Summer Internship
: Brain PET Image Denoising

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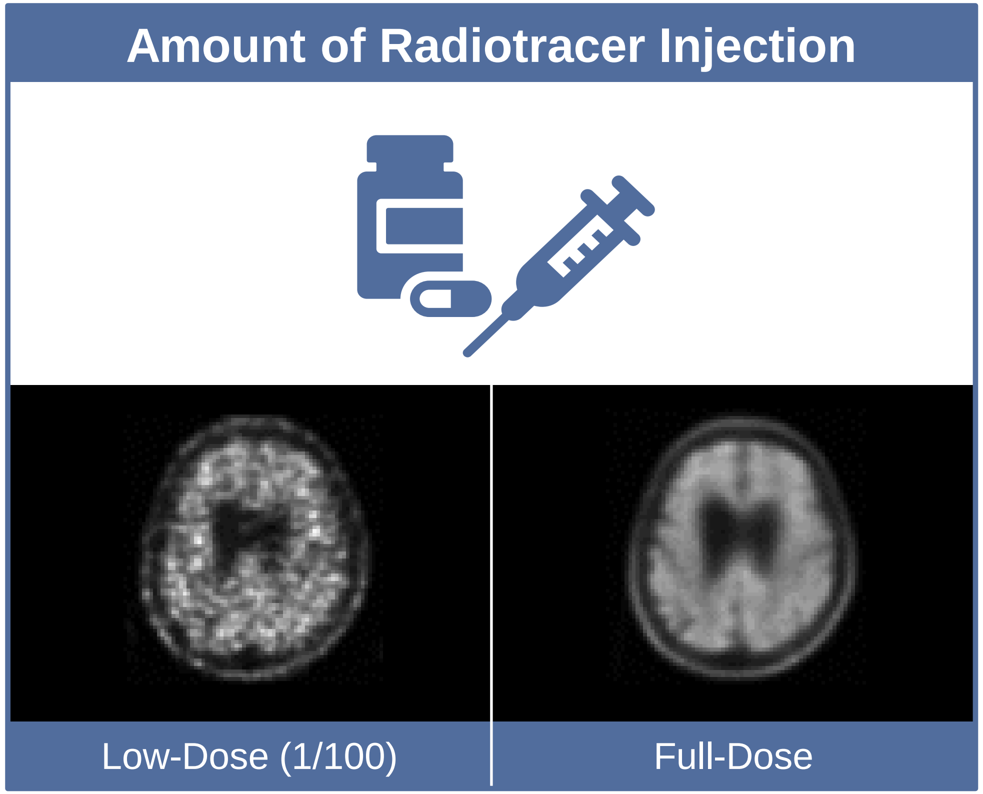
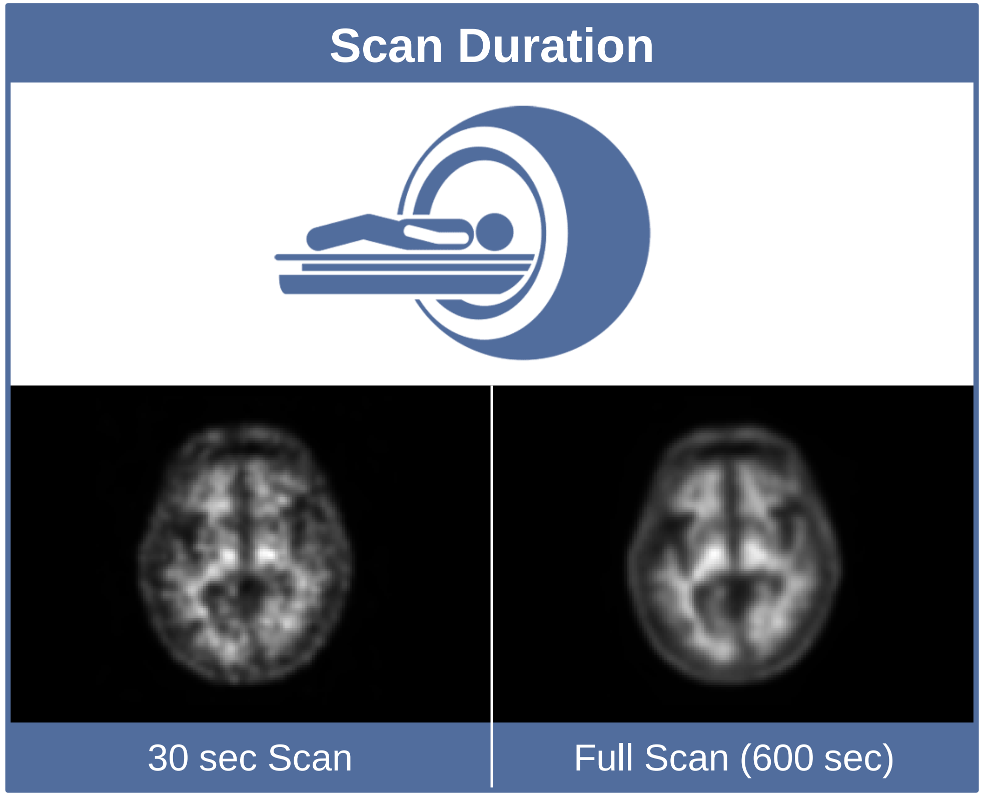
Outline

Brain PET Image Denoising

1. Introduction

- **PET (Positron Emission Tomography) Imaging**
  - **Low spatial resolution** and **signal-to-noise ratio** **limit** the **detection** and **quantitative accuracy** of **PET imaging**

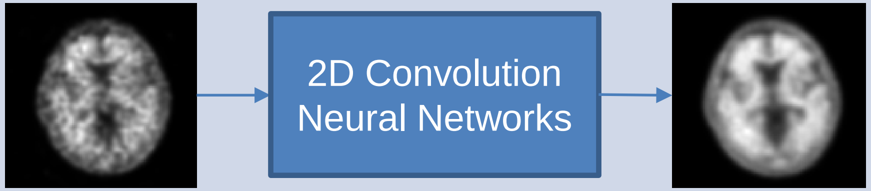
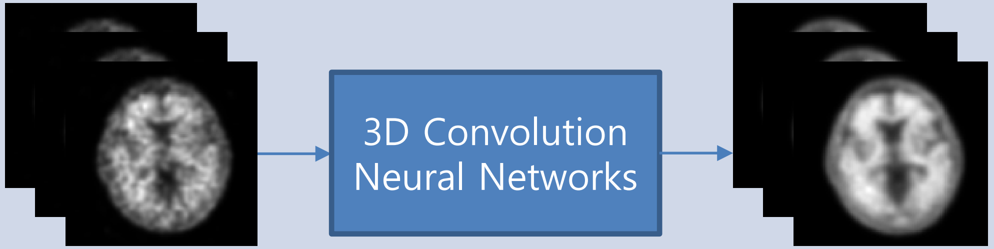
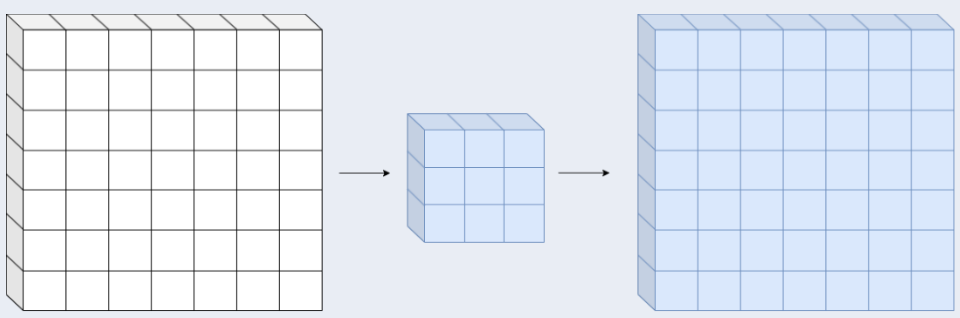
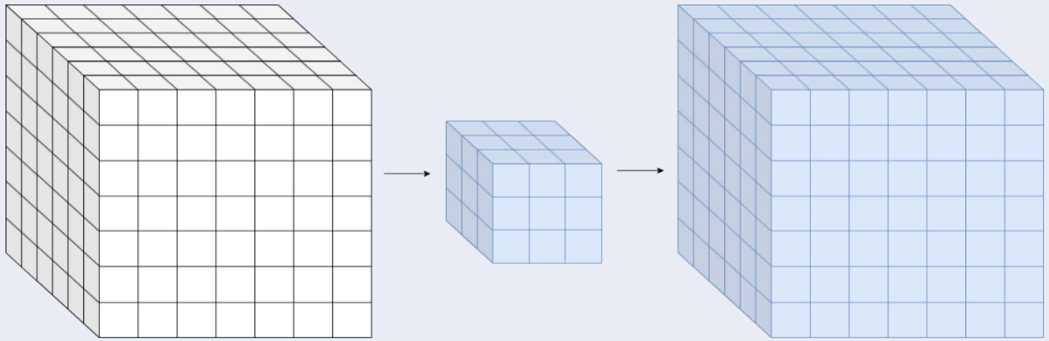




⇒ **To improve PET image quality, denoising** has become a **crucial pre-processing step** for PET imaging

1. Introduction

- **PET image**: three-dimensional, volumetric medical data
- **3D Medical Image**

2D Convolution	3D Convolution
	
 $C_i \times H_i \times W_i$ 2D Inputs; $C_i \times C_o \times K \times K$ 2D Kernels W; $C_o \times H_o \times W_o$ 2D Outputs	 $C_i \times D_i \times H_i \times W_i$ 3D Inputs; $C_i \times C_o \times K \times K \times K$ 3D Kernels W; $C_o \times D_o \times H_o \times W_o$ 3D Outputs
+) Large scale of 2D datasets available for training	**+)** Large 3D contexts can be captured in any axis
-) Limitations in learning large 3D contexts	**-)** Data scarcity and High computational cost

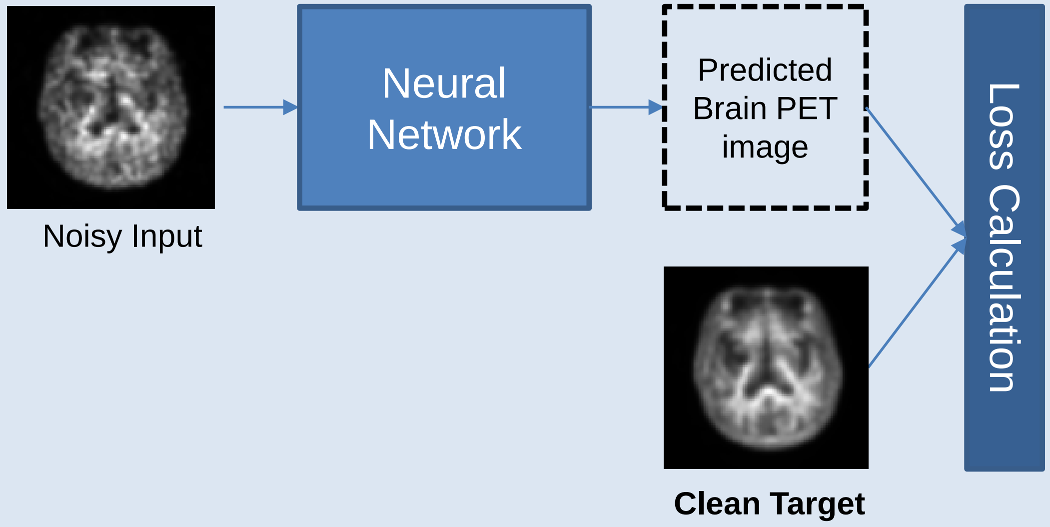
1. Introduction

- **Learning Algorithm**

Noise2Clean

$$\underset{\theta}{\operatorname{argmin}} \sum_i L(f_\theta(\hat{x}_i), y_i)$$

$f_\theta = network\ function,\ \hat{x}_i = noisy\ input,\ y_i = clean\ target$

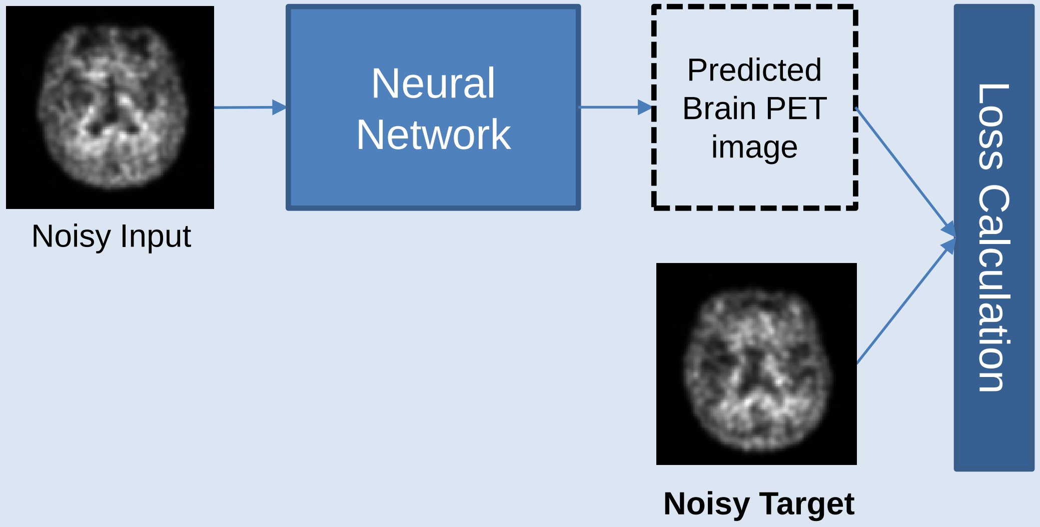


Supervised Learning

Noise2Noise

$$\underset{\theta}{\operatorname{argmin}} \sum_i L(f_\theta(\hat{x}_i), \hat{y}_i)$$

$f_\theta = network\ function,\ \hat{x}_i = noisy\ input,\ \hat{y}_i = noisy\ target$

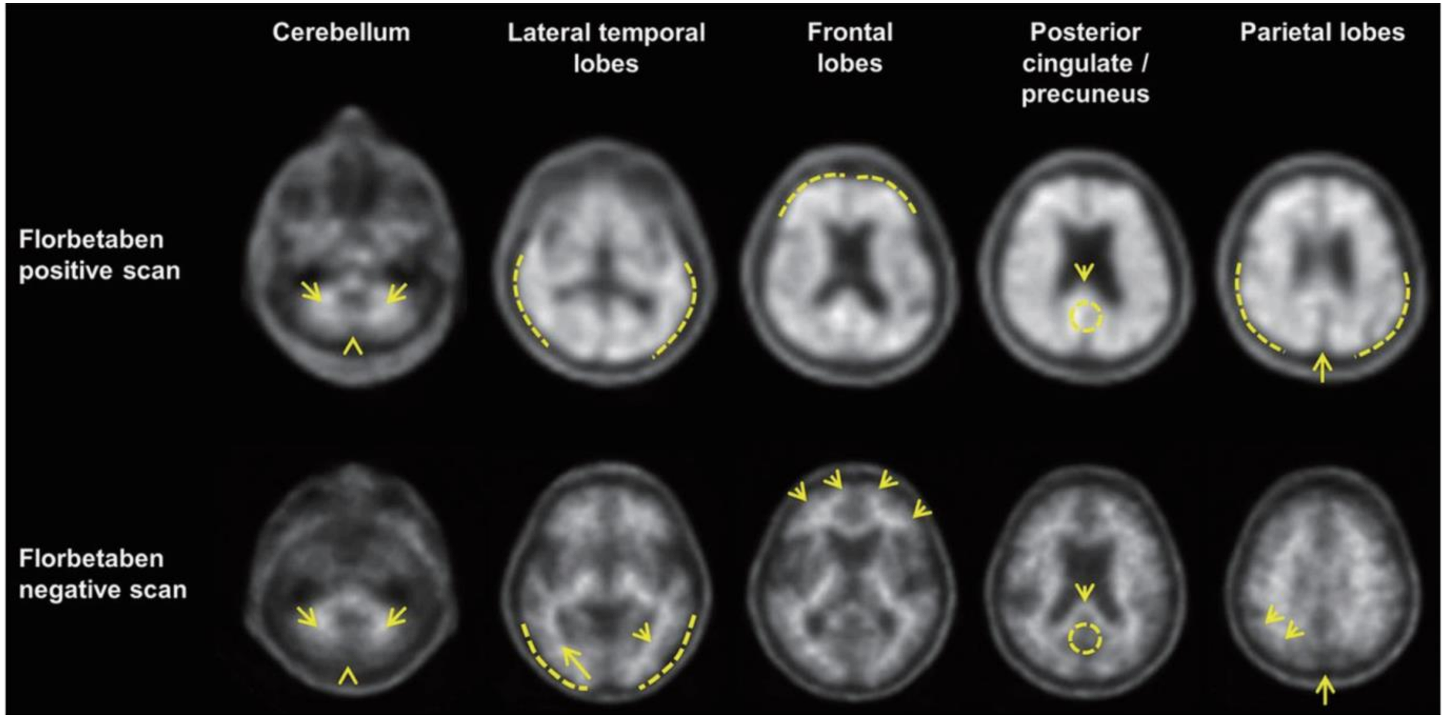


Self-supervised Learning

2. Method

1. Dataset

- **Dataset: ^{18}F-Florbetaben Brain PET data of 47 patients (40 for Training/ 7 for Testing)**
- β-amyloid neuritic plaque density in the brain ⇒ Alzheimer's disease diagnosis
- ^{18}F-Florbetaben is a radiotracer highly specific and sensitive for the β-amyloid neuritic plaque density
- **The intake of β-amyloid deposits in ^{18}F-FBB** informs that it is the progress of **Alzheimer's disease**



Normal and positive 18F-florbetaben scans in regions of interest.

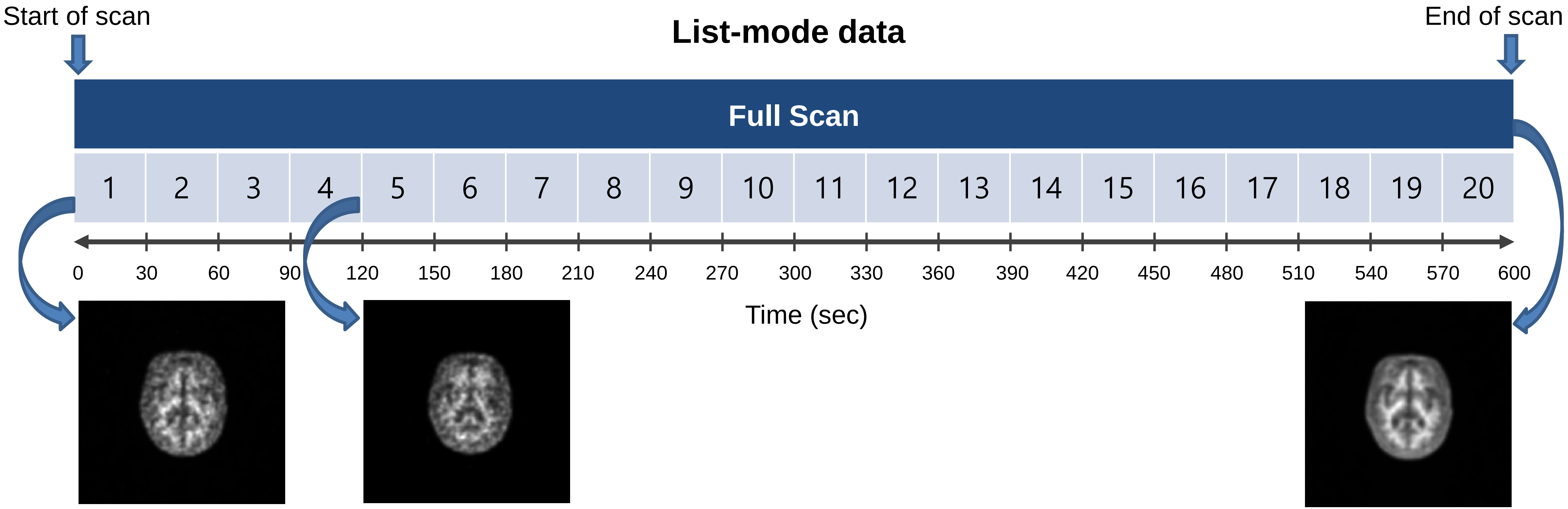
2. Method

1. Dataset

- List-mode PET data

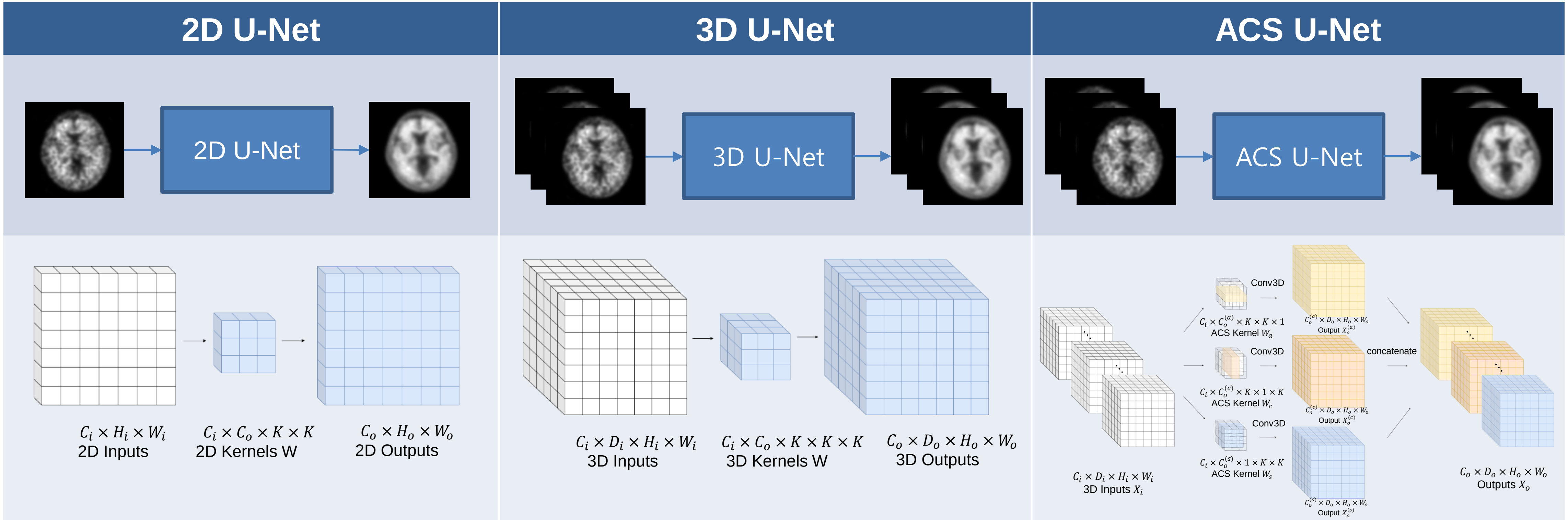
: 20 data bins with 30 second duration and 600 second reference data

- PET image matrix size: $200 \times 200 \times 109$, pixel size: $2.04 \times 2.04 \times 2.03\ mm^3$



2. Method

2. Network Architecture and Training

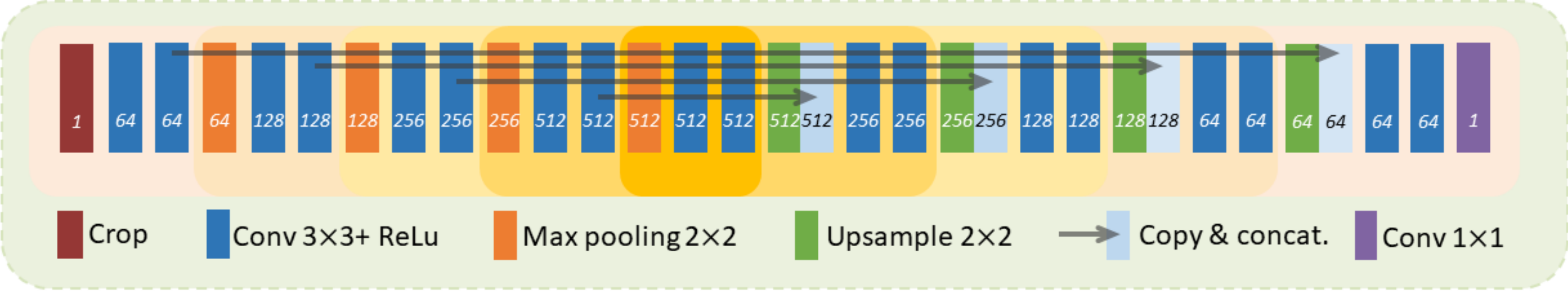


2. Method

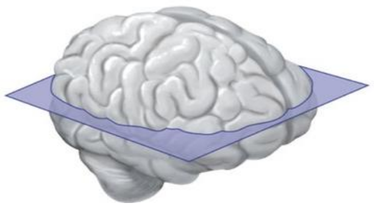
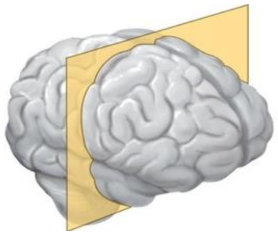
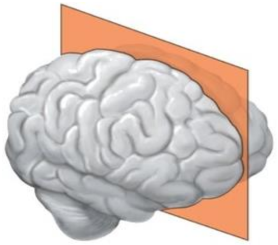
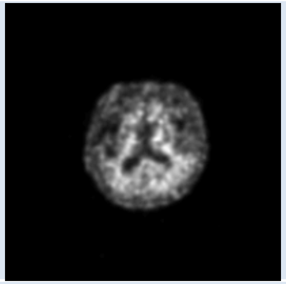
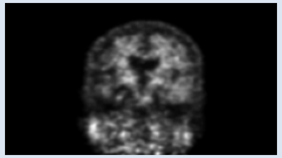
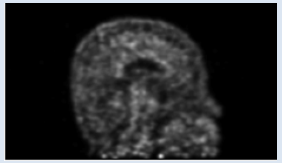
2. Network Architecture and Training

2D U-Net

2D U-Net



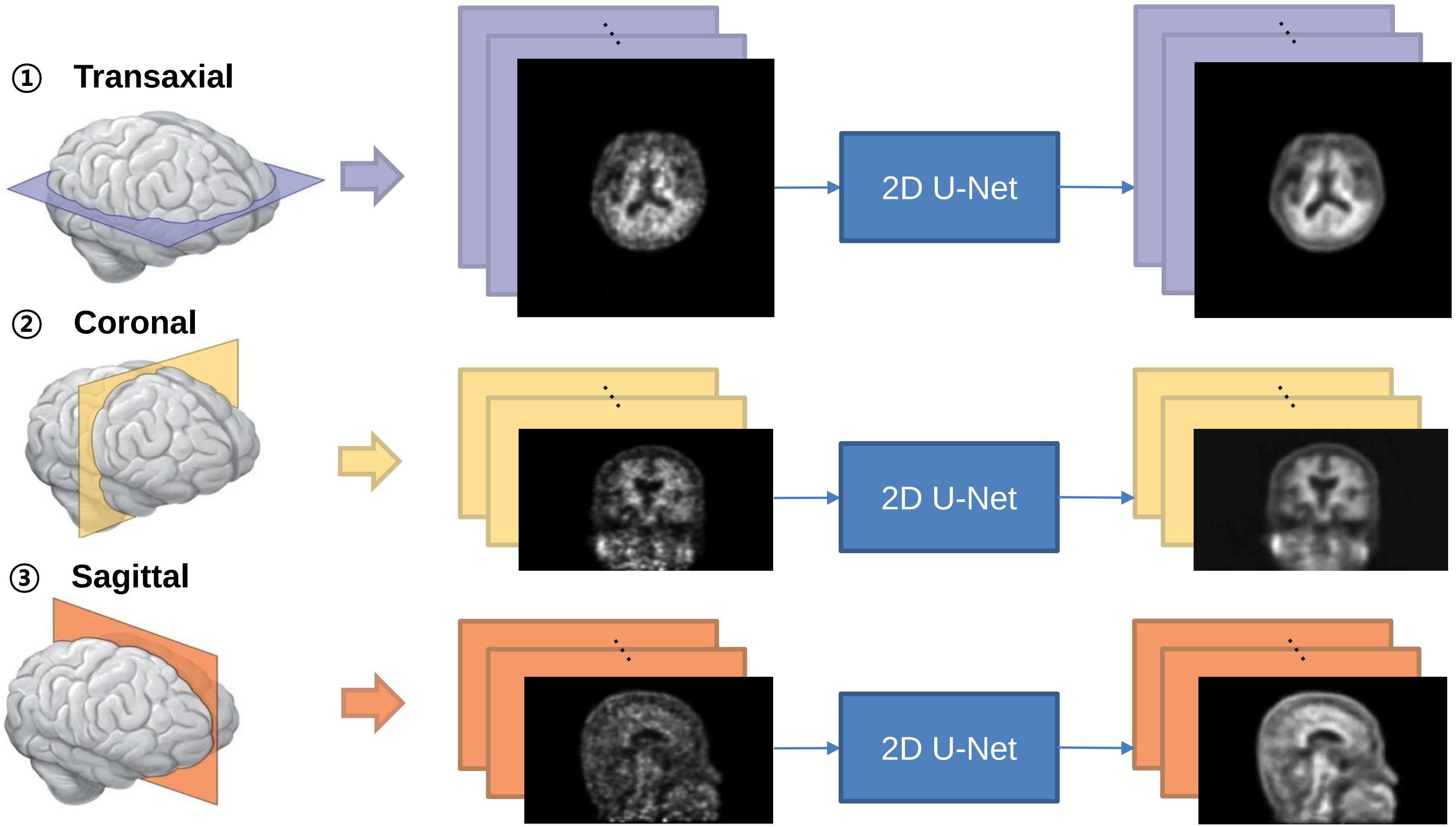
- **2D Data Preprocessing**

Transaxial	Coronal	Sagittal
		
		
200×200	200×109	200×109

2. Method

2. Network Architecture and Training

2D U-Net

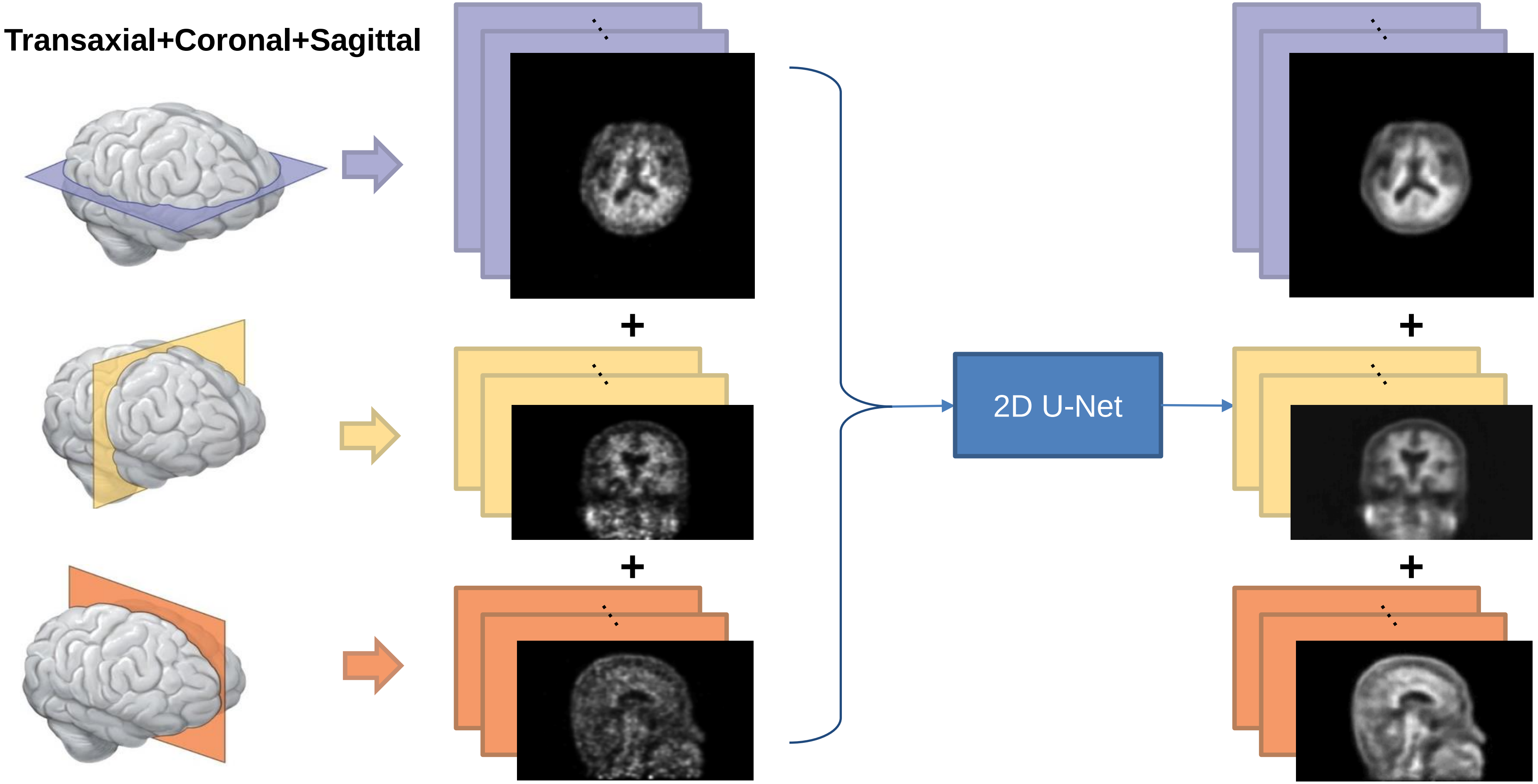


2. Method

2. Network Architecture and Training

2D U-Net

④ Transaxial+Coronal+Sagittal

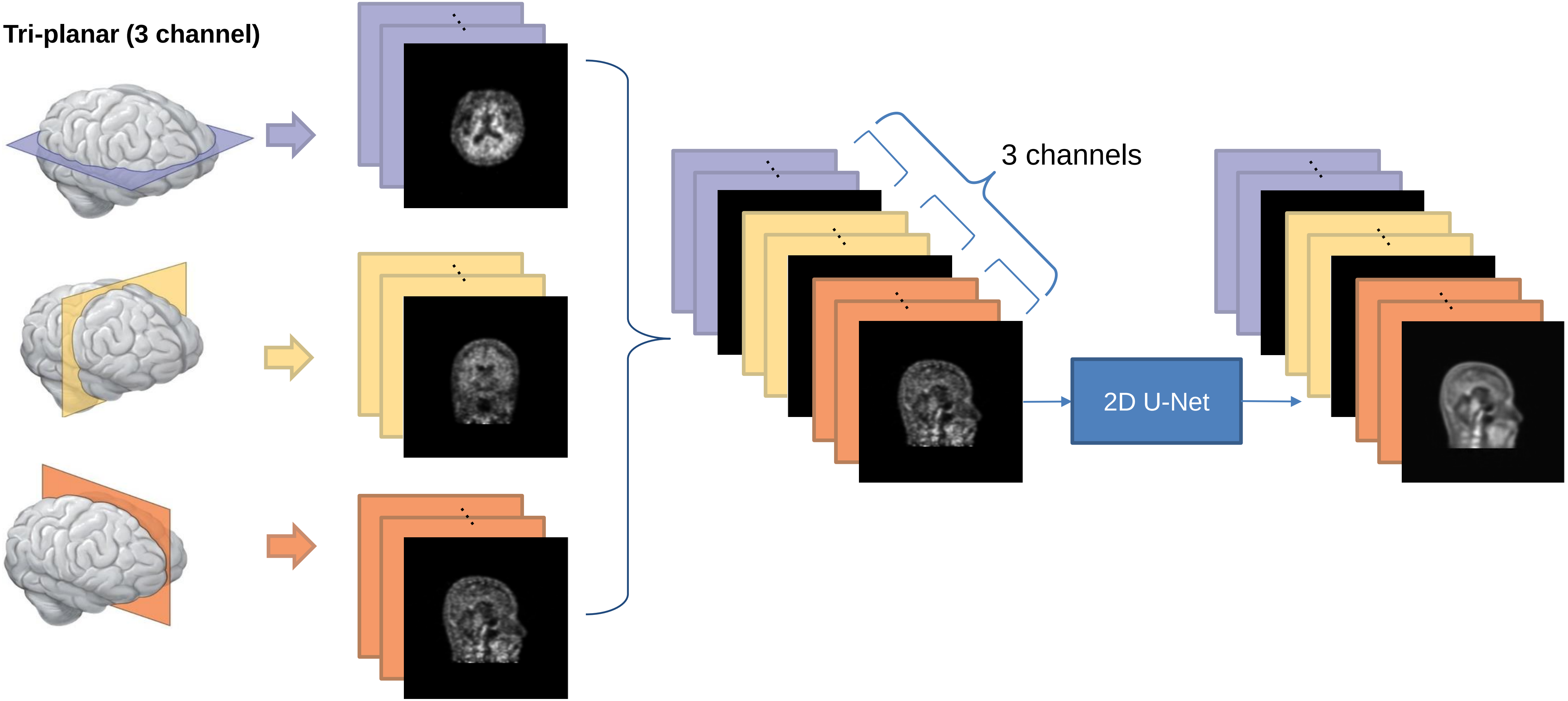


2. Method

2. Network Architecture and Training

2D U-Net

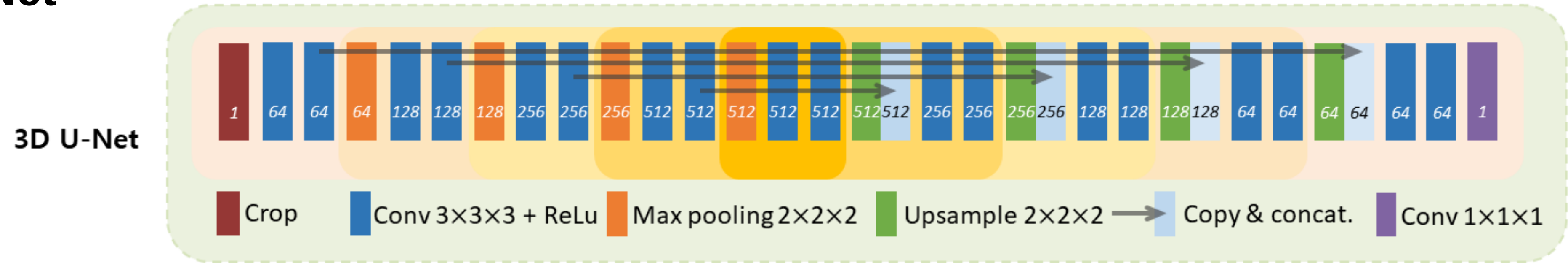
⑤ **Tri-planar (3 channel)**



2. Method

2. Network Architecture and Training

3D U-Net



- **3D Data Preprocessing**
  - $32 \times 32 \times 32$ patch
  - A total of 3200 possible patch center positions are calculated by applying a small random perturbation to the equally distanced 3D grids

    → Randomly select 400 patches
  - Patch Thresholding:

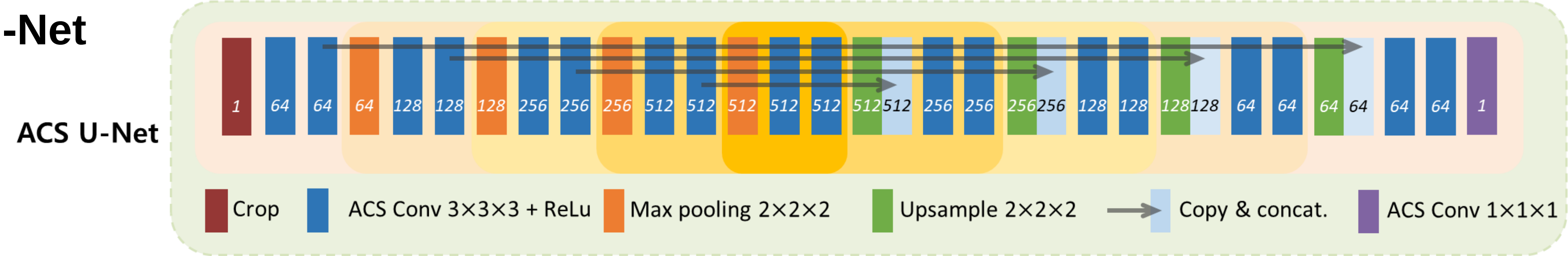
$$p = (1 - |r - 0.5| \times r)$$

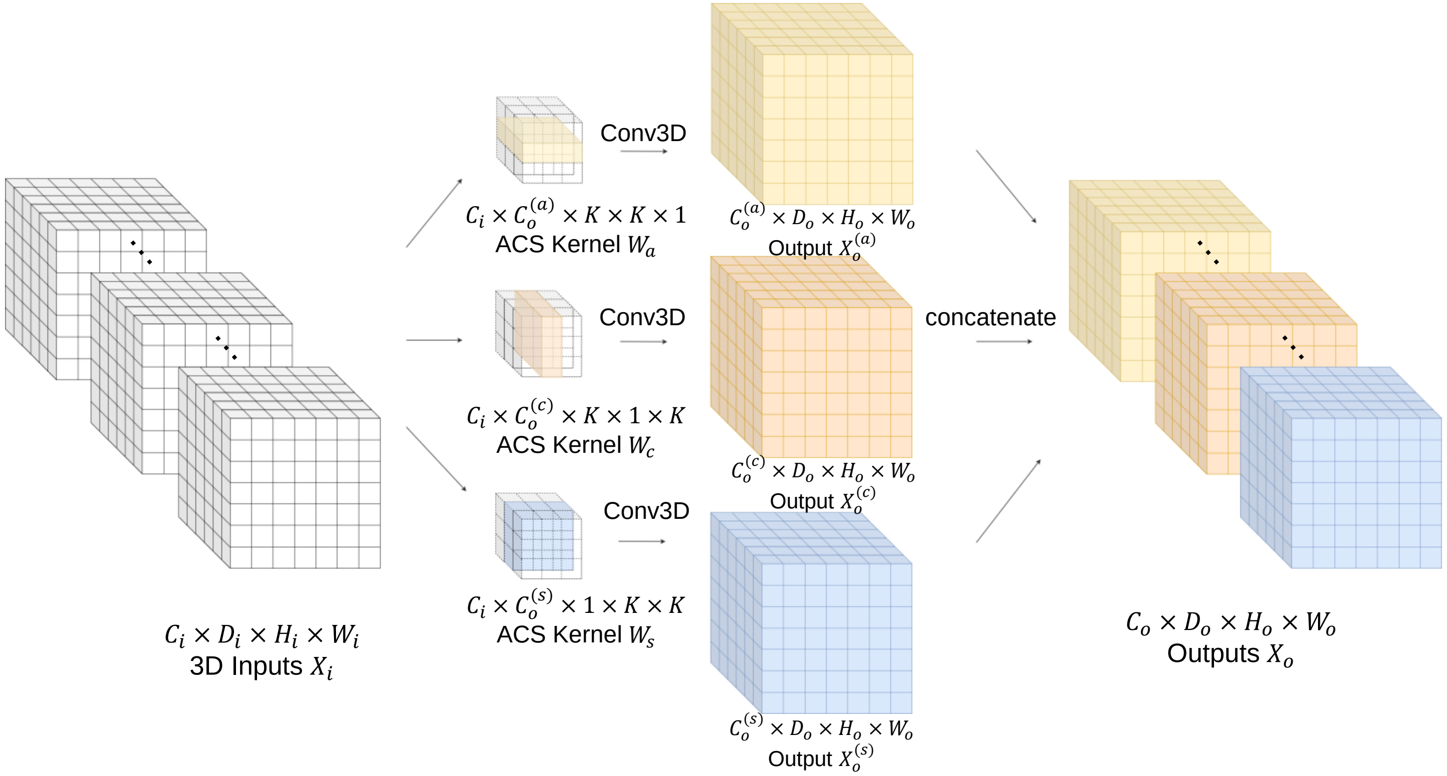
p: The relative probability that a patch center position is selected, r: ratio of foreground pixels in the patch

2. Method

2. Network Architecture and Training

ACS U-Net





2. Method

2. Network Architecture and Training

Normalization

- 99^{th} percentile

⇒ Normalize wide dynamic range of PET image intensity (0~thousands) → (0~1.xx)

Training

- Batch size: 16
- Epoch: 30
- Learning rate: 0.0001(Initial)/ “ReduceOnPlateau” learning rate scheduler
- Optimization: Adam
- Clinical PET images: L2 loss (mean square error)

2. Method

- **Models**
- **2D/3D/ACS Convolution**
  - **2D U-Net**
    - Transaxial
    - Coronal
    - Sagittal
    - Transaxial+Coronal+Sagittal
    - Tri-planar: (Transaxial, Coronal, Sagittal) 3 channels
  - **3D U-Net**
    - 3D patch based
  - **ACS U-Net**
    - 3D patch based

- **Learning Algorithm**
  - **Noise2Clean**
  - **Noise2Noise**

2. Method

3. Image Analysis

1) PSNR

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

$MAX: maximum\ value\ of\ the\ reference\ image,$ $\quad MSE: mean\ square\ error\ between\ the\ tested\ and\ reference\ image$

- **PSNR**: common method to **measure the fidelity** that is independent of the dynamic range of images

2) SSIM

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

$x, y: compared\ images,$ $\quad \mu: mean, \sigma: variance,$ $\quad C_1, C_2: constants$

- **SSIM**: take advantage of the **human visual system**, assessing image quality by extracting **structural information** and **calculating the similarity** by three comparisons: **Luminance, Contrast, and Structure**

3. Results

PSNR: 2D/3D U-Net N2C/N2N

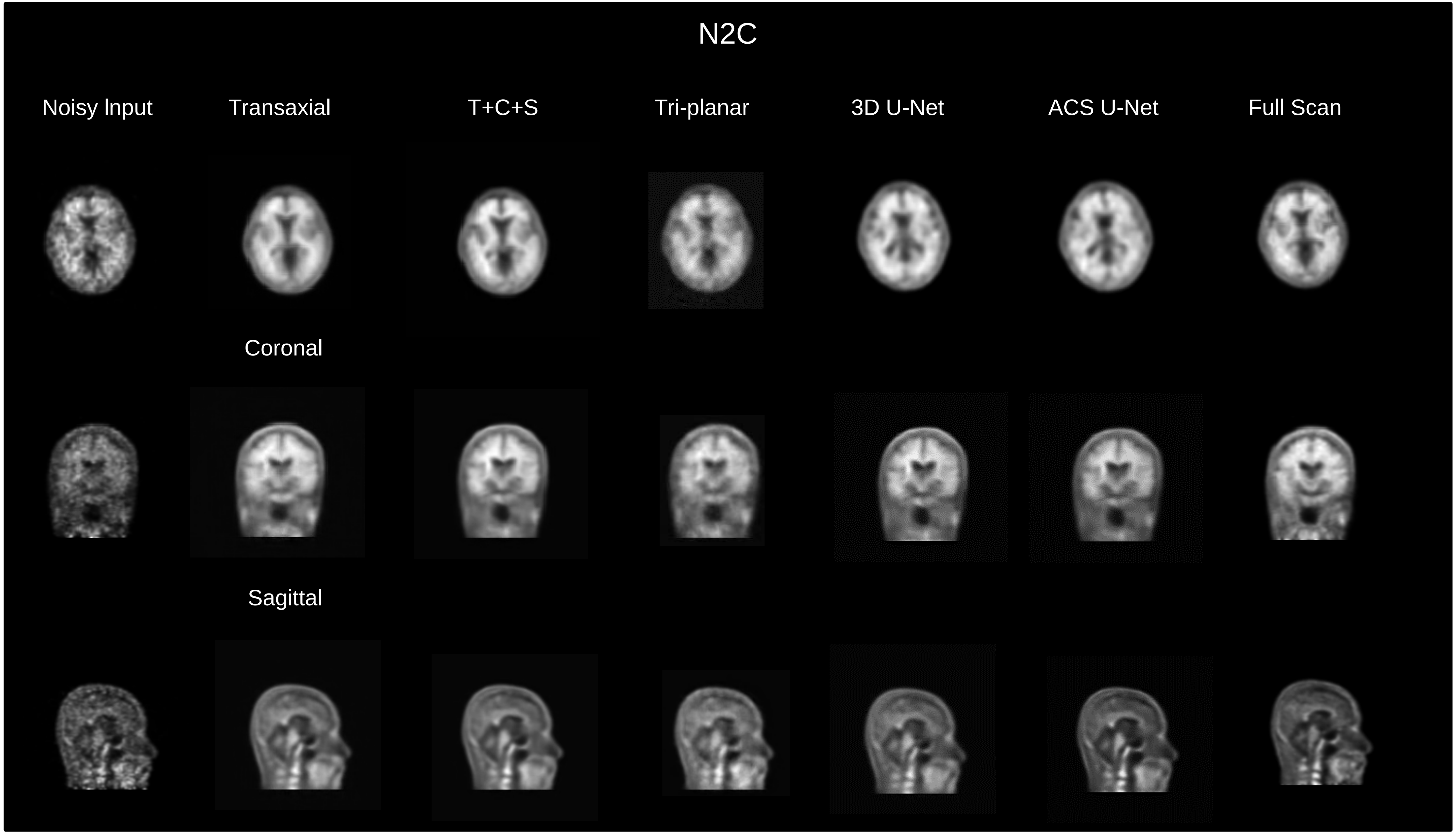
U-Net	Data	Noise2Clean		Noise2Noise	
Input		33.11			
2D U-Net	Transaxial	36.85	37.20	36.57	37.20
	Coronal	37.74		37.86	
	Sagittal	37.01		37.17	
	Transaxial +Coronal +Sagittal	37.08		36.15	
	Tri-planar (3 channels)	36.17		36.28	
3D U-Net	3D Patch	37.36		37.34	
ACS U-Net	3D Patch	37.43		37.41	

3. Results

SSIM: 2D/3D U-Net N2C/N2N

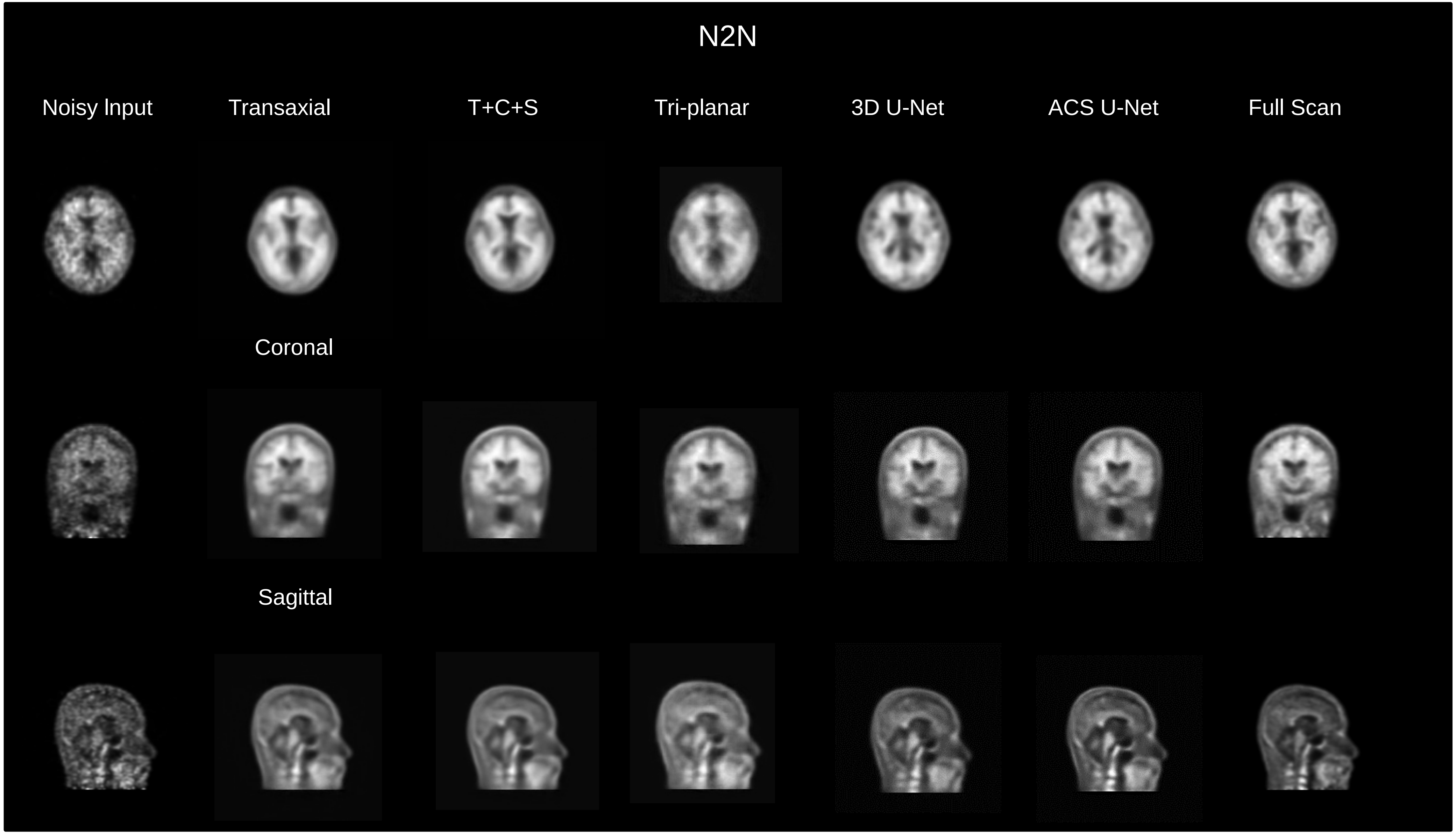
<table>
<tr><th>U-Net</th><th>Data</th><th colspan="2">Noise2Clean</th><th colspan="2">Noise2Noise</th></tr>
<tr><td colspan="2">Input</td><td colspan="4">0.9893</td></tr>
<tr><td rowspan="5">2D U-Net</td><td>Transaxial</td><td>0.9954</td><td rowspan="3">0.9956</td><td>0.9951</td><td rowspan="3">0.9955</td></tr>
<tr><td>Coronal</td><td>0.9959</td><td>0.9956</td></tr>
<tr><td>Sagittal</td><td>0.9954</td><td>0.9957</td></tr>
<tr><td>Transaxial
+Coronal
+Sagittal</td><td colspan="2">0.9948</td><td colspan="2">0.9948</td></tr>
<tr><td>Tri-planar
(3 channels)</td><td colspan="2">0.9946</td><td colspan="2">0.9944</td></tr>
<tr><td>3D U-Net</td><td>3D Patch</td><td colspan="2">0.9972</td><td colspan="2">0.9971</td></tr>
<tr><td>ACS U-Net</td><td>3D Patch</td><td colspan="2">0.9975</td><td colspan="2">0.9974</td></tr>
</table>

N2C Results



N2C
Noisy Input
Transaxial
T+C+S
Tri-planar
3D U-Net
ACS U-Net
Full Scan
Coronal
Sagittal

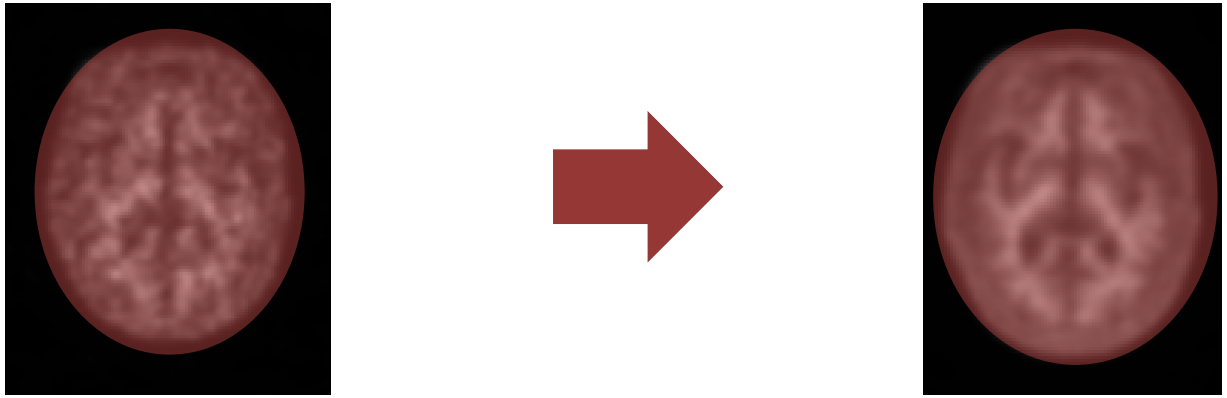
N2N Results


N2N
Noisy Input
Transaxial
T+C+S
Tri-planar
3D U-Net
ACS U-Net
Full Scan
Coronal
Sagittal

4. Discussion

- **Region of Interest (ROI)**
  - Training the image only with the ROI → improve the performance of denoising
  - Brain would be the ROI and background should be excluded
  - If the background of an image is included when measuring PSNR and SSIM

  ⇒ Quality of noisy image can be overestimated



5. Conclusion

- We compared **2D U-Net and 3D U-Net** for **Noise2Clean and Noise2Noise** framework to reduce the noise in short scan time ^{18}F-Florbetaben brain PET images
- The applied deep learning methods showed **remarkable performance** for **reducing noise** in PET images
- Noise2Noise gave comparable results to Noise2Clean without using reference images

⇒ **Self-supervised methods** can replace the traditional supervised method

6. Future Work

- **Other Convolution Methods**
  - Transfer Learning
    - Hybrid Convolution: H-Dense U-Net
    - Uses 2D pretrained networks with multi-slice inputs and 3D networks that are initialized randomly with volumetric inputs together for training

- **Other Learning Methods**
  - Self-supervised Methods
    - Noiser2Noise
    - Image denoising without access to clean training examples or access to paired noisy training examples
    - requires only a single noisy realization of each training example and a statistical model of the noise distribution

Thank you for your attention

For more information,
Codes on GitHub: https://github.com/soyon007
Email Address: soyon0304@naver.com