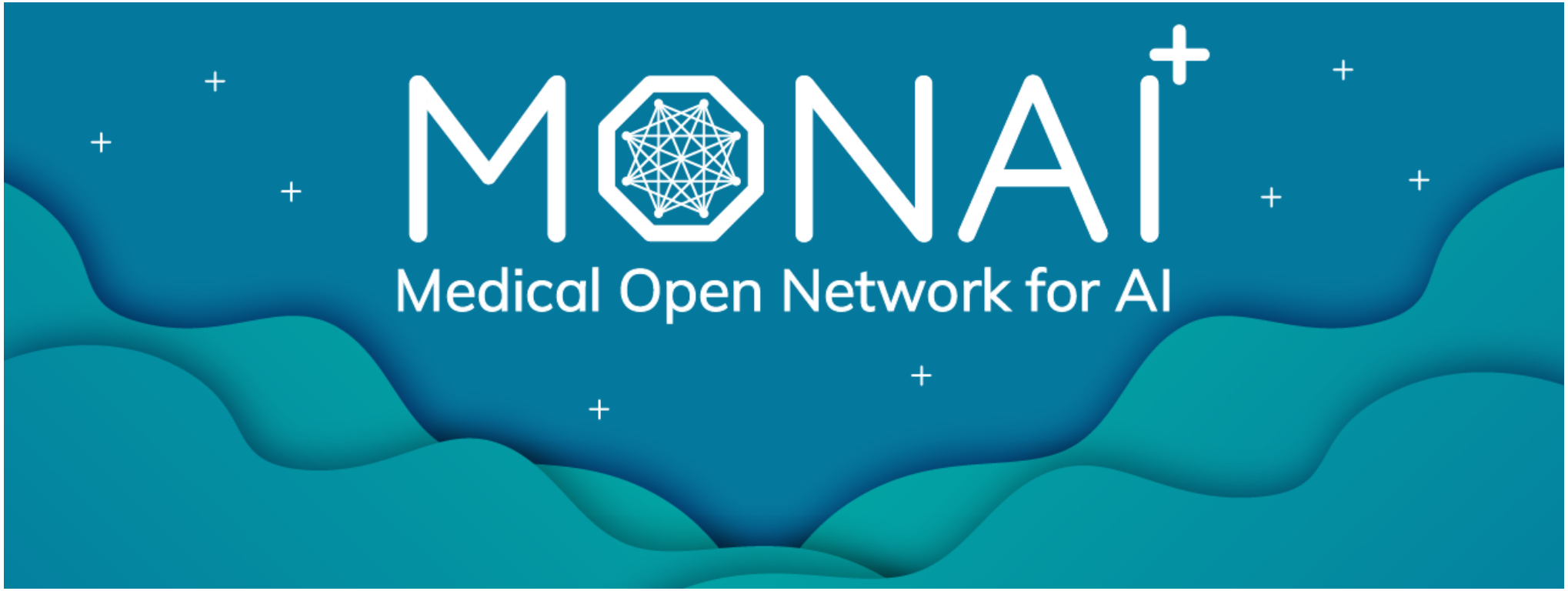
Medical/Bio Research Topics Ⅱ: Week 07 (17.10.2025)

Hands-on AI Segmentation Model Development (2): Model Architecture

인공지능 분할 모델 개발 실습 (2): 모델 구조

Medical Open Network for Artificial Intelligence (MONAI)



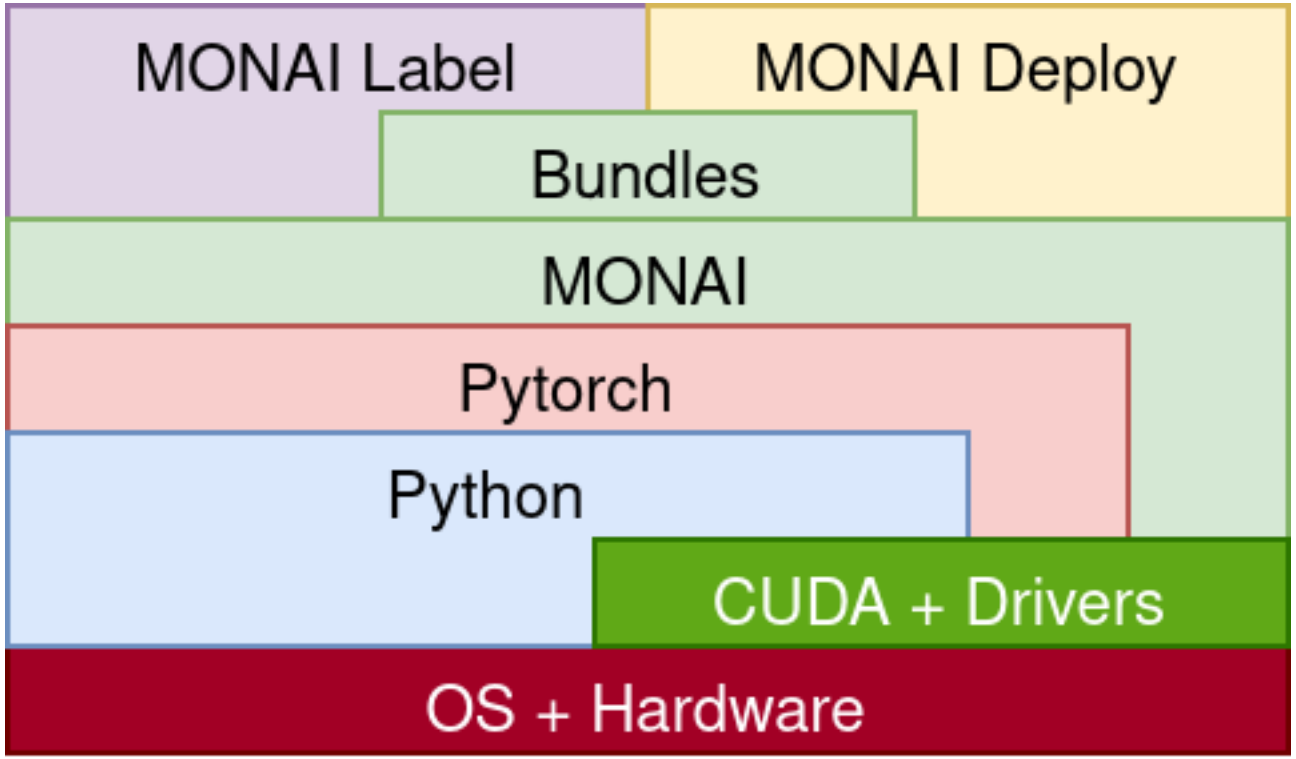
[https://github.com/Project-MONAI]

- Project MONAI
  - Set of open-source, freely available collaborative frameworks
  - For accelerating research and clinical collaboration in medical imaging
  - Originally started by NVIDIA and King's College London and expanded to a consortium of 16 institutions aiming to advance healthcare through medical imaging
  - Has gained widespread recognition as a standard within the medical imaging AI development community

- Key features
  - Open source: Built on PyTorch with Apache 2.0 license
  - Standardized: Best practices for healthcare AI with focus on medical imaging
  - User-friendly: Clear error messages and intuitive API
  - Reproducible: Facilitates replication of research experiments
  - Easy integration: Compatible with existing tools and 3rd party components
  - High quality: Enterprise-grade development with tutorials and robust documentation
- Latest version
  - Stable: 1.5.0 released in June 2025
  - Developing: 1.6.dev2531 released in August 2025

- Released multiple open-source PyTorch-based frameworks for annotating, building, training, deploying, and optimizing AI workflows in healthcare
  - MONAI Core: Foundation framework for medical AI development
    - Domain-specific capabilities for training AI models for medical imaging
    - Built-in medical transforms, networks, losses, and evaluation metrics
    - Integration with PyTorch ecosystem while adding medical-specific functionality
  - MONAI Bundle: Standardized model packaging and sharing system
    - Self-contained model definitions with configs, weights, and metadata
    - Enables reproducible research and easy model distribution
    - Integration with Model Zoo for community collaboration

- MONAI Label: Interactive annotation and active learning platform
  - AI-assisted labeling with DeepEdit and DeepGrow interactive models
  - Active learning strategies to reduce annotation time
  - Integration with 3D Slicer and OHIF viewers
- MONAI Deploy: Clinical deployment and integration framework
  - Robust framework for deploying AI models in clinical settings
  - DICOM integration and clinical workflow support
  - Production-ready containerization and orchestration
- MONAI Model Zoo: Community model repository
  - Collection of pre-trained medical imaging models in Bundle format
  - Easy access to state-of-the-art models for various medical tasks
  - Standardized evaluation and benchmarking



[https://docs.monai.io/en/stable/]

Stack Architecture of Project MONAI

Why Medical-Specific Frameworks Like MONAI?

- Unique challenges in medical imaging AI
  - 3D volumetric complexity
  - Spatial heterogeneity
  - Domain-specific data formats
  - High-dimensional complexity

- Limitations of general AI frameworks for medical applications
  - Missing medical transforms
  - Inadequate 3D support
  - Lack of domain-specific metrics
  - Format incompatibility
- Development challenges with general AI frameworks
  - Extended R&D lifecycle
  - Increased project risks
  - Reduced reproducibility

- MONAI's domain-specific solutions
  - Medical-optimized pipelines: Pre-built transforms and preprocessing workflows
  - 3D-native architectures: Optimized deep learning designs for volumetric medical data
  - Medical-specific metrics: Built-in medical loss functions and evaluation metrics
  - Seamless format integration: Native support for medical file formats
  - Standardized best practices: Proven methodologies for medical AI development

MONAI Core

- Flagship framework created by Project MONAI
- Provides domain-specific capabilities for training AI models for medical imaging
- Supports wrappers and adaptors that allow popular healthcare AI tools to be used from within MONAI
  - Developed with minimal required dependencies, namely PyTorch and NumPy

- Key design principles
  - Looks and feels like PyTorch
  - Opt-in and incremental over PyTorch
  - Fully integrates with the PyTorch ecosystem
- Installation
  - `$ pip install monai`

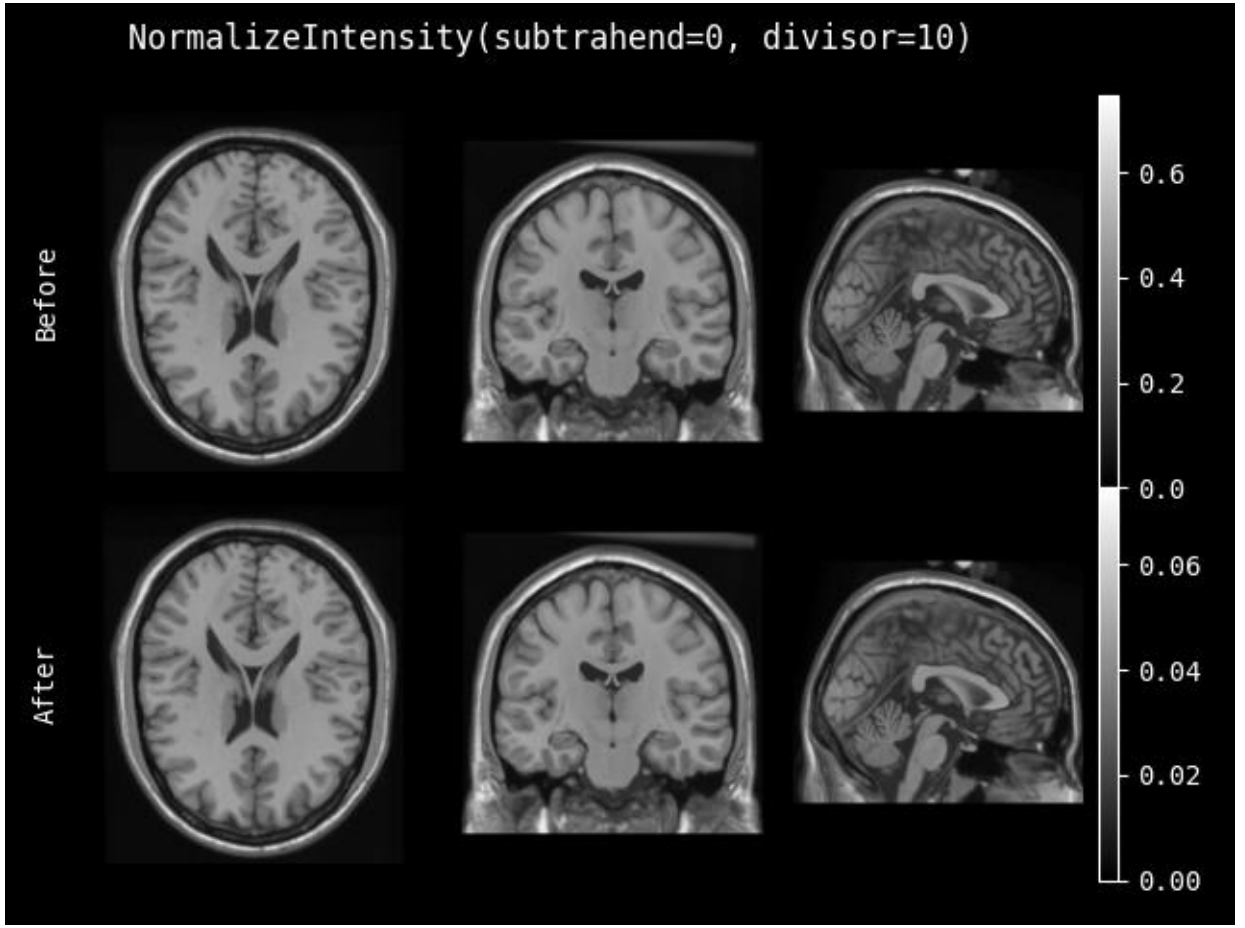
- Key modules
  - **`monai.data`**: Datasets, image readers/writers, and synthetic data generation
  - **`monai.transforms`**: Medical image transforms for preprocessing and postprocessing
  - **`monai.networks`**: Network architectures, building blocks, and PyTorch utilities
  - **`monai.metrics`**: Medical evaluation metrics (Dice, IoU, ROC-AUC, etc.)
  - **`monai.losses`**: Medical-specific loss functions (Dice, Hausdorff, SSIM, etc.)

- **`monai.optimizers`**: Learning rate schedulers and optimization utilities
- **`monai.visualize`**: Visualization tools including CAM, GradCAM, and occlusion sensitivity
- **`monai.engines`**: Workflow engines for training and evaluation pipelines
- **`monai.`**apps: Ready-to-use applications
  - Auto3DSeg: Automated 3D segmentation pipeline
- **`monai.bundle`**: Model packaging and configuration management
- **`monai.utils`**: Utility functions and helper tools
- **`monai.fl`**: Federated learning client support

- **`monai.data`** module
  - Generic interfaces
    - **`Dataset`**: Loads data samples
    - **`ArrayDataset`**: Loads array format input data
    - **`ImageDataset`**: Loads image/segmentation pairs
  - Image readers/writers
    - **`ImageReader`**: Loads medical image files
    - **`ImageWriter`**: Writes images to files
  - Key features
    - Native support for medical file formats
    - Efficient data loading pipelines
    - Synthetic data generation capabilities

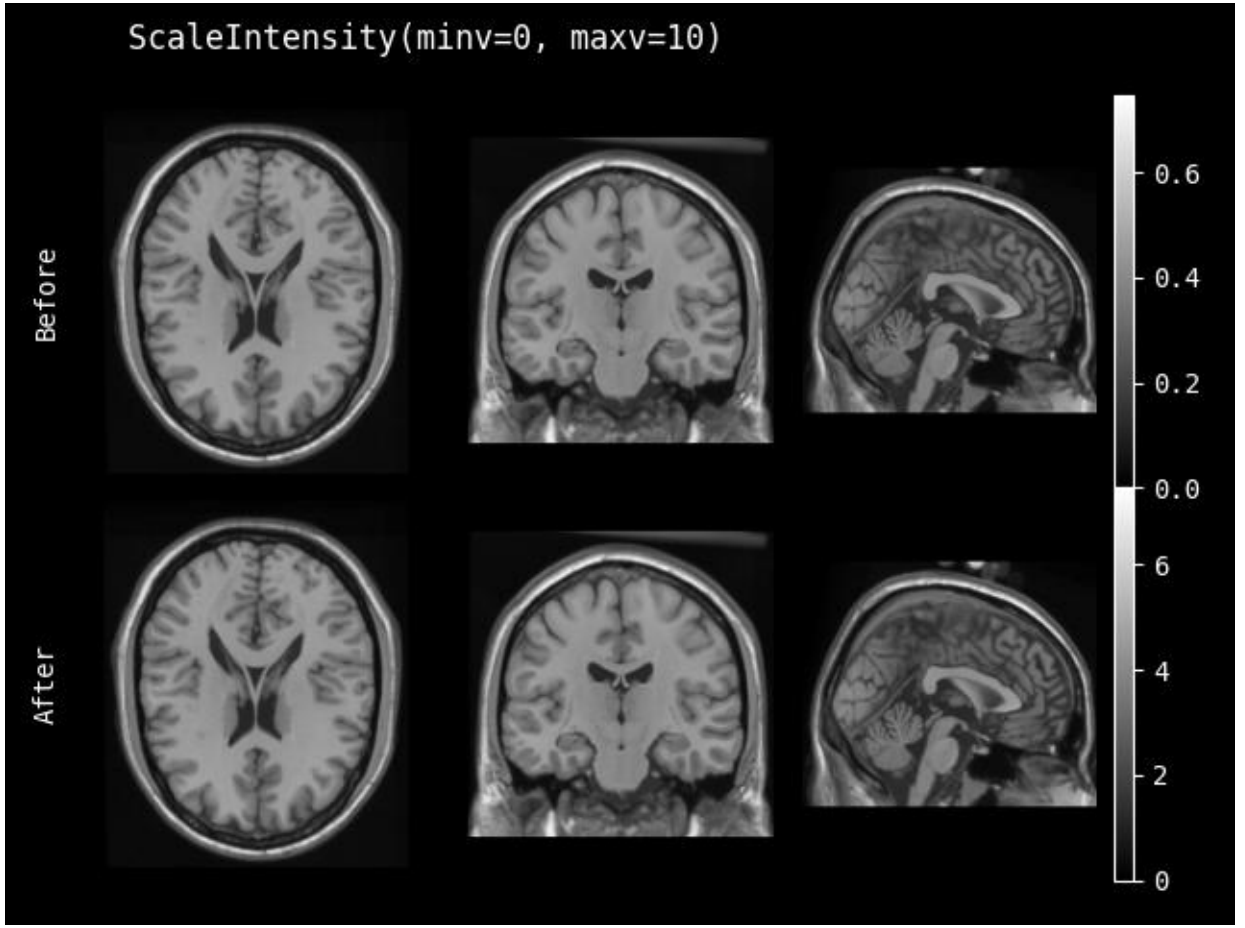
- **`monai.transforms`** module
  - Input/output transforms
    - **`LoadImage`**: Loads images from specified paths with format-specific readers
      - nii, nii.gz: NibabelReader
      - png, jpg, bmp: PILReader
      - npz, npy: NumpyReader
      - nrrd: NrrdReader
      - DICOM file: ITKReader
    - **`SaveImage`**: Saves images and metadata to files

- Intensity transforms
  - **`NormalizeIntensity`**: Normalizes images based on mean and standard deviation
  - **`ScaleIntensity`**: Scales intensity to specified value range
  - **`RandGaussianNoise`**: Adds Gaussian noise for augmentation



[https://docs.monai.io/en/stable/transforms.html]

`monai.transforms.NormalizeIntensity`



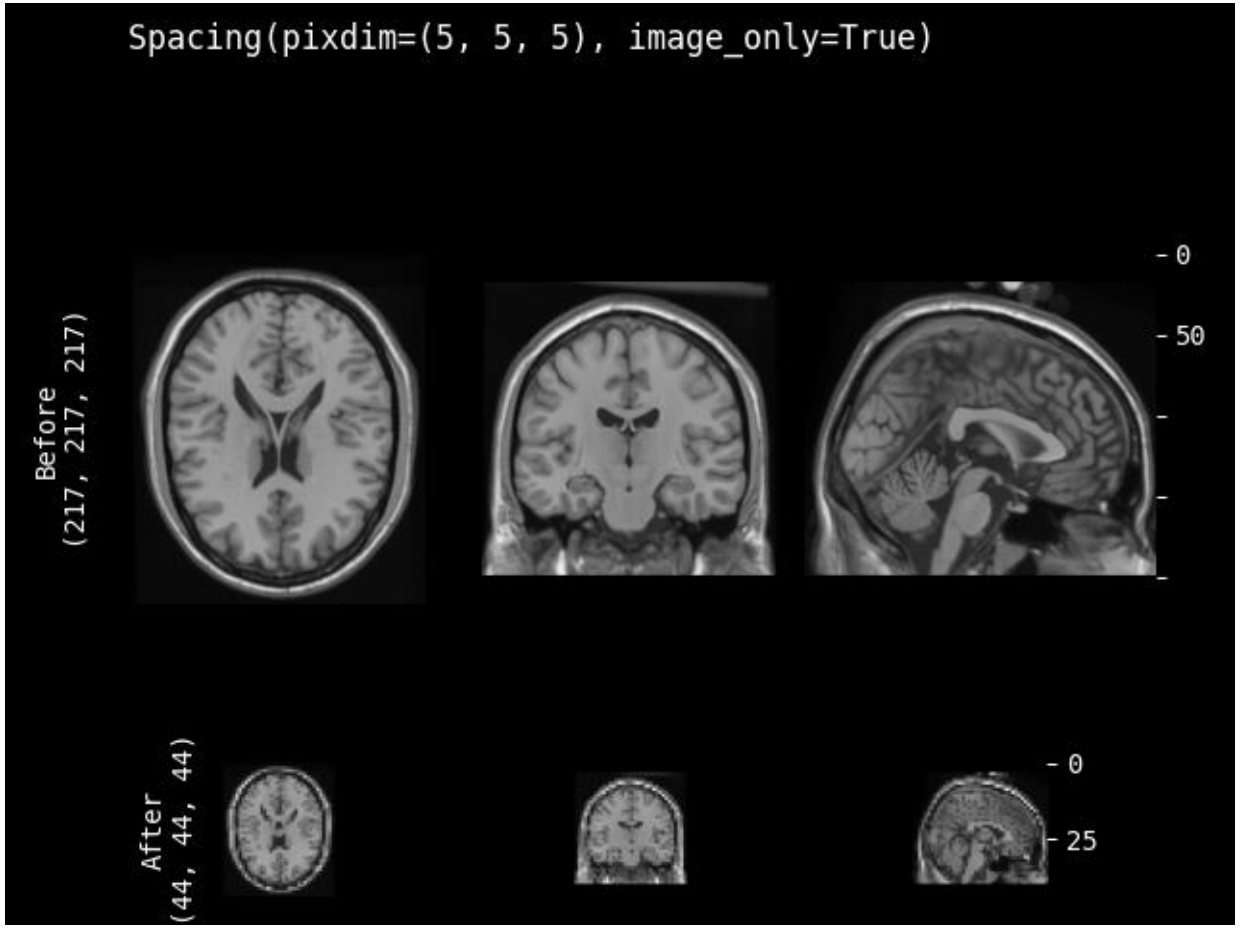
[https://docs.monai.io/en/stable/transforms.html]

`monai.transforms.ScaleIntensity`

[https://docs.monai.io/en/stable/transforms.html]

`monai.transforms.RandGaussianNoise`

- Spatial transforms
  - **`Spacing`**: Resamples images to specified voxel spacing
  - **`Resize`**: Resizes images to specified spatial dimensions
  - **`Orientation`**: Changes image orientation (e.g., 'RAS')
  - **`Flip`**, **`Rotate`**, **`Zoom`**: Basic geometric augmentations

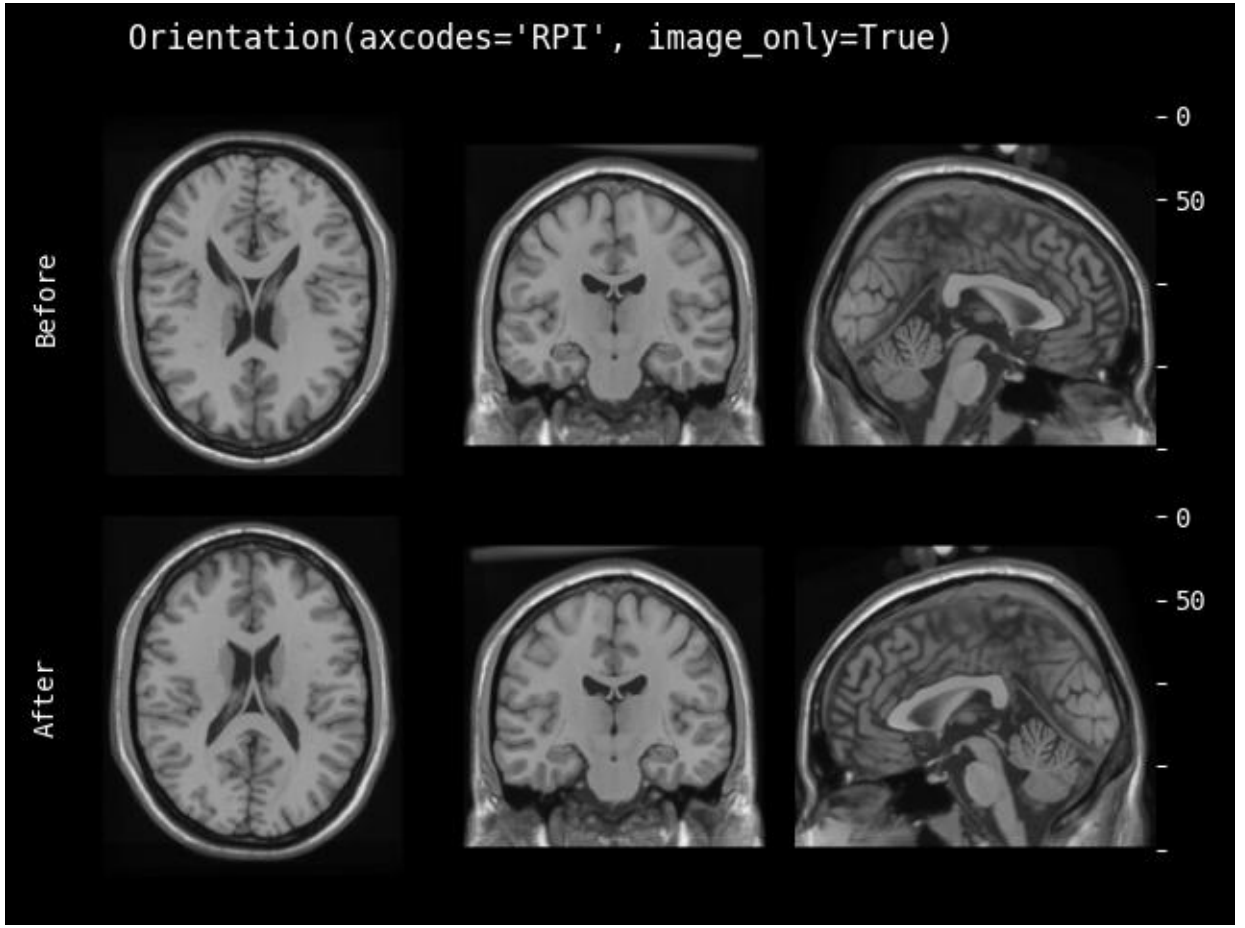


[https://docs.monai.io/en/stable/transforms.html]

monai.transforms.Spacing

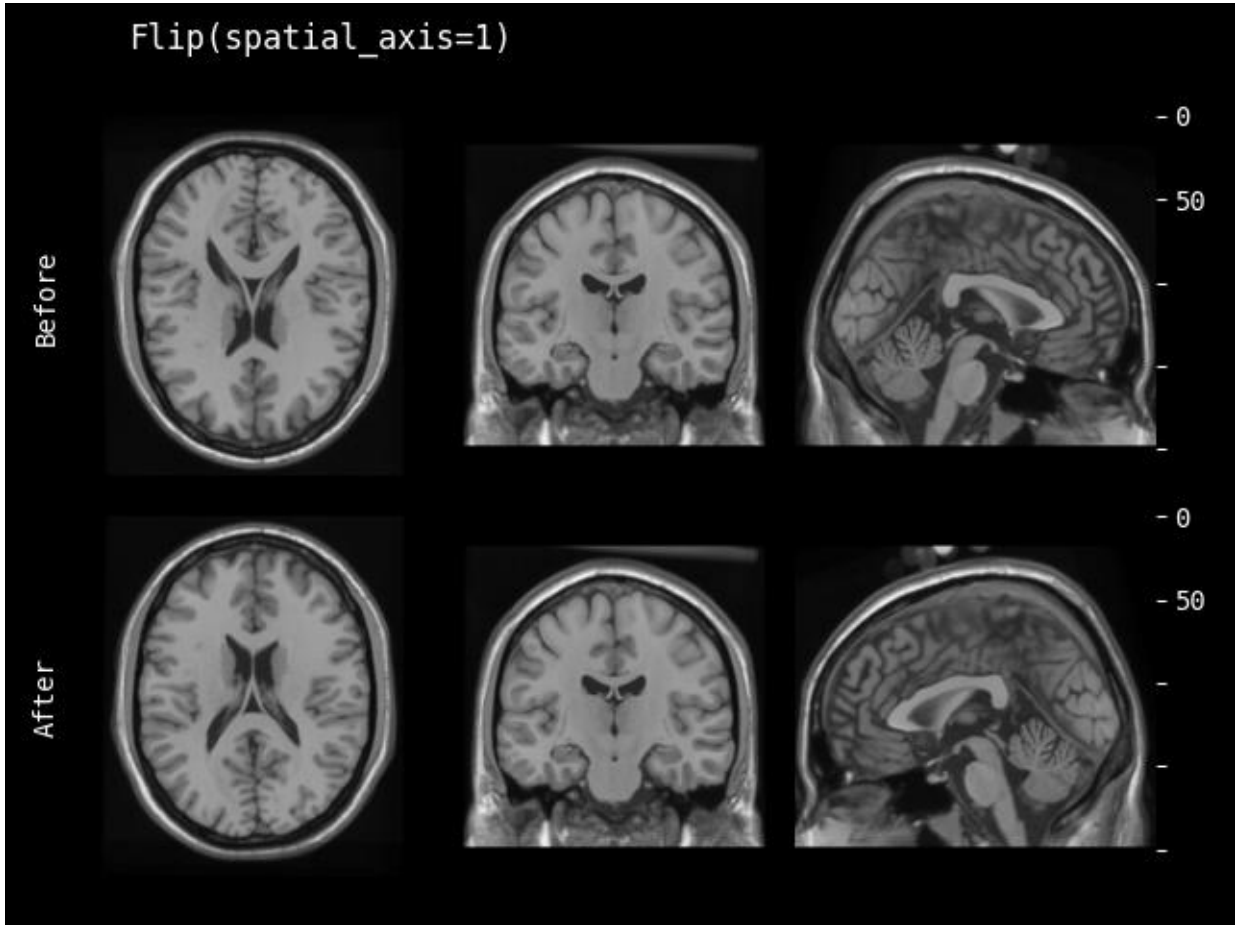
[https://docs.monai.io/en/stable/transforms.html]

monai.transforms.Resize



[https://docs.monai.io/en/stable/transforms.html]

`monai.transforms.Orientation`



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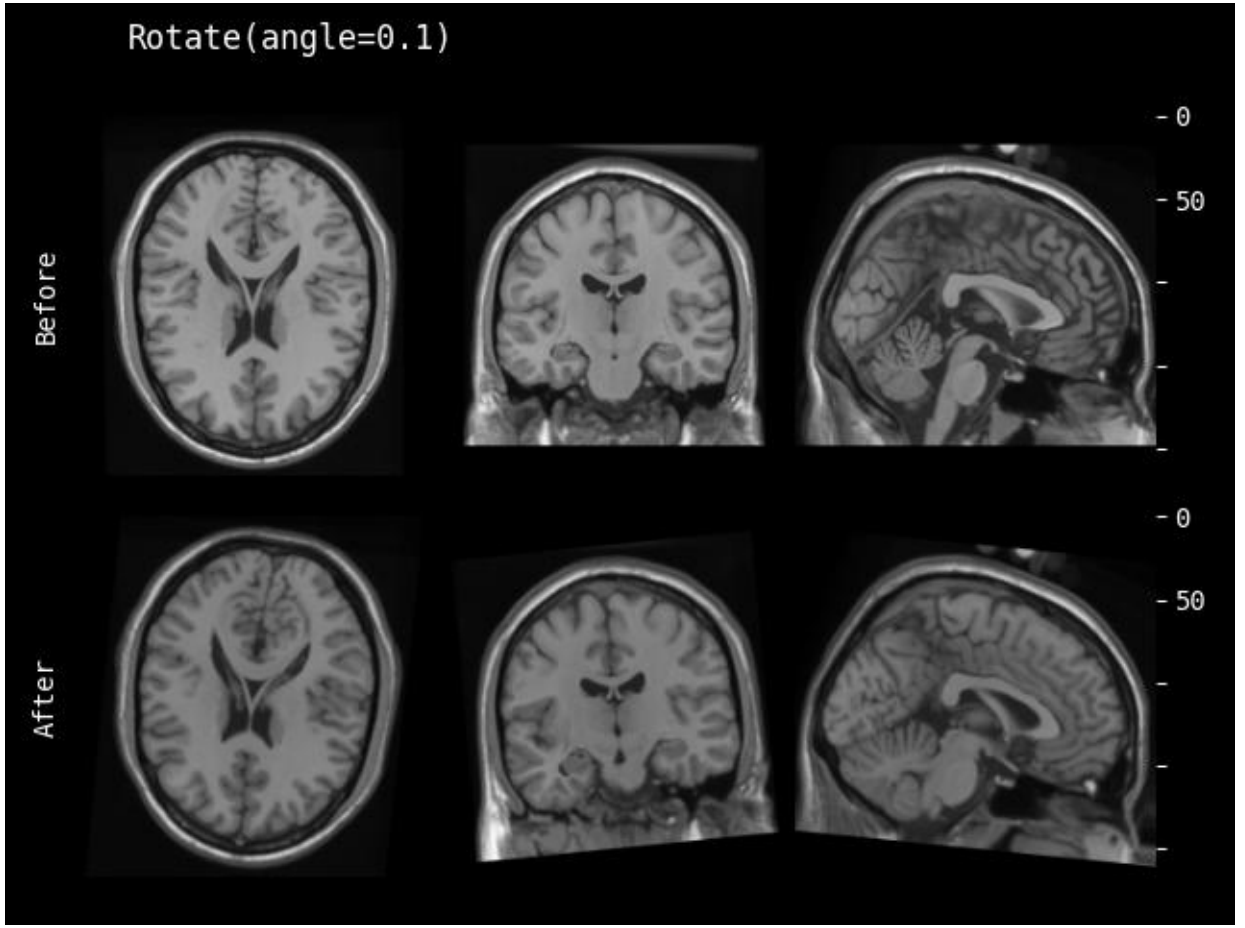
monai.transforms.Flip



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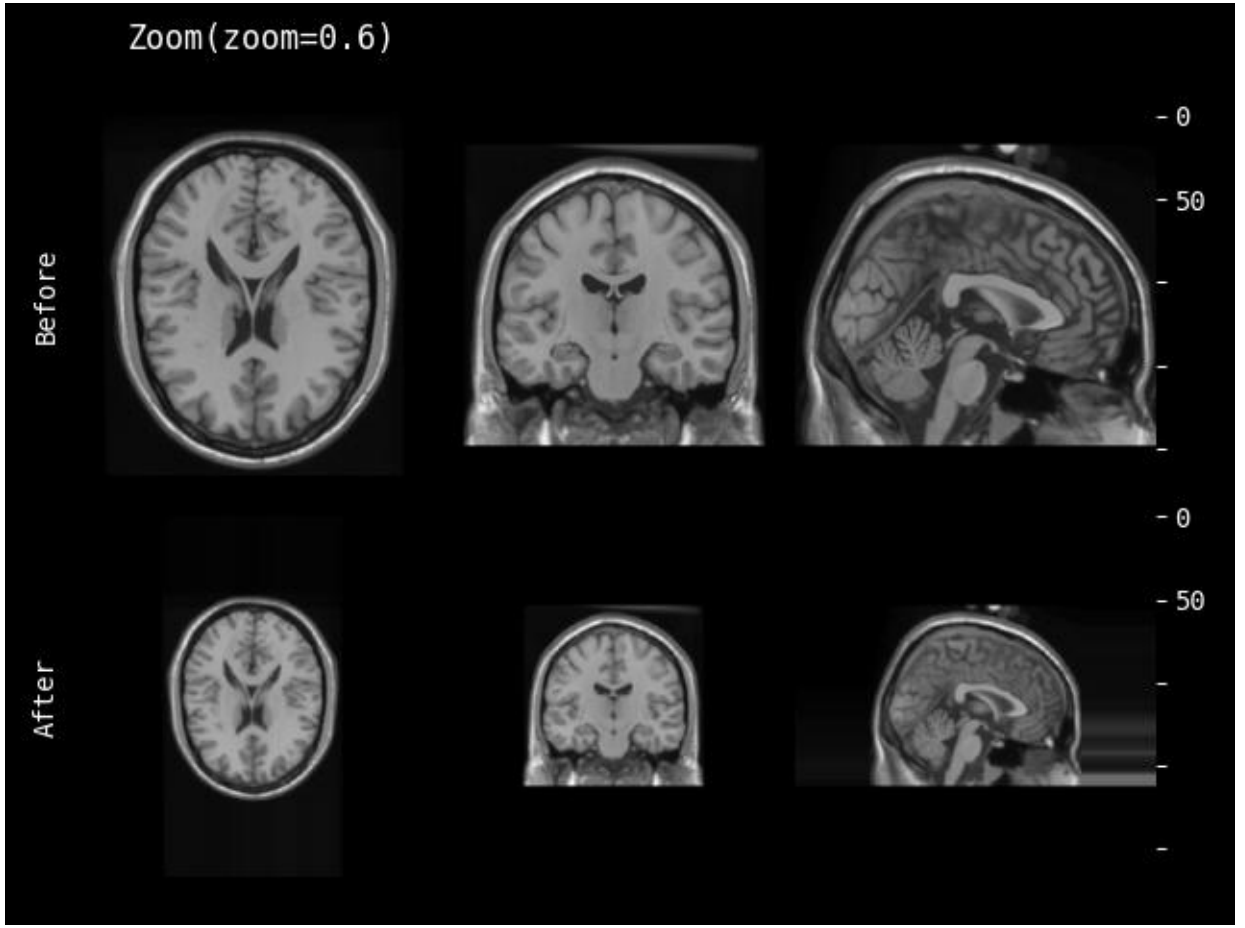
monai.transforms.Rotate



[https://docs.monai.io/en/stable/transforms.html]

`monai.transforms.Zoom`

- **`monai.networks`** module
  - Basic building blocks
    - Layers: **`Conv`**, **`Norm`**, **`Dropout`**, **`Act`**, **`Pool`**, **`Pad`**, **`Flatten`**
    - Blocks: **`Convolution`**, **`DenseBlock`**, **`TransformerBlock`**, **`UnetrBasicBlock`**
  - Complete architectures
    - Traditional: **`UNet`**, **`VNet`**, **`DynUNet`**, **`AttentionUNet`**
    - ResNet-based: **`ResNet`**, **`SegResNet`**
    - Transformer-based: **`UNETR`**, **`SwinUNETR`**
    - General purpose: **`DenseNet`**, **`FullyConnectedNet`**

– Utilities
  - **`convert_to_onnx`**: Converts models to Open Neural Network Exchange (ONNX) format
  - **`convert_to_torchscript`**: Converts models to TorchScript

- `monai.metrics` module
  - Segmentation metrics
    - `DiceMetric`
    - `compute_iou`
  - Classification metrics
    - `ROCAUCMetric`
    - `ConfusionMatrixMetric`
  - Regression metrics
    - `RMSEMetric`
    - `MSEMetric`
    - `MAEMetric`

- `monai.losses` module
  - Segmentation losses
    - `DiceLoss`
    - `HausdorffDTLoss`
  - Registration losses
    - `LocalNormalizedCrossCorrelationLoss`
    - `GlobalMutualInformationLoss`
  - Reconstruction losses
    - `SSIMLoss`

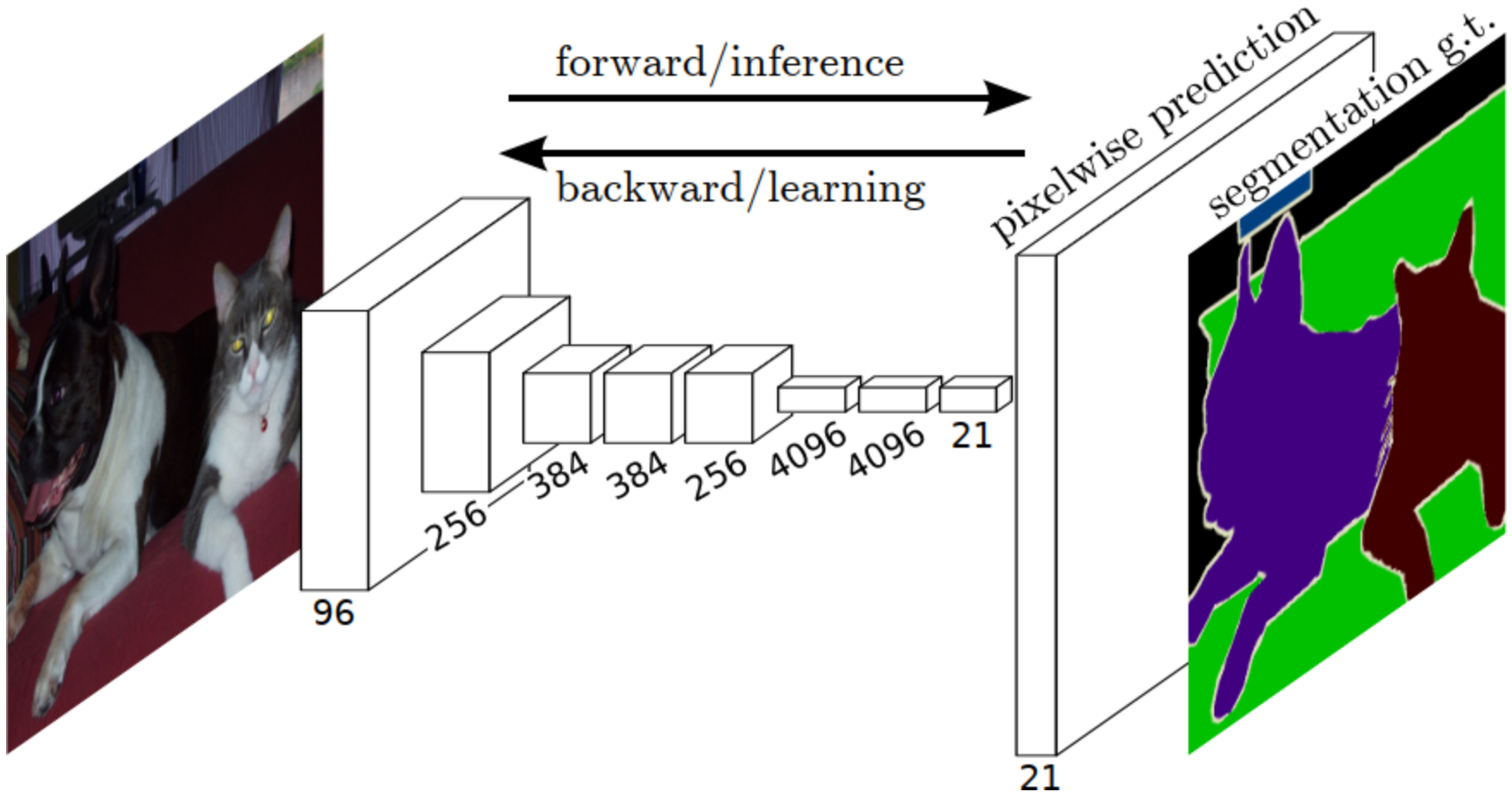
- **`monai.apps`** module
  - **`Auto3DSeg`**: Automated 3D segmentation pipeline
    - **`AutoRunner`**: Core automated segmentation workflow

- **`monai.visualize`** module
  - Class activation mapping
    - **`CAM`**, **`GradCAM`**, **`GradCAMpp`**
  - Occlusion sensitivity analysis
    - **`OcclusionSensitivity`**

Deep Learning Architectures for Lesion Segmentation

- Fully Convolutional Network (FCN)
  - "Fully Convolutional Networks for Semantic Segmentation"

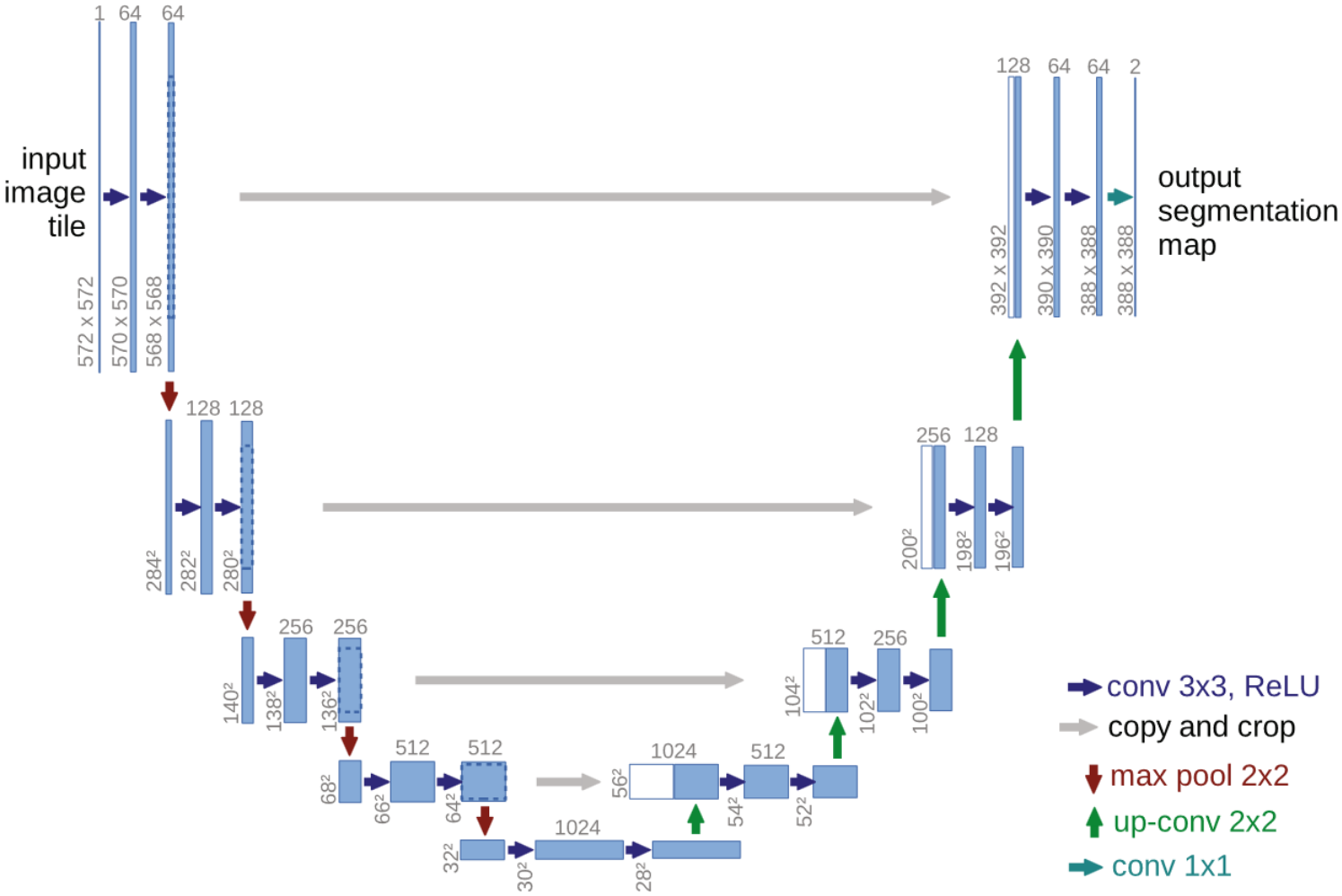
    [Long et al., 2015]
  - As a type of Convolutional Neural Network (CNN), emphasizes full convolution throughout the network, preserving spatial information and enabling pixel/voxel-wise predictions on variable-sized inputs
  - Serves as a foundation for many subsequent architectures



[Long et al., 2015)]

FCN Architecture

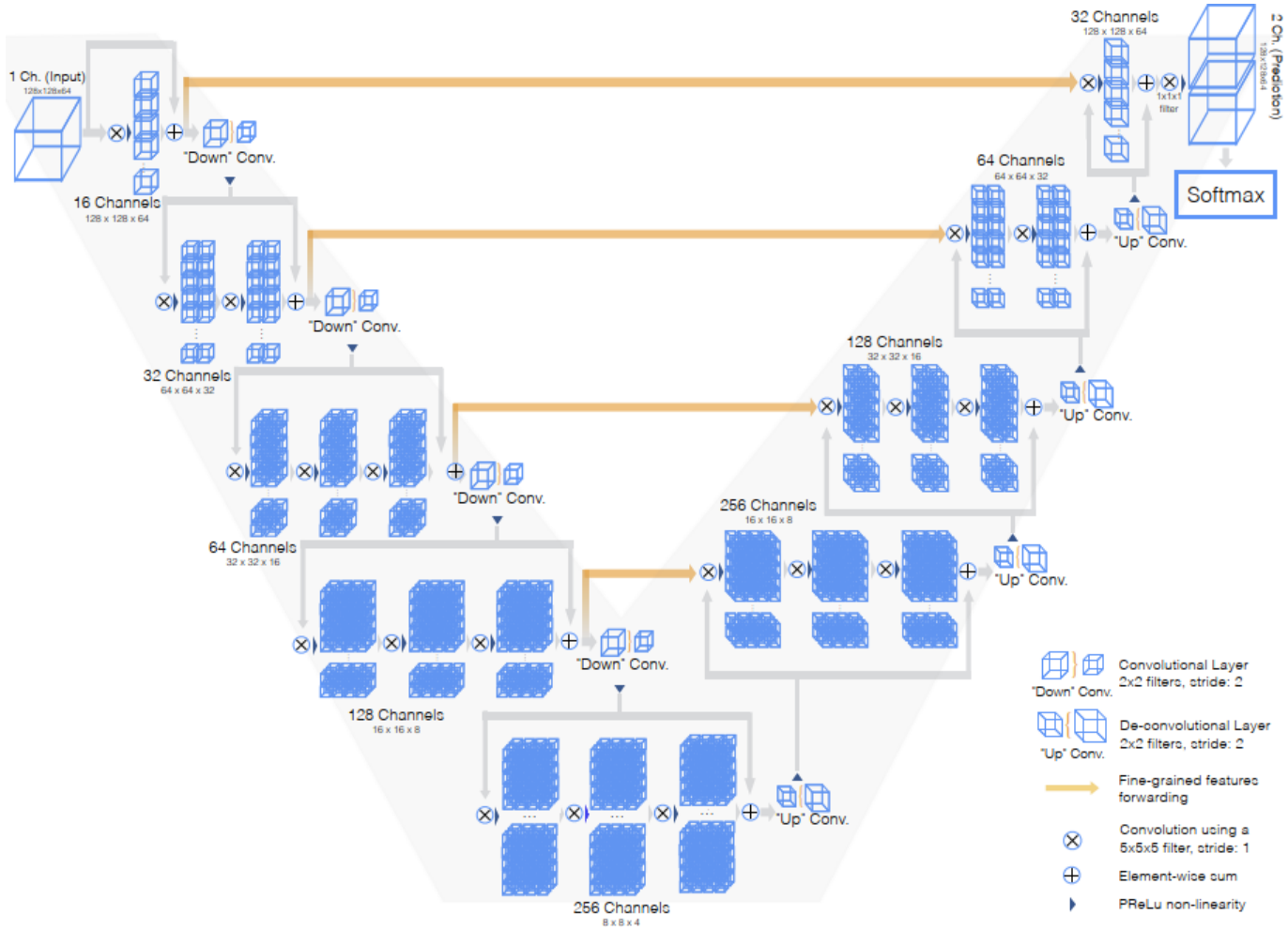
- U-Net
  - "U-Net: Convolutional Networks for Biomedical Image Segmentation" [Ronneberger et al., 2015]
  - Introduces a symmetric encoder-decoder structure with skip connections between corresponding layers
  - Particularly effective in capturing fine-grained details in medical images
  - Remains one of the most commonly used architectures in medical image segmentation



[Ronneberger et al., 2015)]

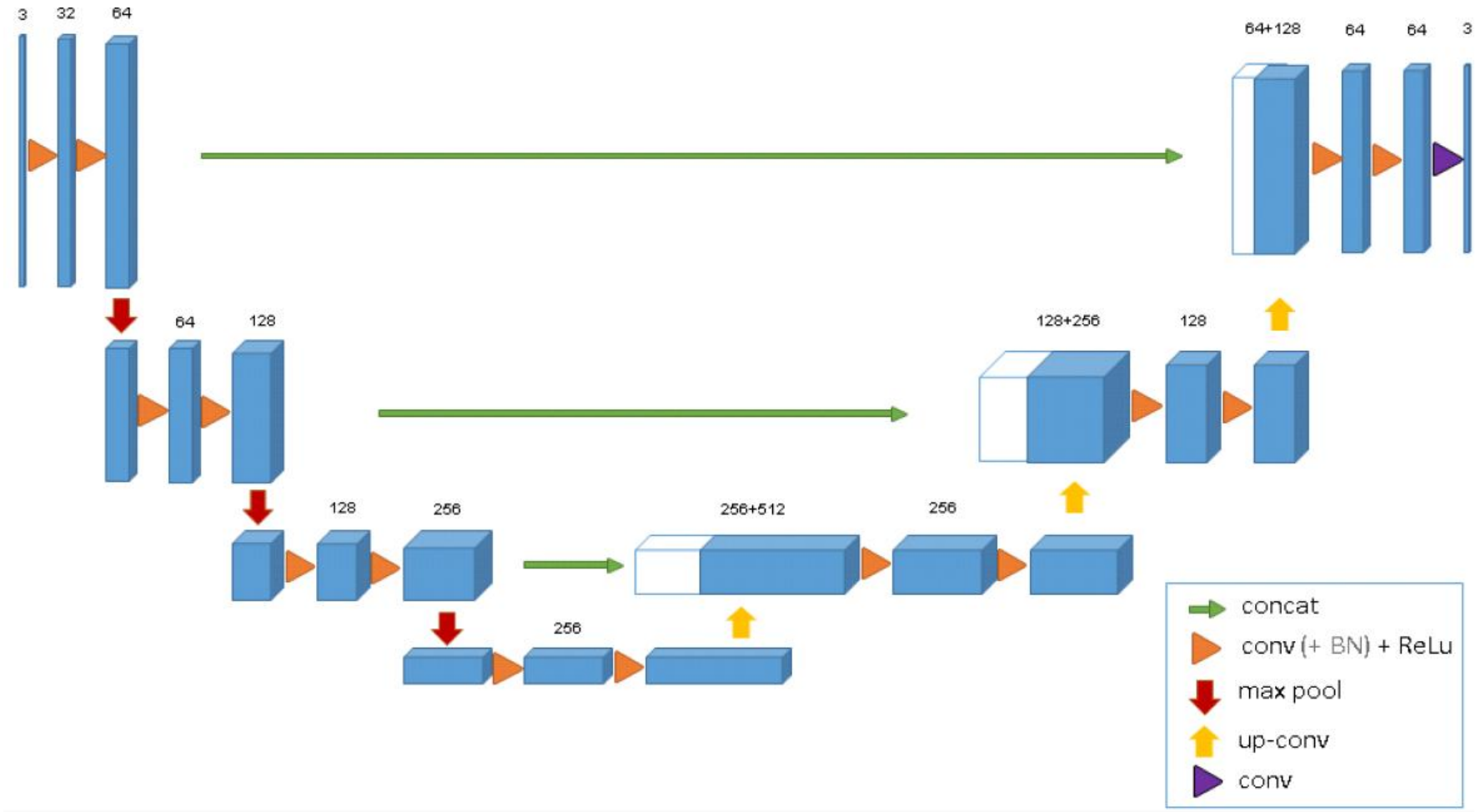
U-Net Architecture

- V-Net and 3D U-Net
  - V-Net: "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation" [Milletari et al., 2016]
  - 3D U-Net: "3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation" [Çiçek et al., 2016]
  - Extend the original 2D U-Net based on the core encoder-decoder structure with skip connections to 3D, but with significant modifications, including the use of a Dice loss function for effectively addressing class imbalance and particularly improving segmentation performance for small structures, in V-Net



[Milletari et al., 2016)]

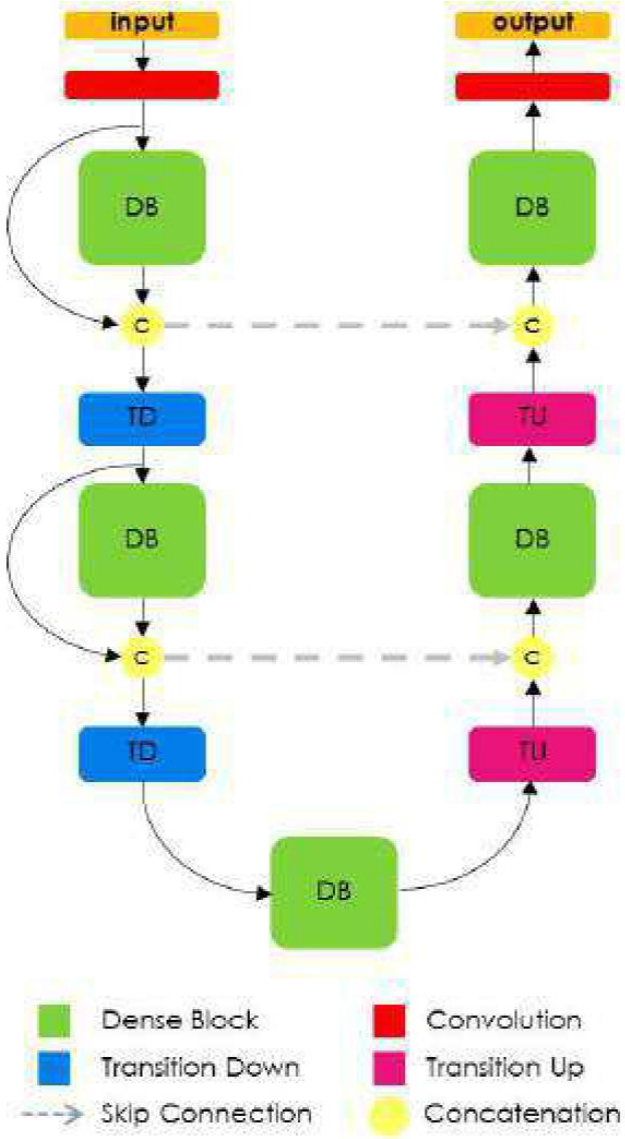
V-Net Architecture



[Çiçek et al., 2016]

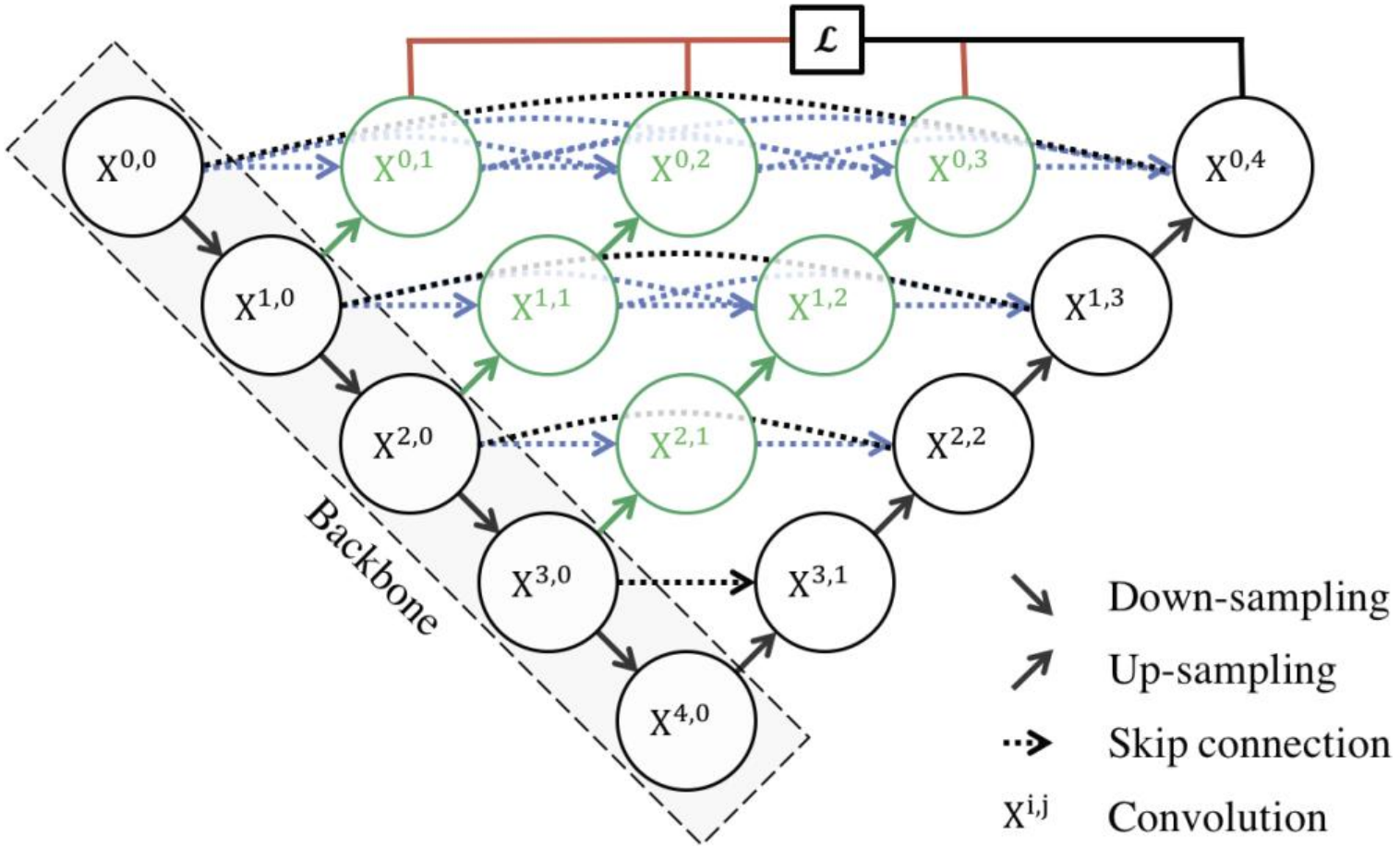
3D U-Net Architecture

- Various U-Net variants
  - Dense U-Net: "The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation" [Jégou et al., 2017]
    - Incorporates dense connections within each encoder and decoder block
  - Nested U-Net (UNet++): "UNet++: A Nested U-Net Architecture for Medical Image Segmentation" [Zhou et al., 2018]
    - Uses dense skip connections between encoder and decoder and introduces intermediate supervision to reduce the semantic gap between encoder and decoder features



[Jégou et al., 2017]

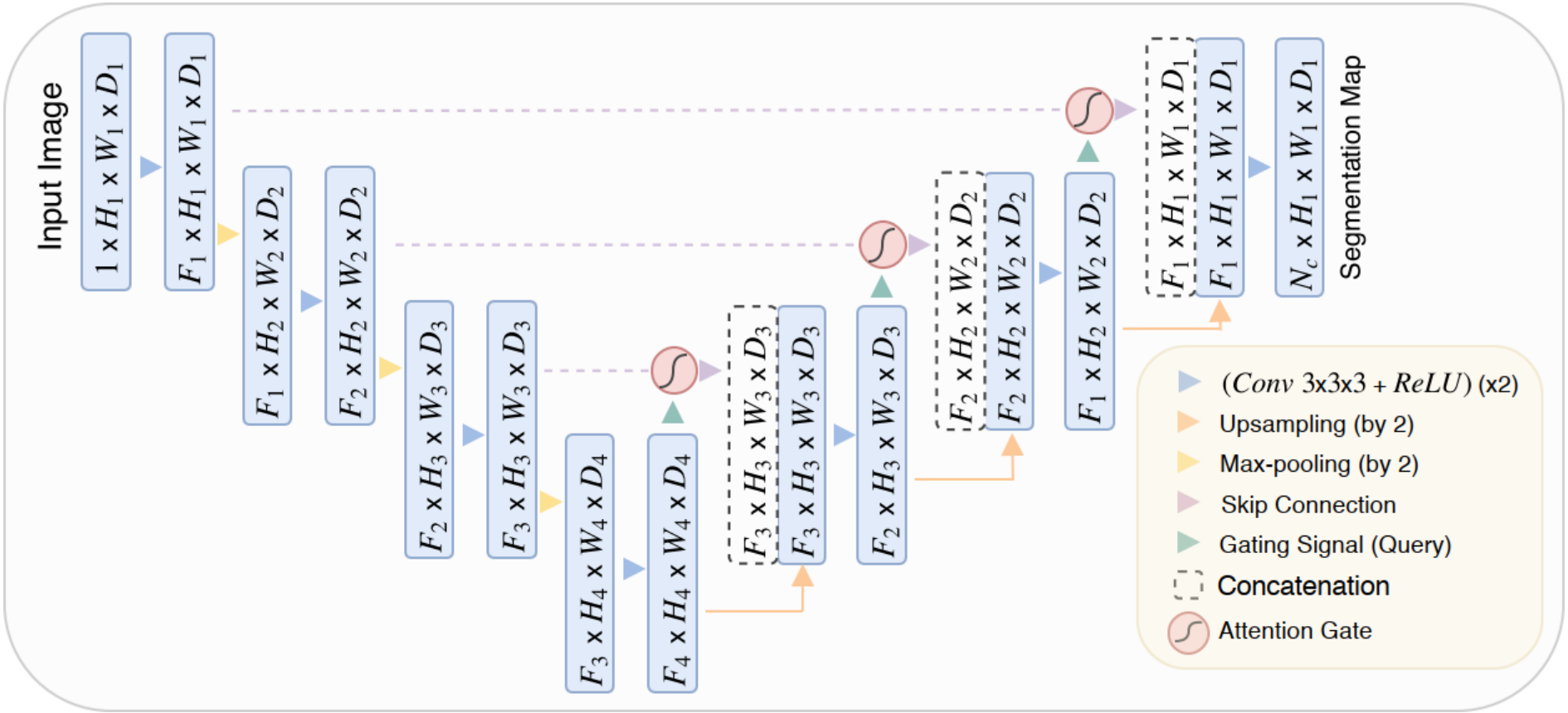
Dense U-Net Architecture



[Zhou et al., 2018]

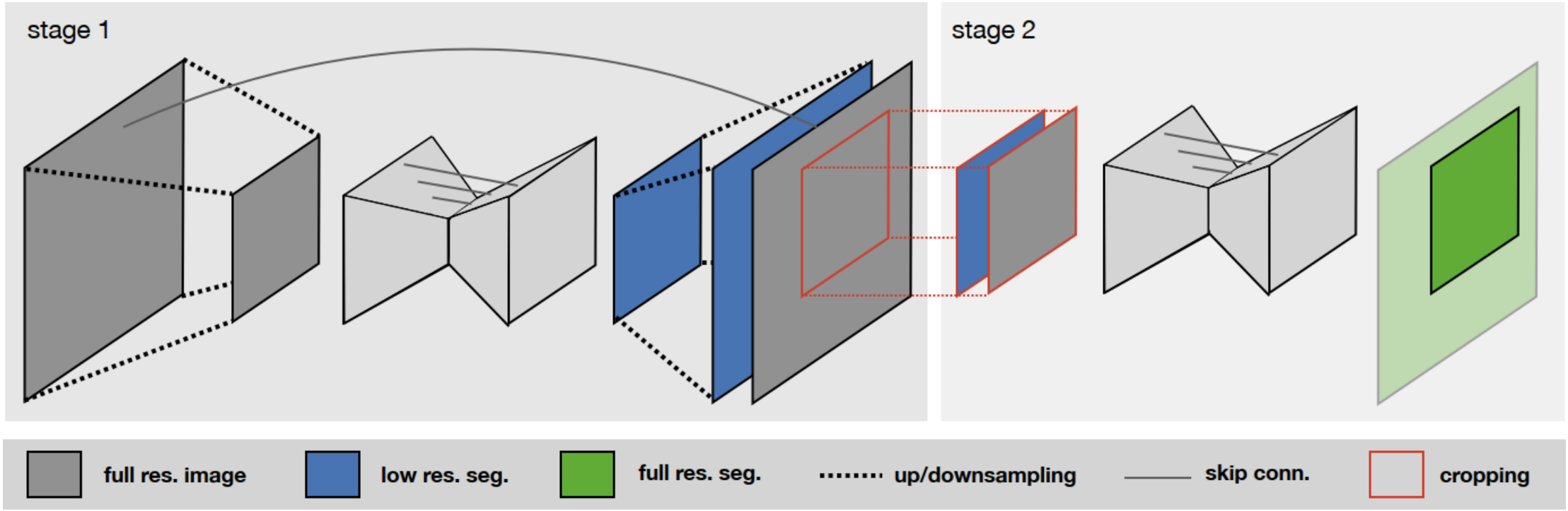
UNet++ Architecture

- Attention U-Net: "Attention U-Net: Learning Where to Look for the Pancreas" [Oktay et al., 2018]
  - Adds attention gates to the skip connections, helping focus on relevant features and suppress irrelevant ones
- nnU-Net (no-new-Net): "nnU-Net: Self-adapting Framework for U-Net-Based Medical Image Segmentation" [Isensee et al., 2018]
  - Automatically configures and optimizes U-Net-based models for various datasets and segmentation tasks



[Oktay et al., 2018]

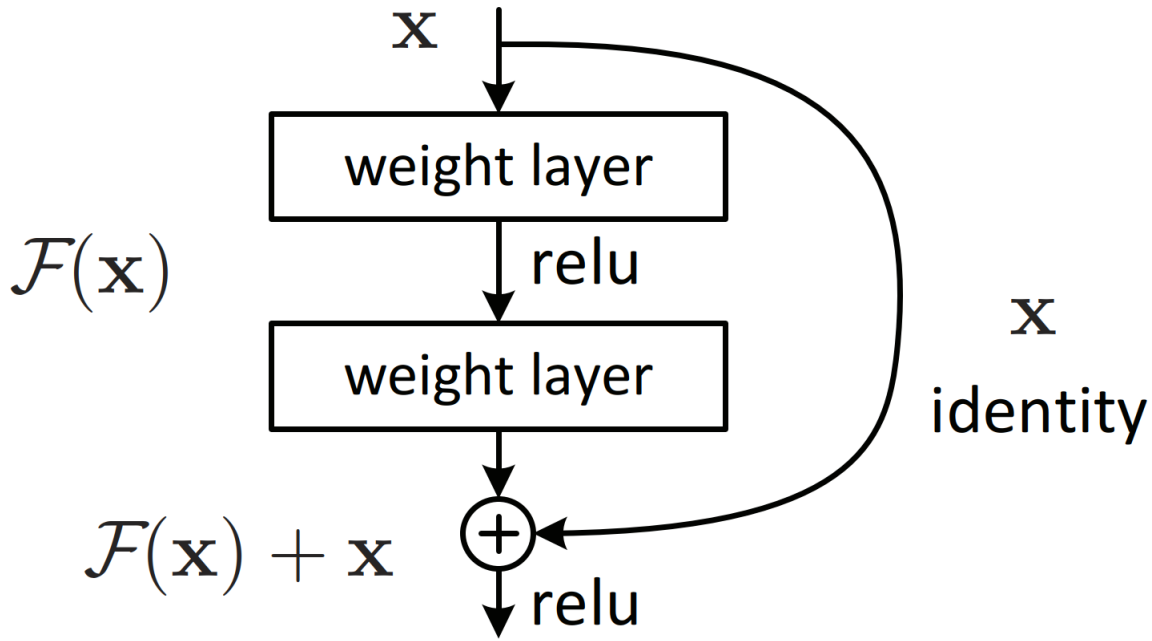
Attention U-Net Architecture



[Isensee et al., 2018]

Cascaded U-Nets as One Possible Configuration Within nnU-Net

- ResNet-based architectures
  - ResNet: "Deep Residual Learning for Image Recognition" [He et al., 2015]
    - Introduces residual learning with skip connections to train very deep networks, primarily for image classification tasks
  - ResUNet / Residual U-Net: "Road Extraction by Deep Residual U-Net" [Zhang et al., 2018]
    - Combines the U-Net architecture with residual learning, incorporating both U-Net style skip connections and ResNet style residual connections
  - ResUNet++: "ResUNet++: An Advanced Architecture for Medical Image Segmentation" [Jha et al., 2019]
    - Enhances ResUNet by adding squeeze and excitation blocks, attention blocks, and a feature fusion mechanism to capture more contextual information

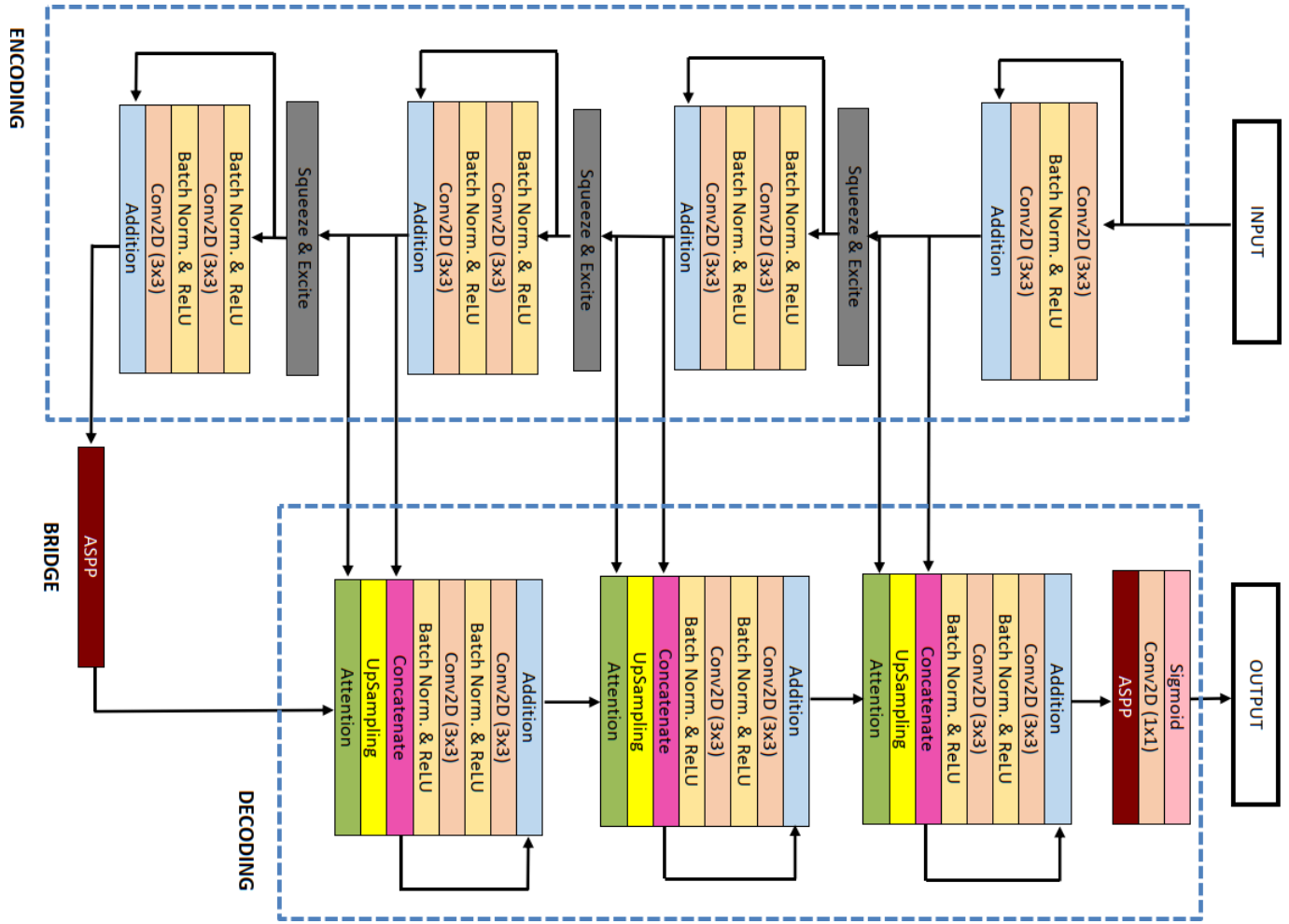


[He et al., 2015]]

Building Block for Residual Learning in ResNet

[Zhang et al., 2018]

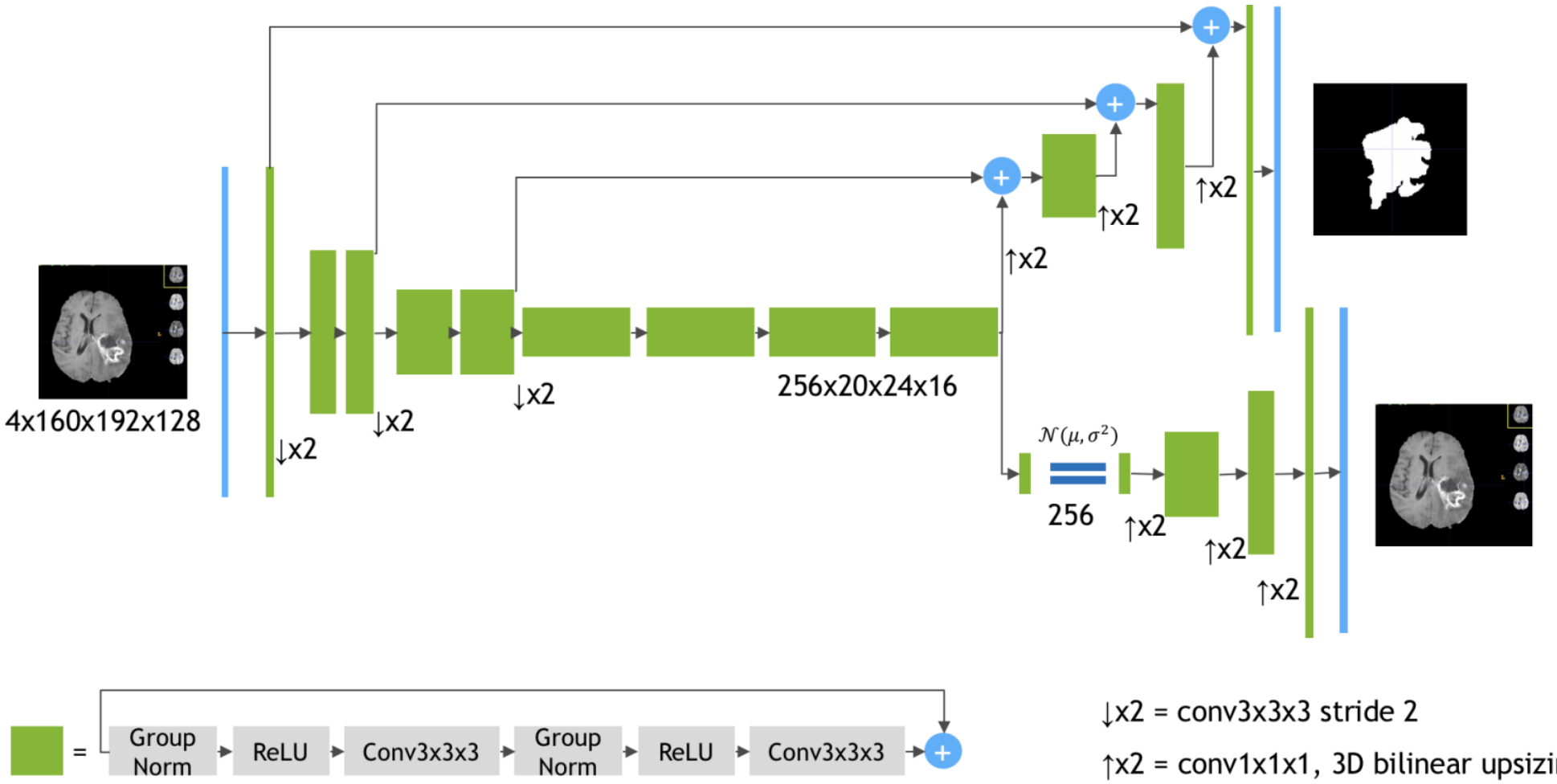
ResUNet Architecture



[Jha et al., 2019]

ResUNet++ Architecture

- SegResNet: "3D MRI Brain Tumor Segmentation Using Autoencoder Regularization" [Myronenko, 2018]
  - Adapts the ResNet architecture for segmentation tasks, incorporating both down-sampling and up-sampling paths with residual connections



[Myronenko, 2018]

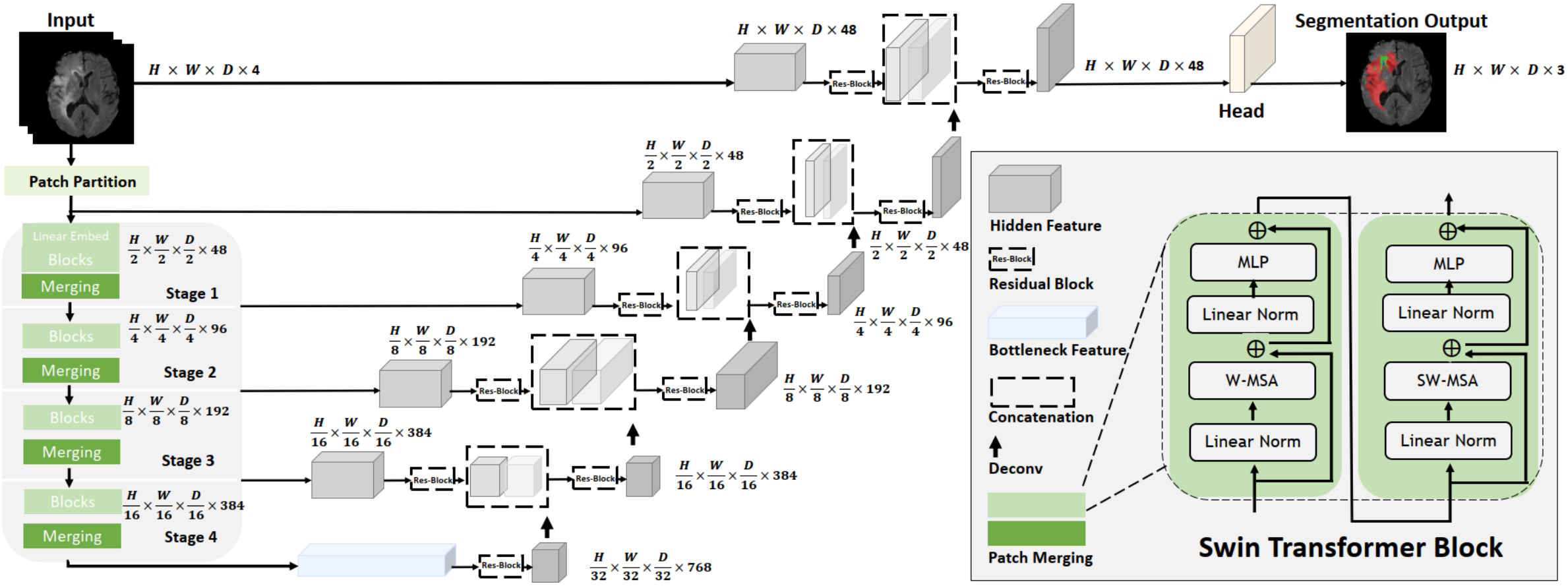
SegResNet Architecture

- Transformer-based architectures: Transformer-dominant architectures
  - Transformer as primary component (minimal CNN usage)
  - SETR (SEgmentation TRansformer): "Rethinking Semantic Segmentation from a Sequence-to-Sequence Perspective with Transformers" [Zheng et al., 2021]
    - First transformer-dominant approach for dense prediction
    - Uses a pure transformer-based architecture by treating semantic segmentation as sequence-to-sequence prediction
    - Encoder: ViT (Vision Transformer) | Decoder: Minimal CNN (1x1 conv + upsampling)

SETR Architecture

[Zheng et al., 2021]

- Swin UNETR: "Swin UNETR: Swin Transformers for Semantic Segmentation of Brain Tumors in MRI Images" [Hatamizadeh et al., 2021]
  - First to apply hierarchical Swin (Shifted Window) Transformer to 3D medical imaging
  - Addresses long-range dependency limitations of CNNs using hierarchical Swin Transformer for 3D images
  - Encoder: Swin Transformer | Decoder: FCNN-based CNN
- Swin-Unet: "Swin-Unet: Unet-like Pure Transformer for Medical Image Segmentation" [Cao et al., 2022]
  - Adapts Swin Transformer for 2D images in a U-Net-like structure
  - Encoder: Swin Transformer | Decoder: Swin Transformer + minimal CNN

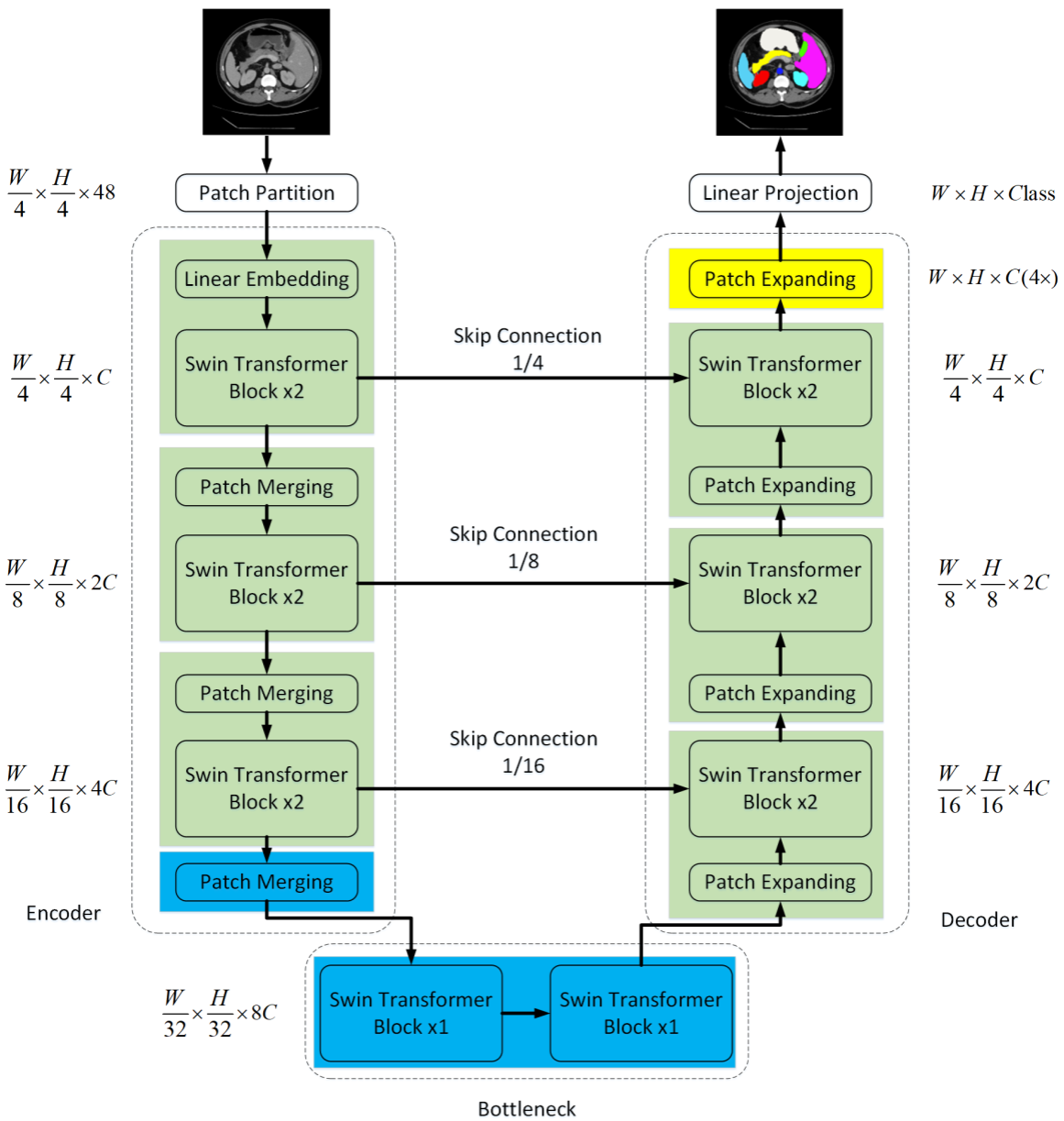


[Hatamizadeh et al., 2022]

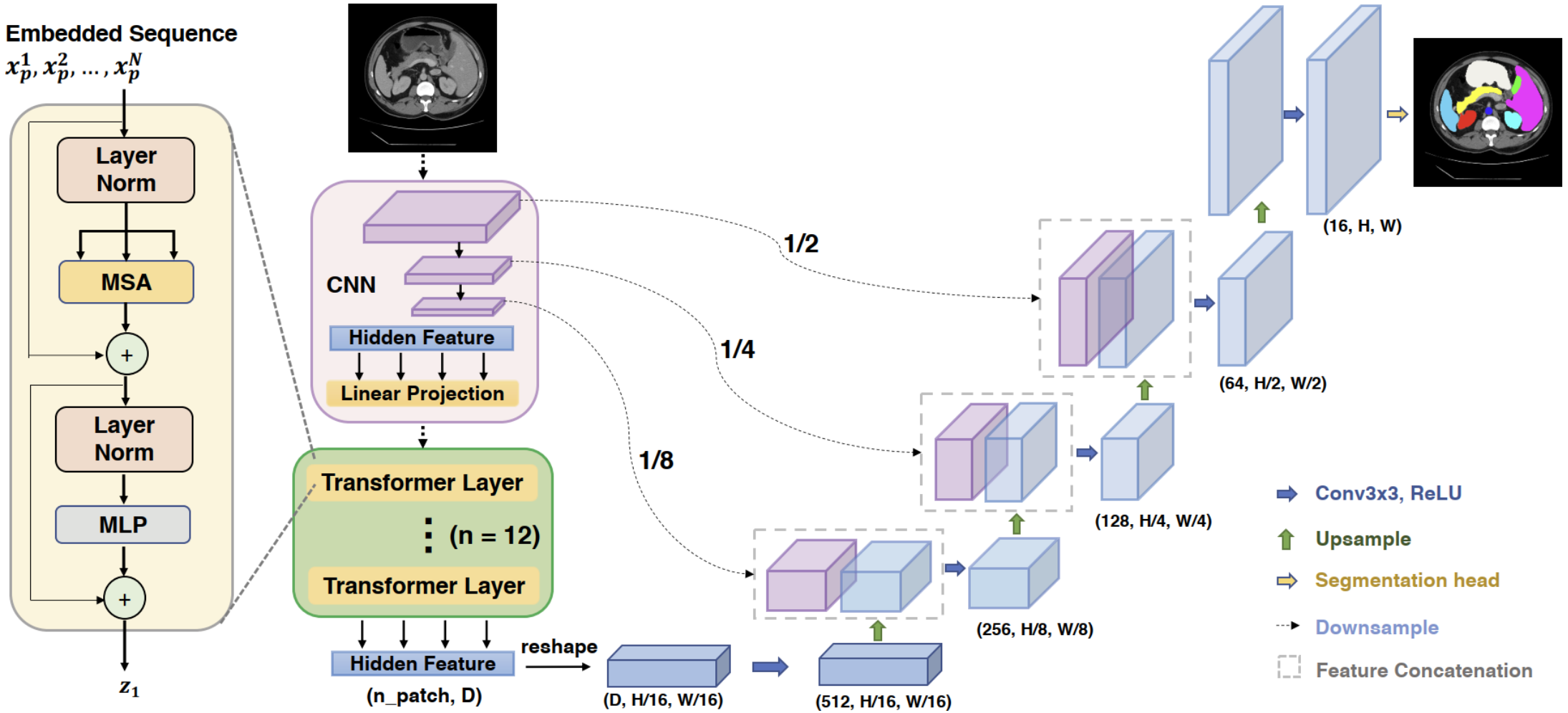
Swin UNETR Architecture

[Cao et al., 2021]

Swin-Unet Architecture



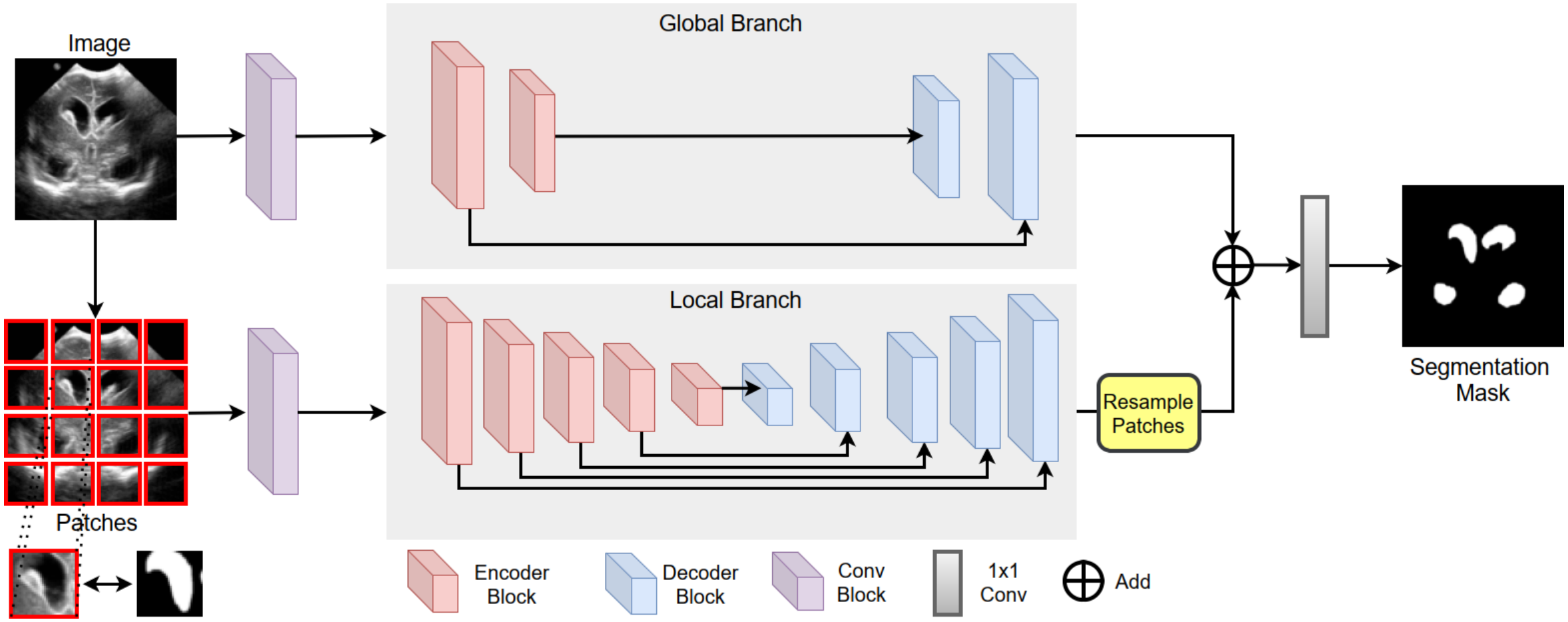
- Transformer-based architectures: CNN-Transformer hybrid architectures
  - Substantial integration of both CNN and Transformer, moving toward efficient hybrids rather than pure architectures
  - TransUNet: "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation" [Chen et al., 2021]
    - First successful balanced CNN-Transformer hybrid
    - Introduces a symmetric encoder-decoder structure combining CNN and Transformer blocks
    - Encoder: CNN (ResNet-like) | Decoder: CNN with Transformer bottleneck



[Chen et al., 2021]

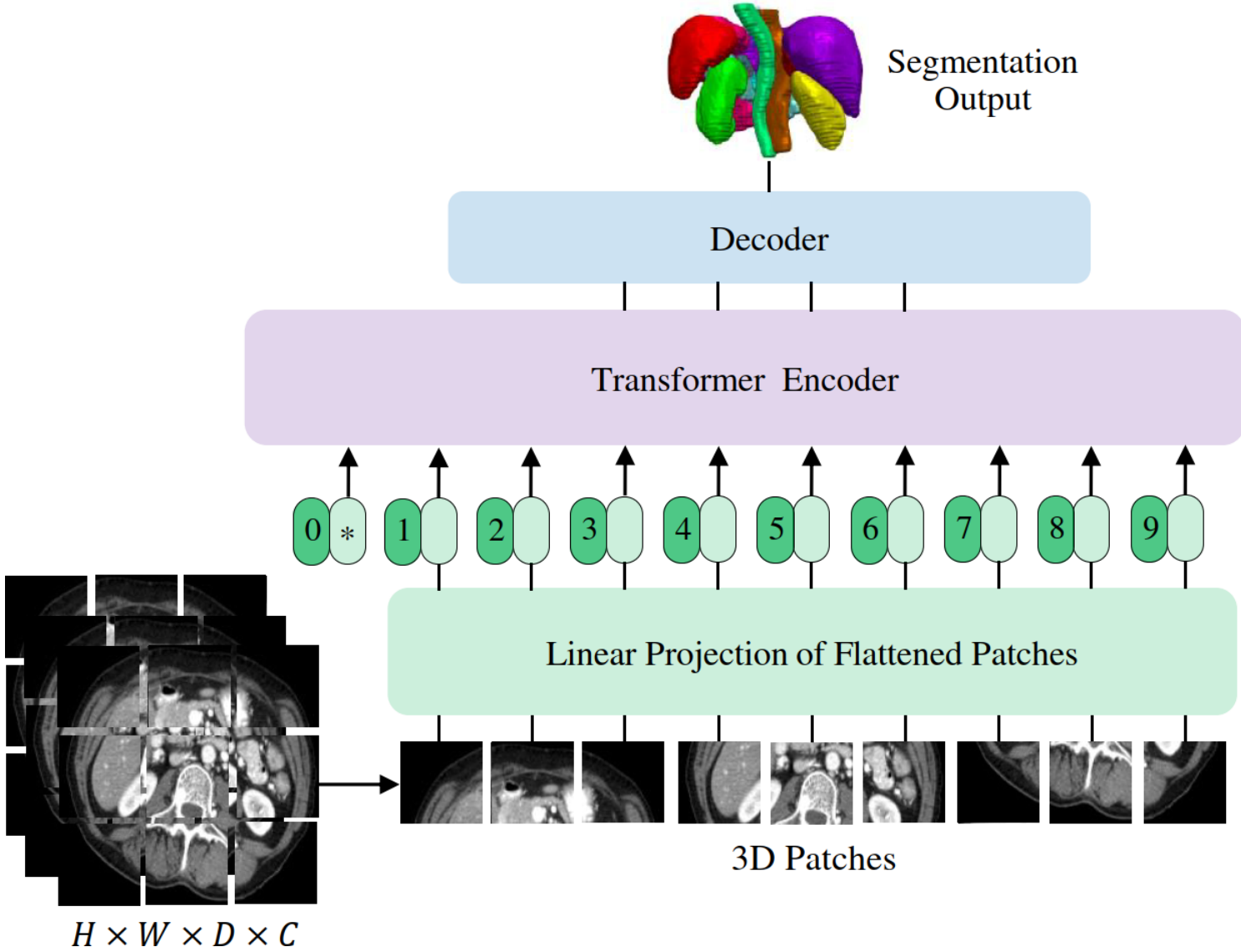
TransUNet Architecture

- MedT (Medical Transformer): "Medical Transformer: Gated Axial-Attention for Medical Image Segmentation" [Valanarasu et al., 2021]
  - Uses a transformer-based architecture designed specifically for medical image segmentation with gated axial-attention
  - Encoder: Interleaved CNN + Transformer | Decoder: Interleaved CNN + Transformer
- UNETR (UNEt TRansformers): "UNETR: Transformers for 3D Medical Image Segmentation" [Hatamizadeh et al., 2022]
  - Uses transformer encoder and CNN decoder with skip connections for 3D medical images
  - Encoder: ViT | Decoder: CNN with skip connections



[Valanarasu et al., 2021]

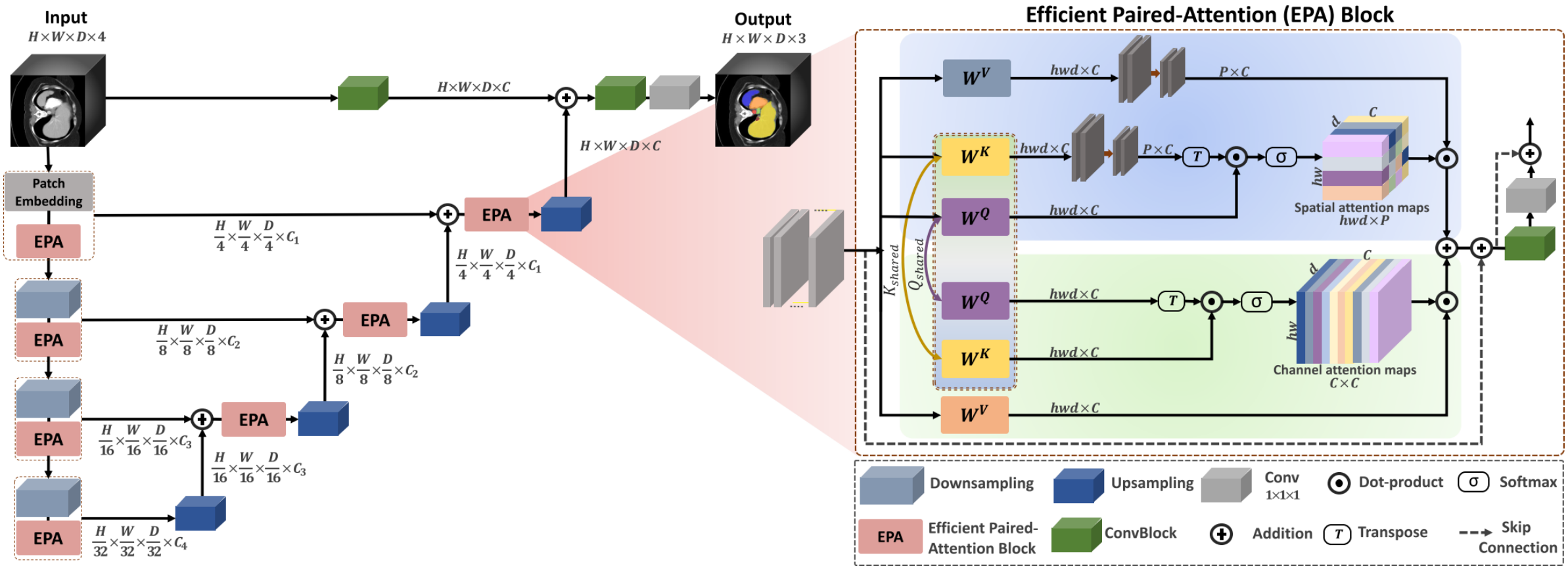
MedT Architecture



[Hatamizadeh et al., 2022]

UNETR Architecture

- UNETR++: "UNETR++: Delving Into Efficient and Accurate 3D Medical Image Segmentation" [Shaker et al., 2024]
  - Builds upon UNETR by incorporating efficient paired attention block for reducing computational complexity
  - Encoder: ViT | Decoder: Enhanced CNN with better fusion



[Shaker et al., 2024]]

UNETR++ Architecture

Foundation Models

- Large-scale AI models trained on vast amounts of data that serve as a foundation for various downstream tasks
  - First defined in the paper "On the Opportunities and Risks of Foundation Models" [Bommasani et al., 2021]
- Initially emerged from the Natural Language Processing (NLP) field and expanded later to other domains (vision, audio, etc.)

- Why 'Foundation'?
  - Act as a foundation/basis for various applications
  - Serve as a building block for specialized models
  - Provide fundamental understanding of data patterns
  - Form the base for transfer learning
- Characteristics
  - Large-scale pre-training
  - Self-supervised or semi-supervised learning
  - Adaptability to multiple downstream tasks
  - Transfer learning capabilities
  - Zero/few-shot learning abilities

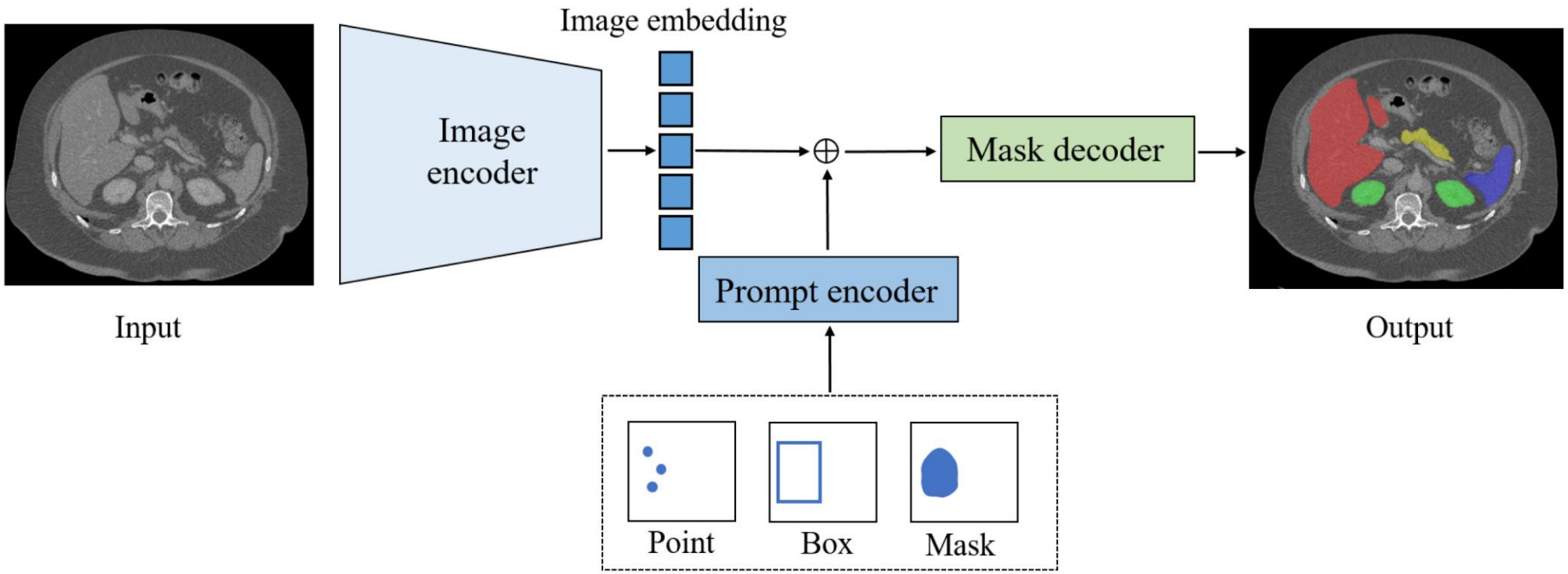
- Impact on AI development
  - Reduced need for task-specific training
  - Improved generalization
  - Cost-effective deployment
- Common examples
  - Language: Bidirectional Encoder Representations from Transformers (BERT), Generative Pre-trained Transformer (GPT)
  - Vision: DALL-E, Contrastive Language-Image Pre-training (CLIP)
  - Multimodal: Segment Anything Model (SAM), Segment Everything Everywhere Model (SEEM)
  - Cross-domain: Pathways Language Model (PaLM), Gato

Segment Anything Model (SAM)

- First foundation model for image segmentation
- Initially developed and introduced by Meta AI (formerly Facebook AI Research): "Segment Anything" [Kirillov et al., 2023]
- Released as open source in April 2023
  - Available on GitHub [https://github.com/facebookresearch/segment-anything]

- Key features
  - Zero-shot segmentation capabilities
  - Prompt-based interface
  - Trained on Segment Anything 1 Billion masks (SA-1B, 1 billion masks extracted from 11 million images) dataset
  - Versatile input prompts (points, boxes, text)
- Notable developments
  - Medical SAM
  - Fast SAM
  - Mobile SAM
  - Other domain-specific variants

- Architecture
  - Based on transformer architecture
  - Main components
    - Image encoder
      - Based on ViT
      - Extracts image embeddings
    - Prompt encoder
      - Processes user interactions
      - Handles different prompt modes
    - Mask decoder
      - Fuses image and prompt embeddings
      - Predicts segmentation masks



[Zhang et al., 2024]

SAM Architecture

Medical Segmentation Foundation Models

- SAM-based models
  - MedSAM [Ma et al., 2024]
    - Fine-tunes SAM on 1.57M medical image-mask pairs across 10 modalities for universal medical segmentation
  - SAM-Med2D [Cheng et al., 2023]
    - Adapts SAM for 2D medical images using comprehensive medical datasets with improved cross-modal performance

– SAM-Med3D [Wang et al., 2023]

- Extends SAM to 3D volumetric medical images, trained from scratch on 131K+ 3D masks across 247 categories

– SAMIHS [Wang et al., 2024]

- Introduces SAM-based parameter-efficient fine-tuning method specifically for intracranial hemorrhage (ICH) segmentation

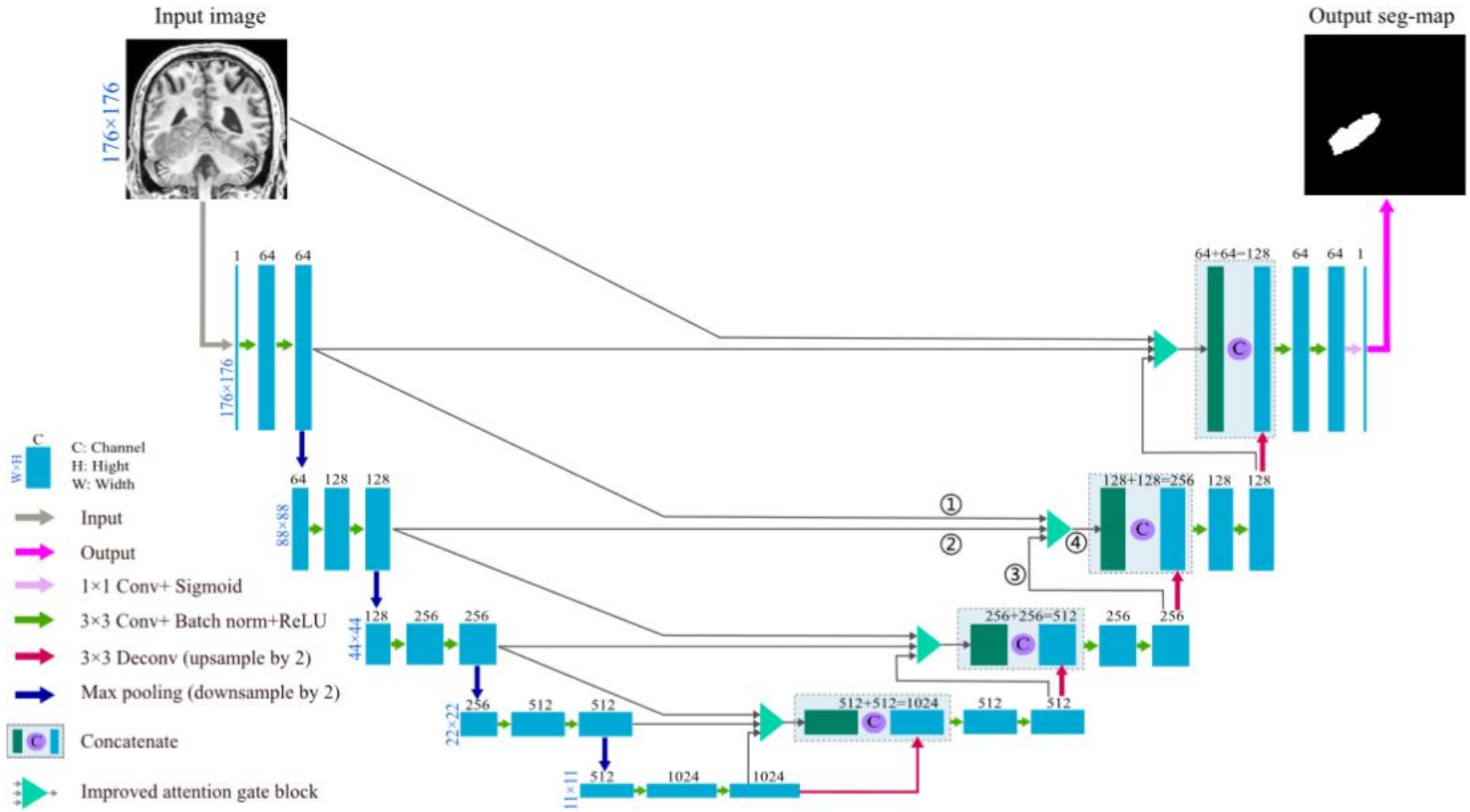
Dataset	BCIHM		Instance		
Method	Dice	HD95	Dice	HD95	Params(M)
U-Net	50.06	3.99	62.07	4.26	7.77
Att-UNet	54.29	3.89	29.74	7.14	34.88
U-Net++	53.80	3.92	53.67	4.86	9.16
TransUNet	46.47	4.05	58.23	4.44	106.17
TransFuse	52.14	3.86	24.83	7.63	26.57
H2Former	48.79	4.03	31.12	5.61	33.86
SAM	49.32	4.29	61.46	5.04	N/A
MedSAM	51.38	4.51	51.38	4.51	N/A
SAMed	66.13	3.56	74.99	3.77	3.93
SAMUS	60.29	3.85	43.85	5.46	42.60
MSA	67.08	3.53	72.65	3.98	11.17
SAMIHS	**69.77**	**3.31**	**76.52**	**3.71**	4.24

- Alternative foundation models
  - VISTA3D [He et al., 2024]
    - NVIDIA's specialized interactive foundation model trained on 11,454 3D CT volumes supporting 127 anatomical classes with state-of-the-art automatic and interactive segmentation
  - MedSegX [Zhang et al., 2025]
    - Open-world medical segmentation foundation model using Contextual Mixture of Adapter Experts (ConMoAE), trained on tree-structured MedSegDB covering 39 organs and tissues with strong out-of-distribution performance

Lesion Segmentation Performance for ATLAS Dataset

- U-Net [Chen et al., 2018]
  - DSC = 0.50
    - ATLAS R1.2 dataset
    - Slice input (128 × 128 or 256 × 256)

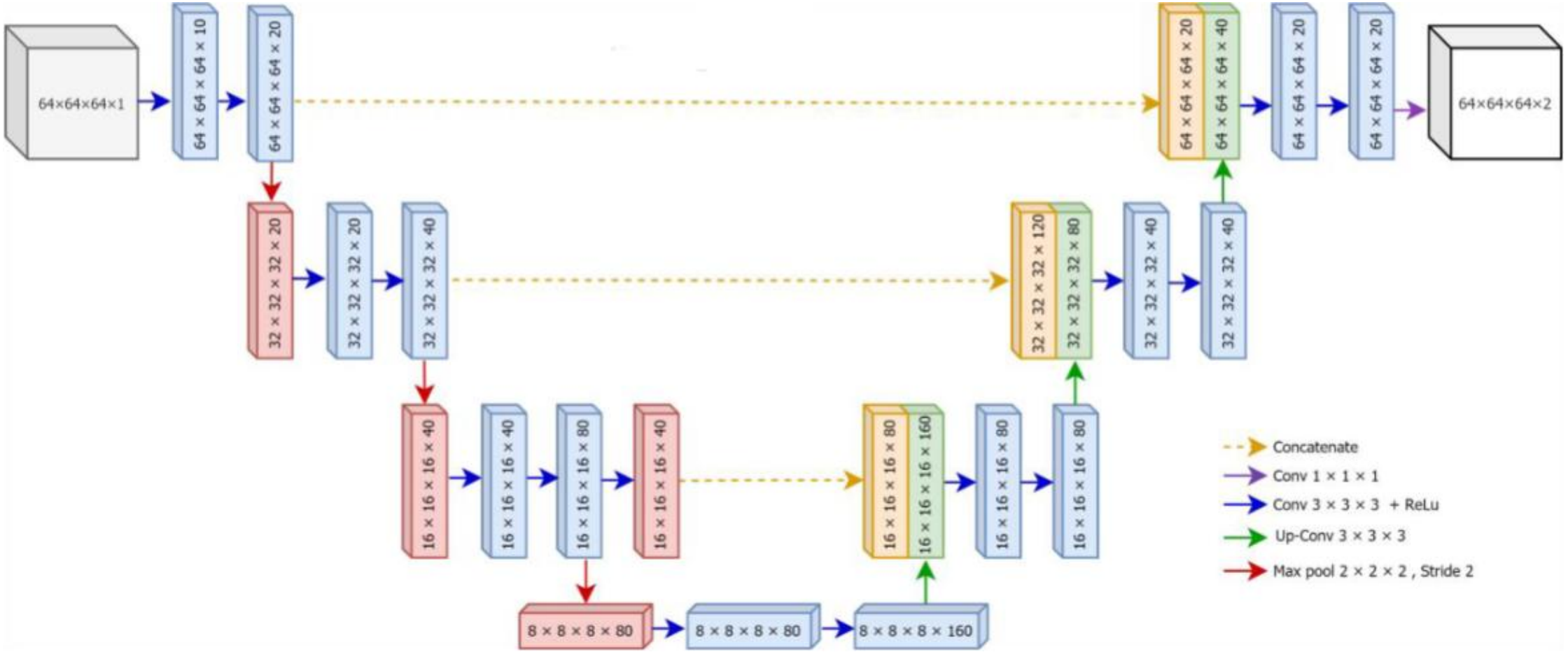
- Attention U-Net [Hui et al., 2020]
  - Partitioning-stacking prediction fusion
  - DSC = 0.593
    - ATLAS R1.2 dataset
    - Slice input (176 × 176)



[Hui et al., 202]0

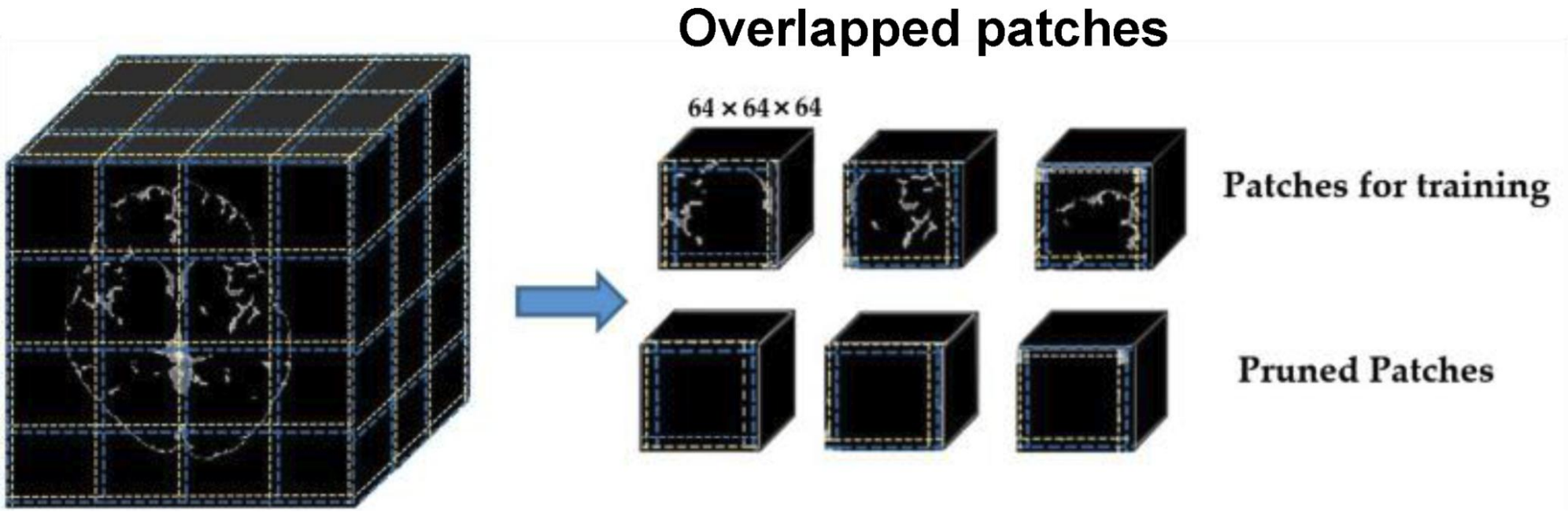
Proposed Attention U-Net-based Architecture

- 3D U-Net [Paing et al., 2021]
  - Variational mode decomposition for preprocessing
  - Overlapped patches strategy
  - DSC = 0.668
    - ATLAS R1.2 dataset
    - Patch input (64 × 64 × 64)



[Paing et al., 2021]

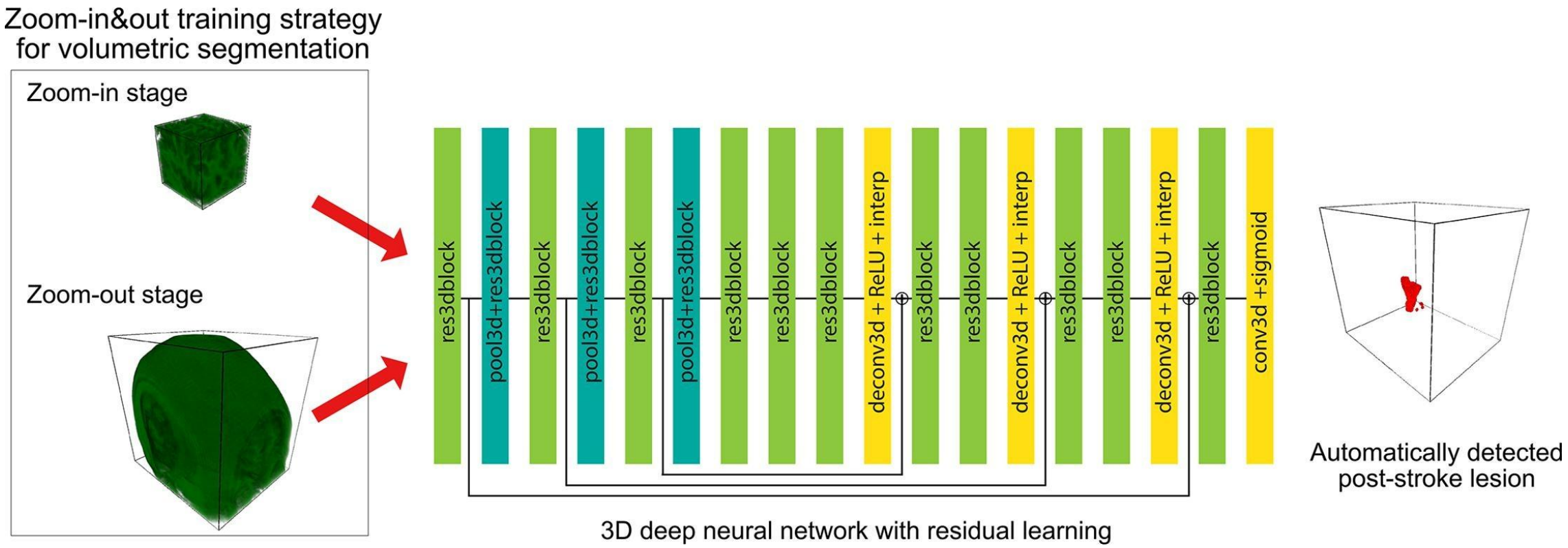
Proposed 3D U-Net-based Architecture



[Paing et al., 2021]

Overlapping Patches Strategy

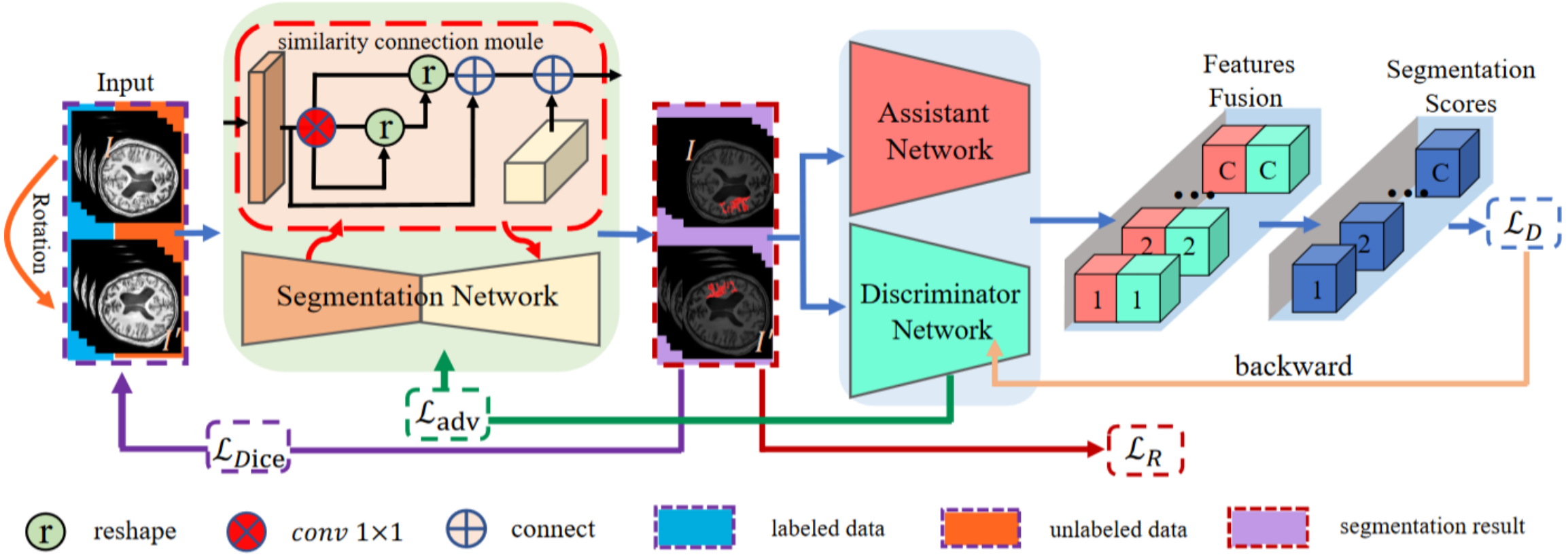
- Residual U-Net [Tomita et al., 2020]
  - Two-stage zoom-in&out training strategy
  - DSC = 0.64 (0.51 ~ 0.76)
    - ATLAS R1.2 dataset
    - Volume input (128 × 128 × 128 for the zoom-in stage and 144 × 172 × 168 for the zoom-out stage)



[Tomita et al., 2020]

Proposed Residual U-Net-based Architecture

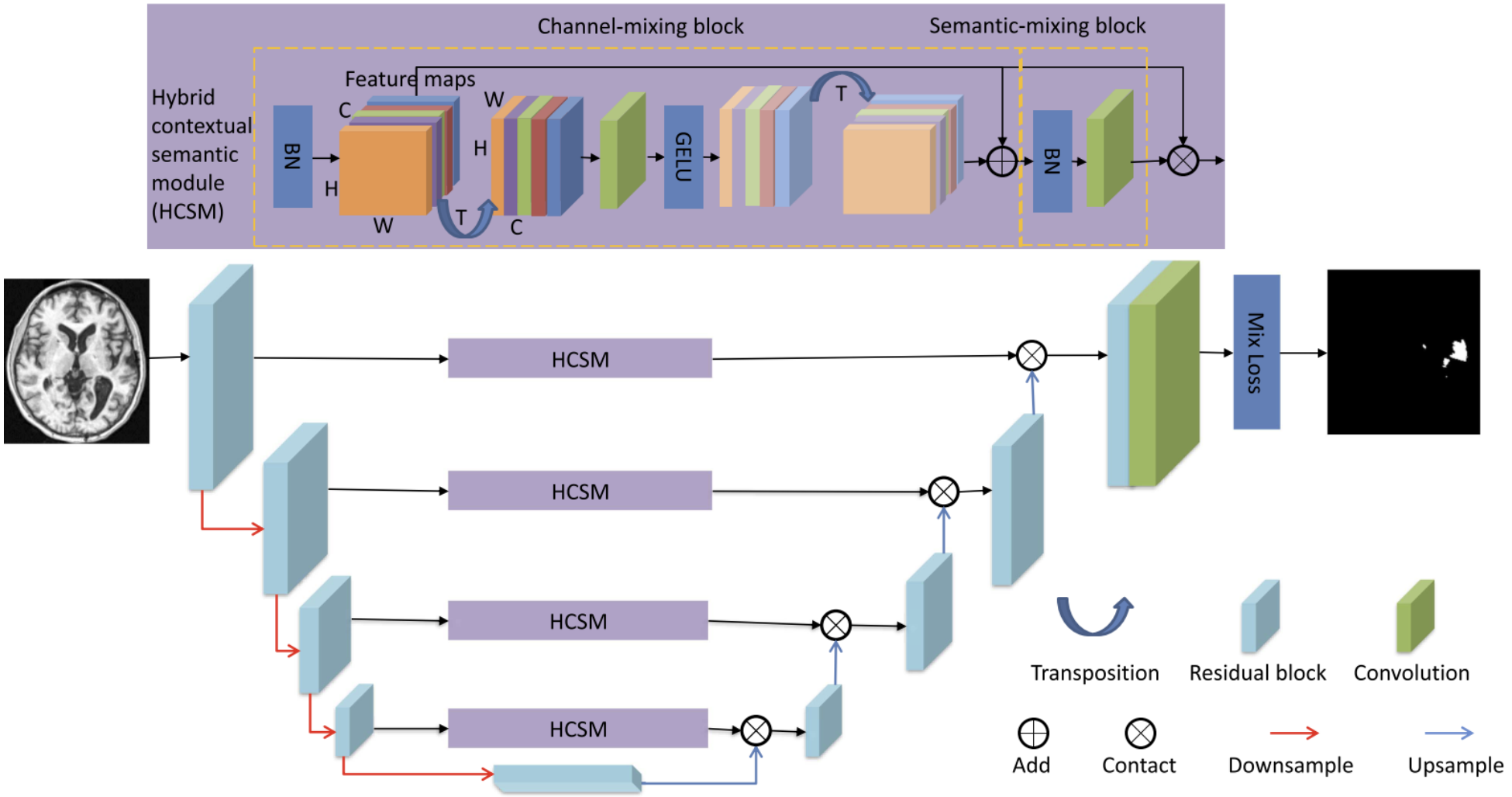
- Consistent Perception Generative Adversarial Network (CPGAN) [Wang et al., 2021]
  - Consistent perception strategy
  - Similarity connection module
  - DSC = 0.617
    - ATLAS R1.2 dataset
    - Slice input (256 × 256)



[Wang et al., 2021]

Proposed CPGAN Architecture

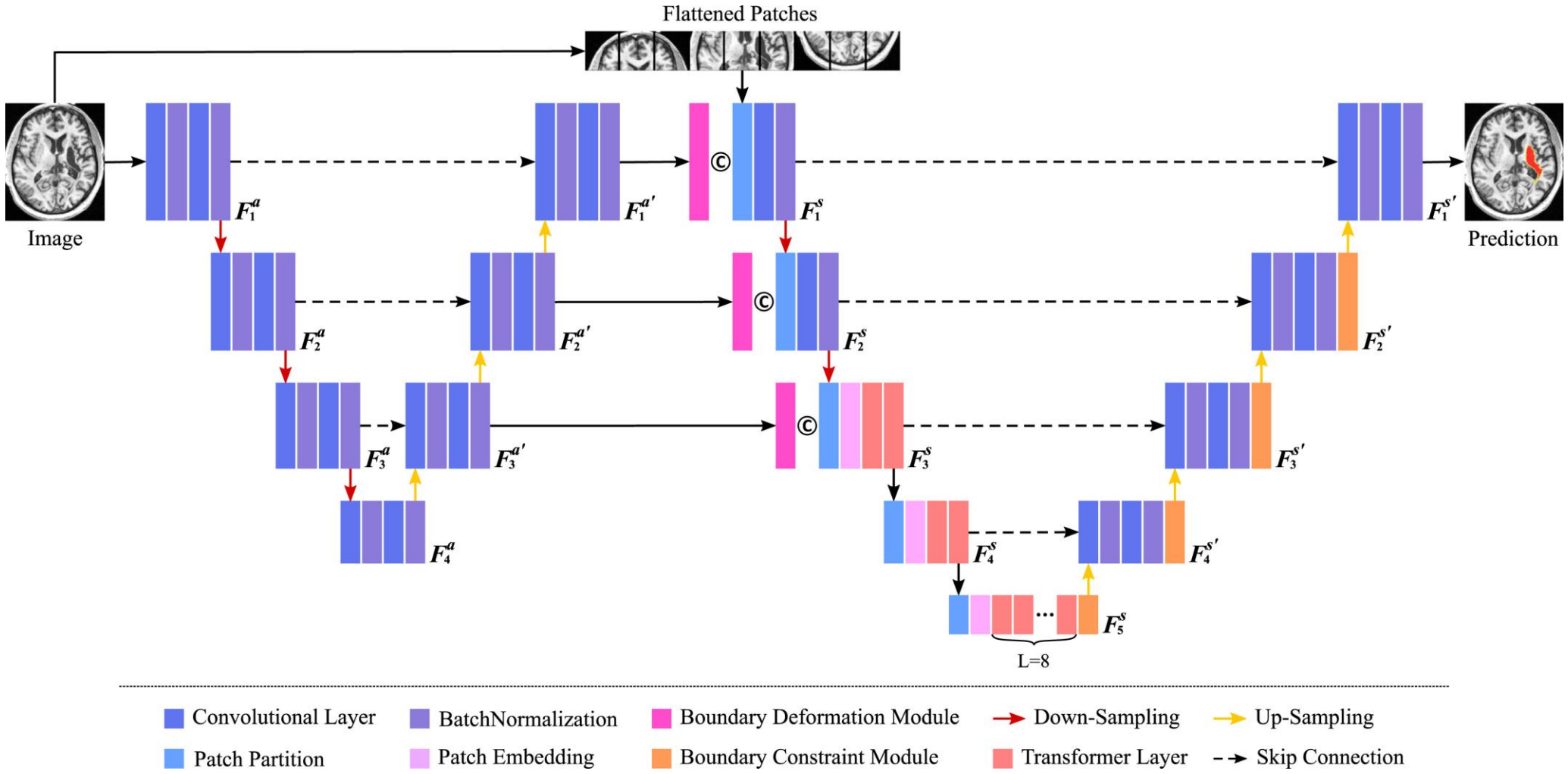
- Hybrid Contextual Semantic (HCS)-Net [Liu et al., 2023]
  - Hybrid contextual semantic module
  - Mixing-loss function for unbalanced small-size lesions
  - DSC = 0.6972
    - ATLAS R2.0 dataset
    - Slice input (240 × 240)



[Liu et al., 2023]

Proposed HCS-Net Architecture

- W-Net [Wu et al., 2023]
  - CNN and Transformer as the backbone network
  - Boundary deformation module
  - Boundary constraint module
  - DSC = 0.6176
    - ATLAS R1.2 dataset
    - Volume input (233 × 197 × 189)



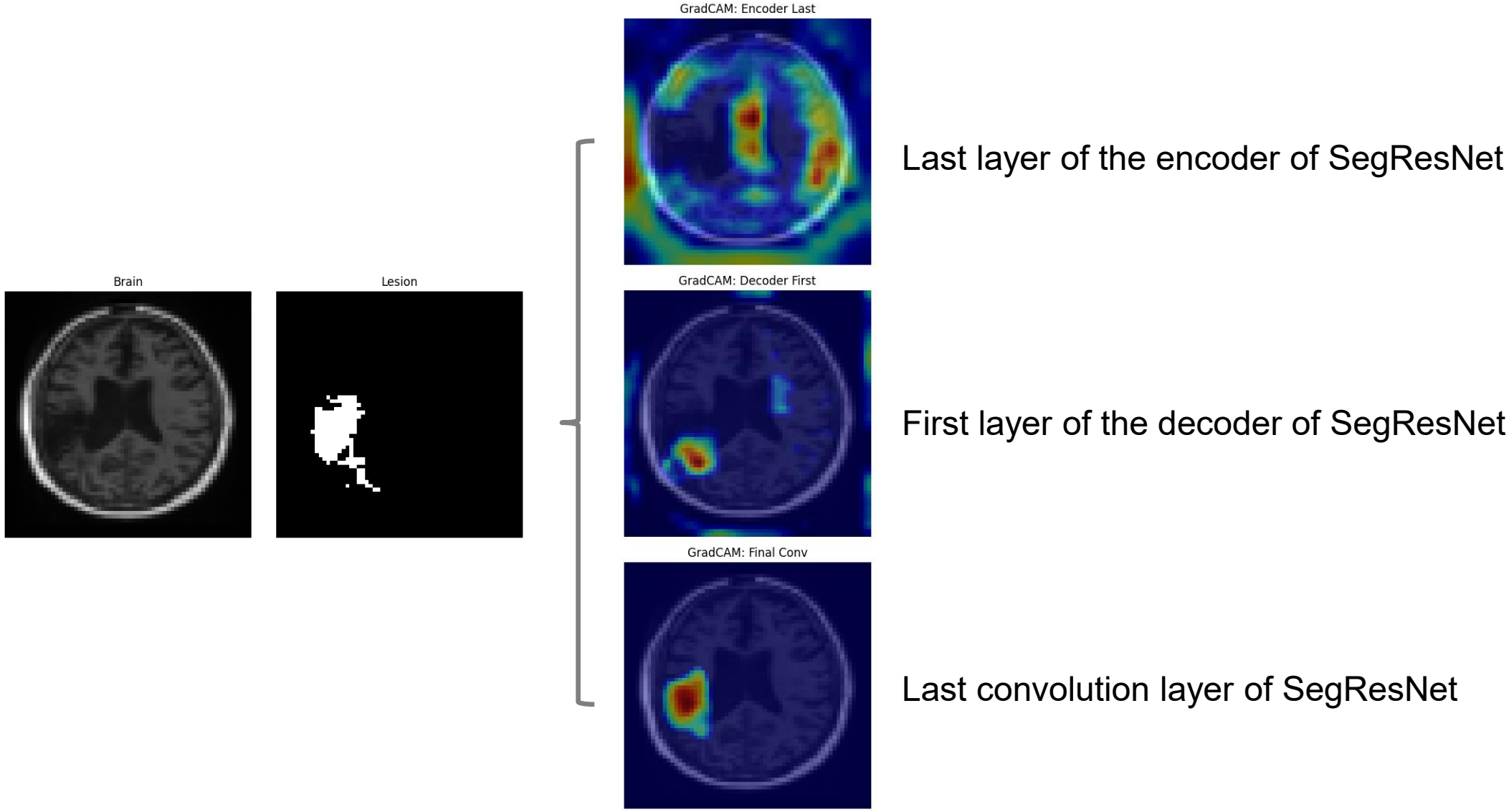
[Wu et al., 2023]

Proposed W-Net Architecture

Model Explanations: CAM Techniques

- Class Activation Mapping (CAM) [Zhou et al., 2016]
  - Highlights discriminative regions for a specific class
  - Requires modification of model architecture (Global Average Pooling (GAP) layer)
  - Each feature map's weight is directly from the final Fully Connected (FC) layer
  - Only applicable to certain network architectures

- Gradient-weighted CAM (Grad-CAM) [Selvaraju et al., 2017]
  - Improvement over CAM
    - No need for model architecture changes
  - Uses gradients to determine feature importance
  - Each feature map's weight is the global average of gradients of the class score with respect to the feature map
  - Applicable to any CNN-based model



Grad-CAM-derived Feature Maps at Different Layers for Lesion Segmentation

- Grad-CAM++ [Chattopadhyay et al., 2018]
  - Further refinement of Grad-CAM
    - Improved multi-object localization
    - Better for detecting small objects
    - Provides smoother and more complete visualization of target objects
  - Uses gradients to determine feature importance
  - Each feature map's weight is calculated using higher-order derivatives and pixel/voxel-wise weighting, considering the spatial distribution of gradients
  - Applicable to any CNN-based model
  - Higher computational complexity compared to Grad-CAM

- Implementation in MONAI
  - Available classes:
    - CAM: **`monai.visualize.CAM`**
    - Grad-CAM: **`monai.visualize.GradCAM`**
    - Grad-CAM++: **`monai.visualize.GradCAMpp`**
  - Supports 2D and 3D medical images
  - Easily integrates with MONAI model pipelines

```python
from monai.visualize import CAM, GradCAM, GradCAMpp

cam = GradCAM(nn_module=model, target_layers="target_layer")
result = cam(x=input_tensor)
```

Demonstration Experiments

- `monai.networks.nets`
  - `UNet`
    - Foundational encoder-decoder architecture with skip connections for medical image segmentation
    - Lesion applicability: Fine detail preservation through skip connections and effectiveness for small lesions
    - Advantages: Simple structure, interpretable design, and baseline performance for most segmentation tasks

- **VNet**
  - 3D-native architecture design with volumetric convolutions and integrated Dice loss
  - Lesion applicability: Spatial continuity leverage of 3D lesions in CT/MRI volumes
  - Advantages: Dice loss integration for medical segmentation and end-to-end 3D optimization
- **SegResNet**
  - Residual learning integration with segmentation for deep network training
  - Lesion applicability: Complex lesion pattern capture through deep structure and contextual relationships
  - Advantages: Lightweight yet effective design with vanishing gradient problem resolution

- **`AttentionUNet`**
  - Attention mechanism introduction for selective feature focusing
  - Lesion applicability: Lesion region focus with irrelevant background suppression
  - Advantages: Enhanced interpretability through attention visualization and improved feature selection
- **UNETR**
  - ViT encoder applied to 3D medical segmentation with global context modeling
  - Lesion applicability: Long-range dependency capture across entire 3D volume (pure global attention)
  - Advantages: Comprehensive global modeling and established transformer principles

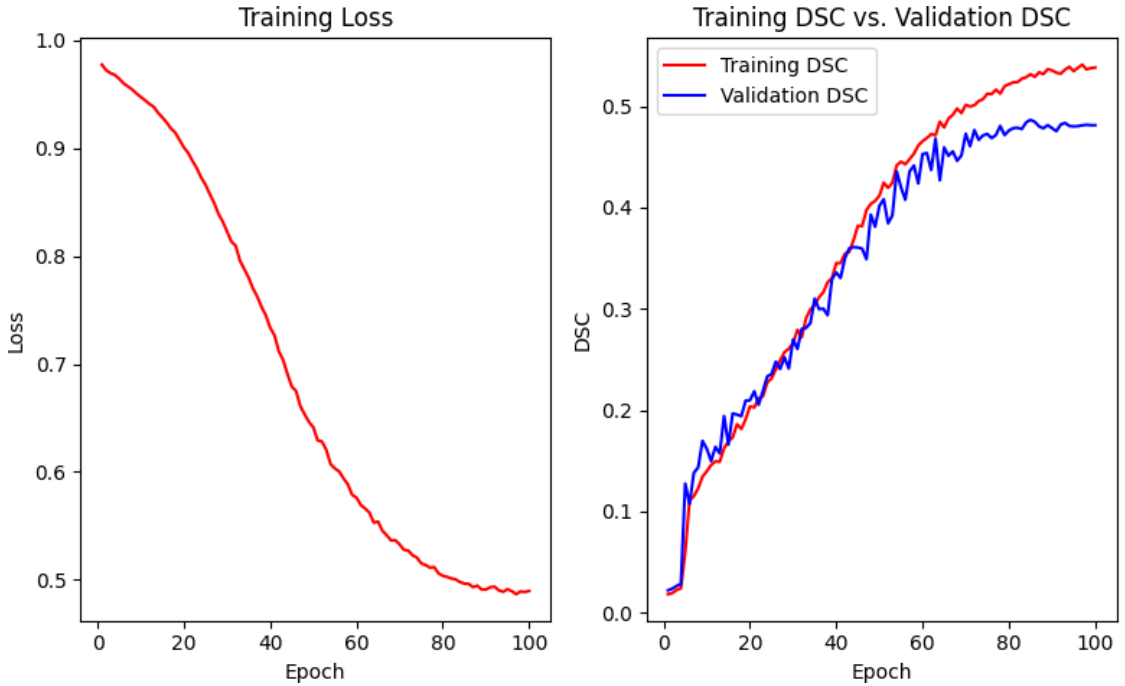
– **SwinUNETR**

- Hierarchical Swin Transformer with shifted window attention for efficient 3D medical segmentation
- Lesion applicability: Efficient processing of lesions with varying sizes and spatial distributions (hierarchical local + global attention)
- Advantages: Computational efficiency through hierarchical feature representation

Category	Parameters	Models
Small	< 10M	SegResNet, UNet, AttentionUnet,
Medium	10-50M	VNet
Large	50-100M	SwinUNETR
Very large	> 100M	UNETR

Architecture Scale Comparison

- Implementation of SegResNet-based lesion segmentation
  - Input: Brain
  - Number of trainable parameters: 1,176,177
  - Validation set: DSC = 0.487
  - Test set: DSC = 0.504 ± 0.238 (0.000 ~ 0.843)



- Padding-based vs. resizing-based approaches
  - Padding-based approach (SegResNet)
    - Preserves original dimensions through adaptive padding: (98, 116, 94) → (112, 128, 96)
    - Validation set: DSC = 0.487
    - Test set: DSC = 0.504 ± 0.238 (0.000 ~ 0.843)
  - Resizing-based approach (SegResNet)
    - Transforms to fixed dimensions through uniform resizing: (98, 116, 94) → (96, 112, 96)
    - Validation set: DSC = 0.460
    - Test set: DSC = 0.468 ± 0.234 (0.000 ~ 0.841)