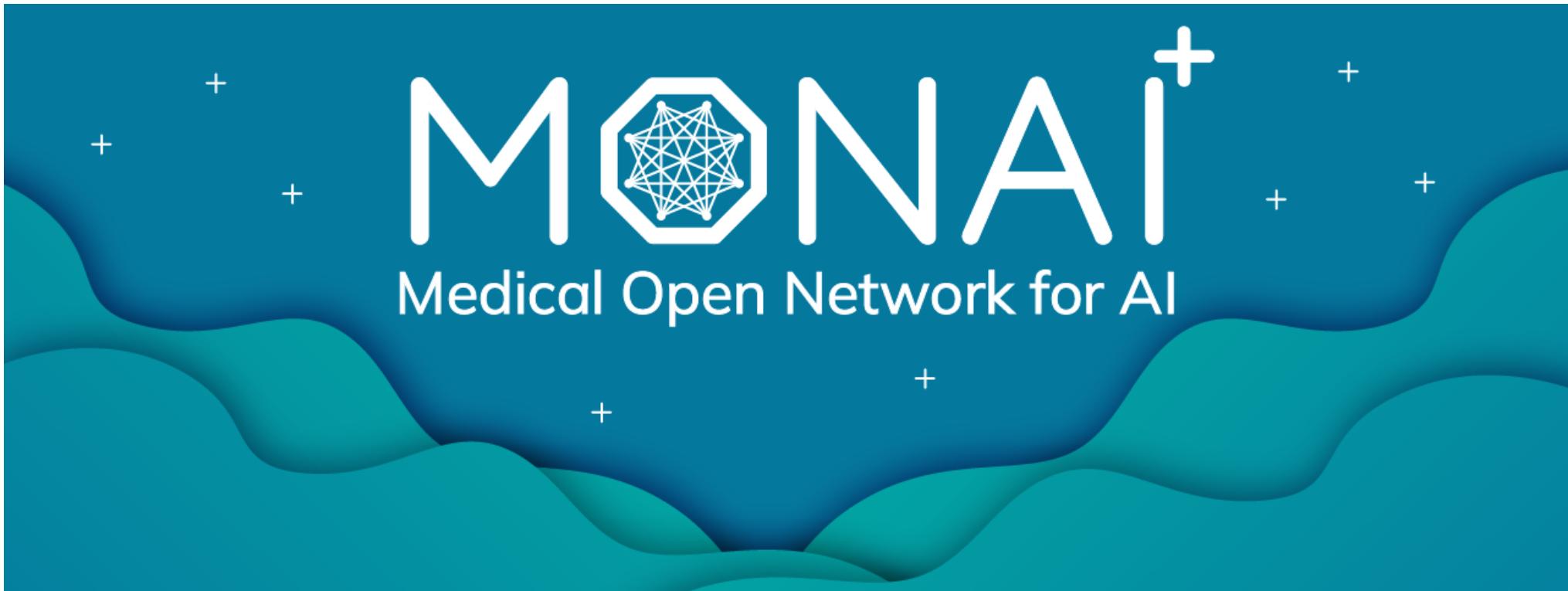


Medical/Bio Research Topics Ⅱ: Week 07 (17.10.2025)

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

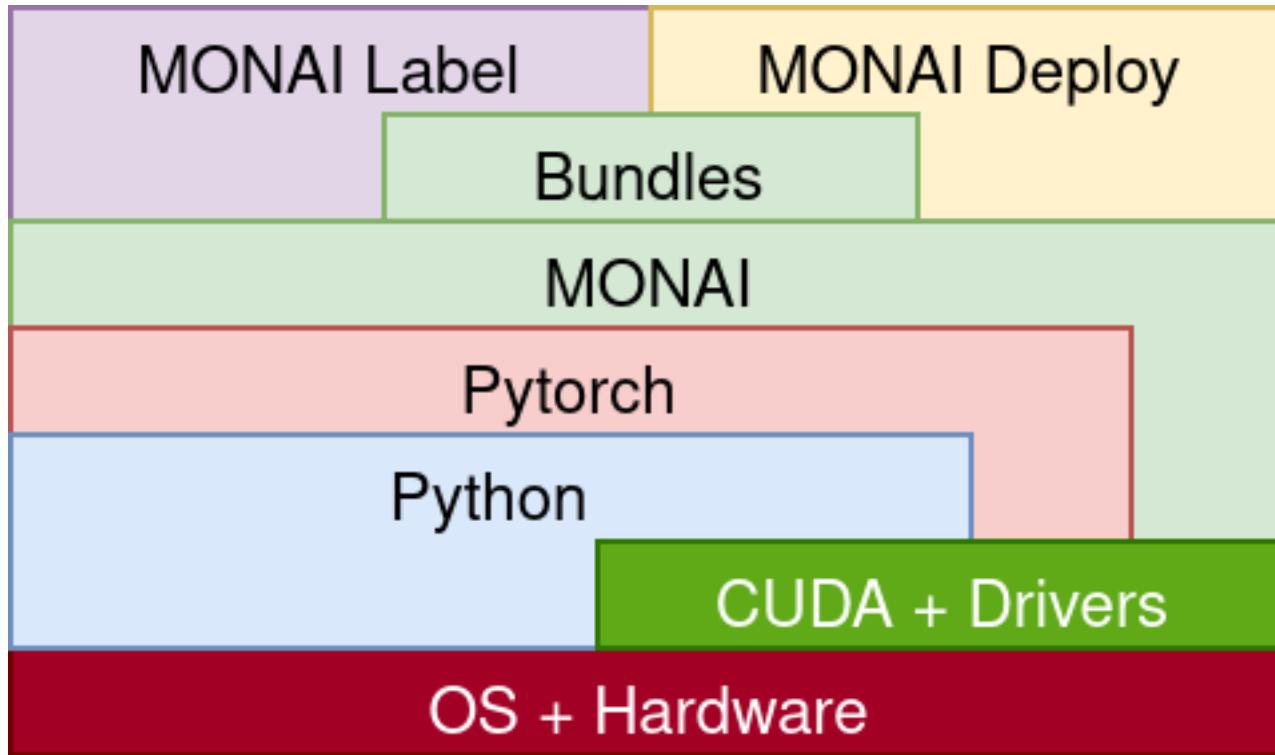
- Open source: Built on PyTorch with Apache 2.0 license
- Standardized: Best practices for healthcare AI with focus on medical imaging
- User-friendly: Clear error messages and intuitive API
- Reproducible: Facilitates replication of research experiments
- Easy integration: Compatible with existing tools and third-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.dev2541 released in October 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.)

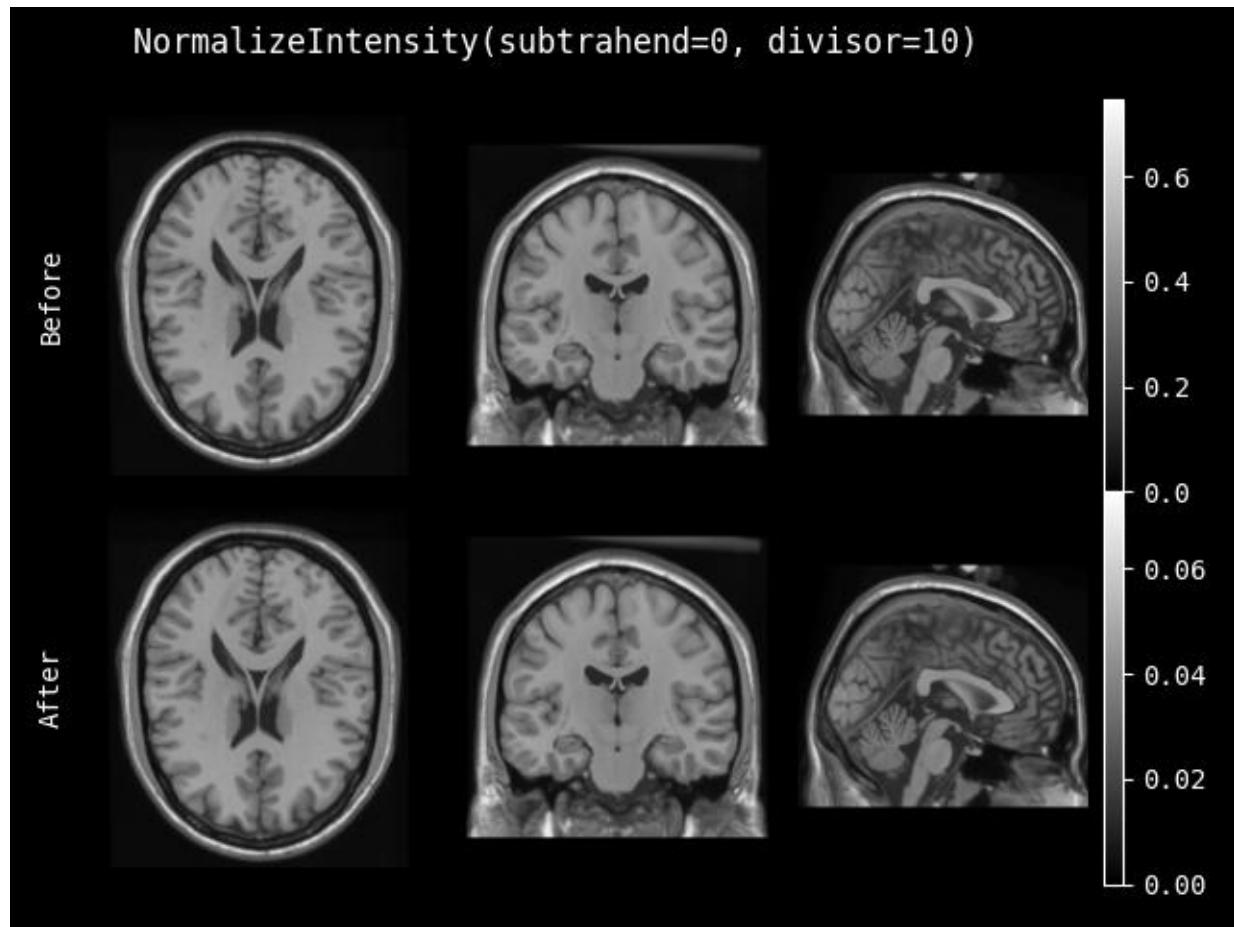
- **monai.optimizers**: Learning rate schedulers and optimization utilities
- **monai.visualize**: Visualization tools including class activation mapping and occlusion sensitivity analysis
- **monai.engines**: Workflow engines for training and evaluation pipelines
- **monai.apps**: Ready-to-use applications
 - Auto3DSeg: Automated 3D segmentation pipeline
- **monai.bundle**: Model packaging and configuration management
- **monai.utils**: Utility functions and helper tools
- **monai.f1**: 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

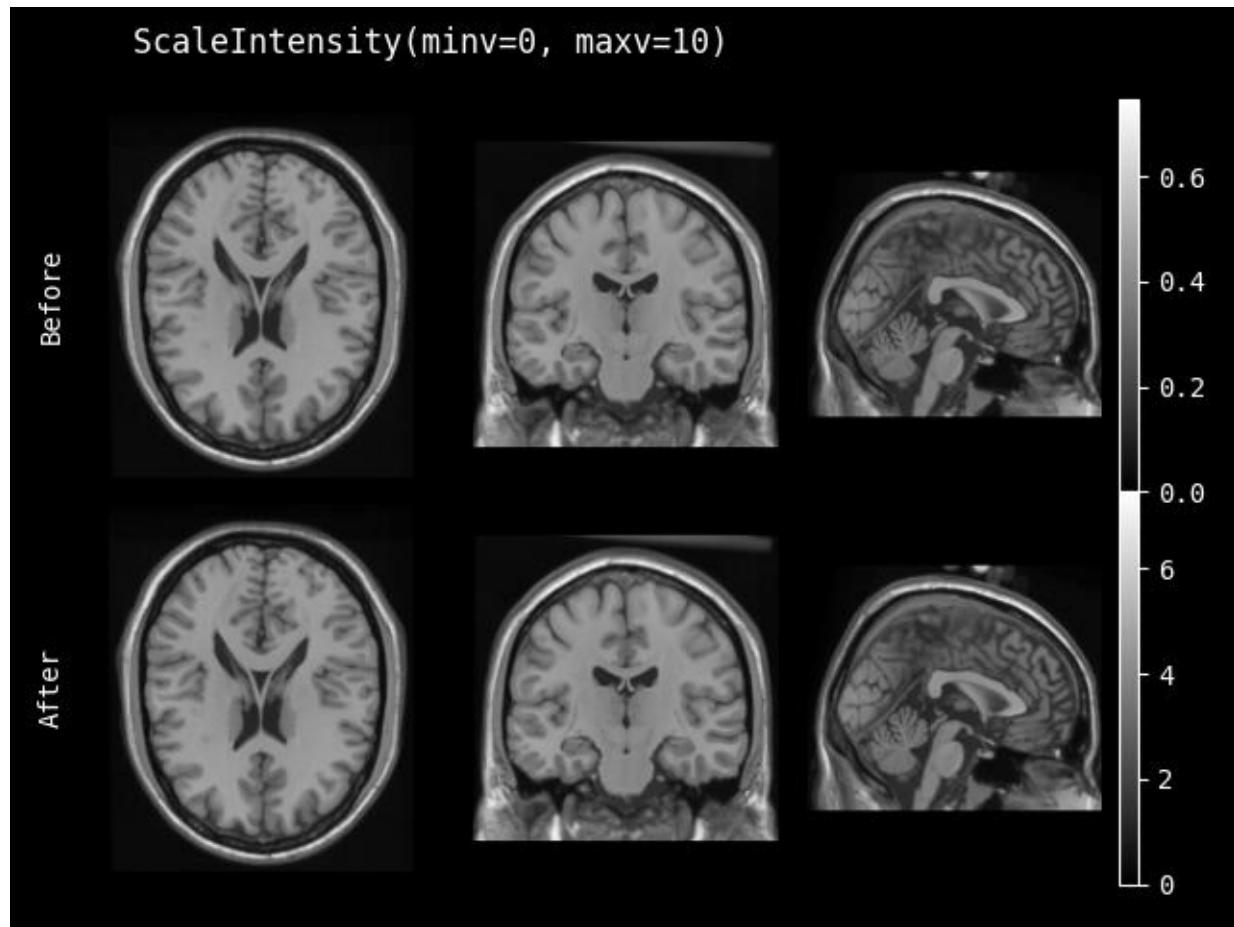
- Intensity transforms

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



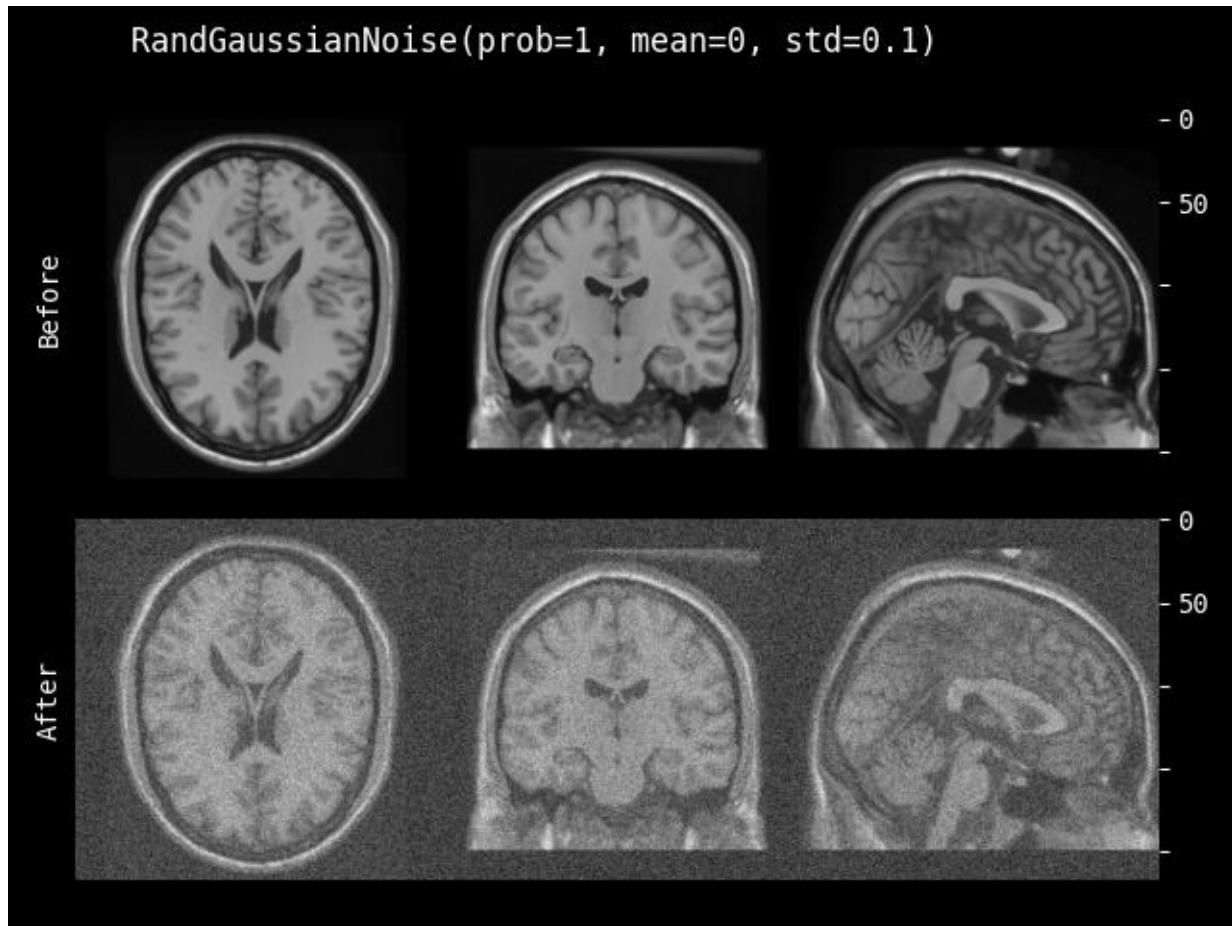
[<https://docs.monai.io/en/stable/transforms.html>]

monai.transforms.NormalizeIntensity



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

monai.transforms.ScaleIntensity



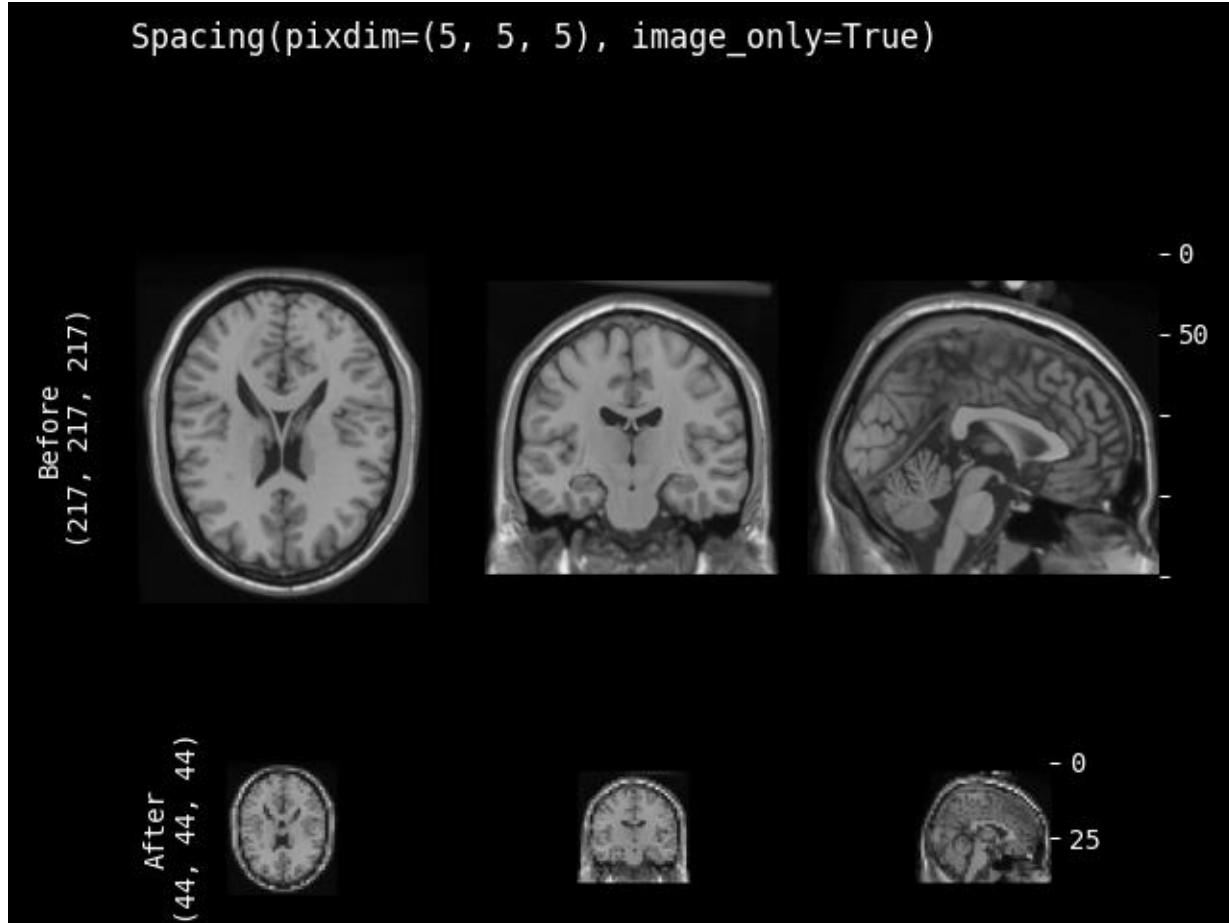
[<https://docs.monai.io/en/stable/transforms.html>]

monai.transforms.RandGaussianNoise

- Spatial transforms

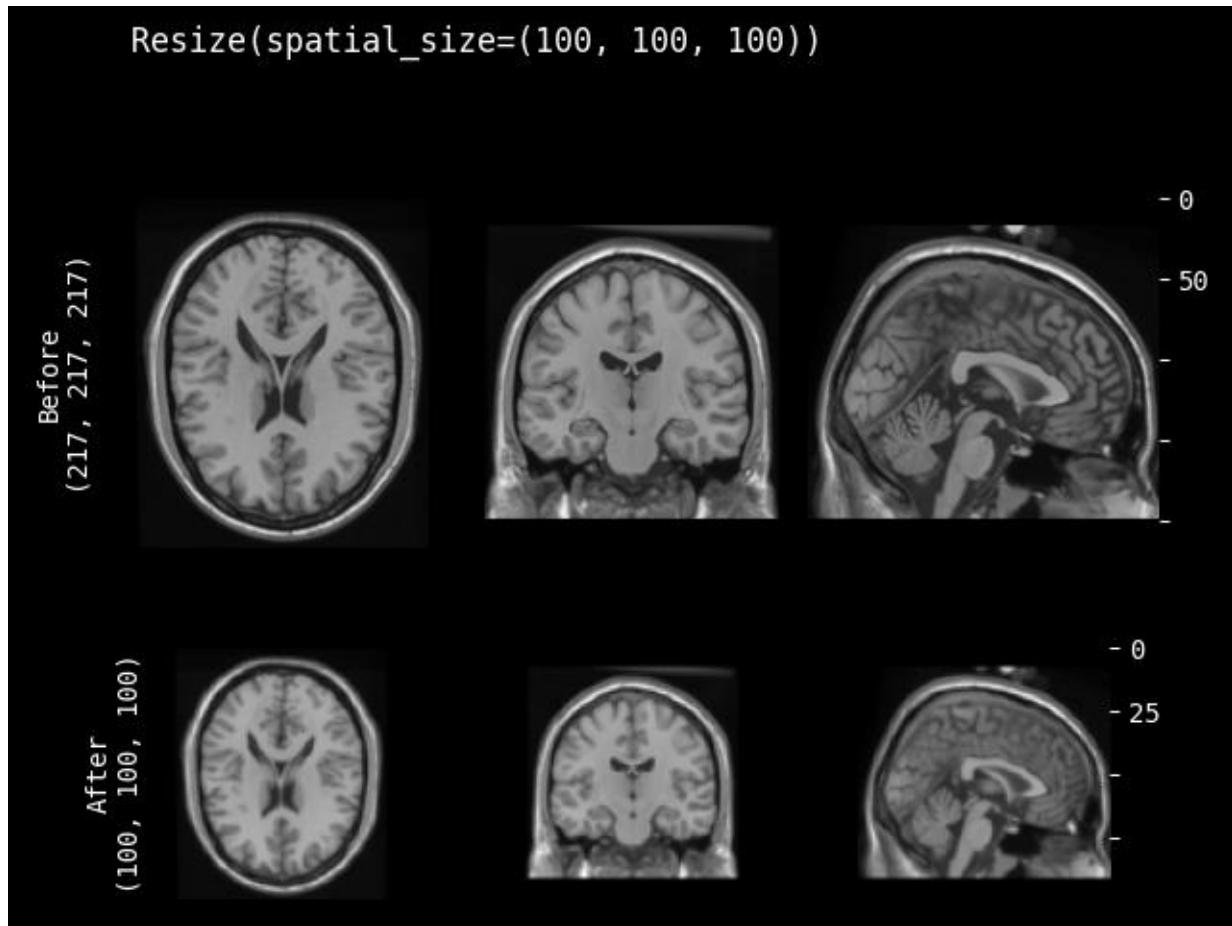
- **Spacing:** Resamples images to specified voxel spacing
- **Resize:** Resizes images to specified spatial dimensions
- **Orientation:** Changes image orientation (e.g., 'RAS')
- **Flip, Rotate, Zoom:** Basic geometric augmentations

```
Spacing(pixdim=(5, 5, 5), image_only=True)
```



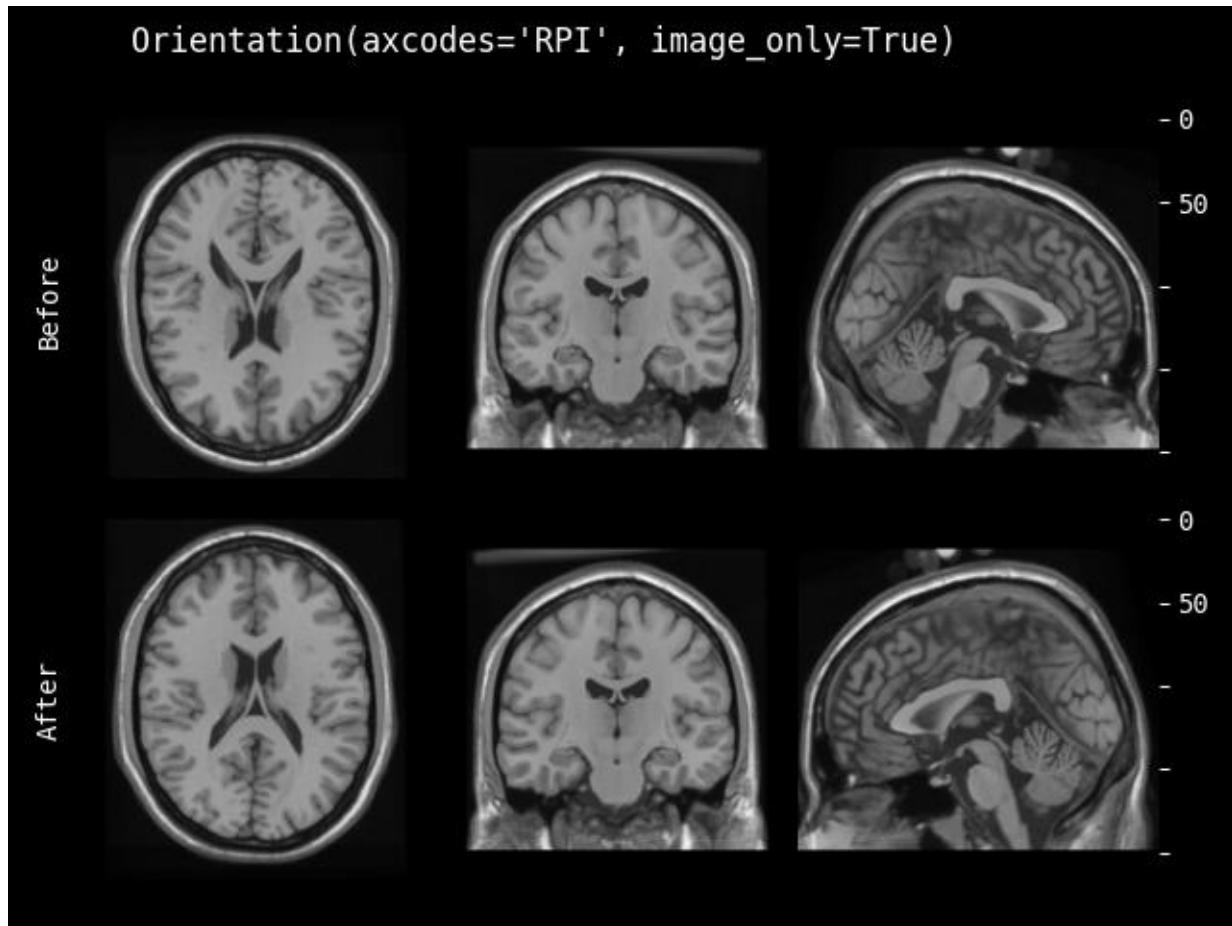
[<https://docs.monai.io/en/stable/transforms.html>]

monai.transforms.Spacing



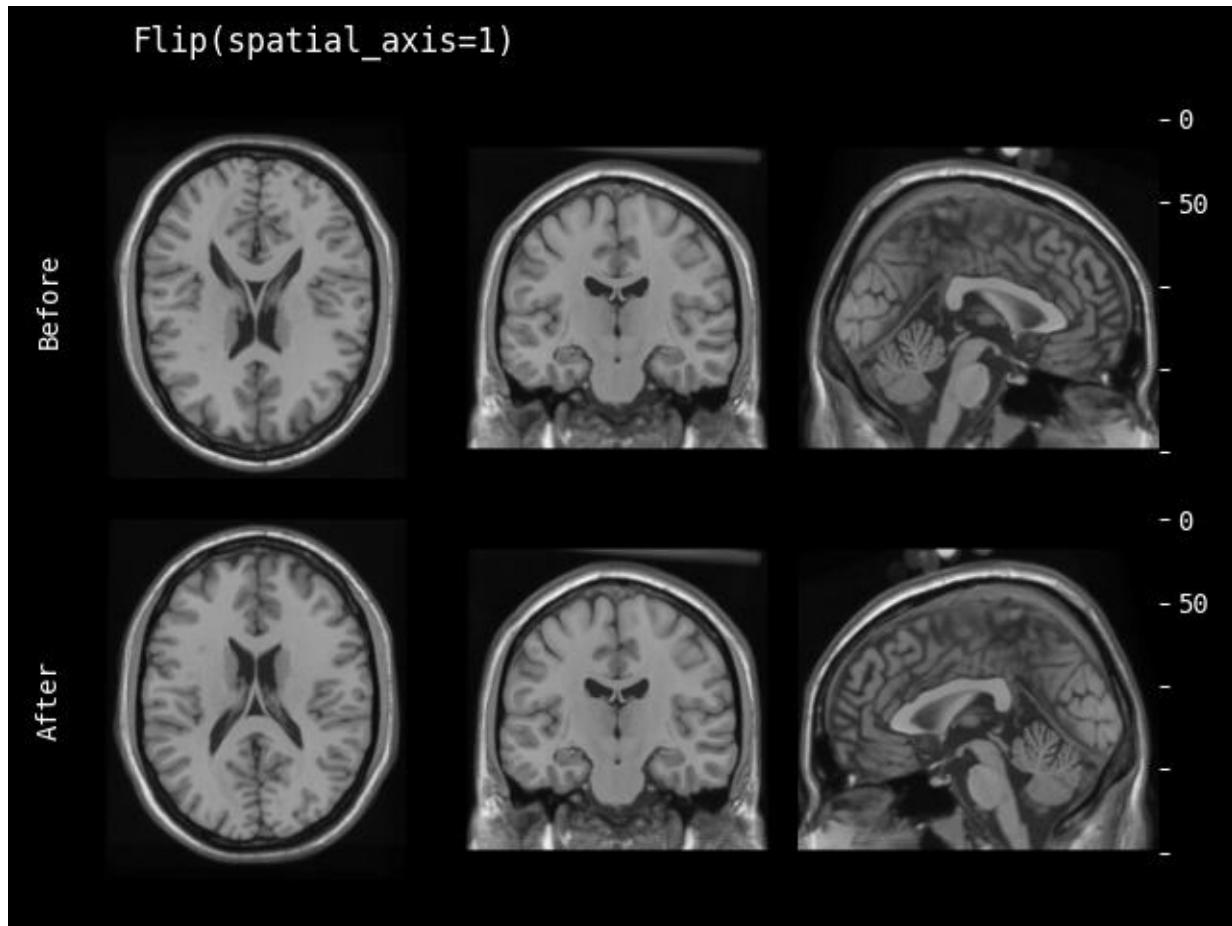
[<https://docs.monai.io/en/stable/transforms.html>]

monai.transforms.Resize



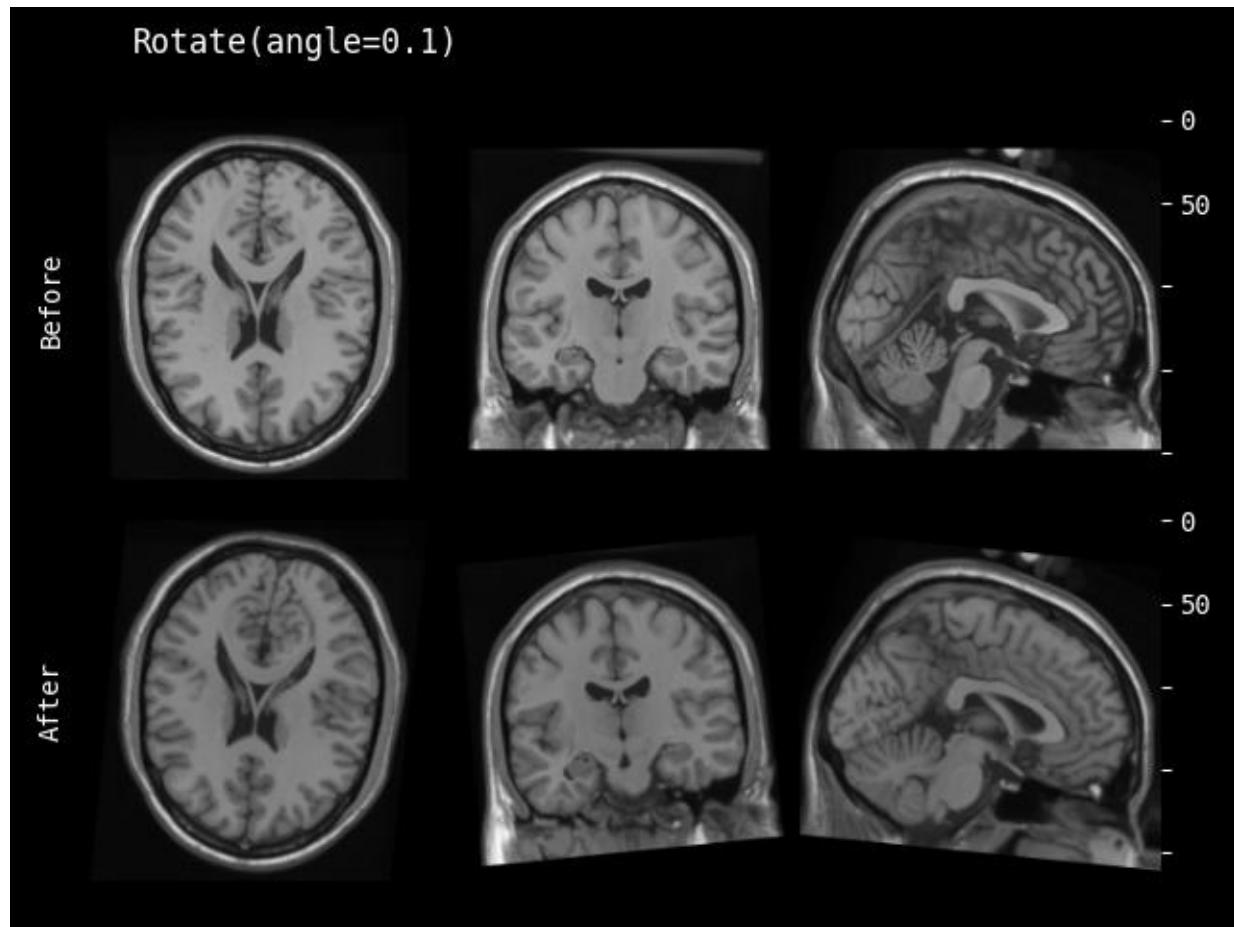
[<https://docs.monai.io/en/stable/transforms.html>]

monai.transforms.Orientation



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

monai.transforms.Flip



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

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 ONNX (Open Neural Network Exchange) 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**

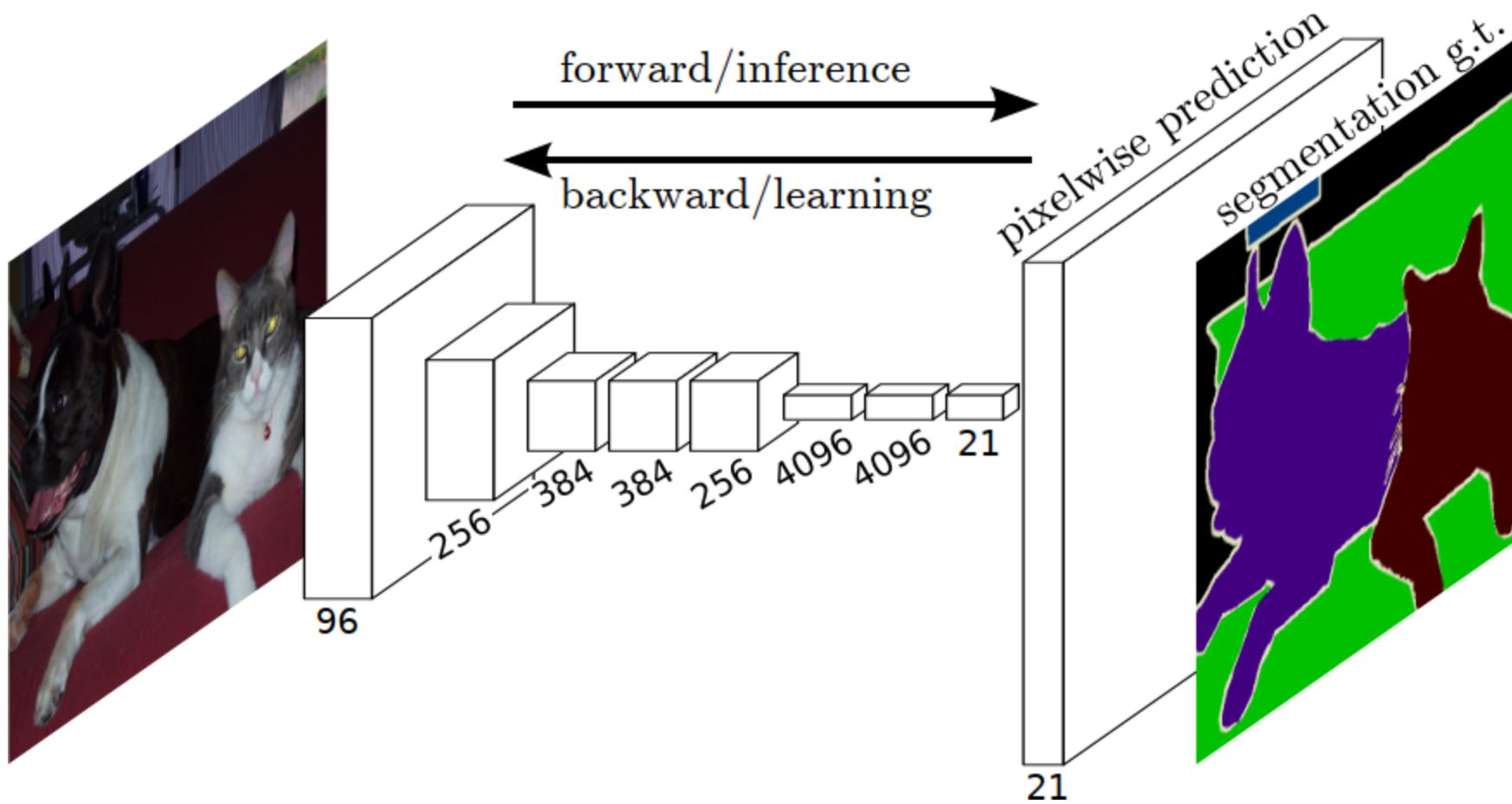
- `monai.losses` module
 - Segmentation losses
 - `DiceLoss`
 - `HausdorffDTLoss`
 - Registration losses
 - `LocalNormalizedCrossCorrelationLoss`
 - `GlobalMutualInformationLoss`
 - Reconstruction losses
 - `SSIMLoss`

- **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

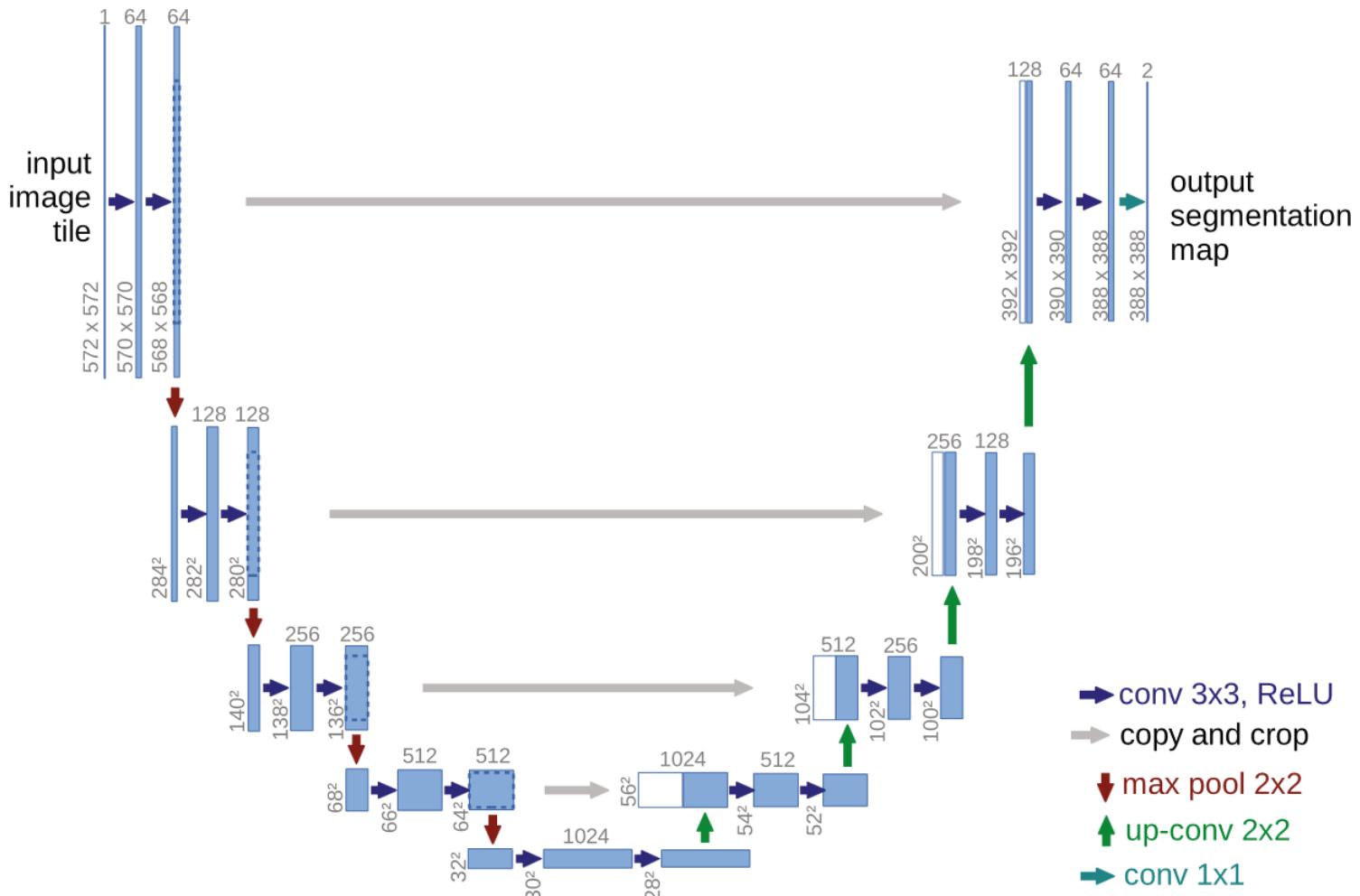
- Fully convolutional network (FCN)
 - "Fully Convolutional Networks for Semantic Segmentation"
[Long et al., 2015]
 - As a type of convolutional neural network (CNN), emphasizes full convolution throughout the network, preserving spatial information and enabling pixel/voxel-wise predictions on variable-sized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



[Long et al., 2015])

FCN Architecture

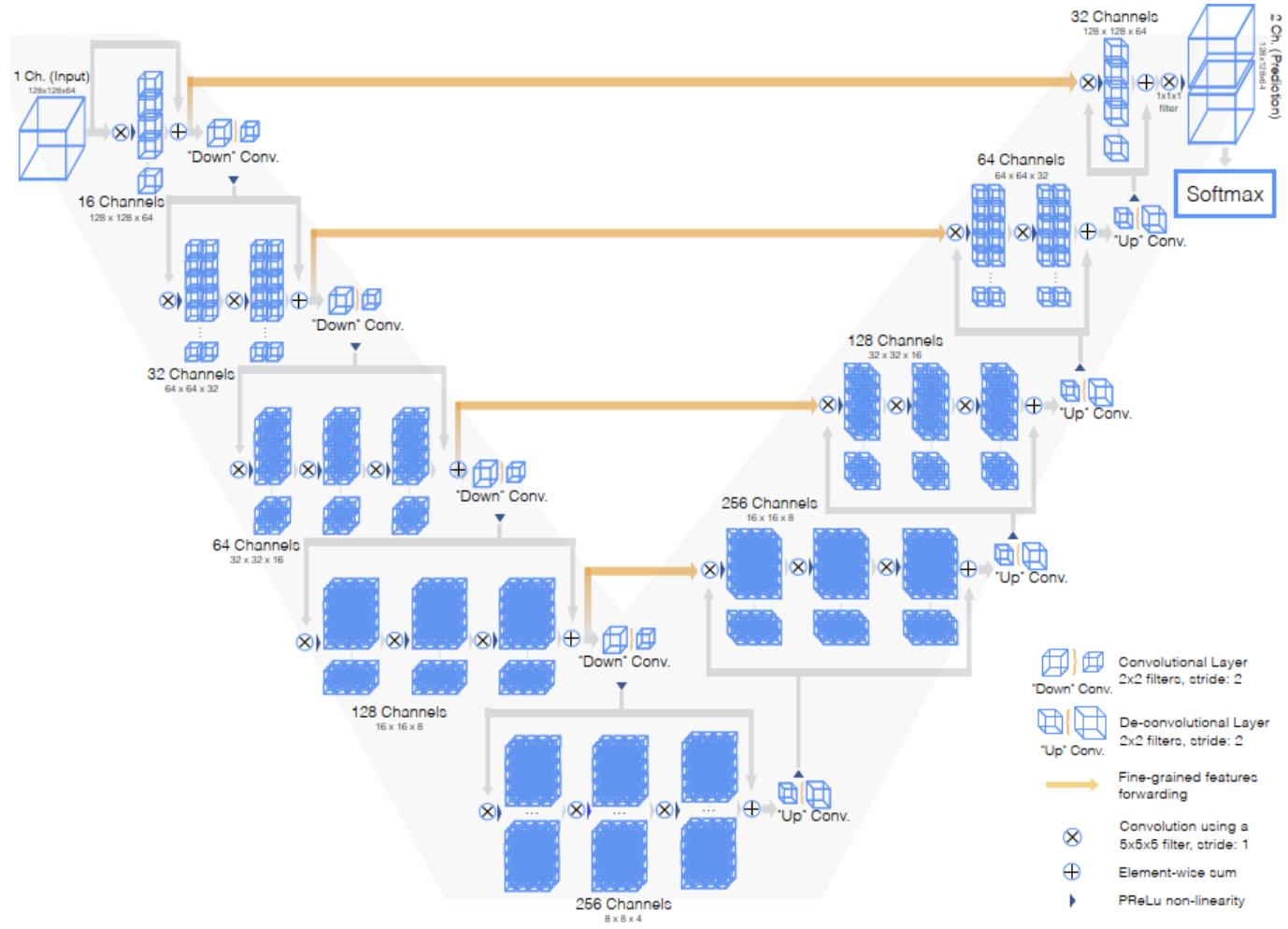
- U-Net
 - "U-Net: Convolutional Networks for Biomedical Image Segmentation" [\[Ronneberger et al., 2015\]](#)
 - Introduces a symmetric encoder-decoder structure with skip connections between corresponding layers
 - Particularly effective in capturing fine-grained details in medical images
 - Remains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



[Ronneberger et al., 2015])

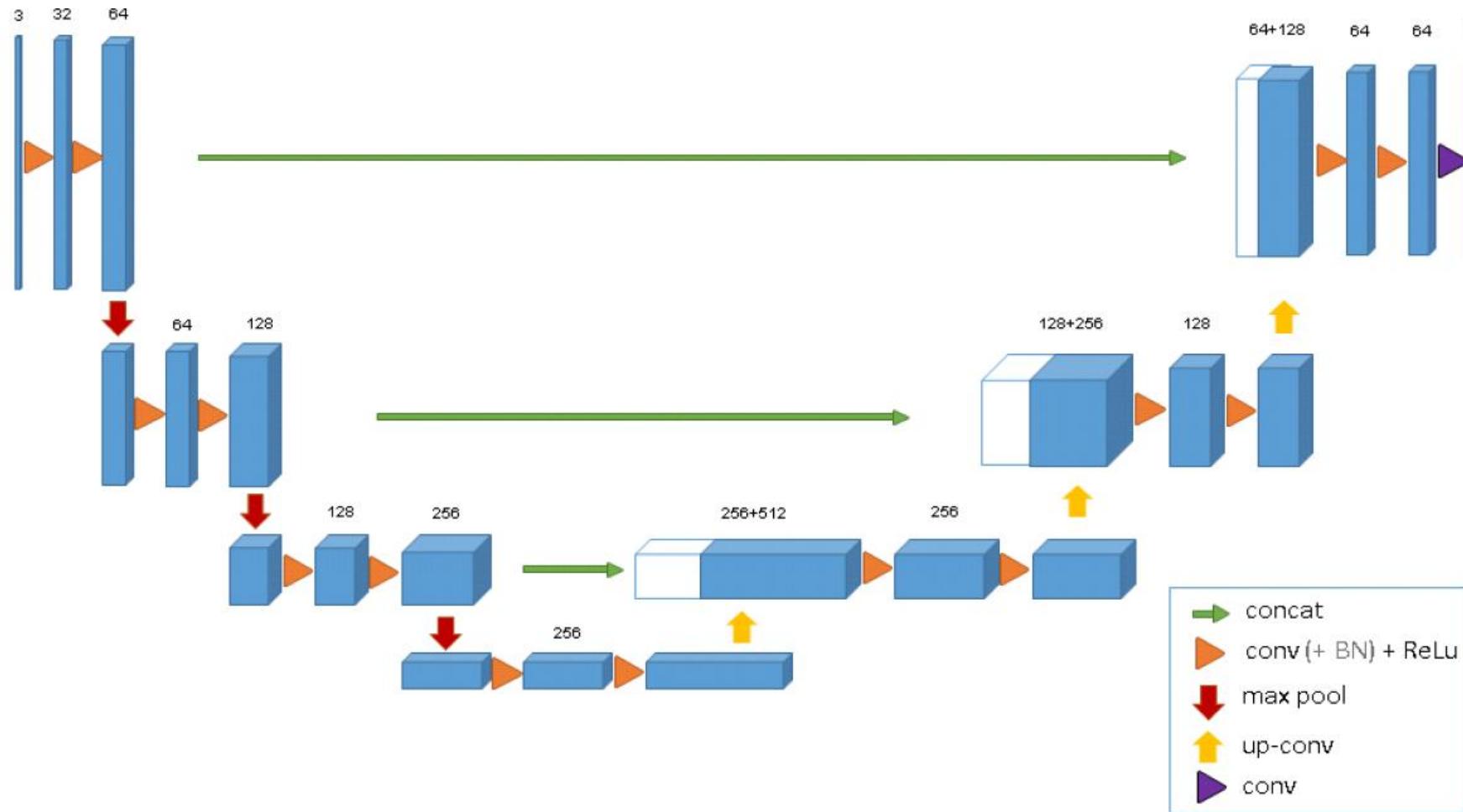
U-Net Architecture

- 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])

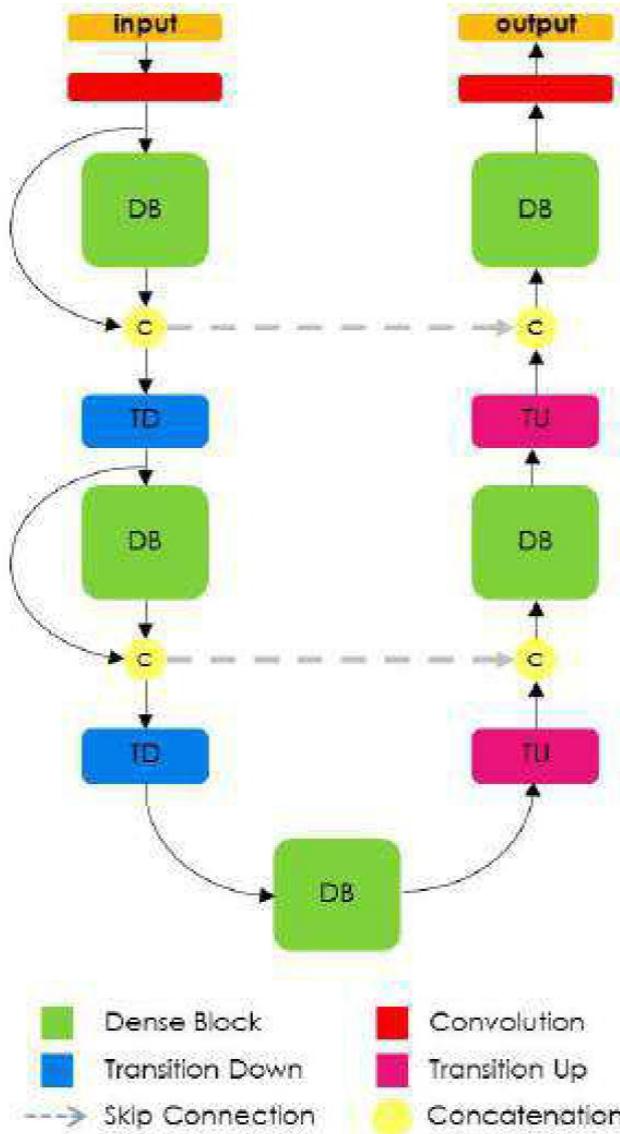
V-Net Architecture



[Çiçek et al., 2016]

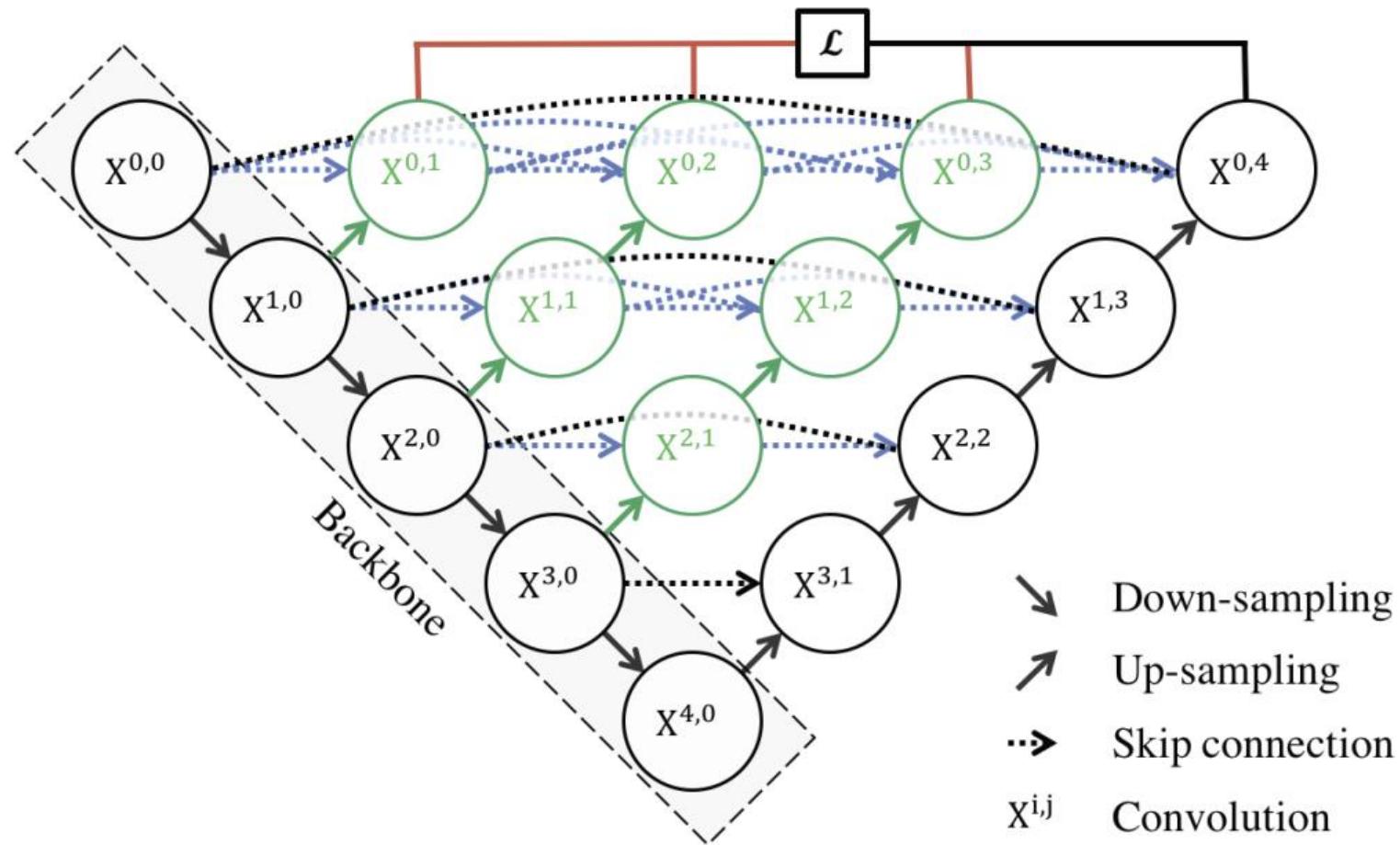
3D U-Net Architecture

- 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]

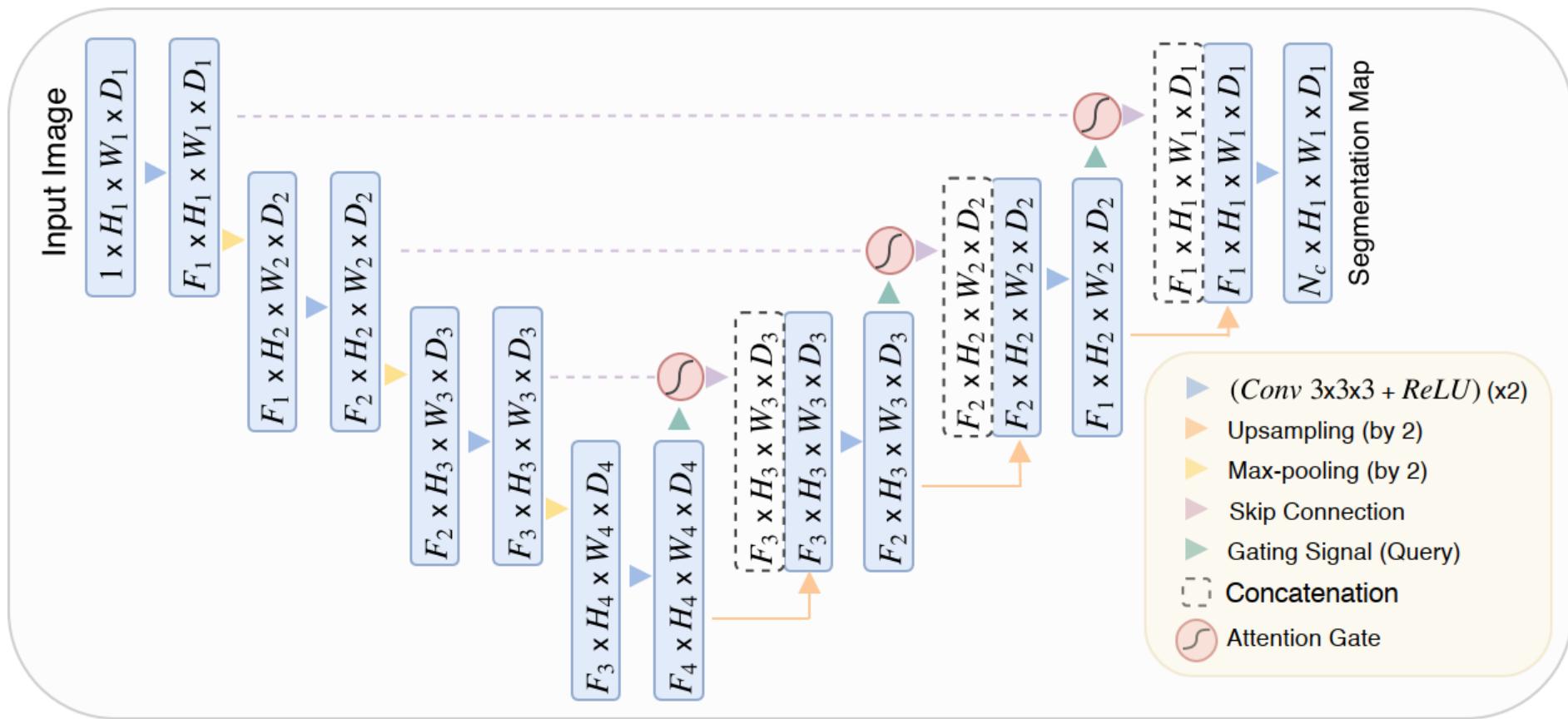
Dense U-Net Architecture



[Zhou et al., 2018]

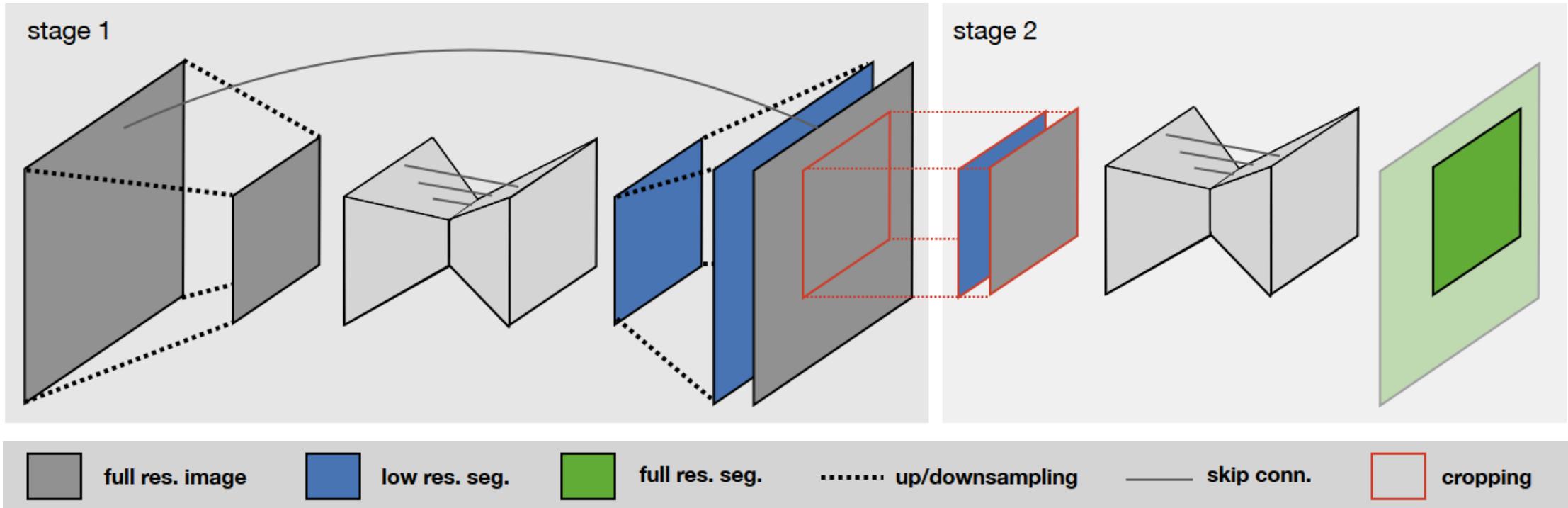
UNet++ Architecture

- 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]

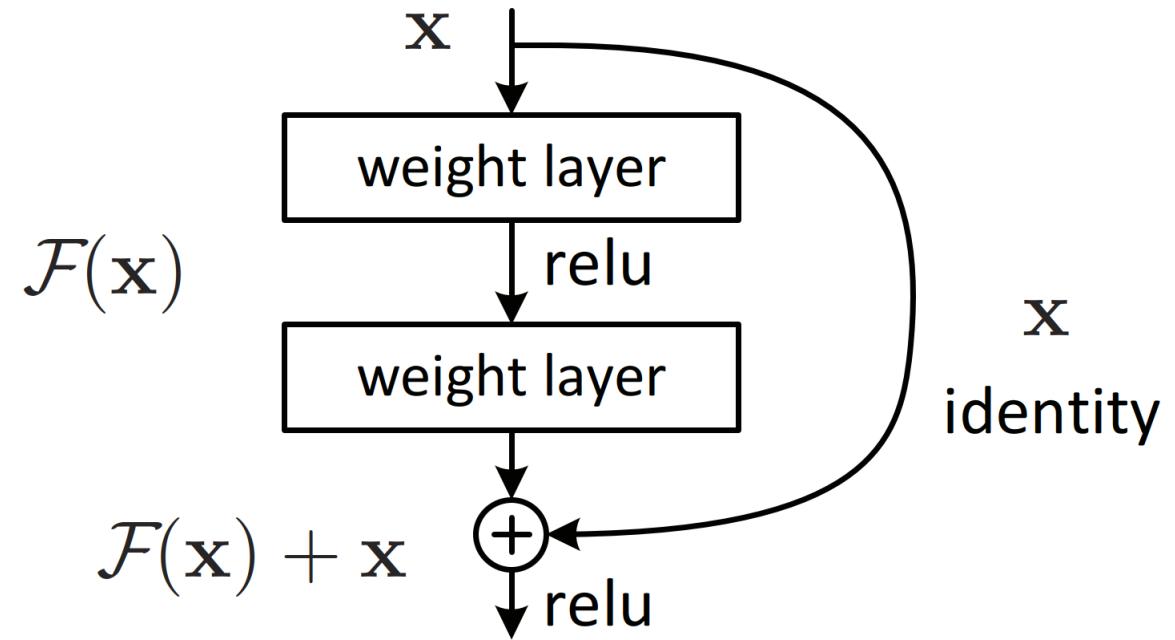
Attention U-Net Architecture



[Isensee et al., 2018]

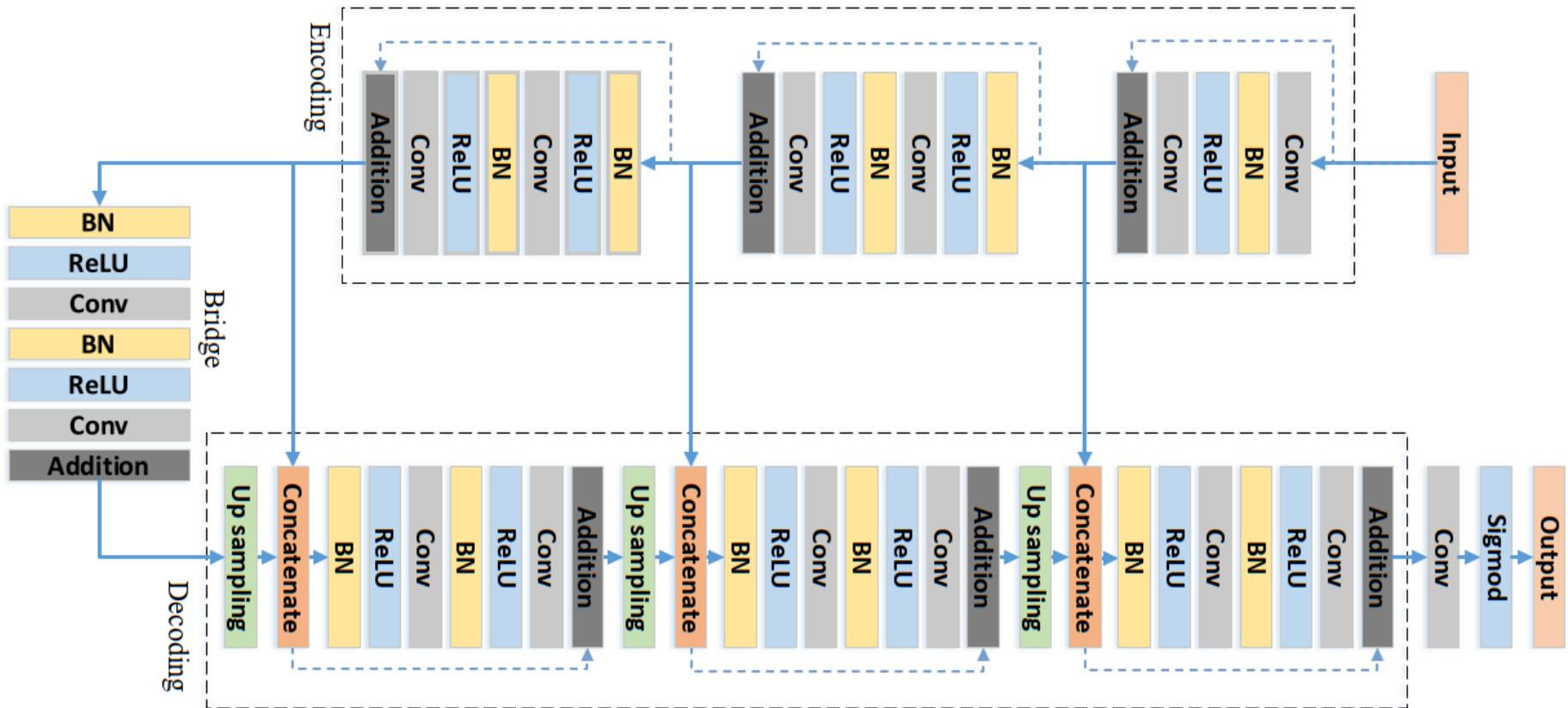
Cascaded U-Nets as One Possible Configuration Within nnU-Net

- 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



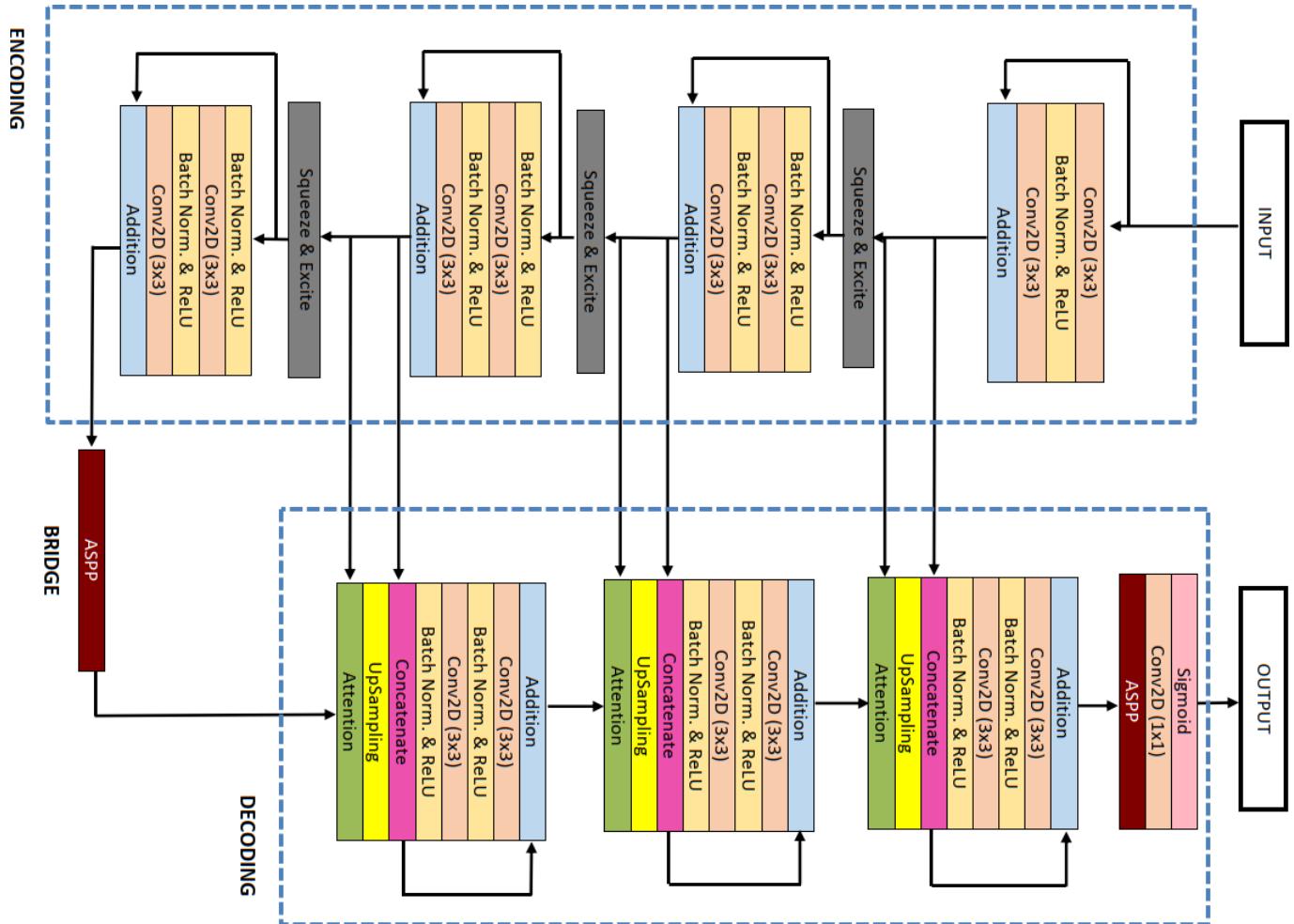
[He et al., 2015]

Building Block for Residual Learning in ResNet



[Zhang et al., 2018]

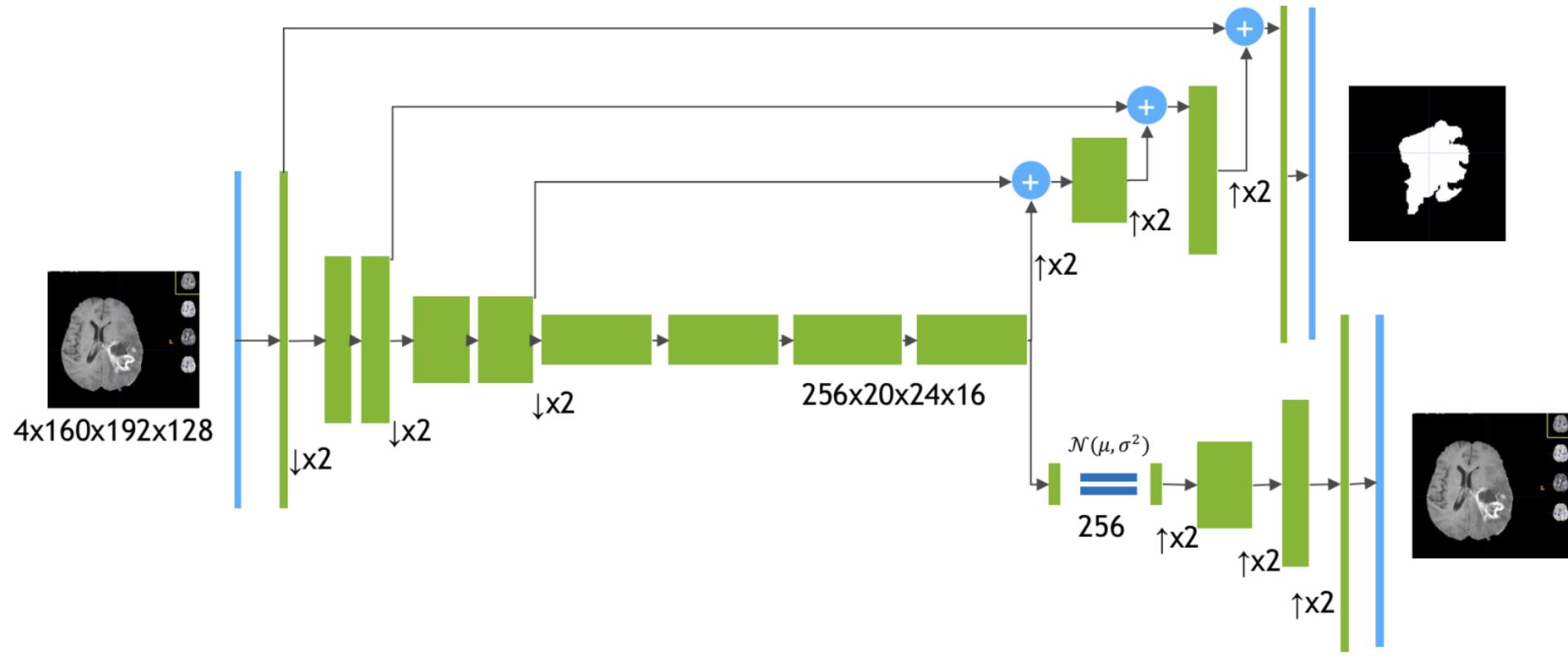
ResUNet Architecture



[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

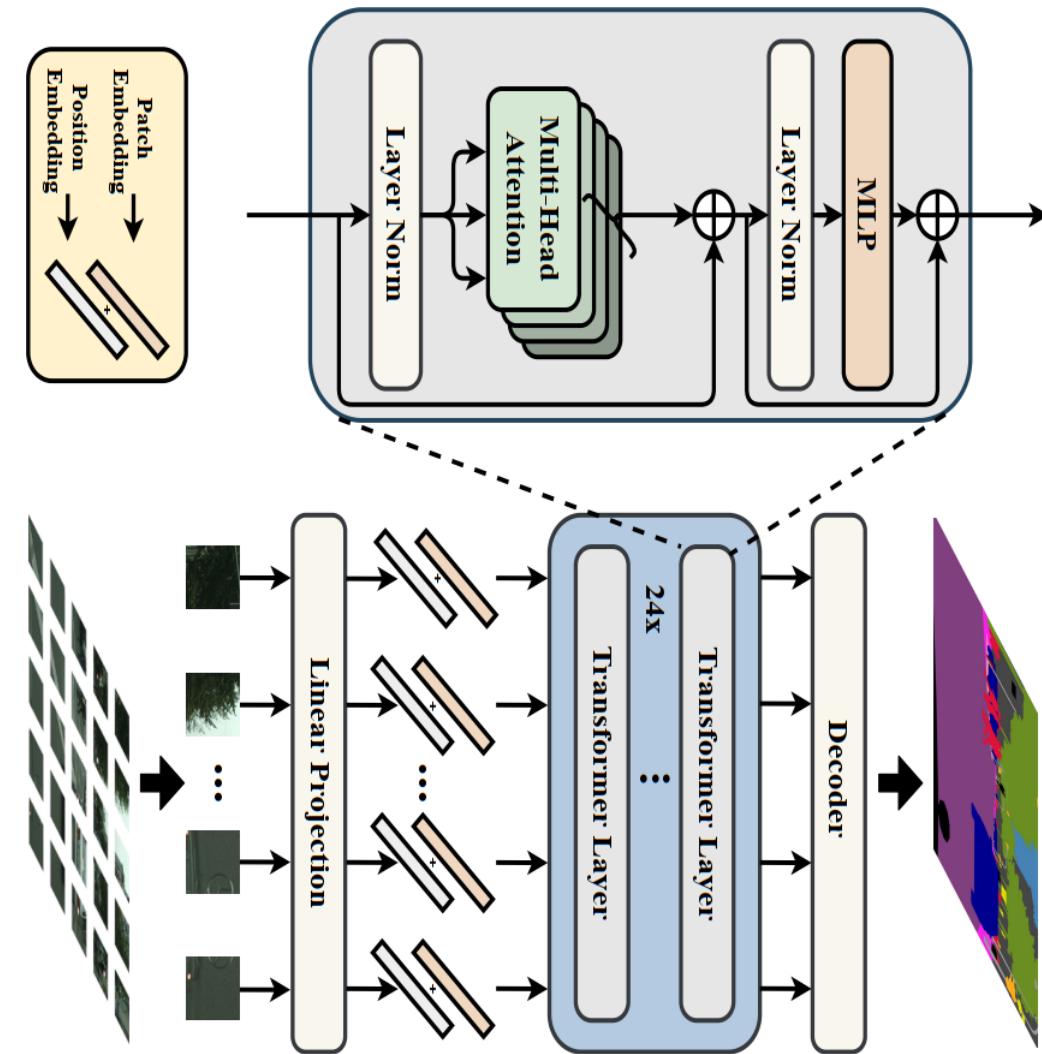


$\downarrow \times 2 = \text{conv}3 \times 3 \times 3 \text{ stride } 2$
 $\uparrow \times 2 = \text{conv}1 \times 1 \times 1, 3\text{D bilinear upsizing}$

[Myronenko, 2018]

SegResNet Architecture

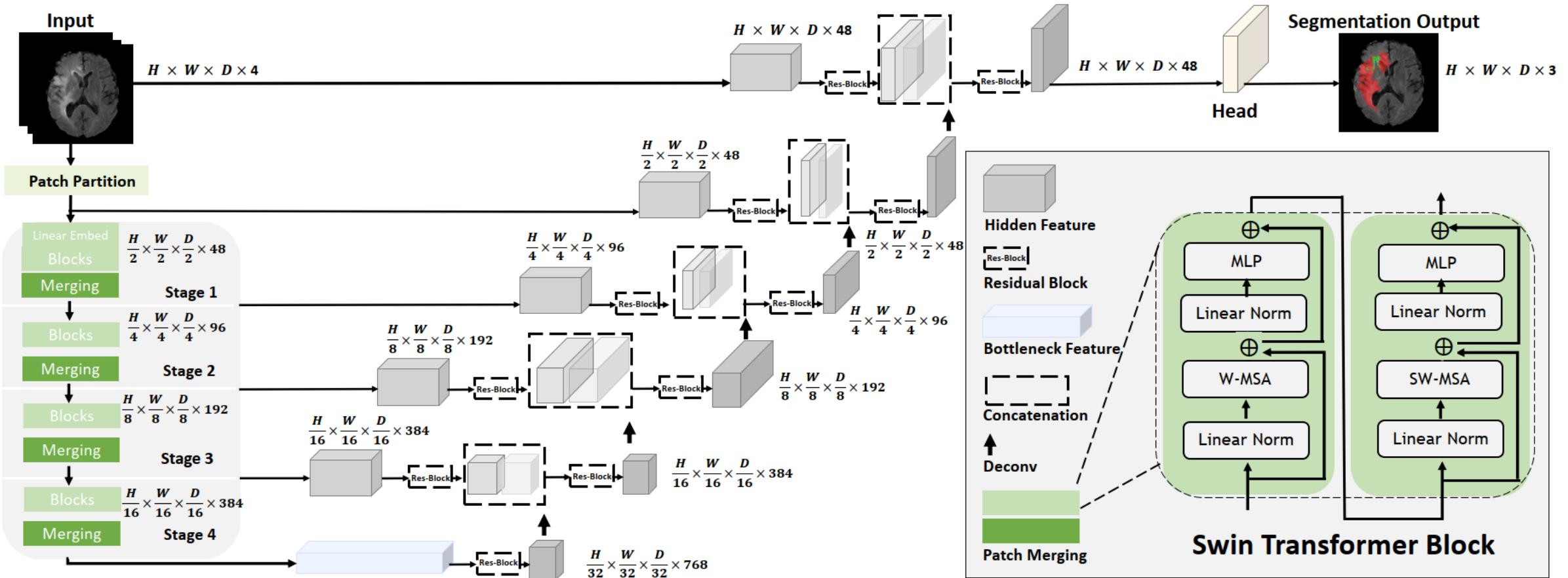
- Transformer-based architectures: Transformer-dominant architectures
 - Transformer handles most feature extraction
 - SETR (Segmentation Transformer): "Rethinking Semantic Segmentation from a Sequence-to-Sequence Perspective with Transformers" [\[Zheng et al., 2021\]](#)
 - First transformer-dominant 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 (no intermediate blocks)



SETR Architecture

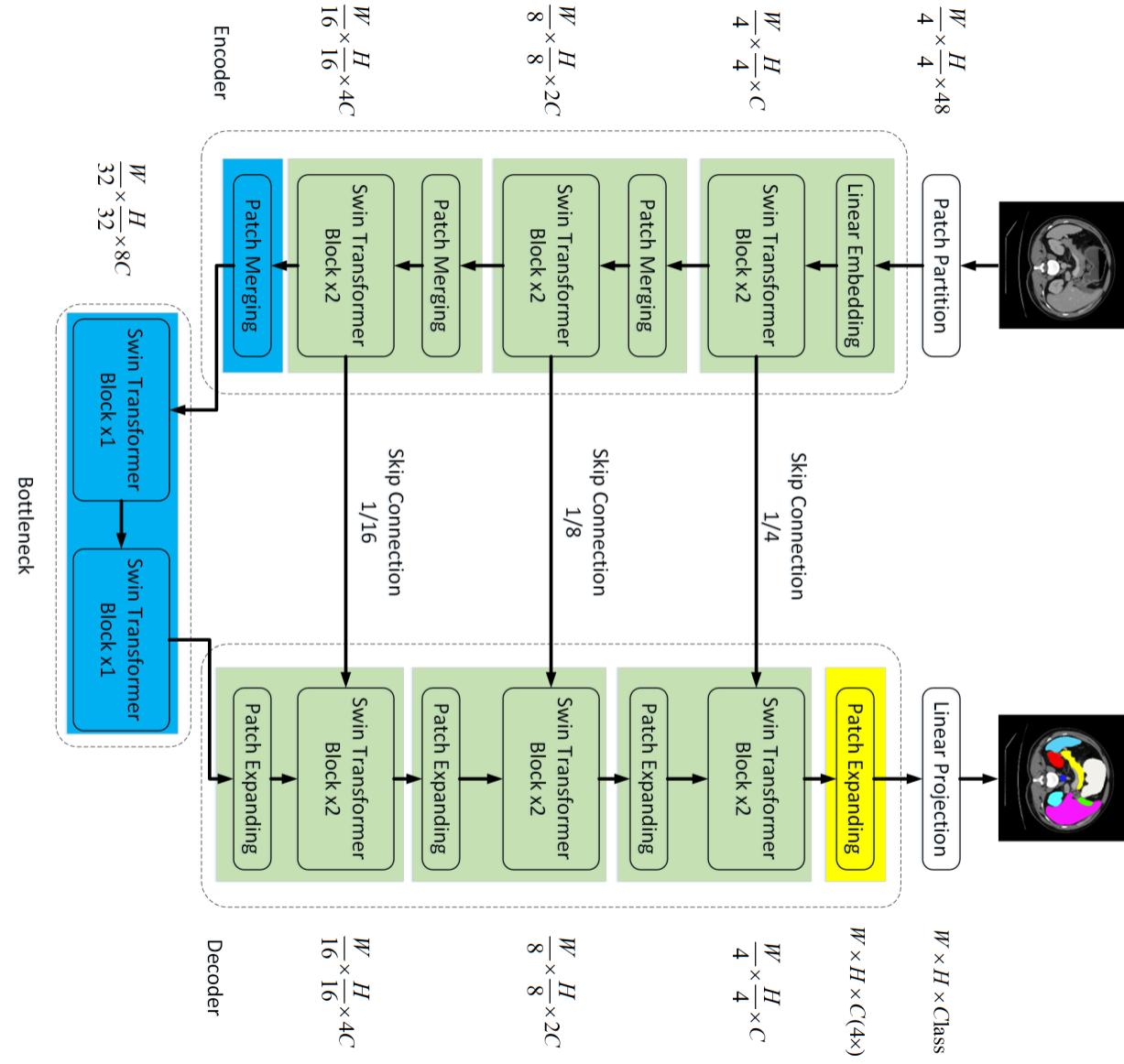
[Zheng et al., 2021]

- 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 CNN using hierarchical Swin Transformer for 3D images
 - Encoder: Swin Transformer | Decoder: U-Net style
- 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 (patch merging) | Decoder: Swin Transformer (patch expanding) + minimal CNN



[Hatamizadeh et al., 2022]

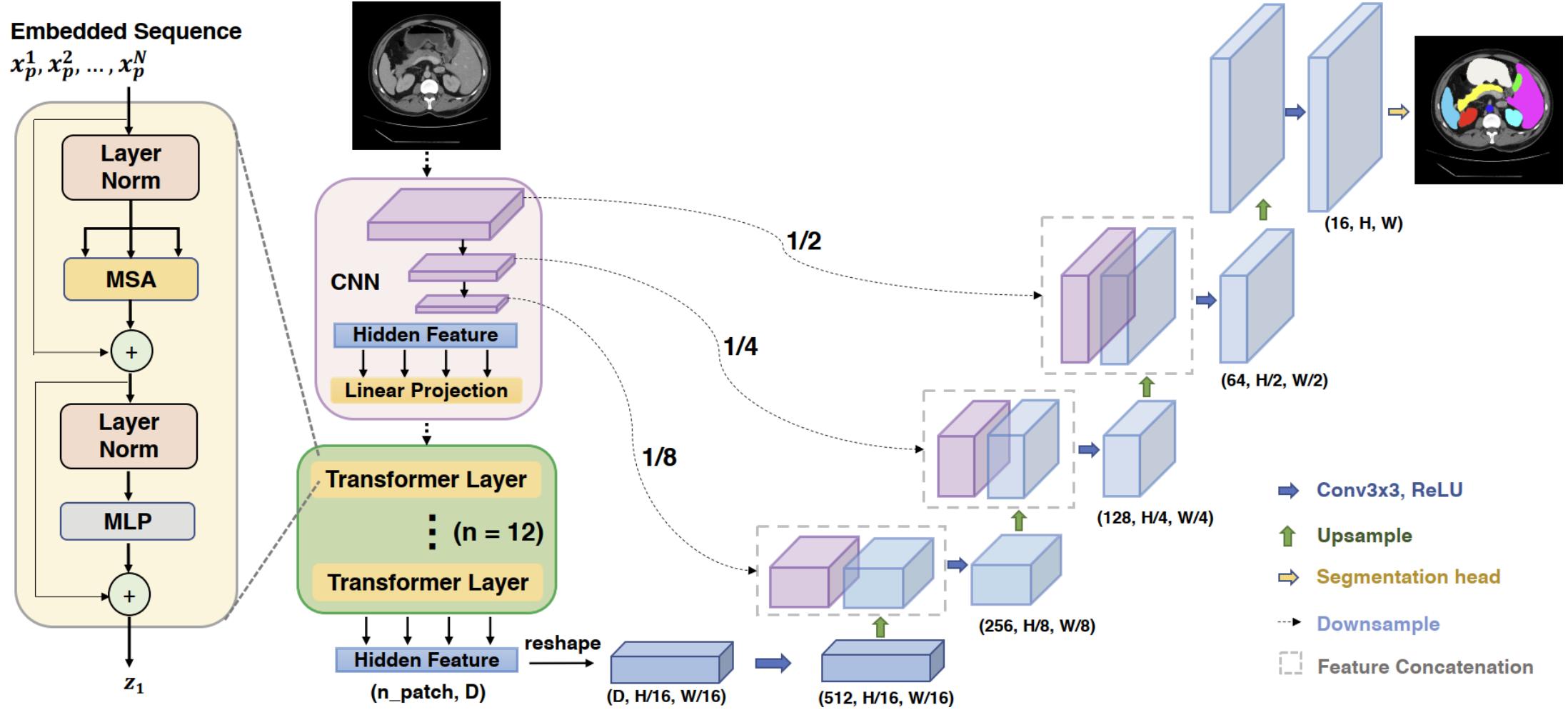
Swin UNETR Architecture



[Cao et al., 2021]

Swin-UNet Architecture

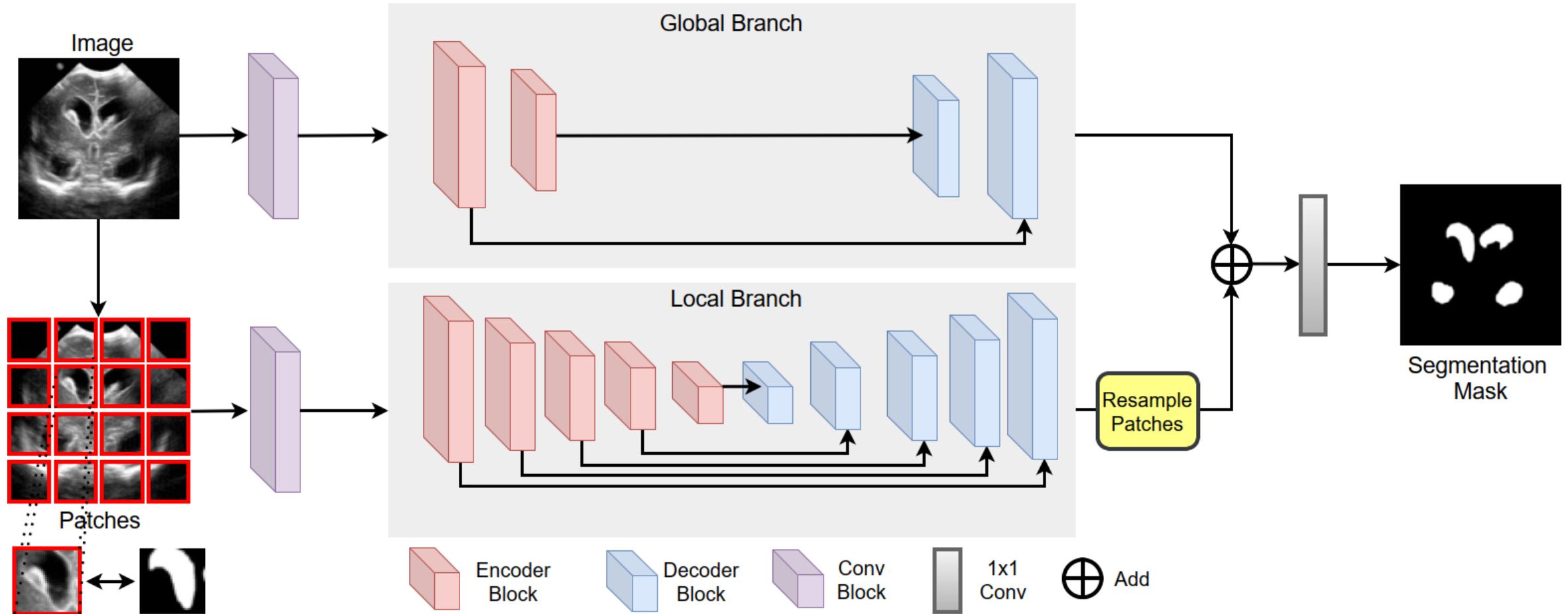
- Transformer-based architectures: CNN-Transformer hybrid architectures
 - Substantial integration of both CNN and Transformer, moving toward efficient hybrids rather than pure architectures
 - TransUNet: "TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation" [\[Chen et al., 2021\]](#)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



[Chen et al., 2021]

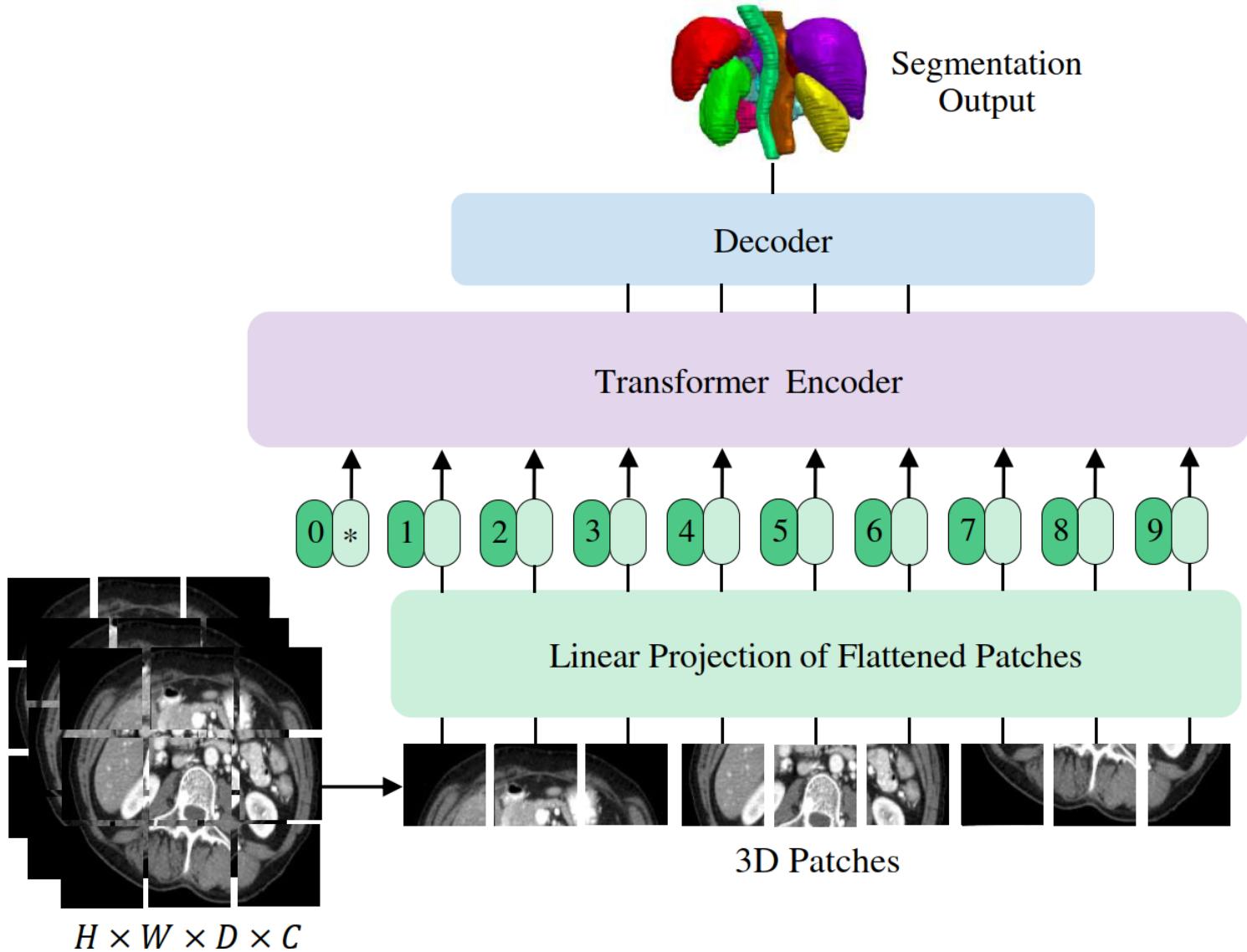
TransUNet Architecture

- 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: U-Net style



[Valanarasu et al., 2021]

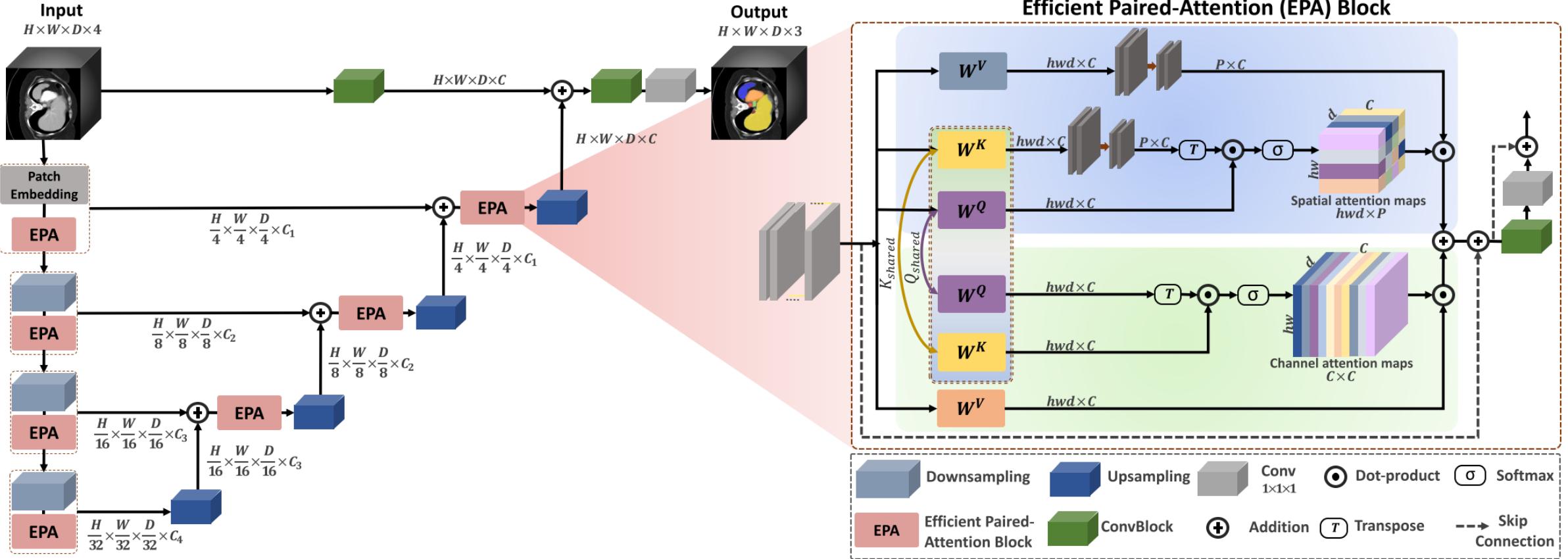
MedT Architecture



[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: Efficient ViT | Decoder: U-Net style with attention-gated skip connections



[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

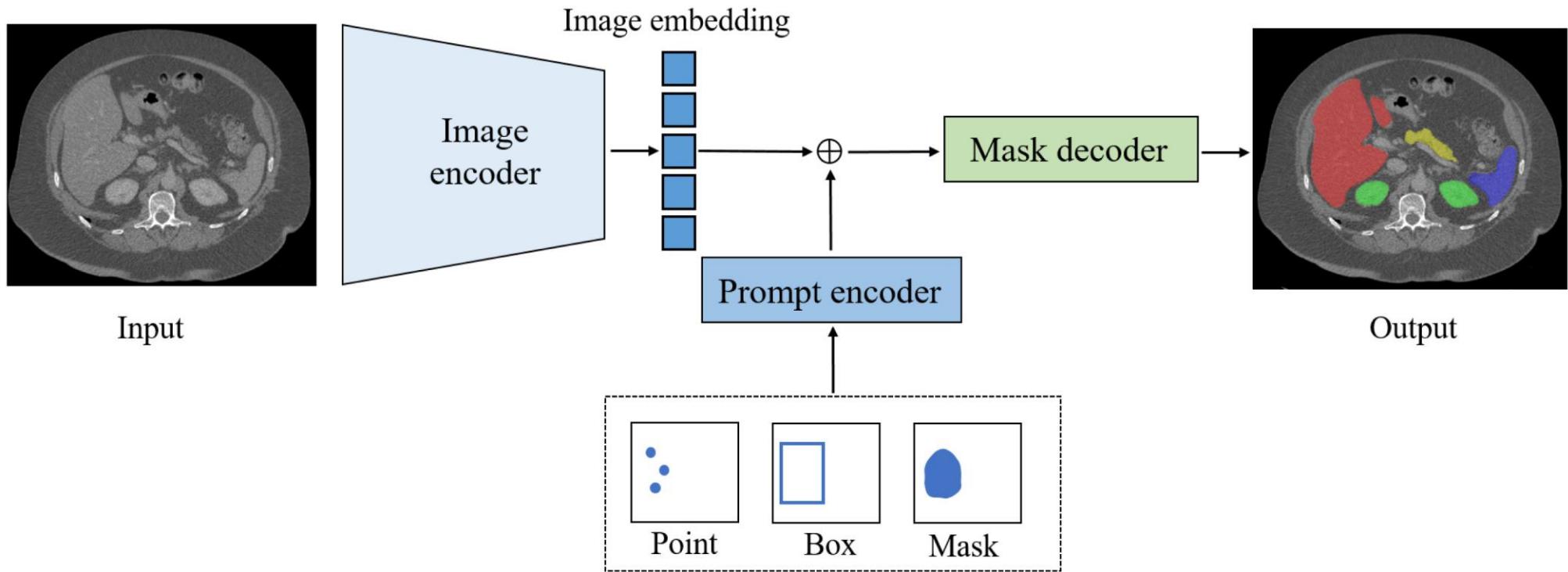
- Impact on AI development
 - Reduced need for task-specific training
 - Improved generalization
 - Cost-effective deployment
- Common examples
 - Language: BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer)
 - Vision: DALL-E, CLIP (Contrastive Language-Image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

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 [\[https://github.com/facebookresearch/segment-anything\]](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

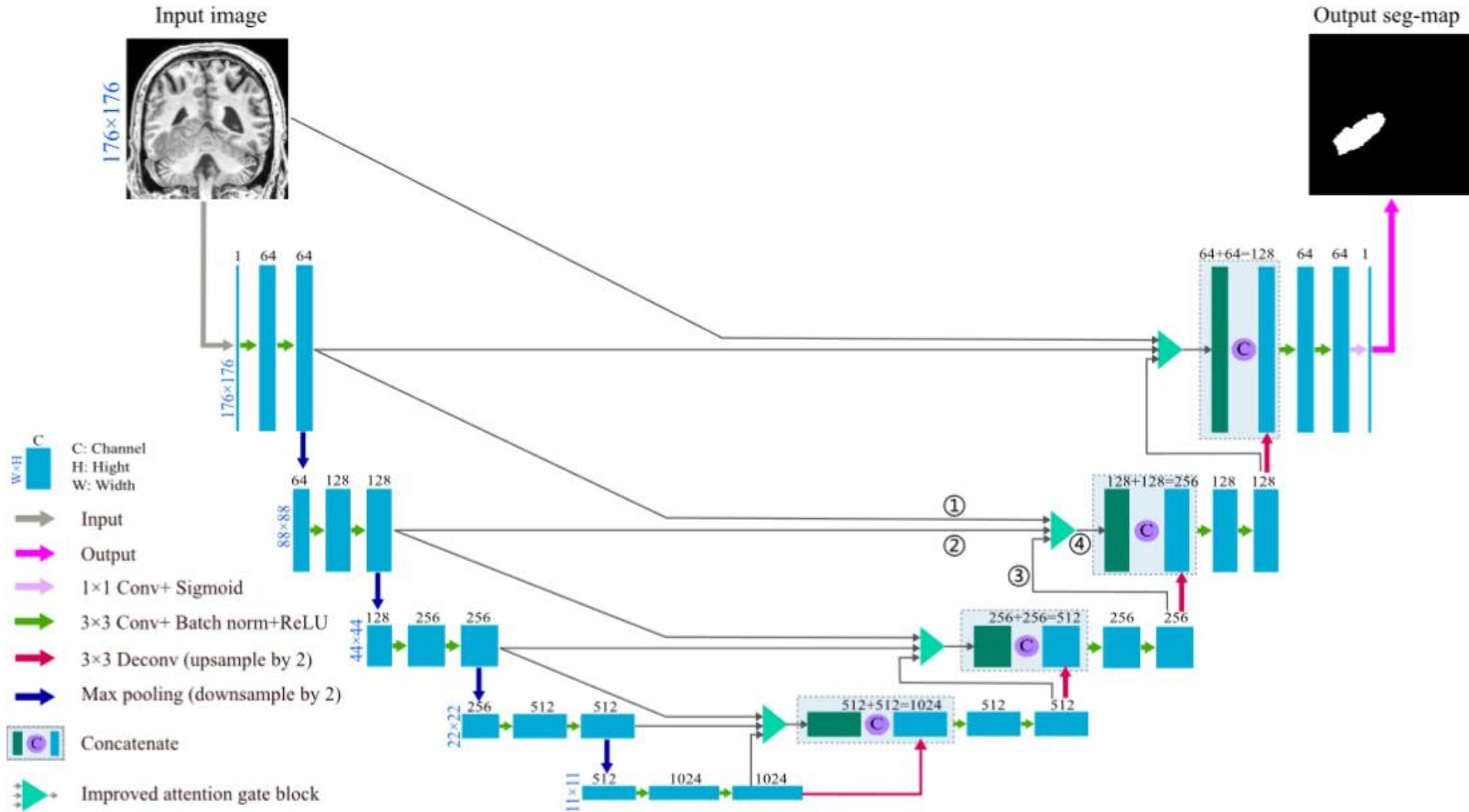
Dataset	BCIHM		Instance		Params(M)	
	Method	Dice	HD95	Dice	HD95	
	U-Net	50.06	3.99	62.07	4.26	7.77
	Att-UNet	54.29	3.89	29.74	7.14	34.88
	U-Net++	53.80	3.92	53.67	4.86	9.16
	TransUNet	46.47	4.05	58.23	4.44	106.17
	TransFuse	52.14	3.86	24.83	7.63	26.57
	H2Former	48.79	4.03	31.12	5.61	33.86
	SAM	49.32	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 ConMoAE (Contextual Mixture of Adapter Experts), 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]
 - Dice similarity coefficient (DSC) = 0.50
 - ATLAS R1.2 dataset
 - Slice input (128×128 or 256×256)

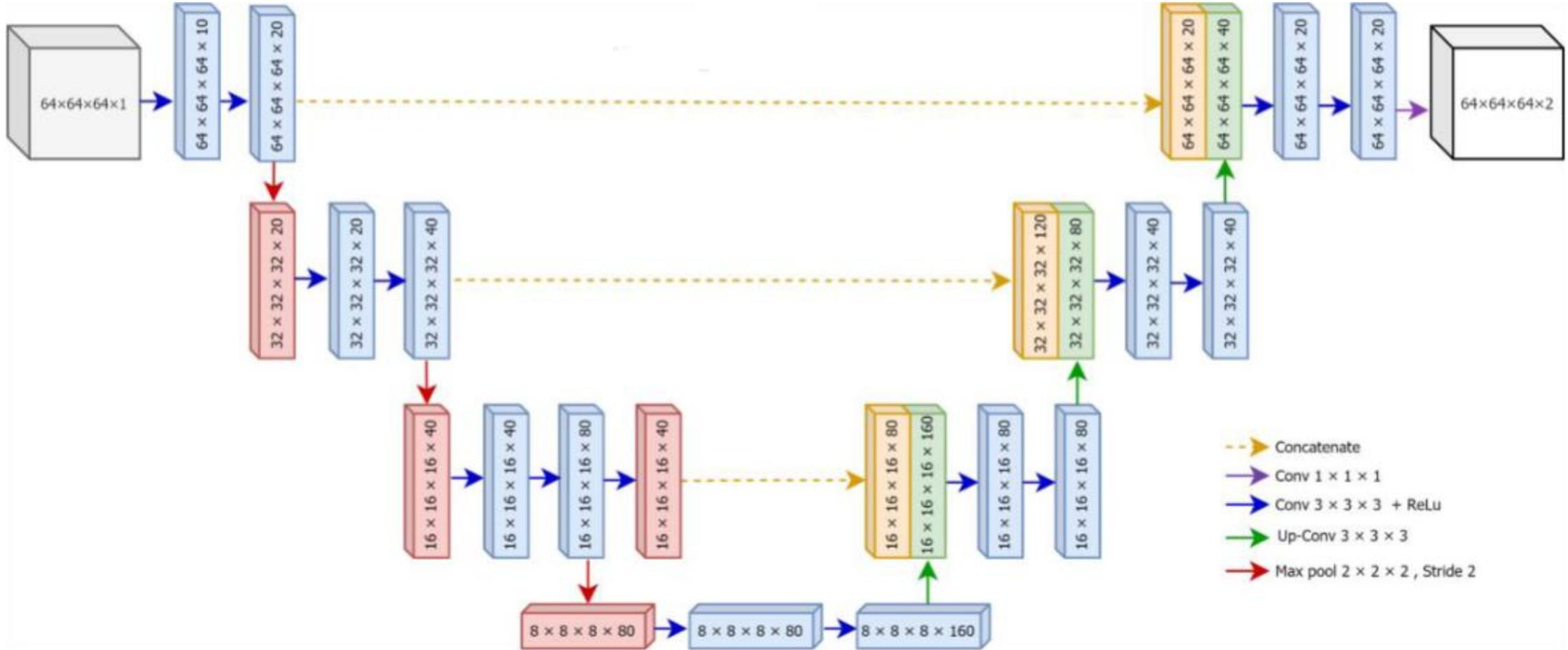
- Attention U-Net [Hui et al., 2020]
 - Partitioning-stacking prediction fusion
 - DSC = 0.593
 - ATLAS R1.2 dataset
 - Slice input (176×176)



[Hui et al., 202]0

Proposed Attention U-Net-based Architecture

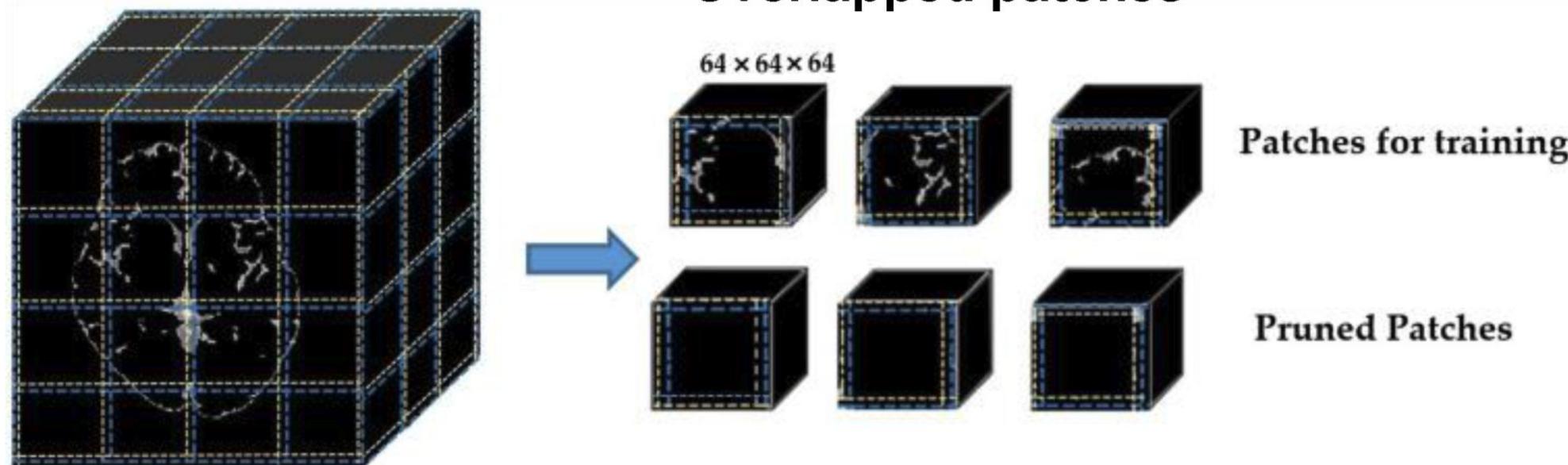
- 3D U-Net [Paing et al., 2021]
 - Variational mode decomposition for preprocessing
 - Overlapped patches strategy
 - DSC = 0.668
 - ATLAS R1.2 dataset
 - Patch input ($64 \times 64 \times 64$)



[Paing et al., 2021]

Proposed 3D U-Net-based Architecture

Overlapped patches

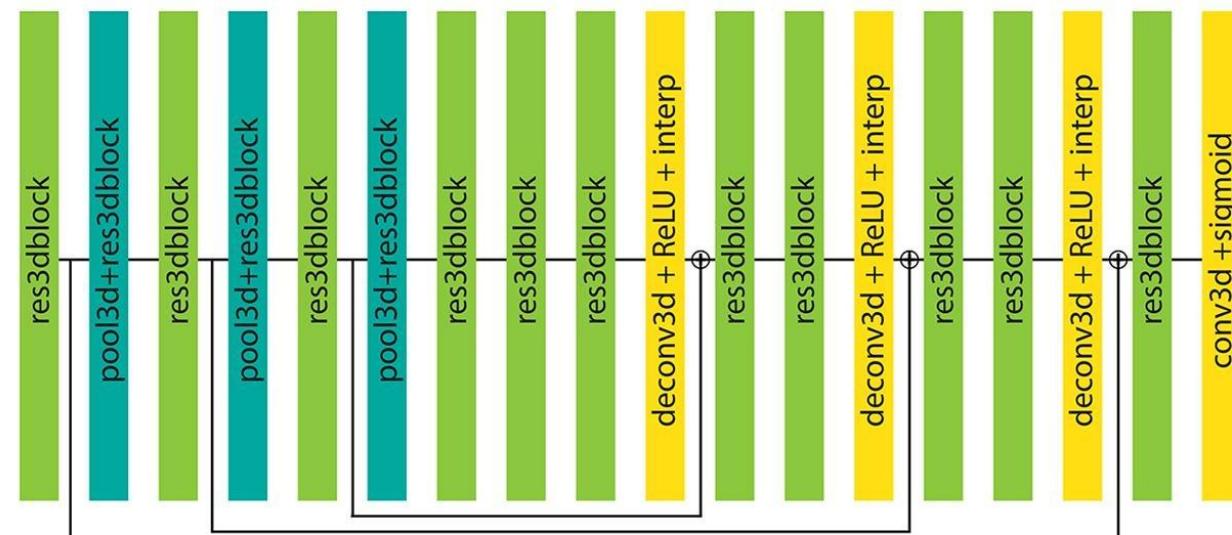
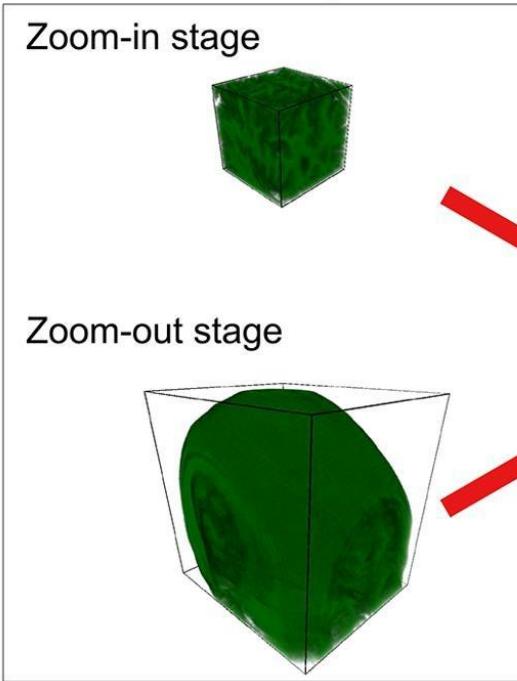


[Paing et al., 2021]

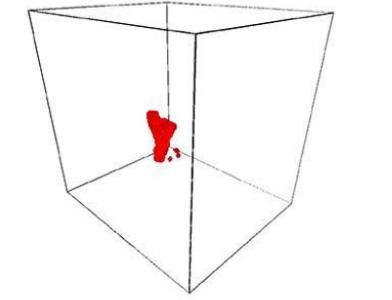
Overlapping Patches Strategy

- 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 ($128 \times 128 \times 128$ for the zoom-in stage and $144 \times 172 \times 168$ for the zoom-out stage)

Zoom-in&out training strategy
for volumetric segmentation



3D deep neural network with residual learning

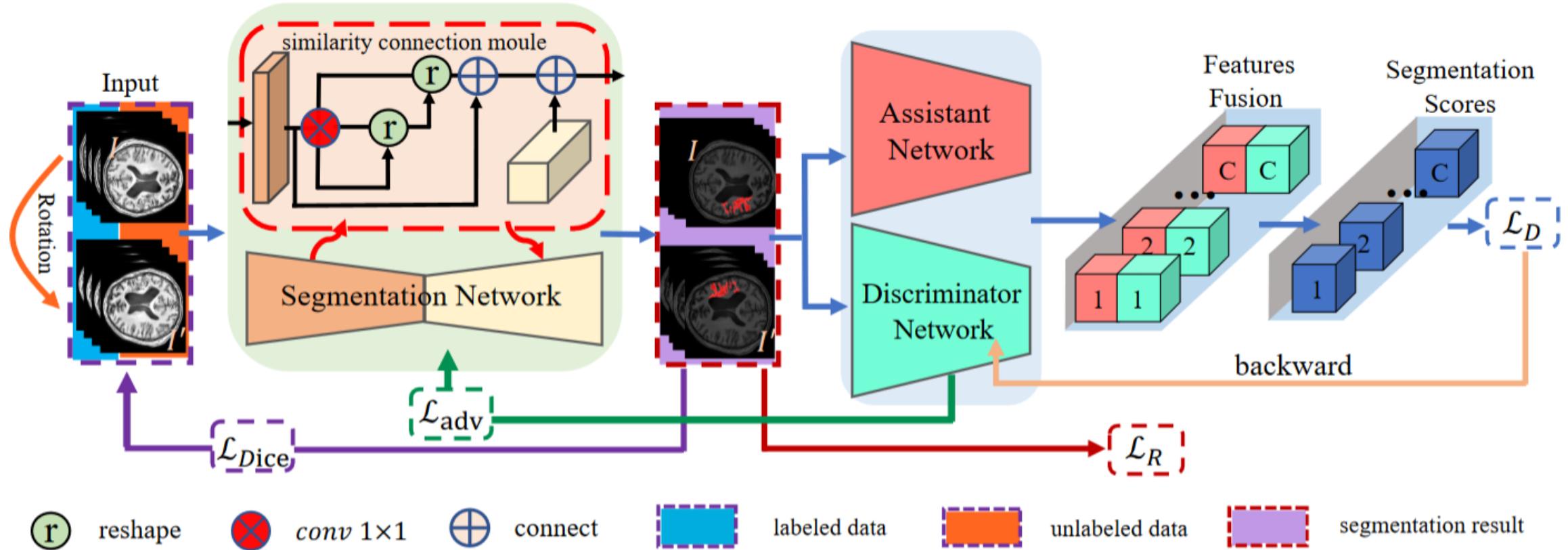


Automatically detected
post-stroke lesion

[Tomita et al., 2020]

Proposed Residual U-Net-based Architecture

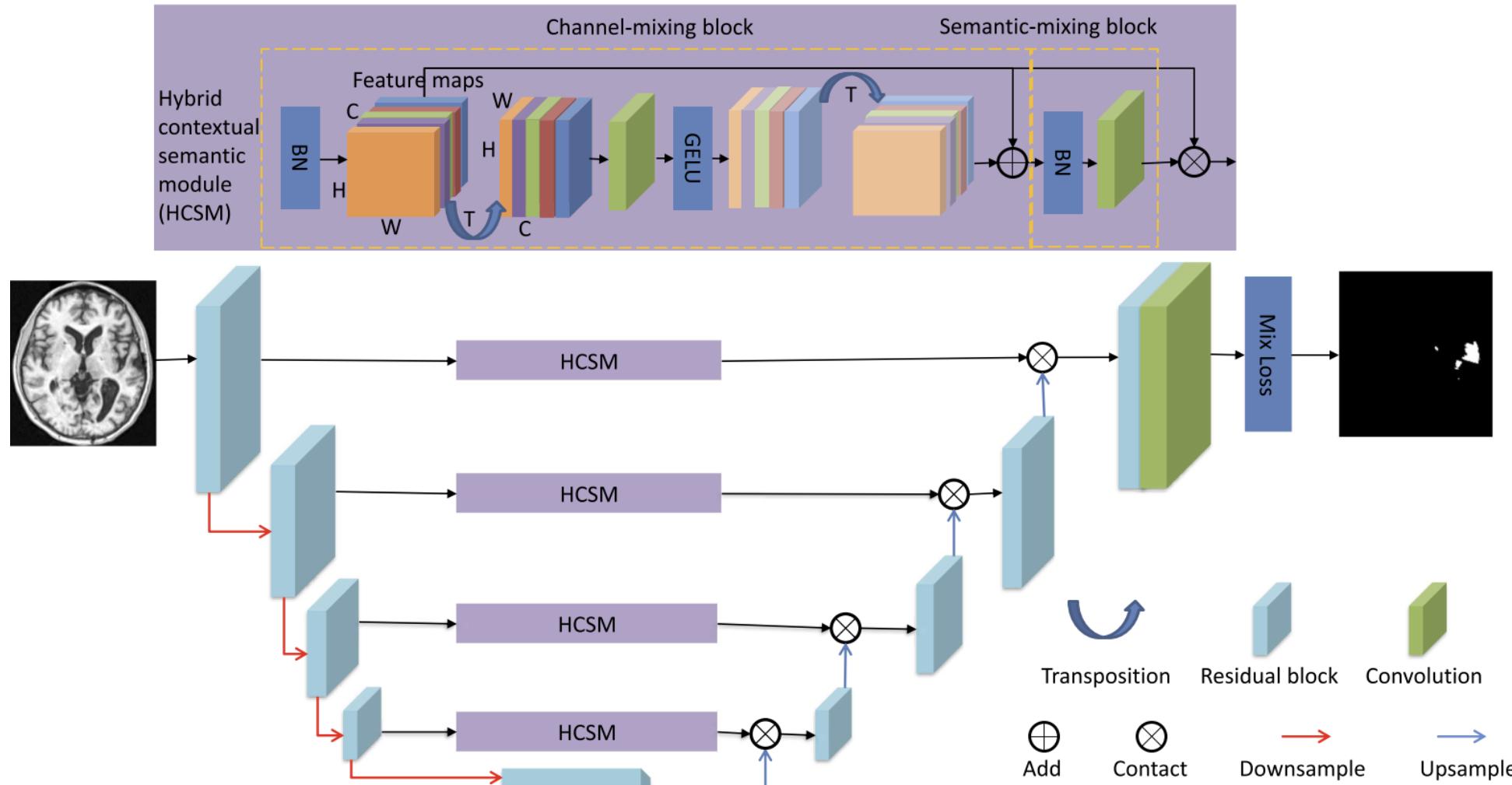
- CPGAN (Consistent Perception Generative Adversarial Network) [Wang et al., 2021]
 - Consistent perception strategy
 - Similarity connection module
 - DSC = 0.617
 - ATLAS R1.2 dataset
 - Slice input (256×256)



[Wang et al., 2021]

Proposed CPGAN Architecture

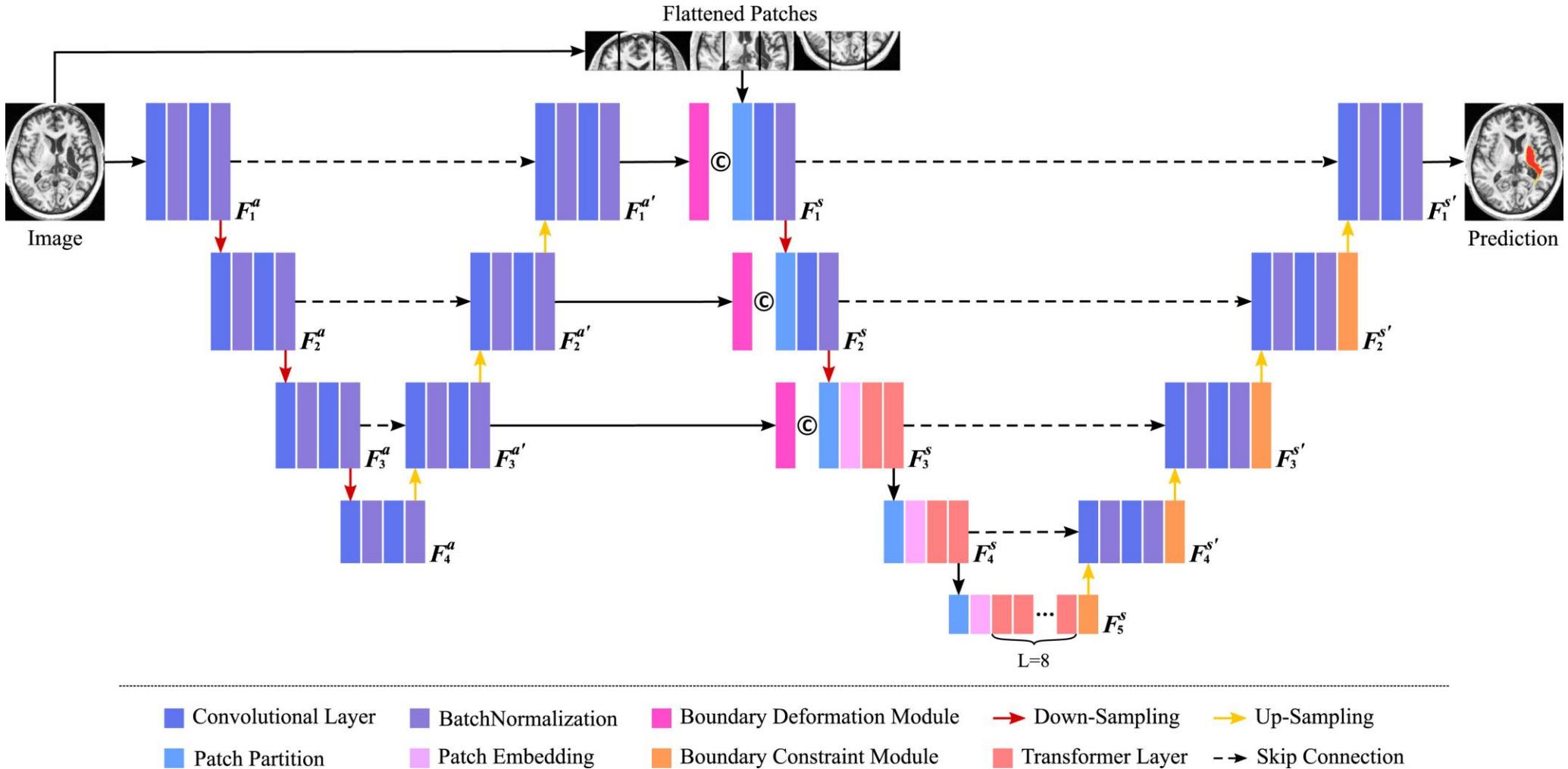
- HCS (Hybrid Contextual Semantic)-Net [Liu et al., 2023]
 - Hybrid contextual semantic module
 - Mixing-loss function for unbalanced small-size lesions
 - DSC = 0.6972
 - ATLAS R2.0 dataset
 - Slice input (240×240)



[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 ($233 \times 197 \times 189$)



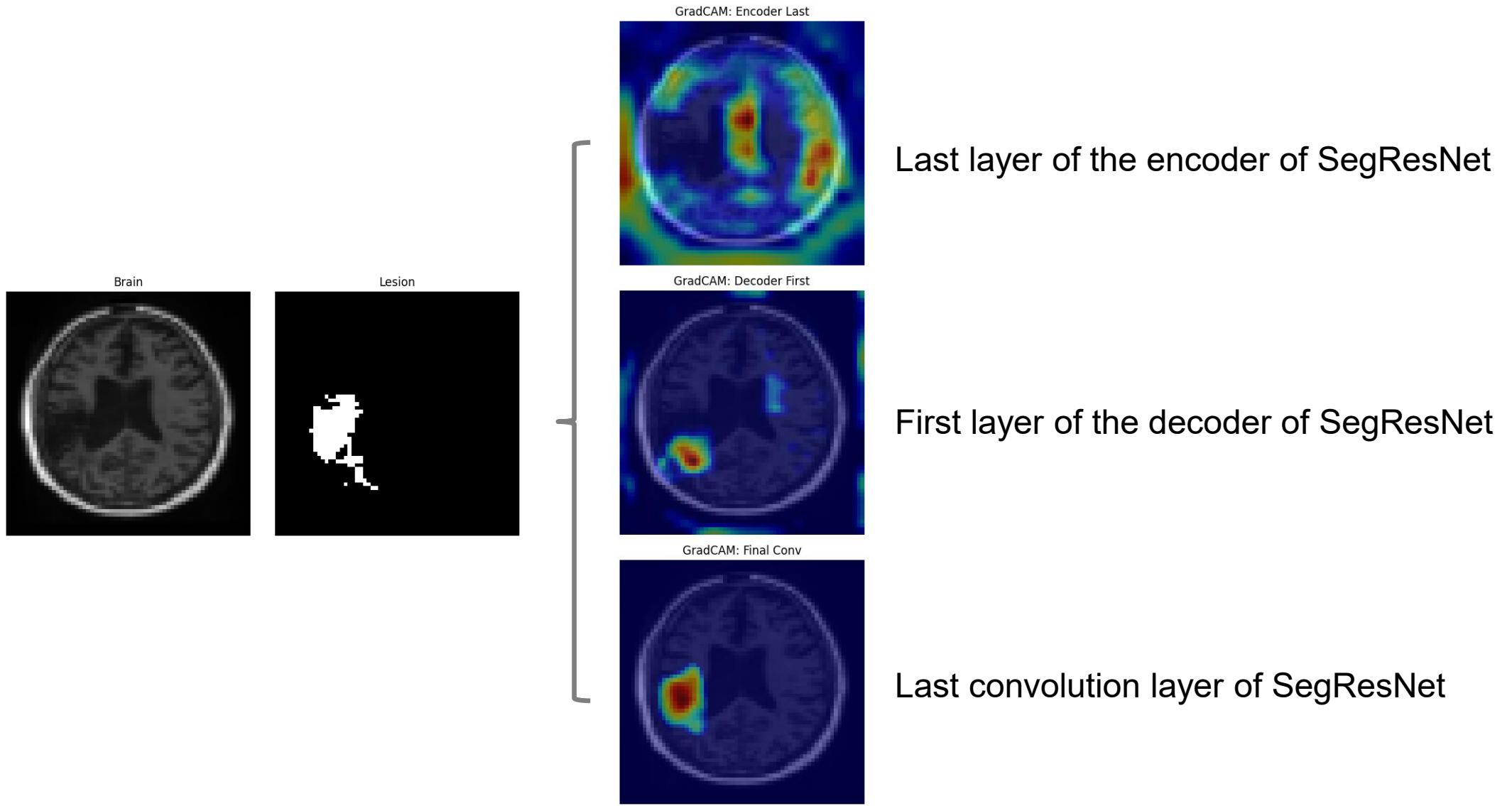
[Wu et al., 2023]

Proposed W-Net Architecture

Model Explanations: Class Activation Mapping 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

```
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

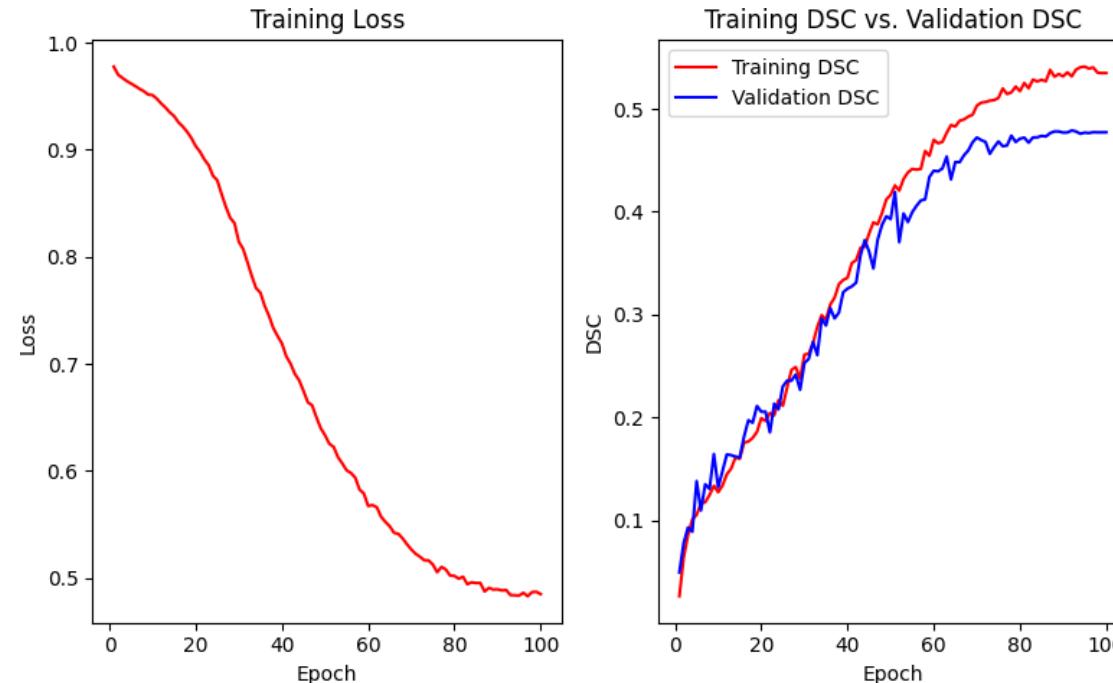
– SwinUNETR

- 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 = 0.479
 - Test set: DSC = 0.519 ± 0.239 ($0.000 \sim 0.861$)



- 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 = 0.479
 - Test set: DSC = 0.519 ± 0.239 (0.000 ~ 0.861)
 - 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)