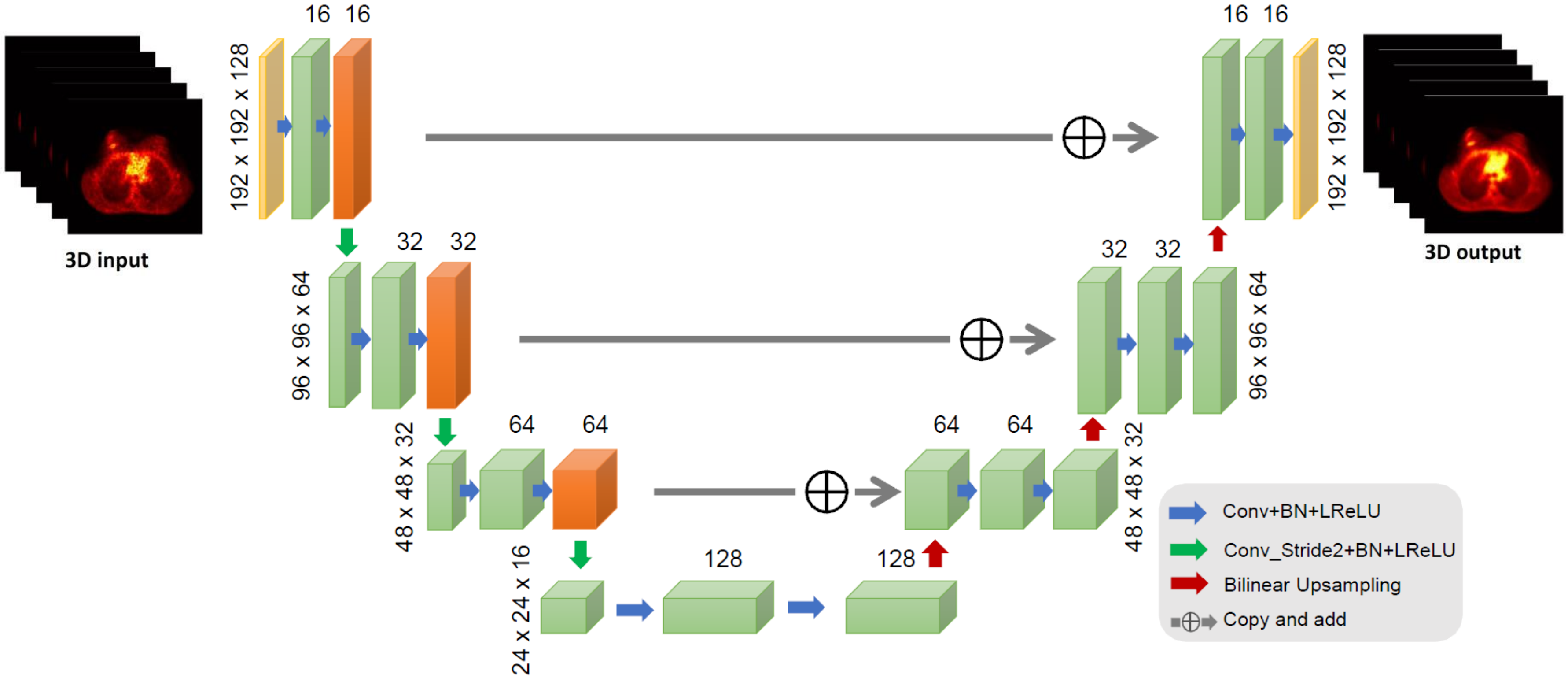
- Based on the distribution of the measurement data,

$$\hat{\boldsymbol{z}} = \arg\max_{\boldsymbol{z}} L(\boldsymbol{y}|f(\boldsymbol{z}|\boldsymbol{\theta})) \qquad (1)$$

  - Directly optimizing (1) is difficult as the projector is coupled with network output

K. Gong, …, Q. Li, IEEE transactions on medical imaging 38 (3), 675-685

Network Structure

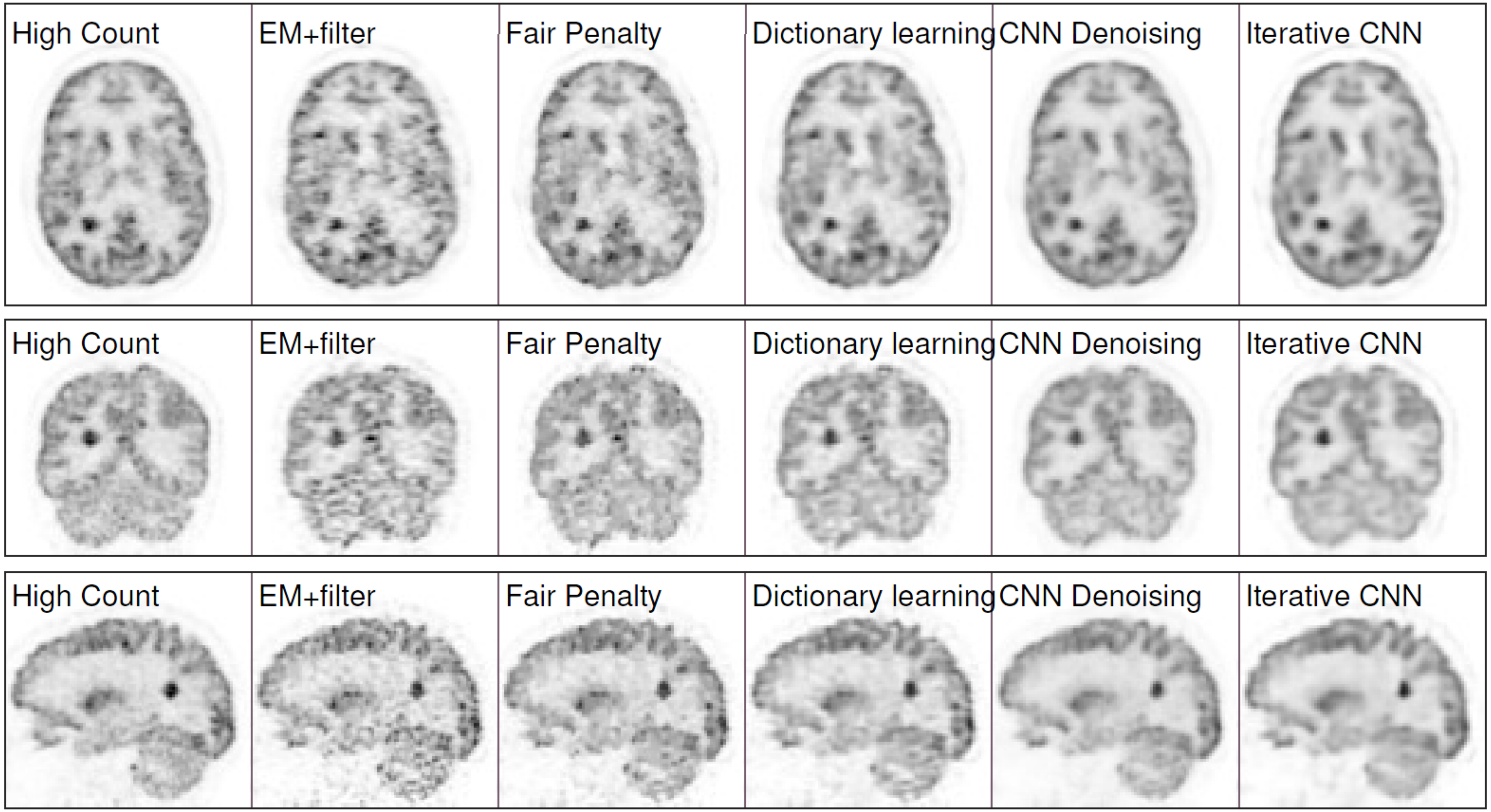


- 3D U-net was employed as the network structure, pretrained using high-quality training pairs.

K. Gong, …, Q. Li, IEEE transactions on medical imaging 38 (3), 675-685

Result: brain datasets

- Acquired from GE Signa PET-MR



- Proposed Iterative CNN can have *higher uptake* in synthetic tumor and *lower noise*

K. Gong, …, Q. Li, IEEE transactions on medical imaging 38 (3), 675-685

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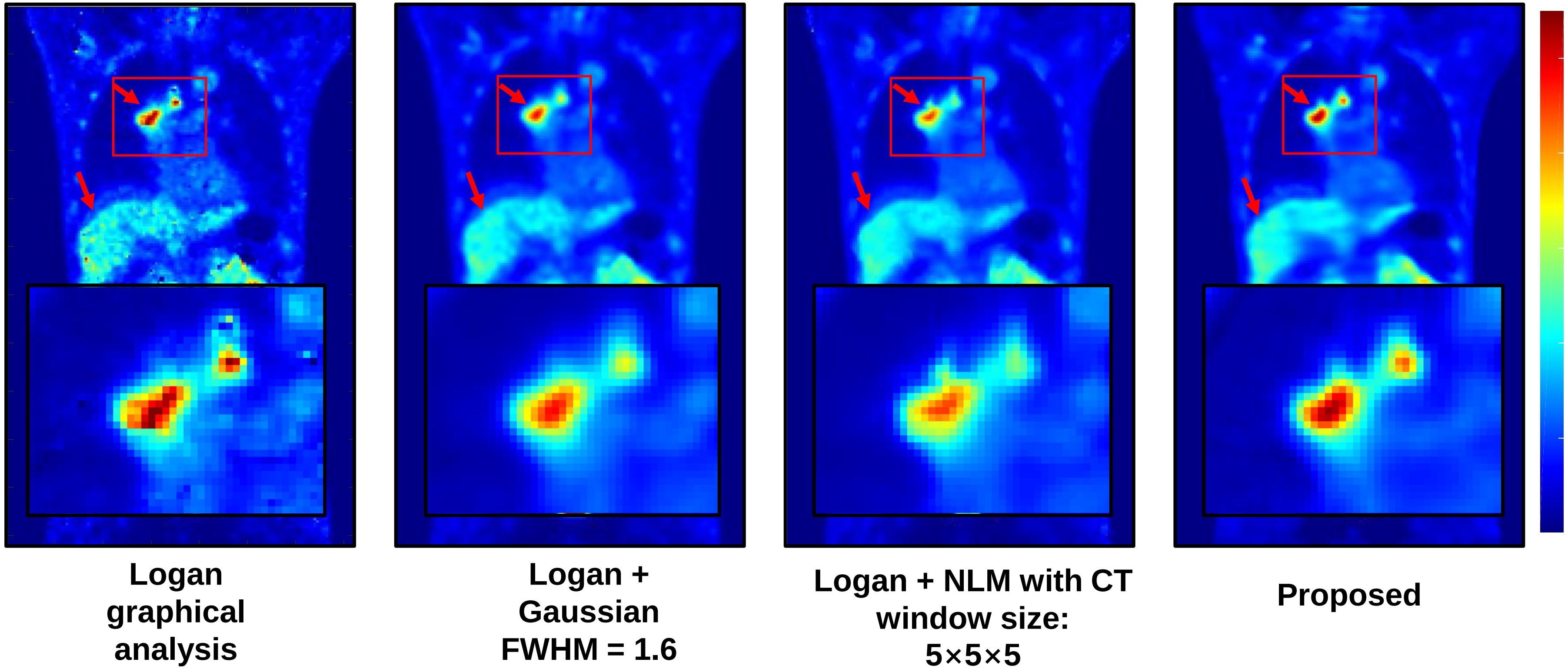
Indirect Parametric Imaging - real data

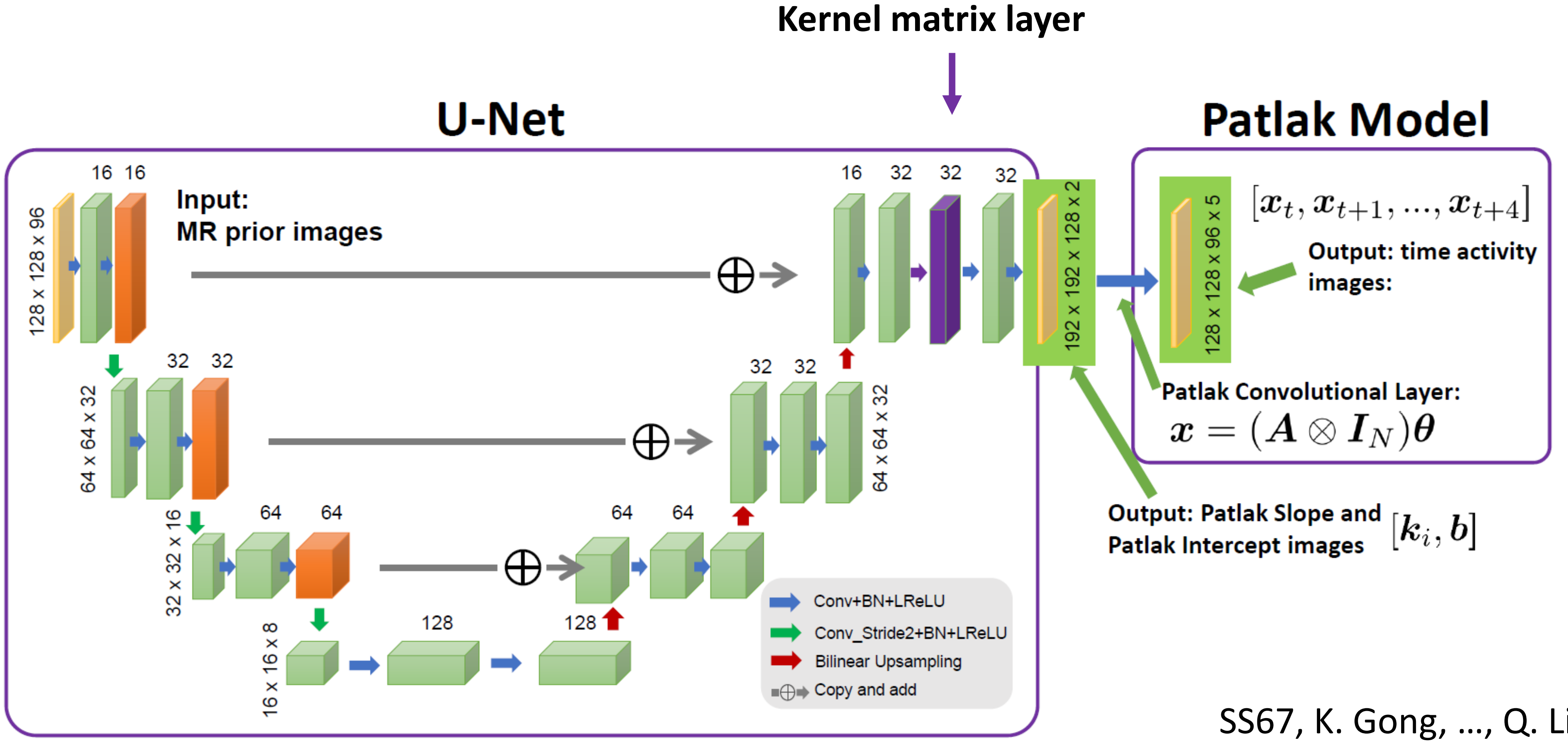


- The proposed method *reduces* image noise, while *preserving* tumor uptake.

Cui, J., …, Li, Q., 2019, March. CT-guided PET parametric image reconstruction using deep neural network without prior training data. In *Medical Imaging 2019: Physics of Medical Imaging* (Vol. 10948, p. 109480Z).

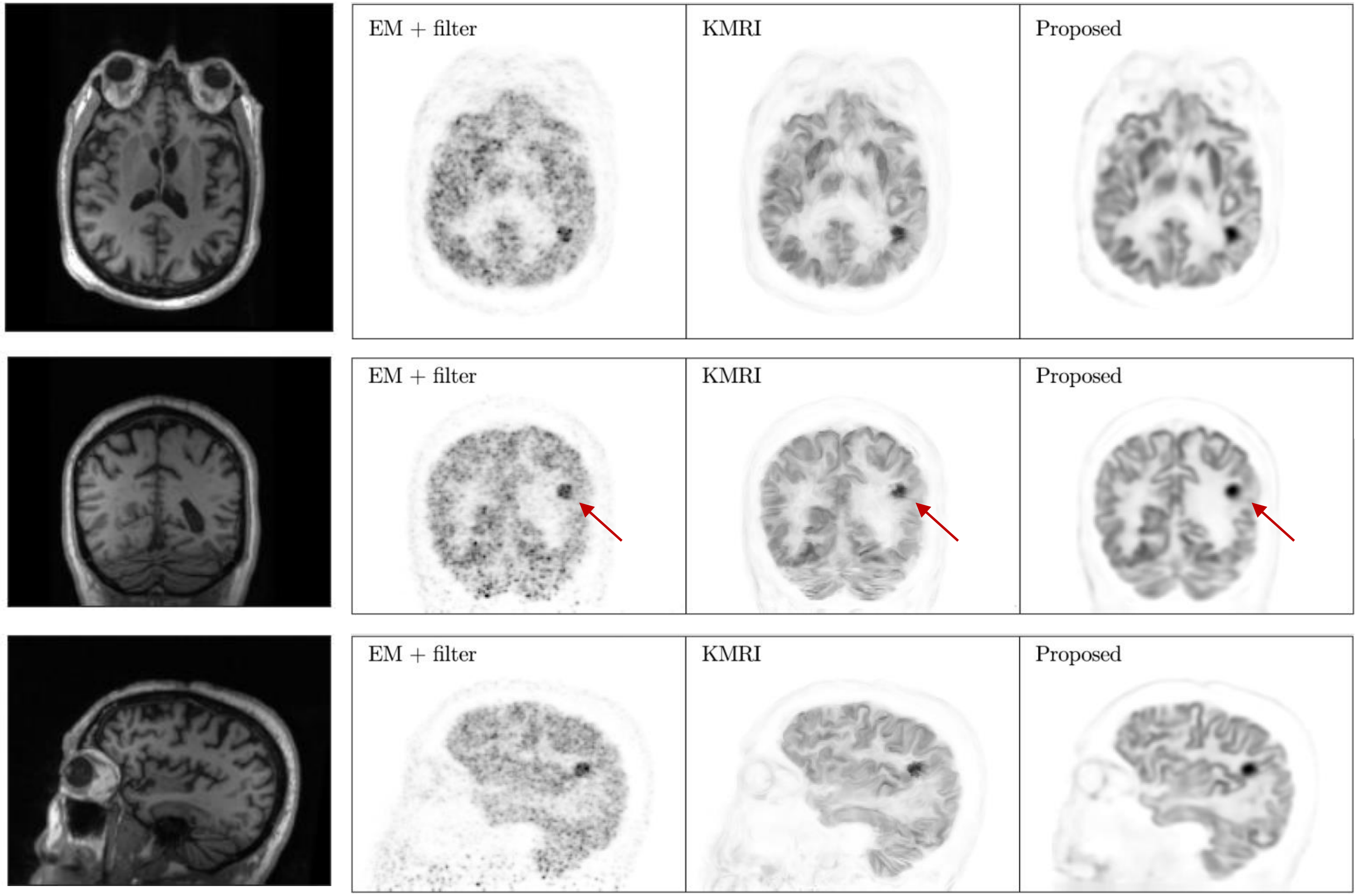
Direct Parametric Imaging - Patlak

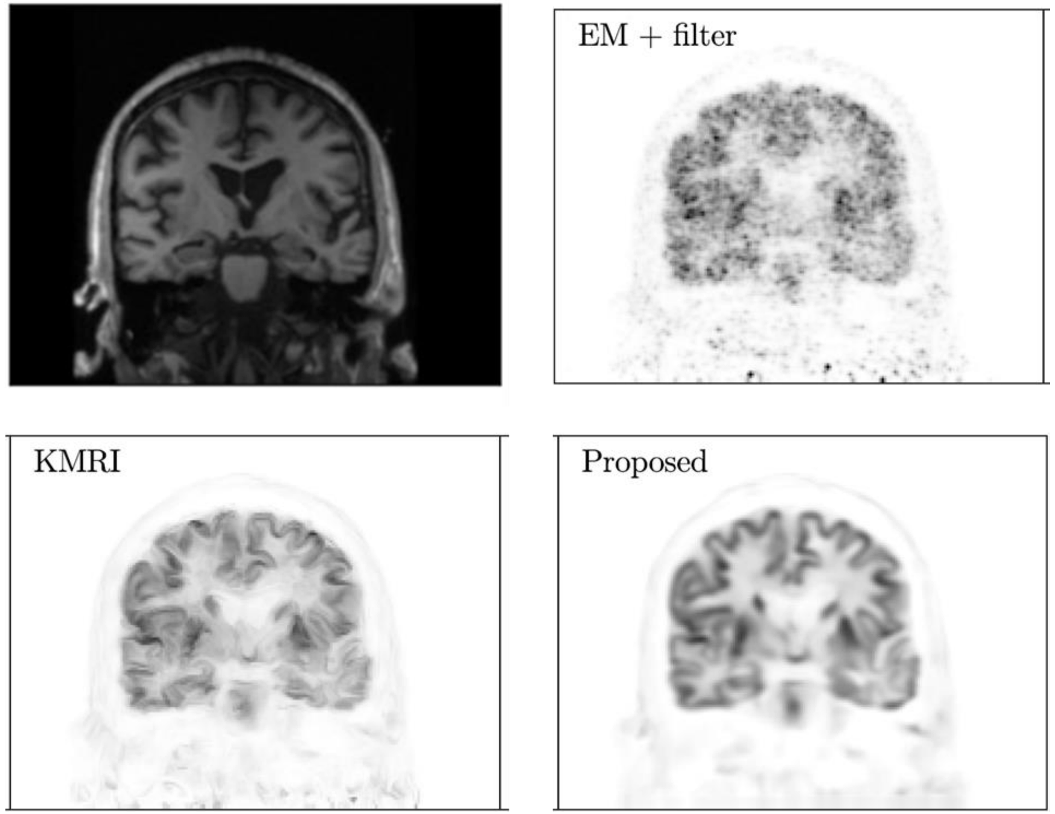
- 3D modified U-net structure (Ronneberger *et al* 2015) is employed as part of the network $f(\boldsymbol{\theta}|\boldsymbol{z}, \boldsymbol{A}, \boldsymbol{K})$:
- Backpropagation of the Kernel matrix layer is $\boldsymbol{K}'\boldsymbol{x}$.
- Patlak layer is 1x 1 x 2 convolution.



SS67, K. Gong, ..., Q. Li, SNMMI 2019

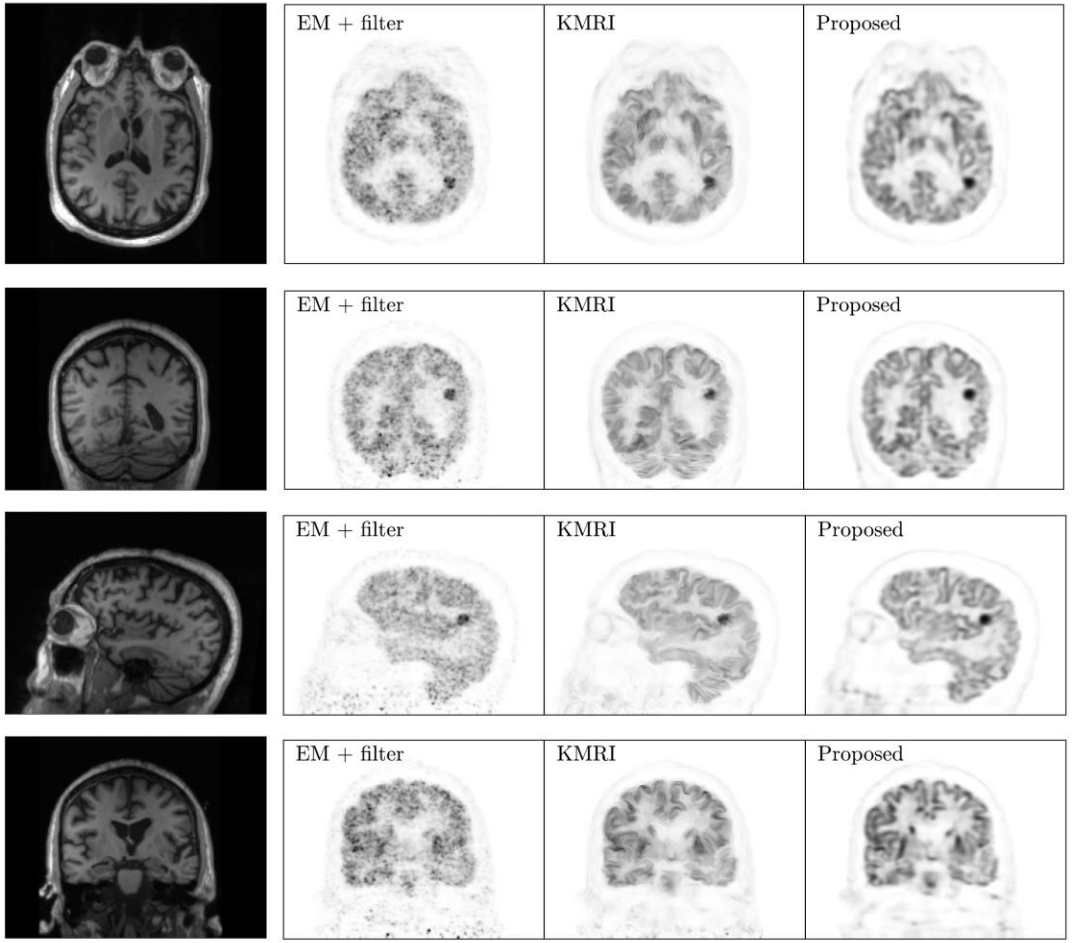
Direct Parametric Imaging – Patlak - Clinical Data Results





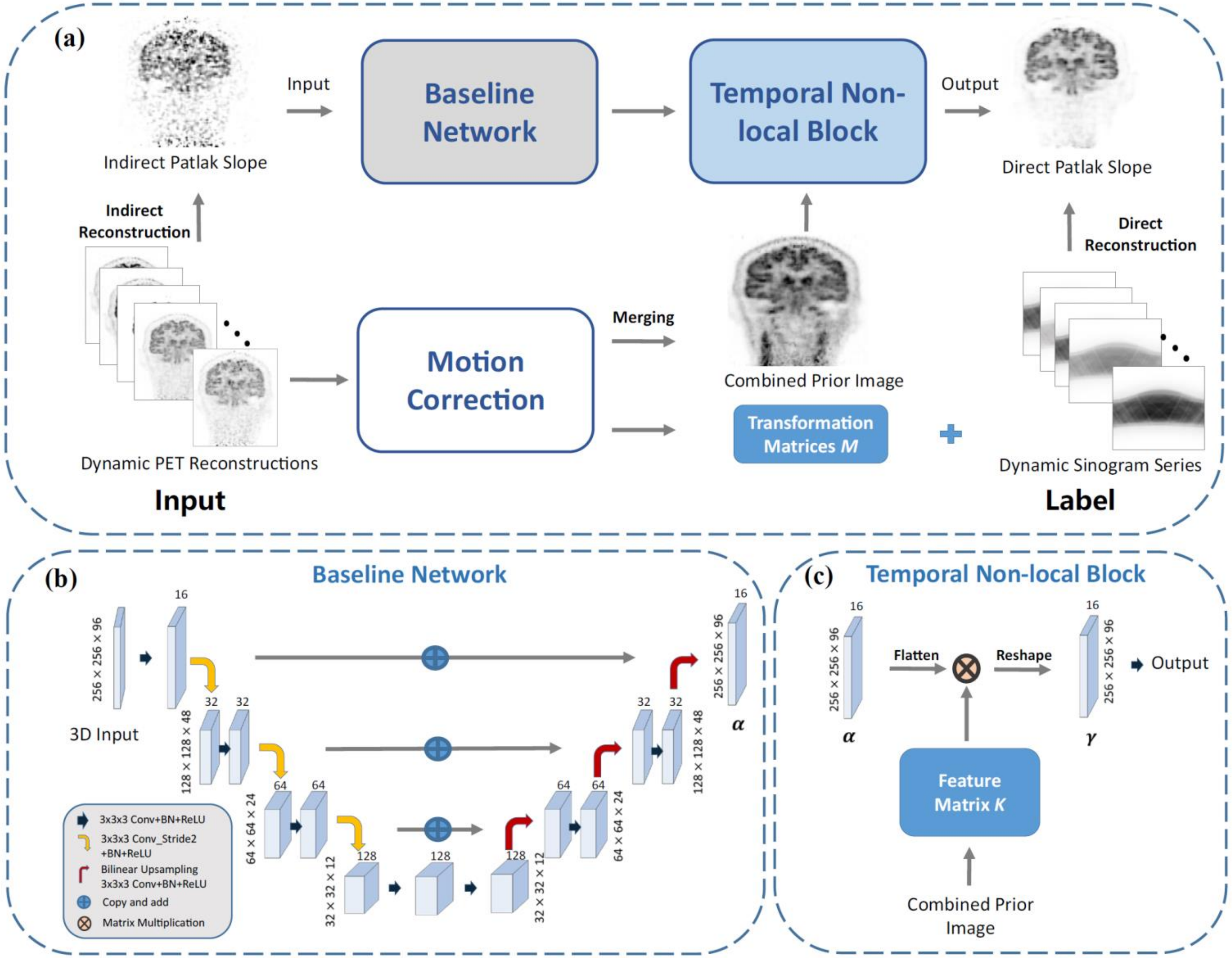
SS67, K. Gong, …, Q. Li, SNMMI 2019

Direct Parametric Imaging – Logan - Clinical Data Results



K. Gong, …, Q. Li, IEEE TMI, submitted

Rapid High-Quality PET Patlak Parametric Imaging



N. Xie … Q. Li, Neuroimage, in press

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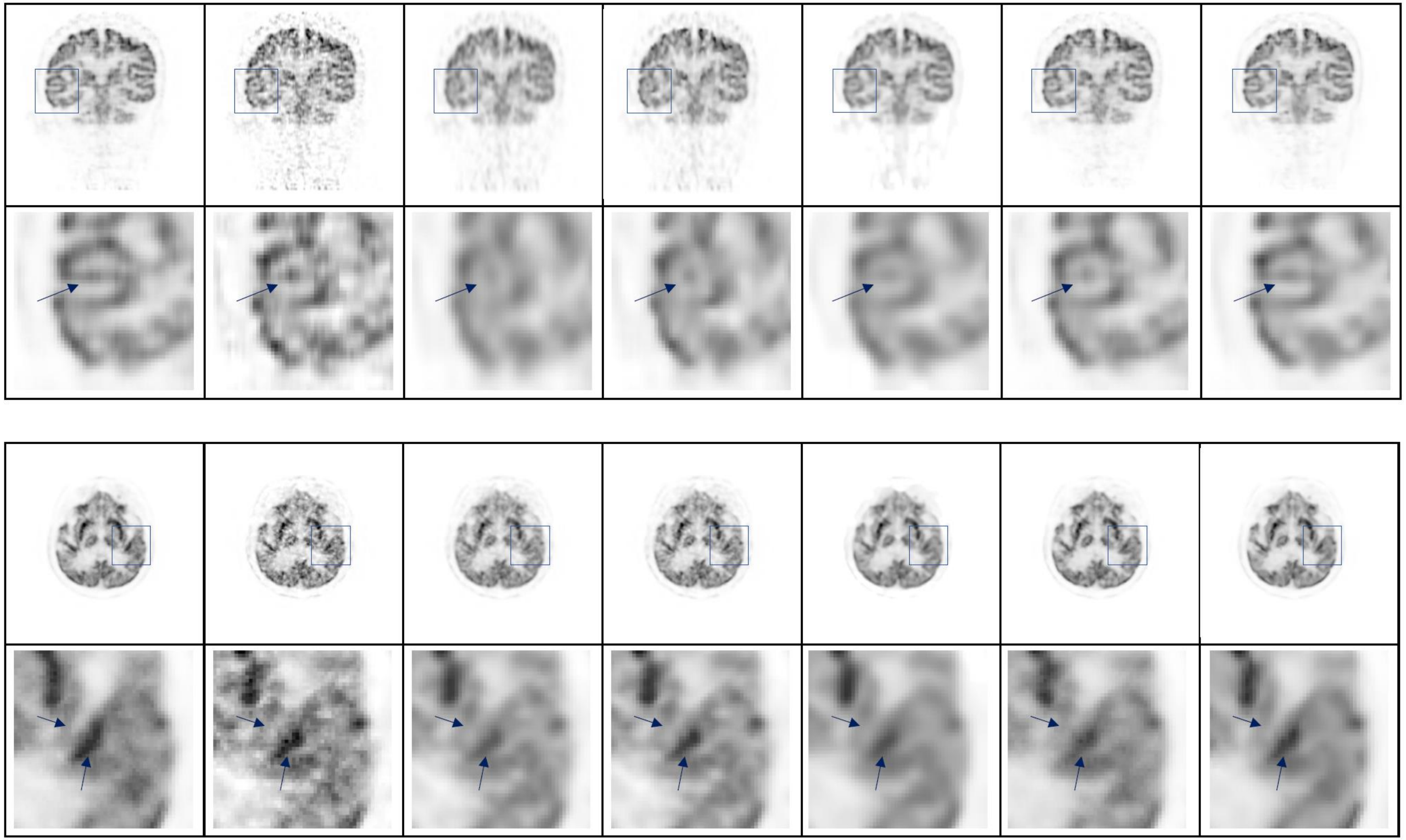

(a) Label (b) Full-dose Input (c) Gaussian (d) NLM (e) BM4D (f) Proposed-Base (g) Proposed-TNL

N. Xie … Q. Li, Neuroimage, in press

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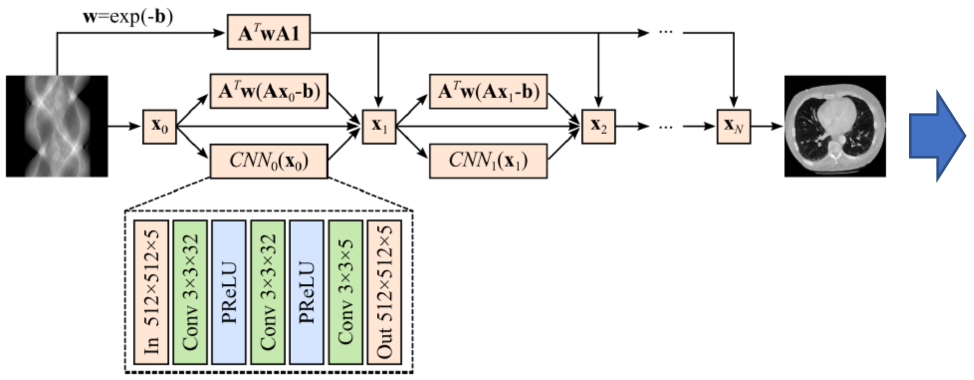
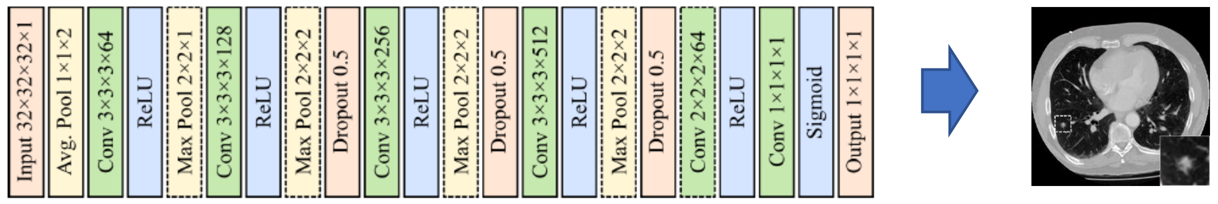
Opportunities

- End2End Image Reconstruction (e.g. task-based image reconstruction, theranostics)





D. Wu, …, Q. Li, International Workshop on Machine Learning in Medical Imaging, 37-45

- Explainable AI
  - Uncertainty
  - Explainable patterns

- Transfer Learning for new contrast mechanism
  - Domain adaptation with few shot learning
  - Domain generalization with few shot learning

- Reliable detection of weak signal
  - Super low count rate scan
  - Nonstationary kinetic modeling,　treatment response

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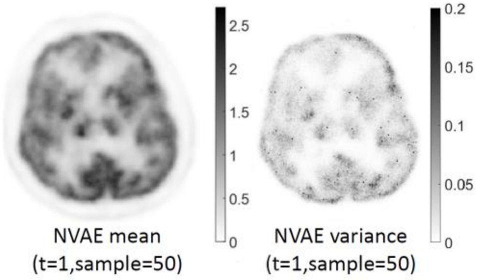

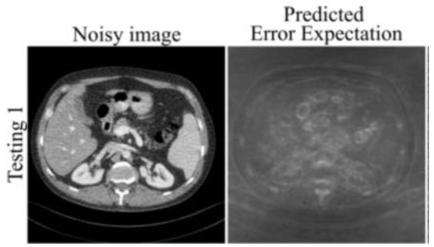

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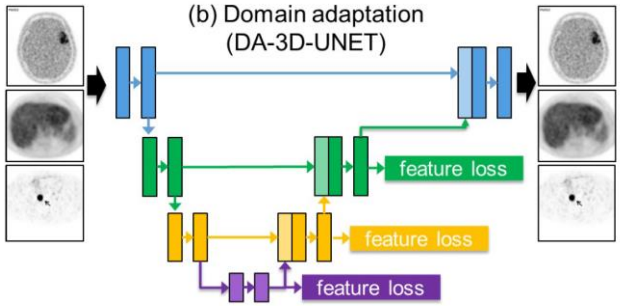

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Challenges

- Lack of standards
  - Common database
- Bias, equality and diversity
- Training of MD and PhD
- Deployment
- Post-market surveillance and continuous learning

Thanks for your attention！

NIA RF1AG052653
NIBIB P41EB022544

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