Seminar - Fall 2023

Medical Image Segmentation for Realizing Human Digital Twin

Approaches and Technical Methods

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Outline

1. **Recap**

2. **Approaches & Technical Methods**

3. **Implementation**

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3. Implementation

Recap

Problem

- **To identify precise structure of bones and muscles from CT/MRI images in order to build human digital twin**

Motivation

- **Lack of research focusing on Segmentation of Bones and Muscles**
- **Advancing Healthcare**
- **Personalized treatment strategies, optimizing outcomes and reducing risks.**
- **Assisment in surgical planning, leading to safer and more efficient surgical procedures.**
- **Segmentation-driven digital twins are at the forefront of biomedical research and technology.**

Recap

Research Goals

- Understanding State-of-the-art techniques for medical image segmentation
- Aquiring the latest Vision Transformer-based expertise
- Development of segmentation model for bones and muscles on Visible Korean

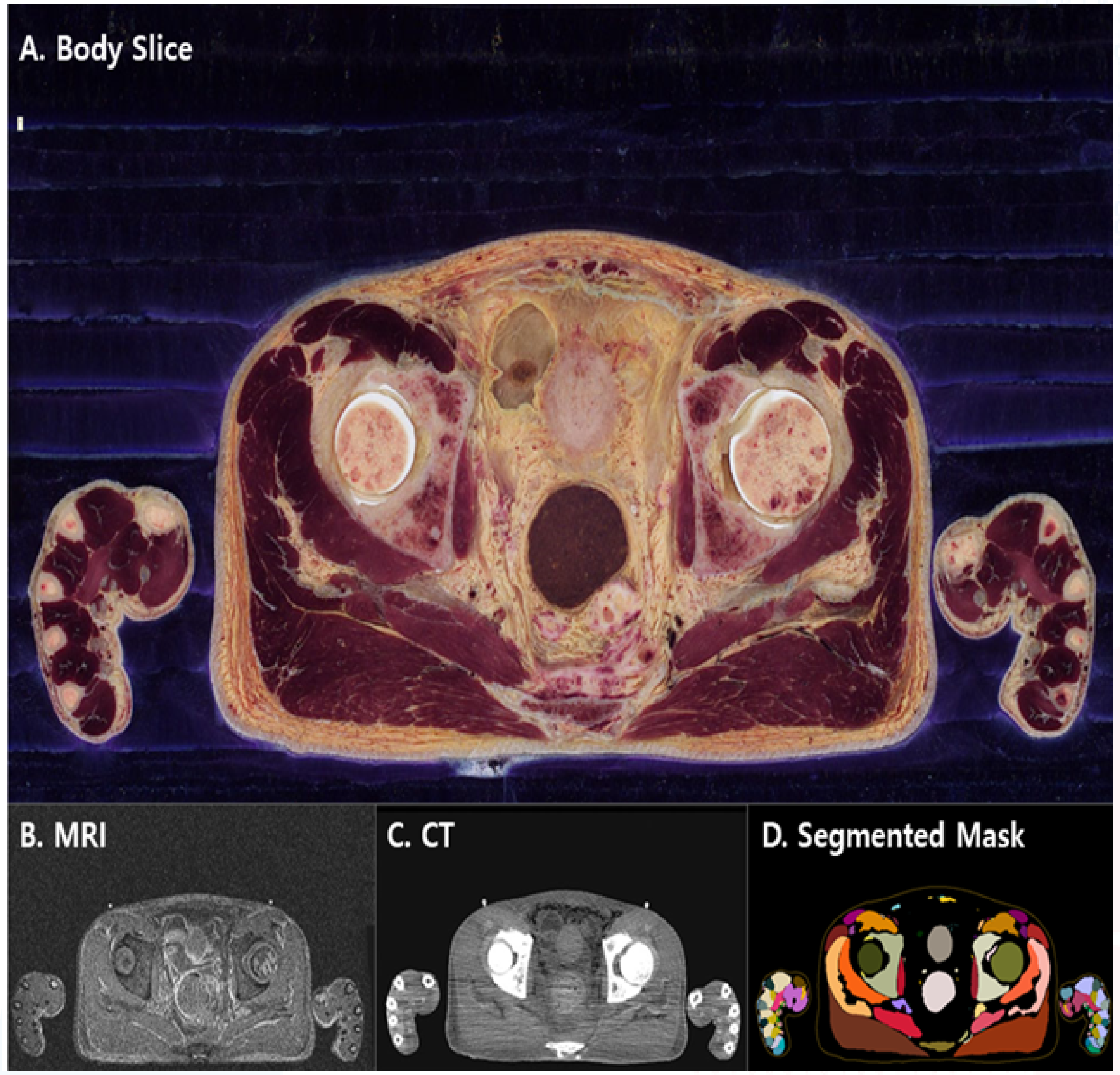
Recap

Visible Korean Dataset

- Full-body scans of a Korean man and a woman, and the corresponding CT, MRI, and segmentation masks

- The segmentation mask consists of a total of 13 major categories

    - MRI: 4mm (256x256, 12bit)
    - CT : 1mm (512,512, 12bit, 1702 in total)
    - BodySlice: 1mm (2048x1216, 24bit, 1702 in total)



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Approaches & Technical Methods

Medical Image Segmentation on Automatic Cardiac Diagnosis Challenge (ACDC)

Rank	Model	Avg DSC	Paper	Code	Result	Year	Tags
1	**FCT**	93.02	The Fully Convolutional Transformer for Medical Image Segmentation			2022	
2	**MERIT**	92.32	Multi-scale Hierarchical Vision Transformer with Cascaded Attention Decoding for Medical Image Segmentation			2023	
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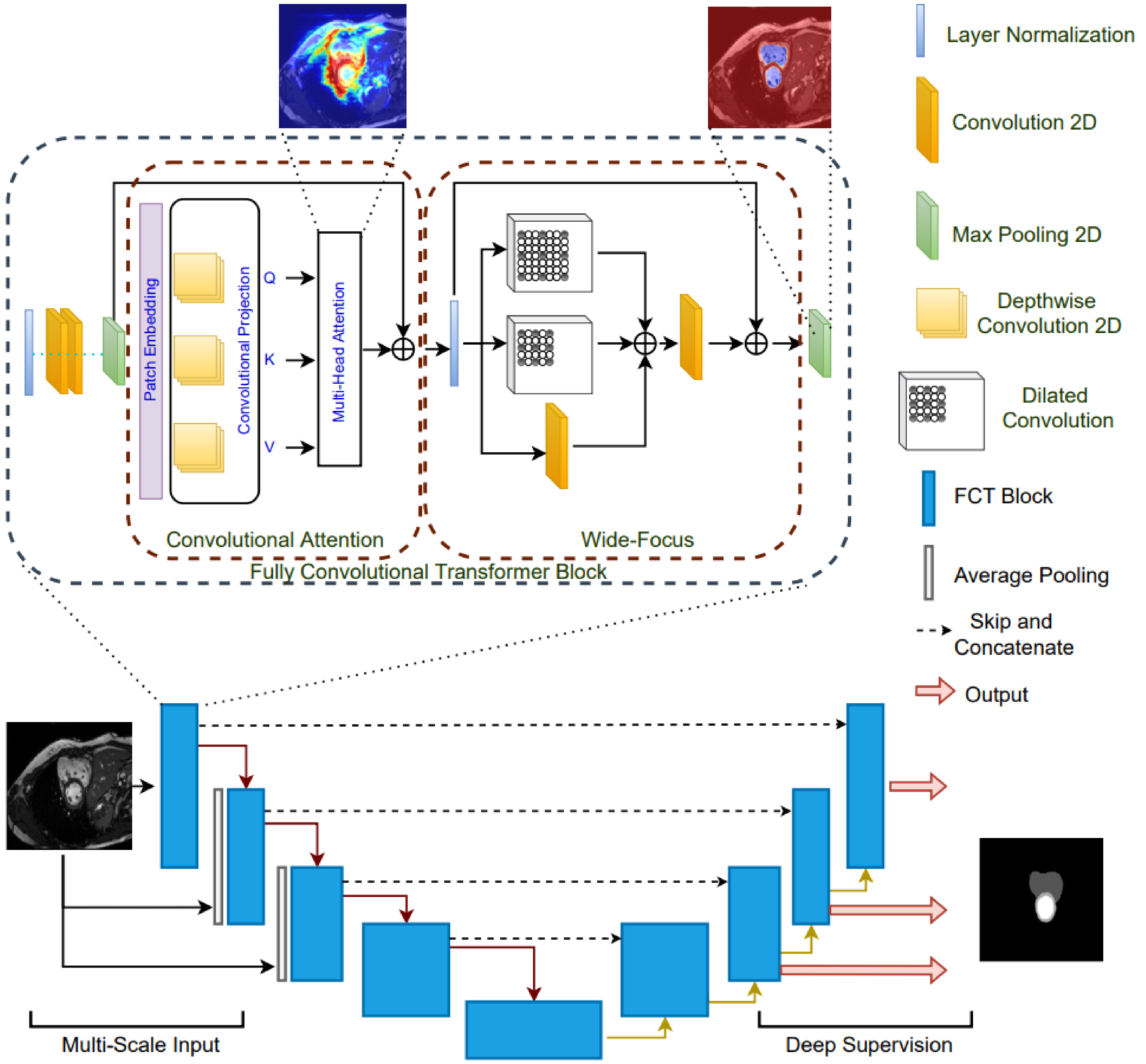
Fully Convolutional Transformer

Neither Transformer-CNN hybrid nor Transformer-UNet

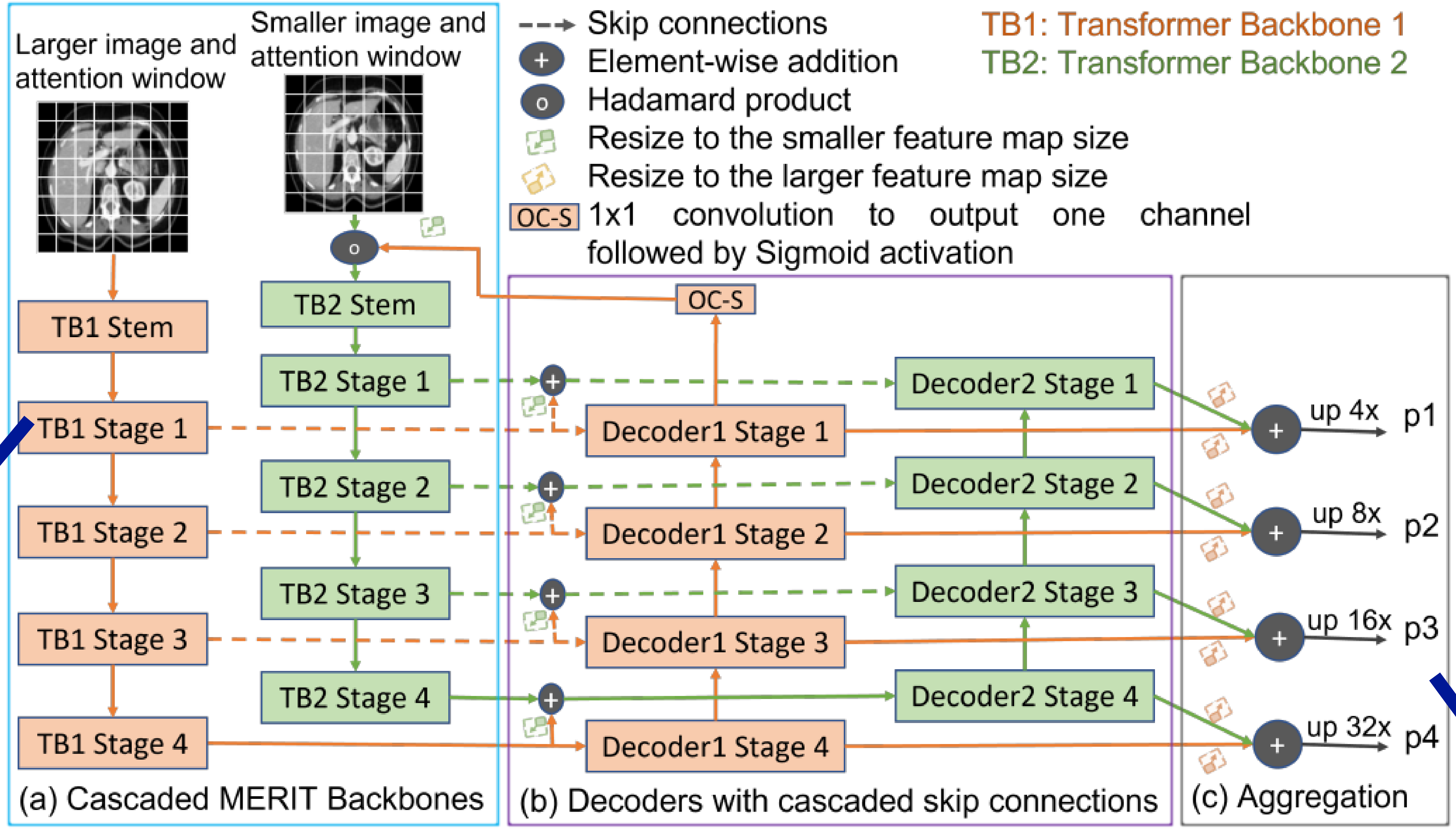
Uses *FCT layer* as building block

- consists of convolutional layers followed by Gelu activation function
- convolutional attention module replacing linear projection with Depthwise-Convolutions, removes positional encoding
- wide focus module contains dilated convolutions and convolutional layer for feature aggregation



"The fully convolutional transformer for medical image segmentation." Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2023.

Multi-scale Heirarchical Vision Transformer (MERIT)



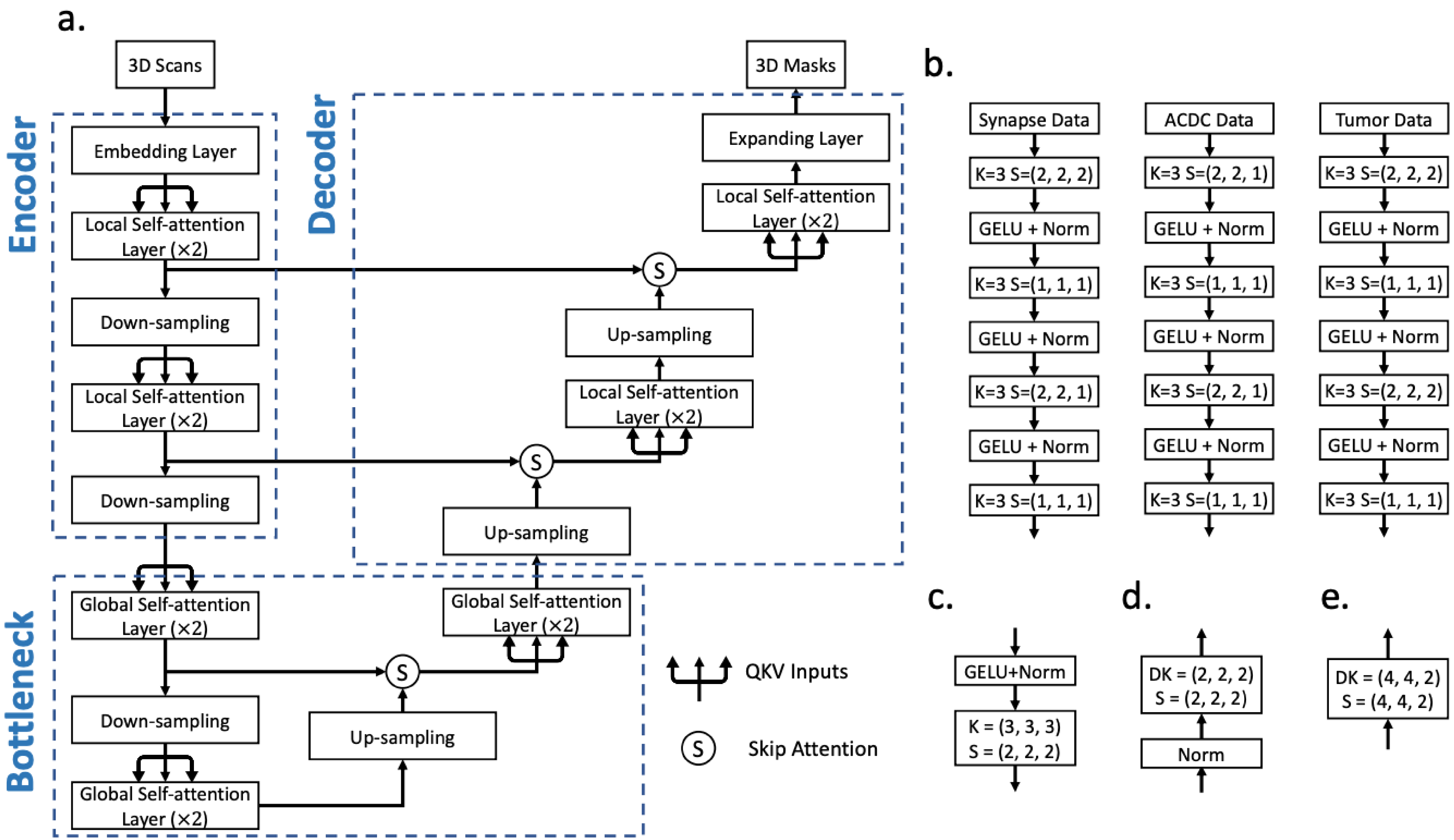
MaxViT blocks

$$\hat{y} = \alpha \times p1 + \beta \times p2 + \gamma \times p3 + \psi \times p4$$

- **combines MaxViT and Cascaded Decoders**
- **captures both multi-scale and multi-resolution features**

"Multi-scale Hierarchical Vision Transformer with Cascaded Attention Decoding for Medical Image Segmentation", MIDL 2023

nnFormer

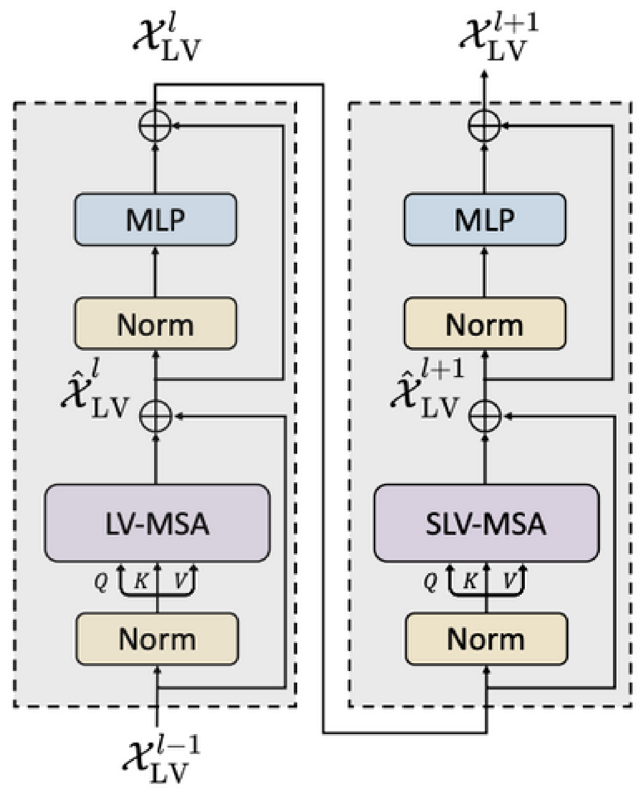


"nnFormer: Volumetric Medical Image Segmentation via a 3D Transformer," in IEEE Transactions on Image Processing, vol. 32, pp. 4036-4045, 2023

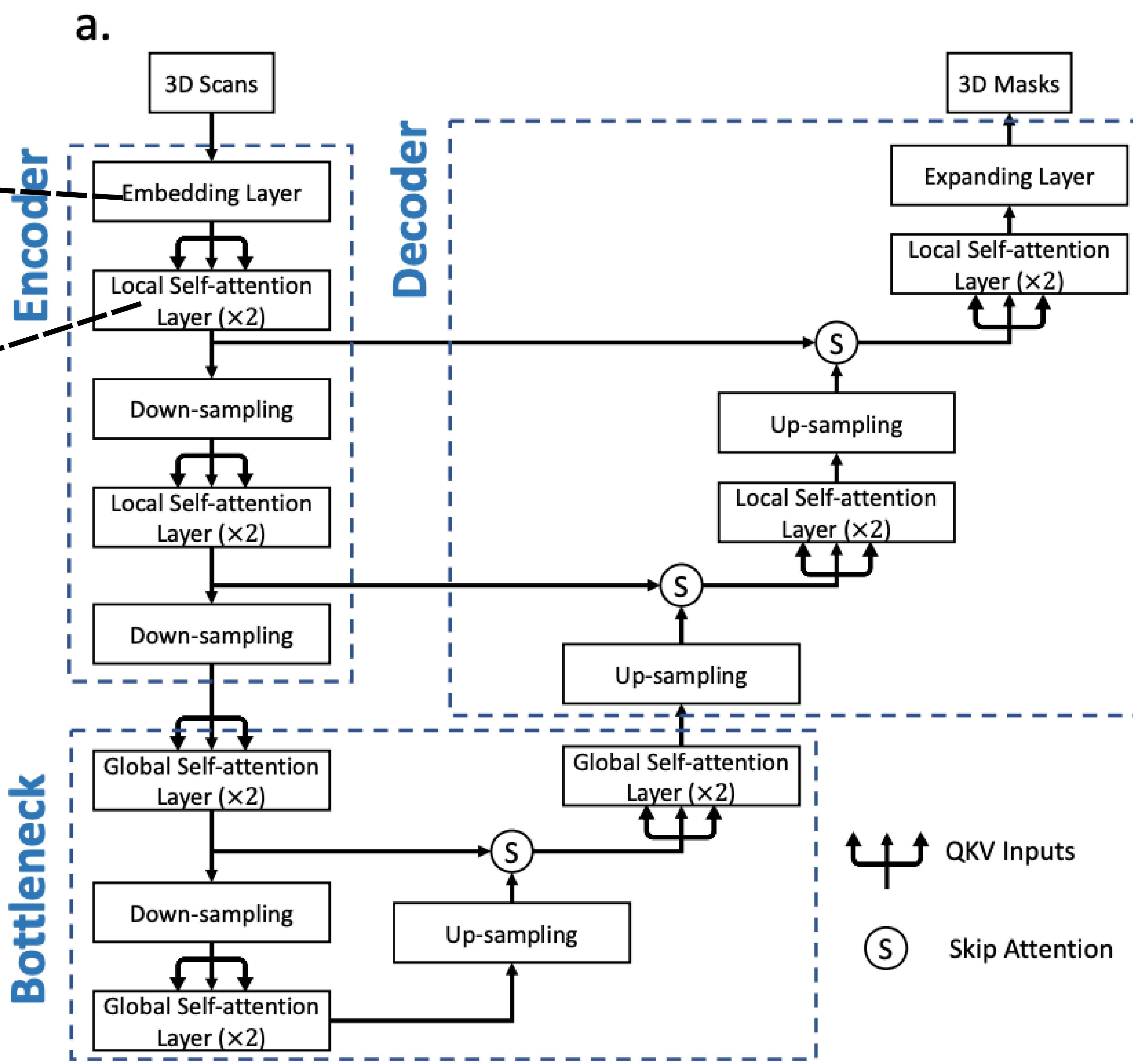
nnFormer

consists of convolution layers

1. precise spatial information
2. high resolution low level features



computes long range dependencies within 3D local volumes



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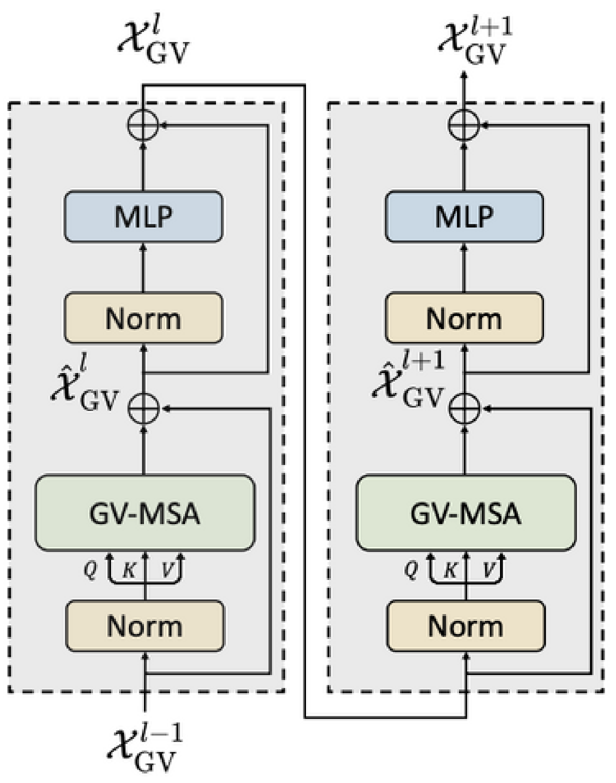
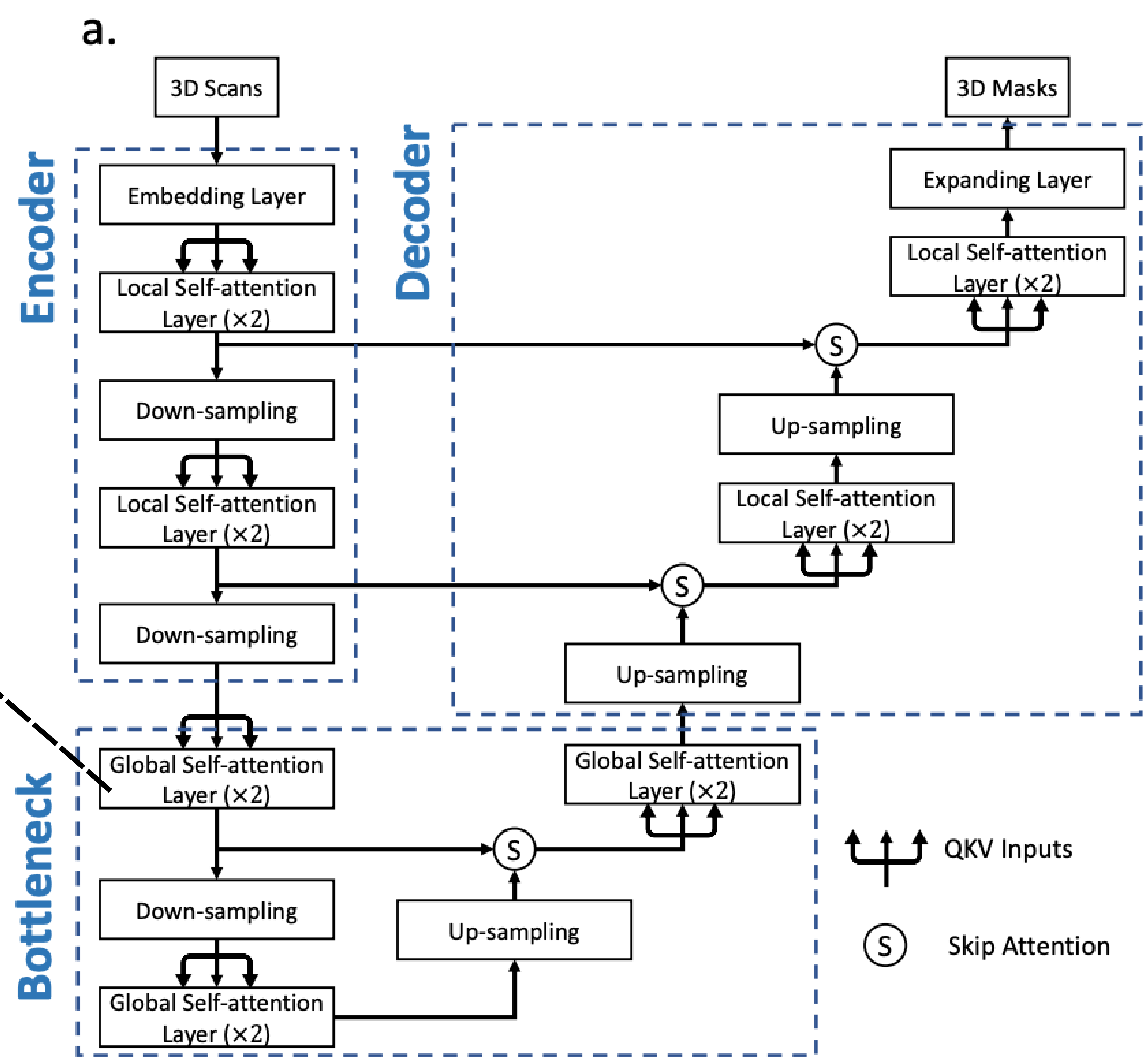


computes long range dependencies within 3D global volumes



"nnFormer: Volumetric Medical Image Segmentation via a 3D Transformer," in IEEE Transactions on Image Processing, vol. 32, pp. 4036-4045, 2023

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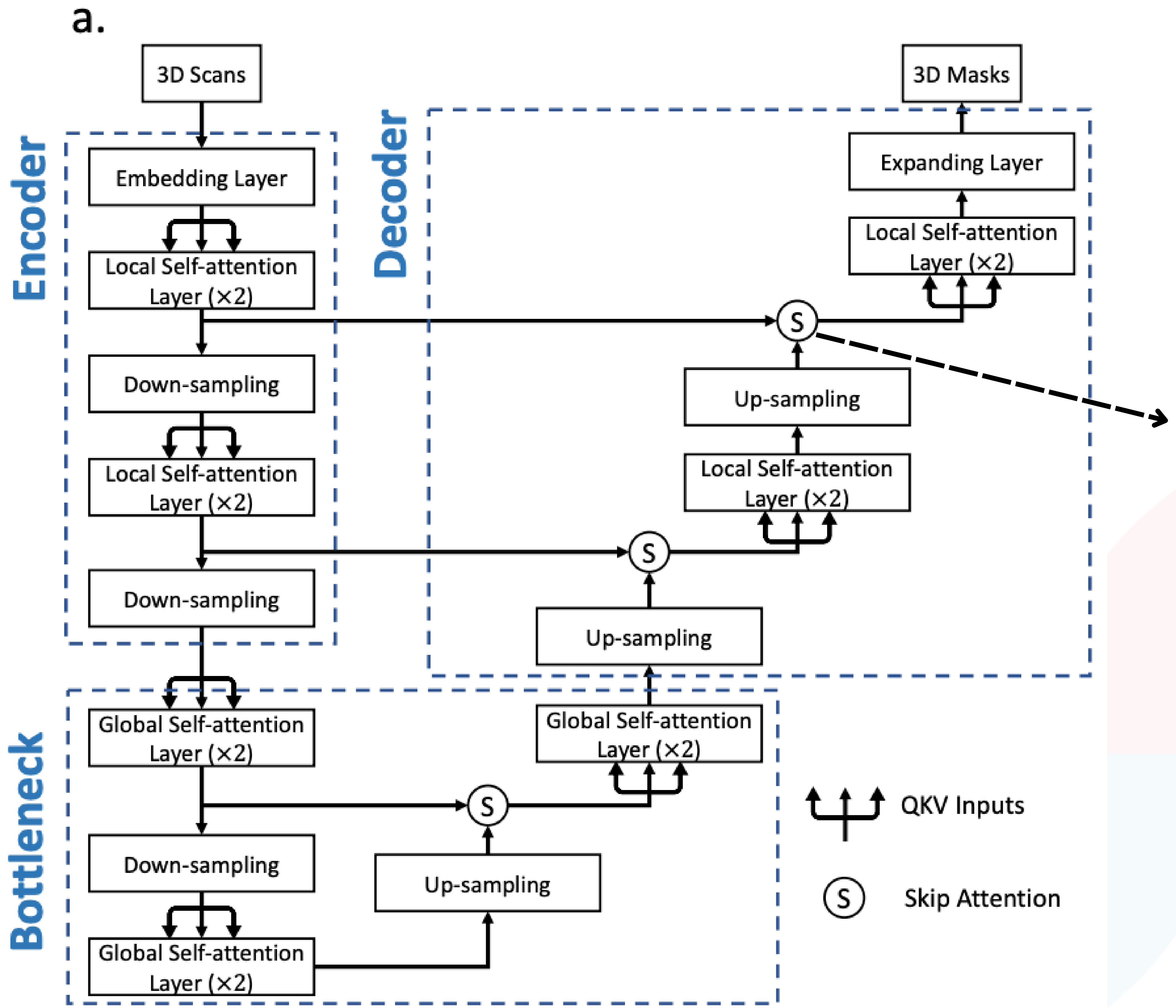
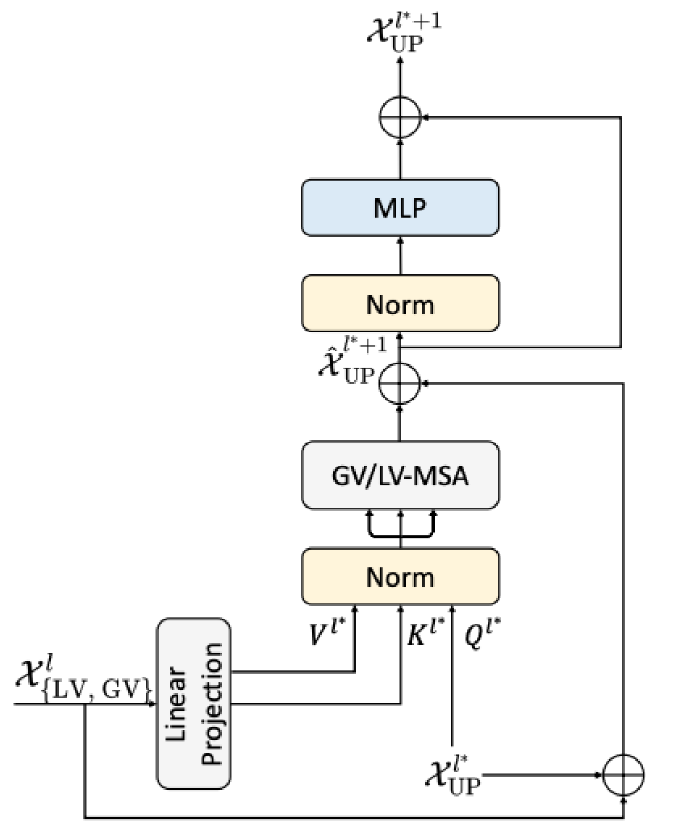


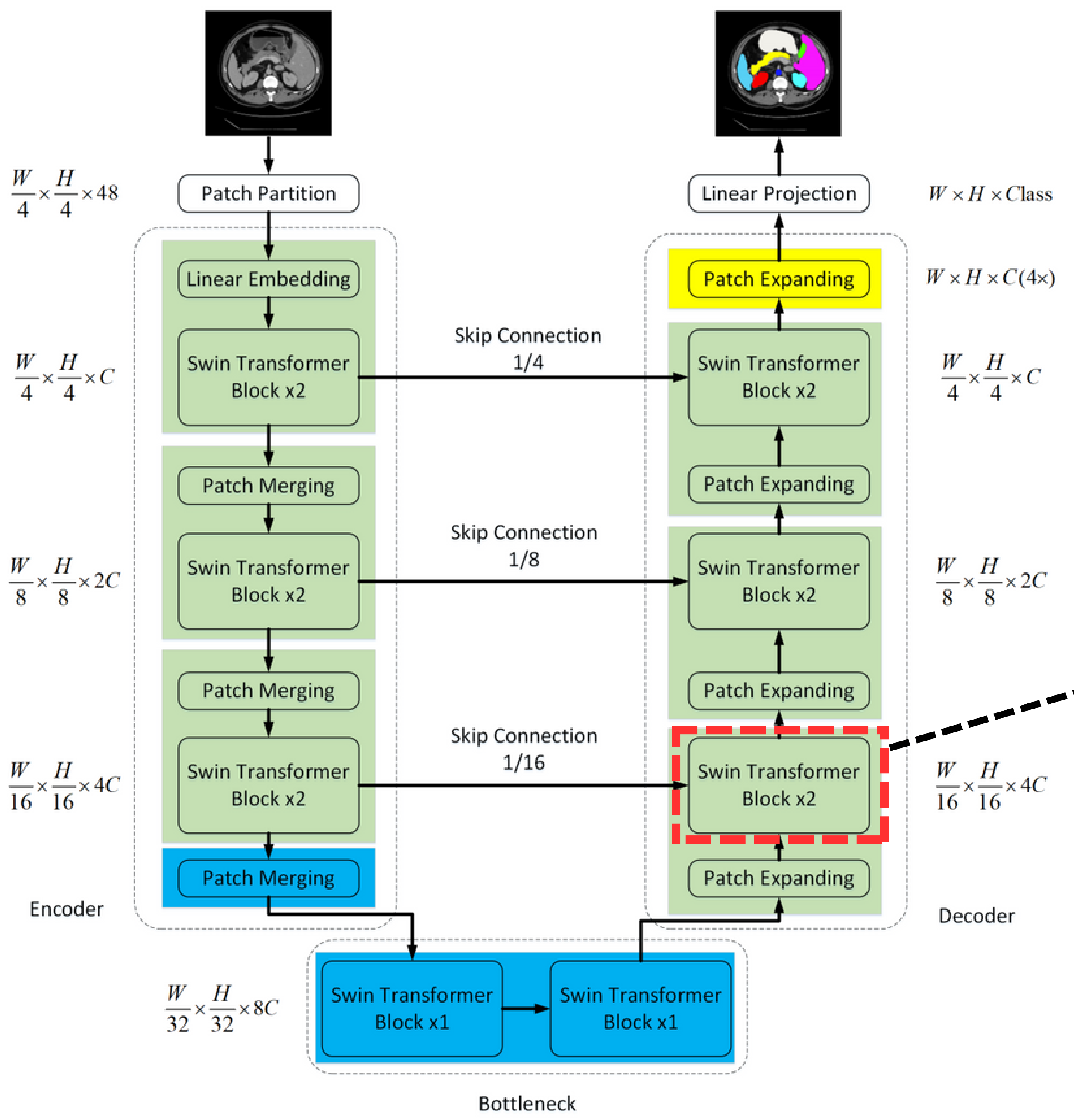


replaces traditional skip connection with skip attention

"nnFormer: Volumetric Medical Image Segmentation via a 3D Transformer," in IEEE Transactions on Image Processing, vol. 32, pp. 4036-4045, 2023

SwinUnet

Swin-Unet: Unet-like Pure Transformer for Medical Image Segmentation 5



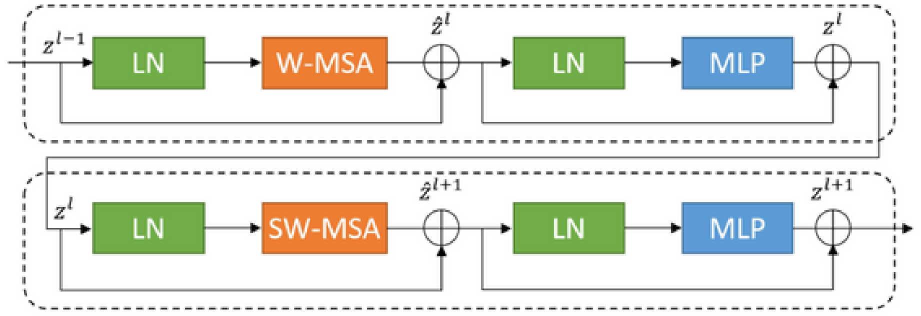
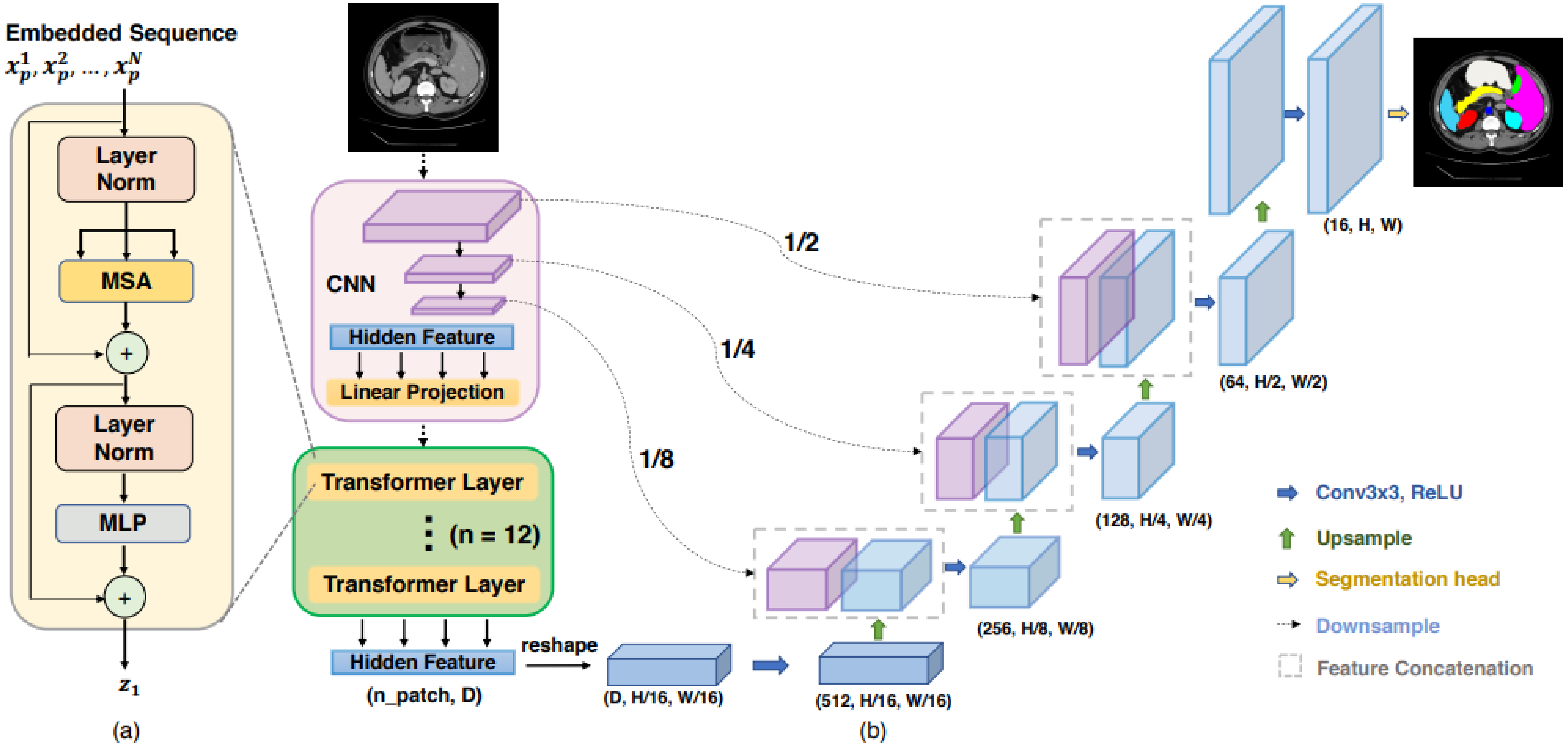


Fig. 2. Swin transformer block.

"Swin-unet: Unet-like pure transformer for medical image segmentation." European conference on computer vision. Cham: Springer Nature Switzerland, 2022

TransUnet



"Transunet: Transformers make strong encoders for medical image segmentation." arXiv preprint arXiv:2102.04306 (2021)

Summary

Model	Pros	Cons
FCT	• Outperforms existing models • Compact, accurate and robust • Able to reduce model parameters • five times smaller than nnFormer and three times smaller than TransUNet and LeViT-Unet	• Still relies on CNNs which may limit its ability to handle complex and diverse data distributions. • Uses fixed number of attention layers and heads which may not be optimal for different datasets
MERIT	• Captures multi-scale and multi-resolution features • Improves generalizability using self attention at multiple scales • Incorporates attention-based decoder	• Requires more computational resources and memory due to multi-scale and cascade design
nnFormer	• Able to model both local and global dependencies in 3d data • Exploits the advantage of convolutional and self attention operation in an interleaved manner	• High computation cost • Complex architecture and hard to interpret behaviour and results
SwinUnet	• Benefits of Swin Transformer and Unet • Enables multi-scale feature learning	• Requires pre-trained swin transformer model • sensitive to window size • require longer training time due to patch merging and splitting
TransUnet	• Employs benefits of both transformer and CNN	• requires pre-trained ViT models as the backbone of the Transformer encoder

Our Initial Approach

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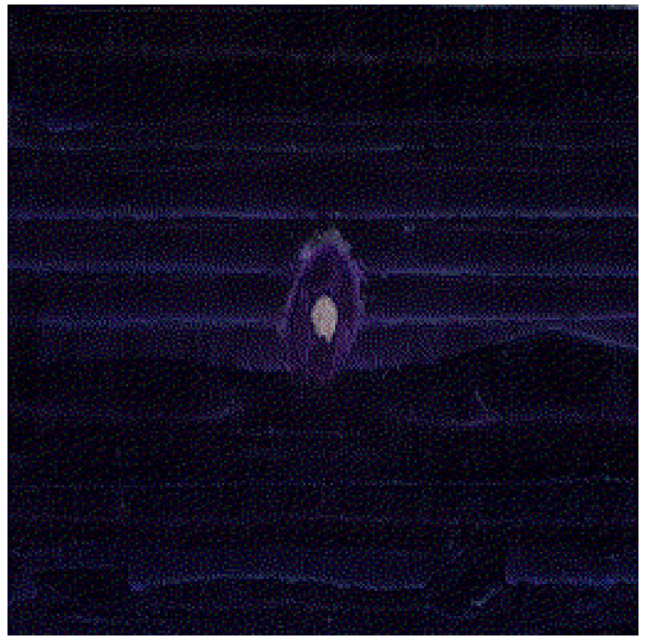
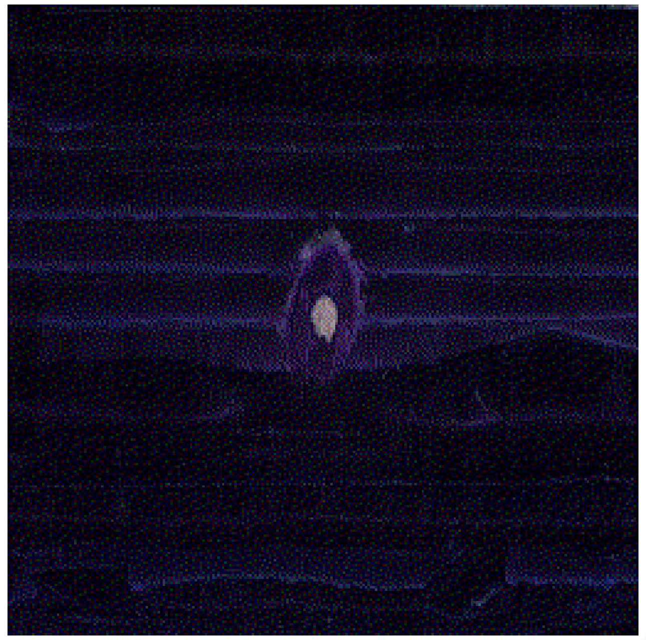
Implementation

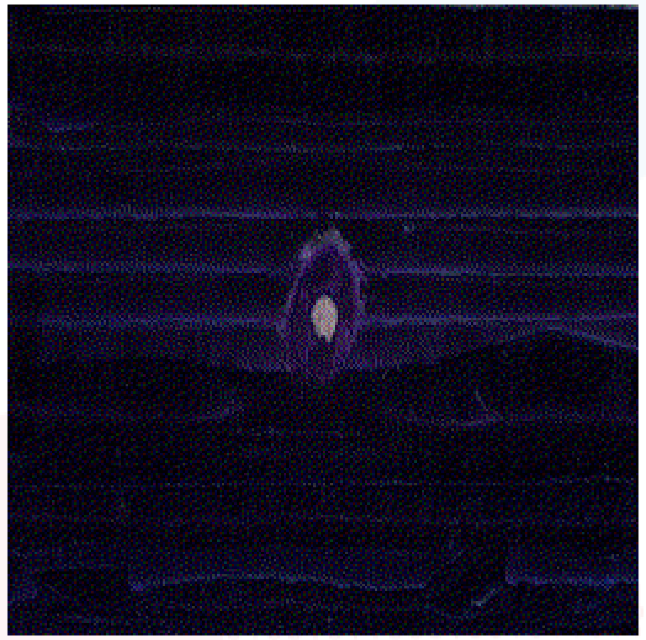
Data Preprocessing



VK-Male



VK-Male with Musclular Mask



VK-Male with Skeletal Mask

- Using body slice images of a full-body male (total of 1,702 images) and bone/muscle segmentation masks.
- Bone and muscle segmentation masks consist of 191 and 265 subcategories, respectively.
- For each consecutive slice, a musculoskeletal segmentation mask was created by integrating bone subcategories and muscle subcategories respectively.

Implementation

Dataset

- *Visible Korean Body Slice (1702 in total)*
- *Preprocessed GT Masks*
- *6:2:2 (train:validation:test)*

Performance Measure

Dice coefficient

Training Setting

RTX 4090

Tensorflow 2.0

Pytorch

Thank You!