M-Net: MRI Brain Tumor Sequential Segmentation Network via Mesh-Cast

Presenter: Jiacheng Lu

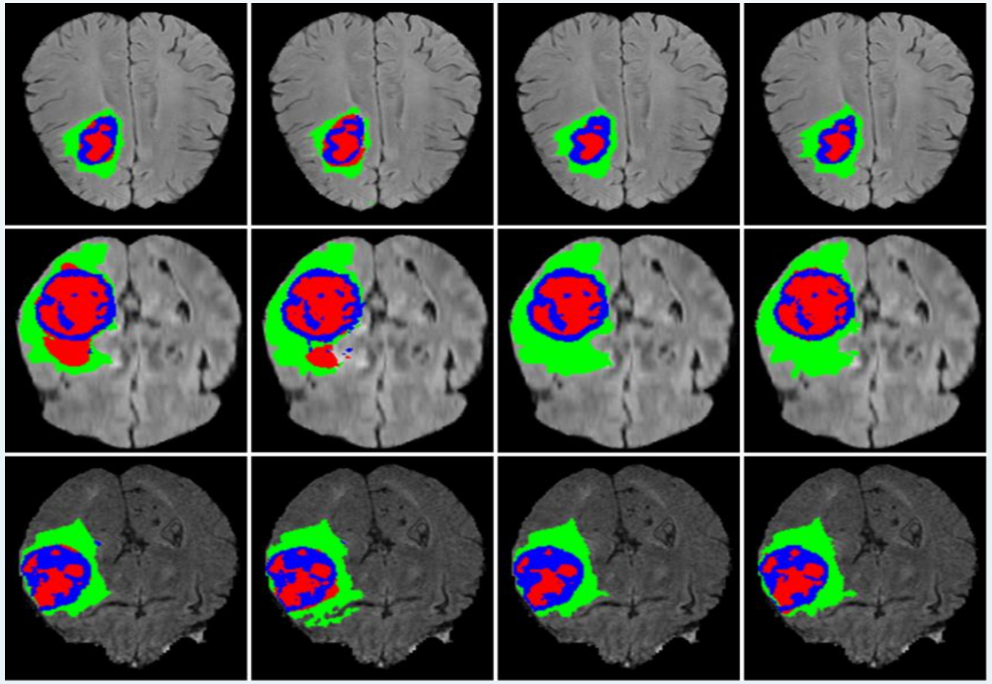
Advisor: Hui Ding

01 Research Background and Current Status

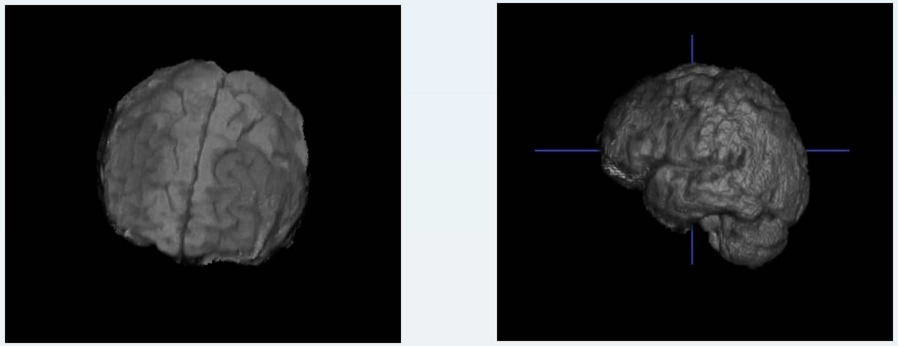
1 Fundamentals of Brain Tumor MRI Segmentation

Brain Tumor MRI Imaging Process

- Medical image segmentation, especially brain tumor MRI segmentation, is a core task in intelligent medical diagnosis. Accurate segmentation results can significantly improve lesion localization accuracy and enhance the efficiency of treatment planning.



Example of Brain Tumor MRI Segmentation Task



3D MRI Example

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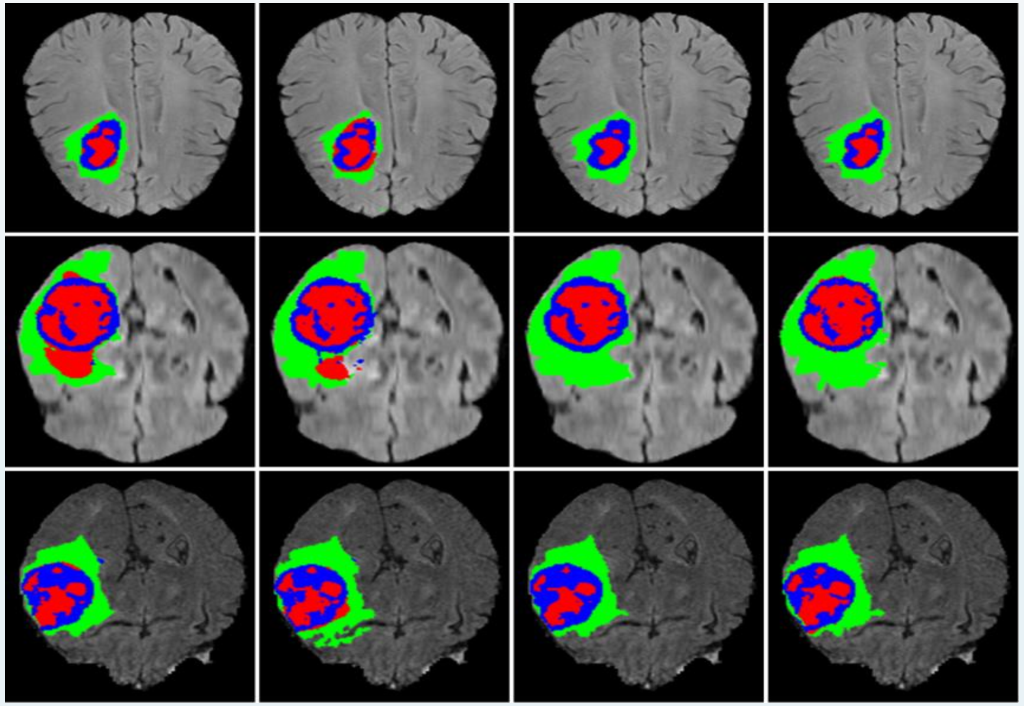

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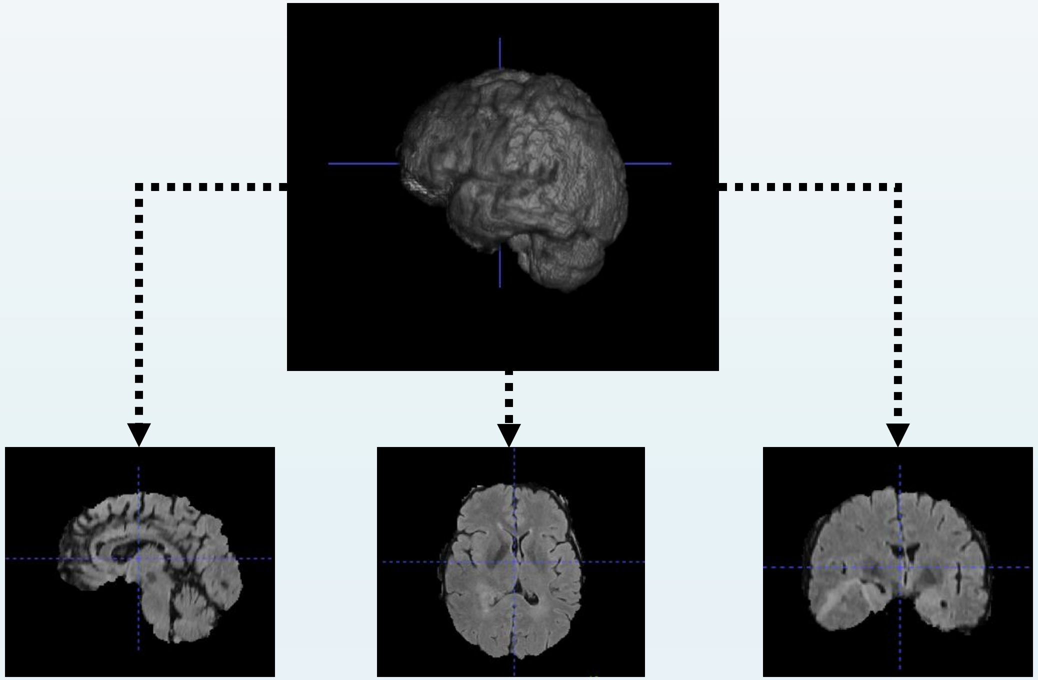

2D MRI Acquisition Process

- Medical image segmentation, especially brain tumor MRI segmentation, is a core task in intelligent medical diagnosis. Accurate segmentation results can significantly improve lesion localization accuracy and enhance the efficiency of treatment planning.

- To reduce computational costs, 3D MRI scans are often processed as 2D slices, which include images from the coronal, sagittal, and axial planes.

2 Related Work

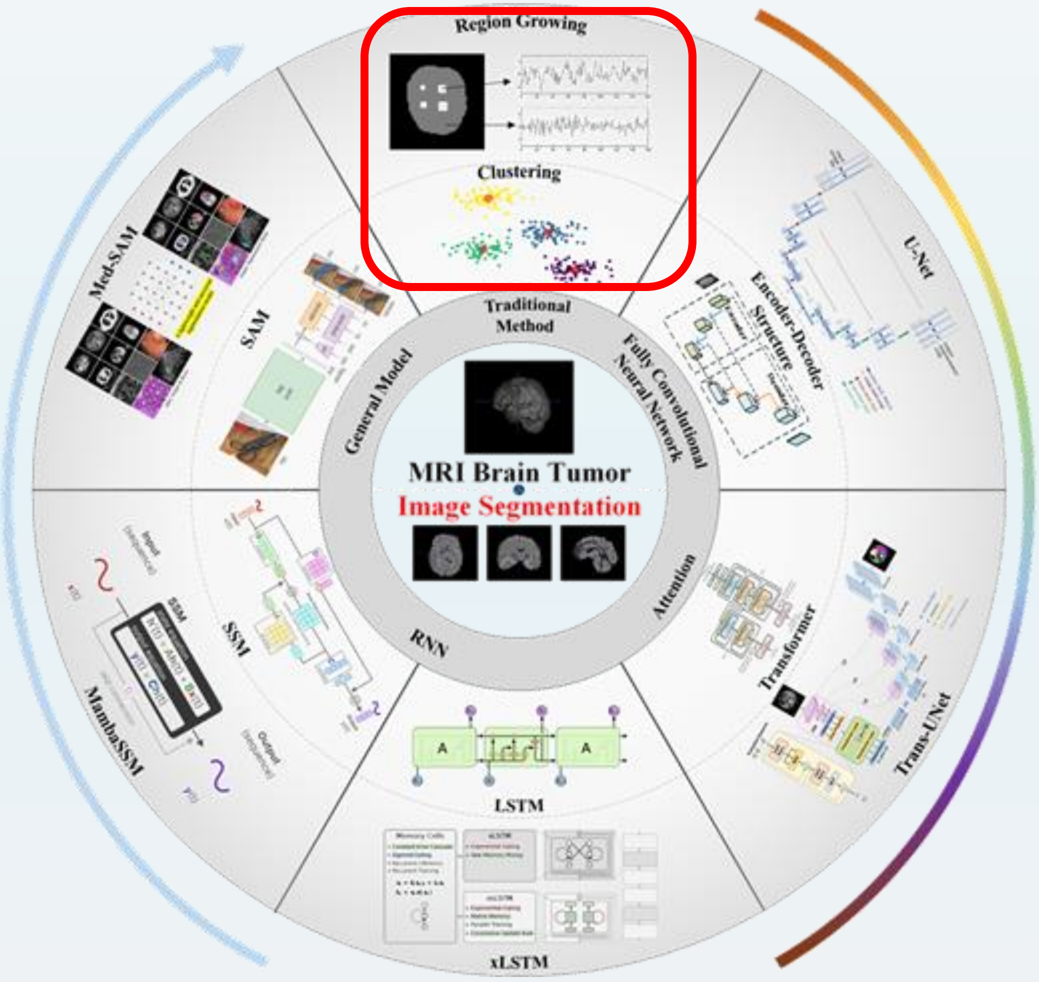

Illustration of Development Trends
in Brain Tumor MRI Segmentation Methods

- **Traditional Segmentation Algorithms**
  - Conventional methods based on thresholding and region growing struggle to meet clinical requirements for accuracy and robustness.

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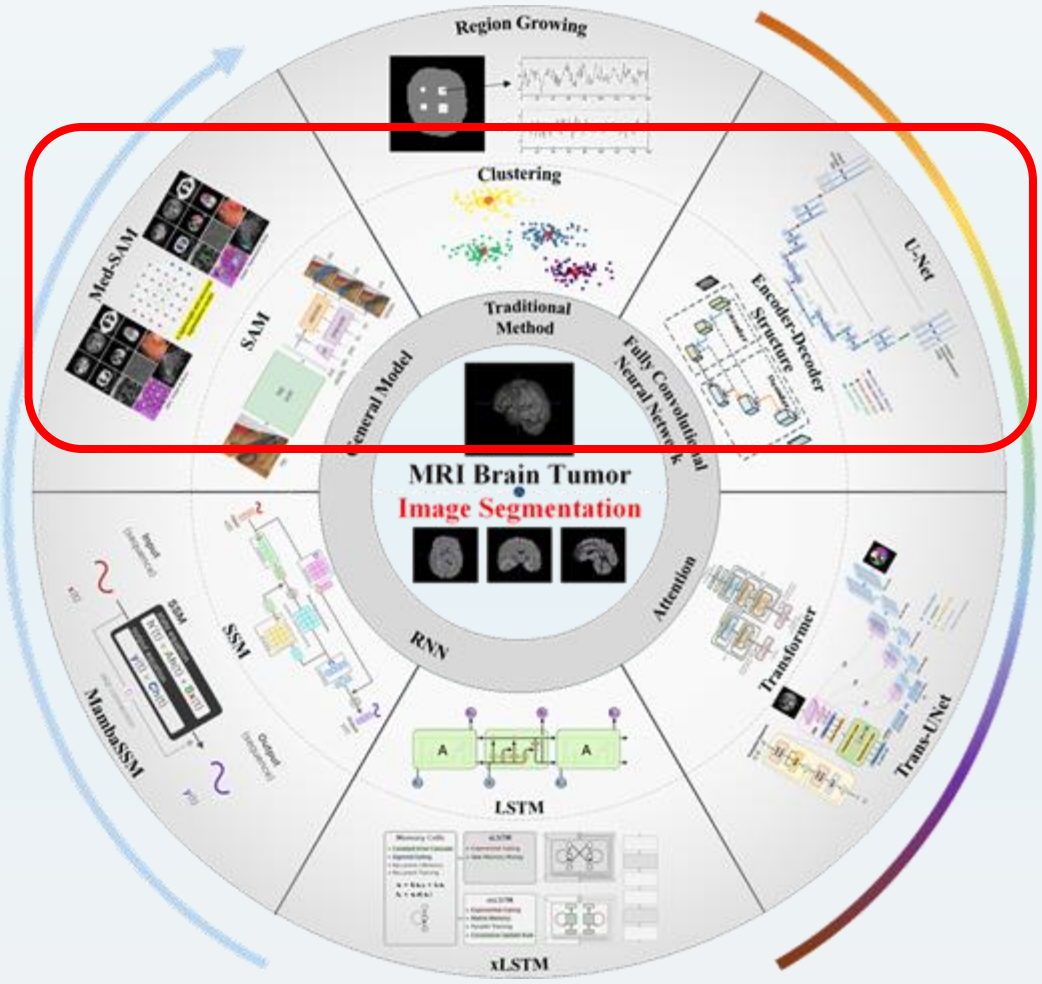

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  - Convolutional neural network architectures represented by U-Net have achieved significant breakthroughs in brain tumor MRI segmentation through their encoder–decoder structure and skip connections, inspiring numerous improved variants.

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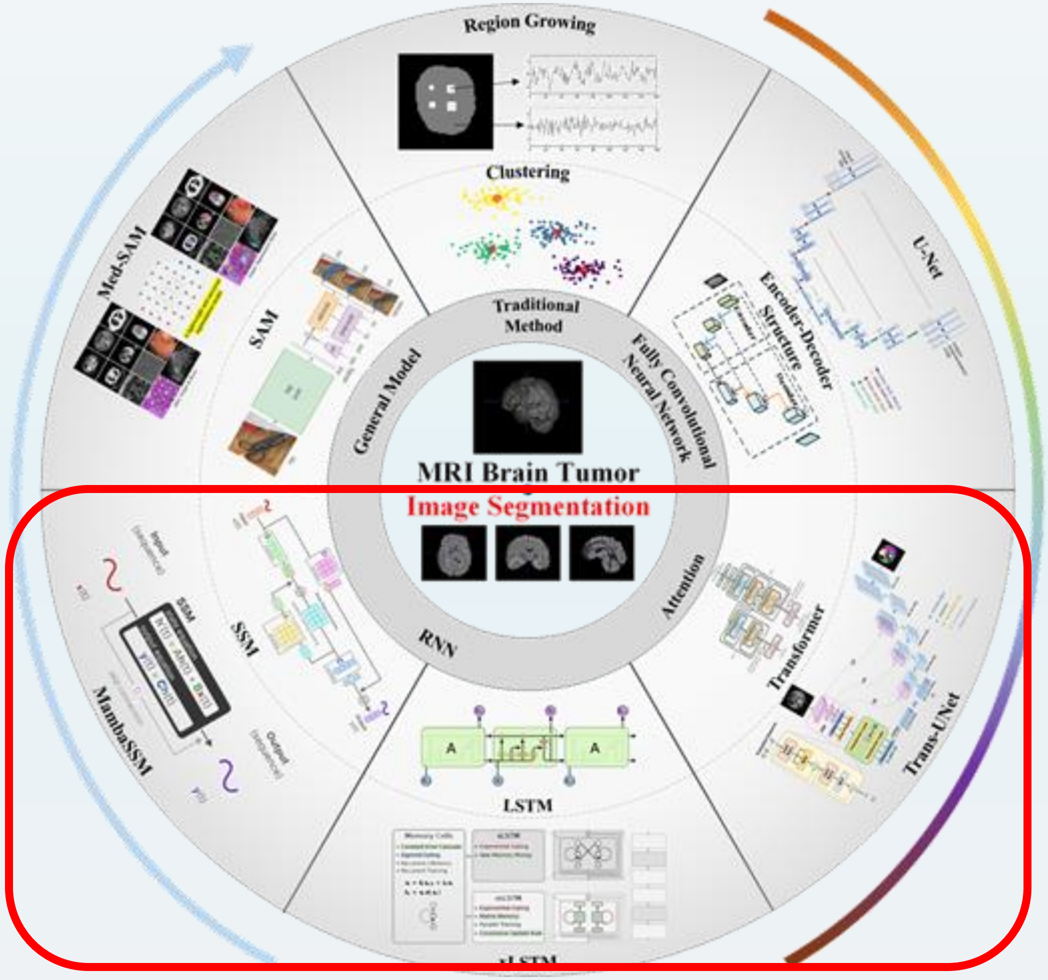

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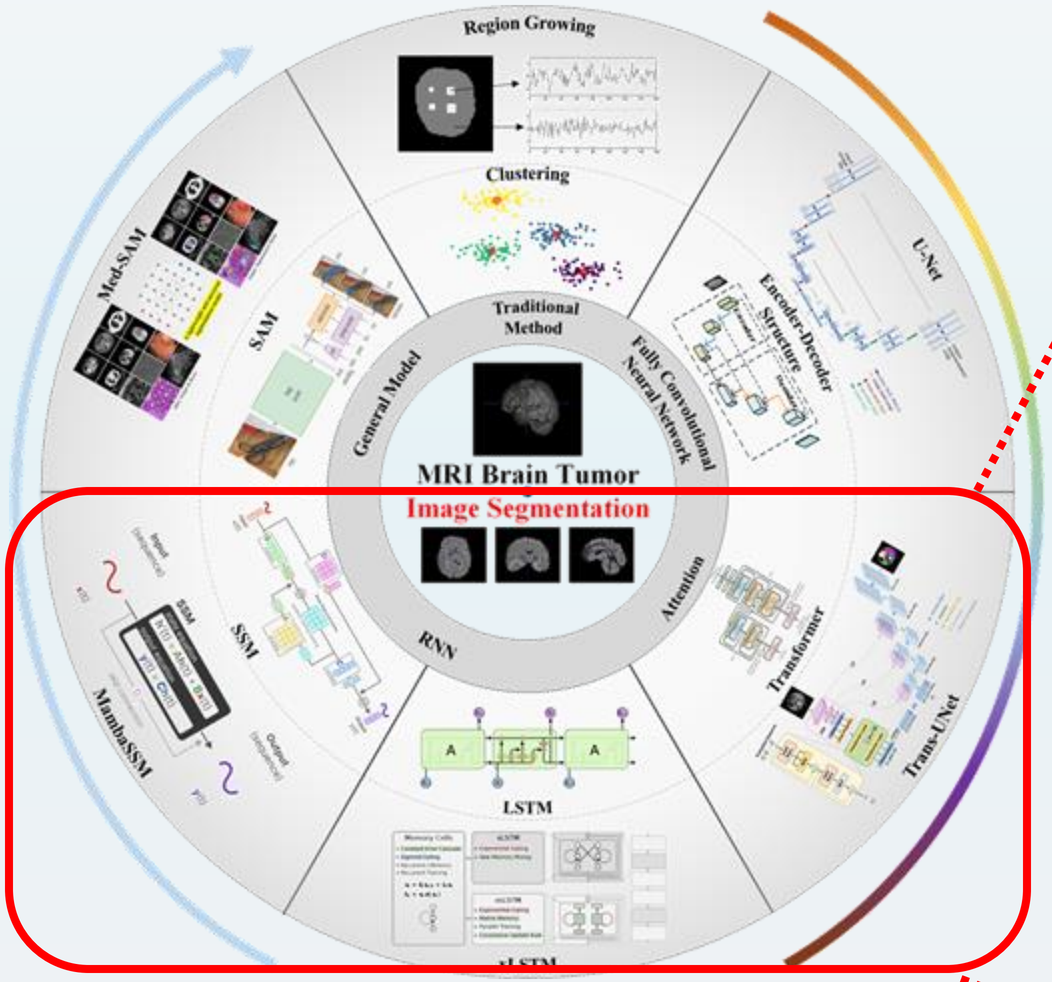
- **Sequence-Based Segmentation Algorithms**
  - With advances in natural language processing, sequence attention models such as Transformer, LSTM, and Mamba have been introduced into segmentation tasks. These models capture long-range dependencies and global contextual relationships, further enhancing the performance of brain tumor segmentation.

2 Related Work



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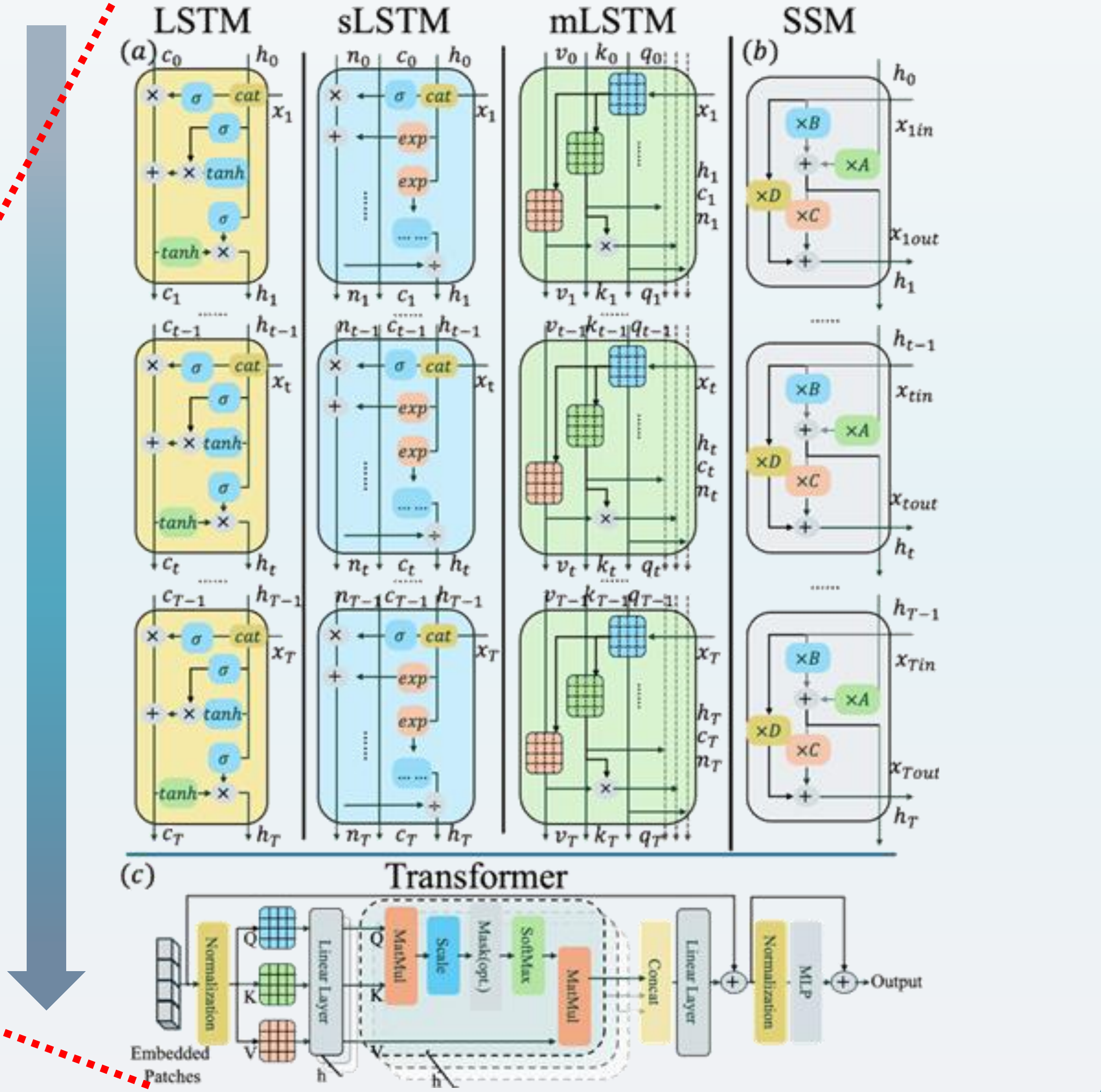

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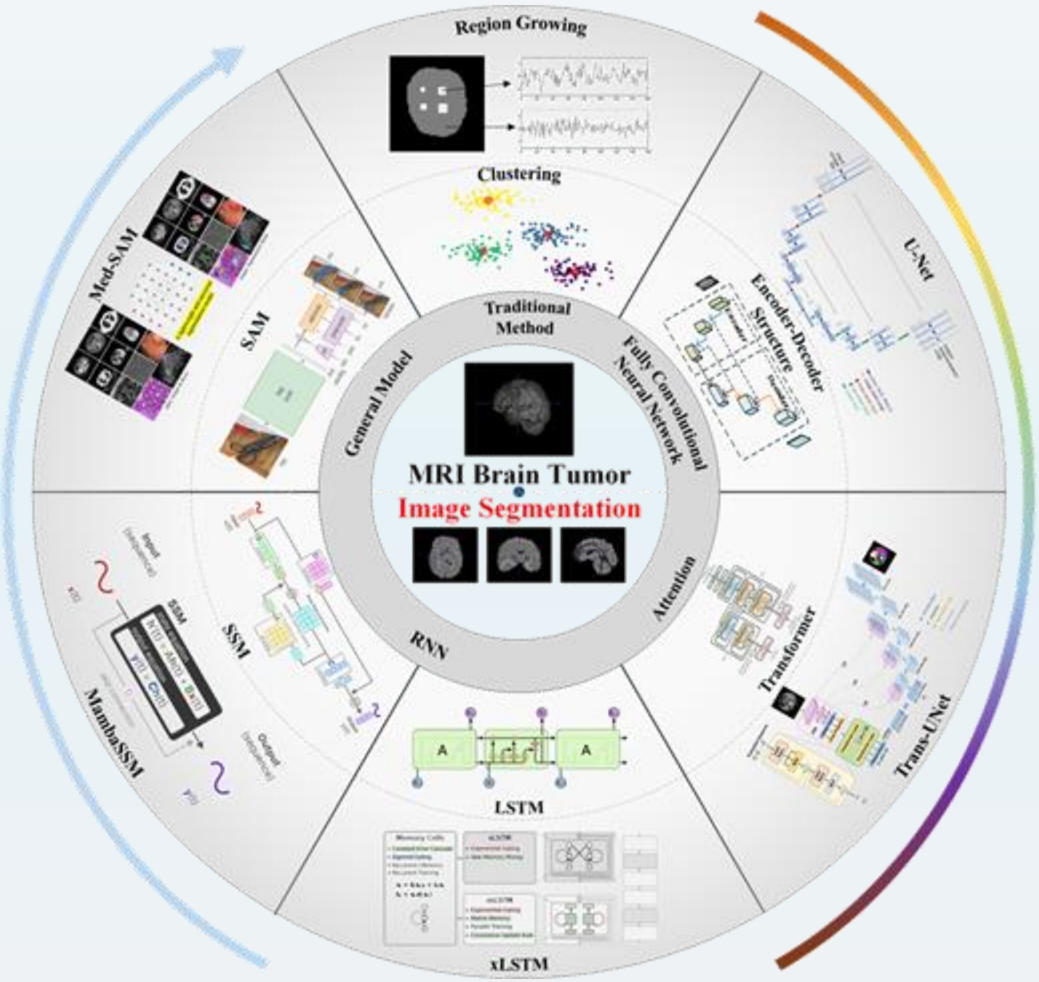

Illustration of Development Trends
in Brain Tumor MRI Segmentation Methods

- Q1: However, existing 2D algorithms suffer from low accuracy, while 3D algorithms incur high computational costs. What causes this gap?

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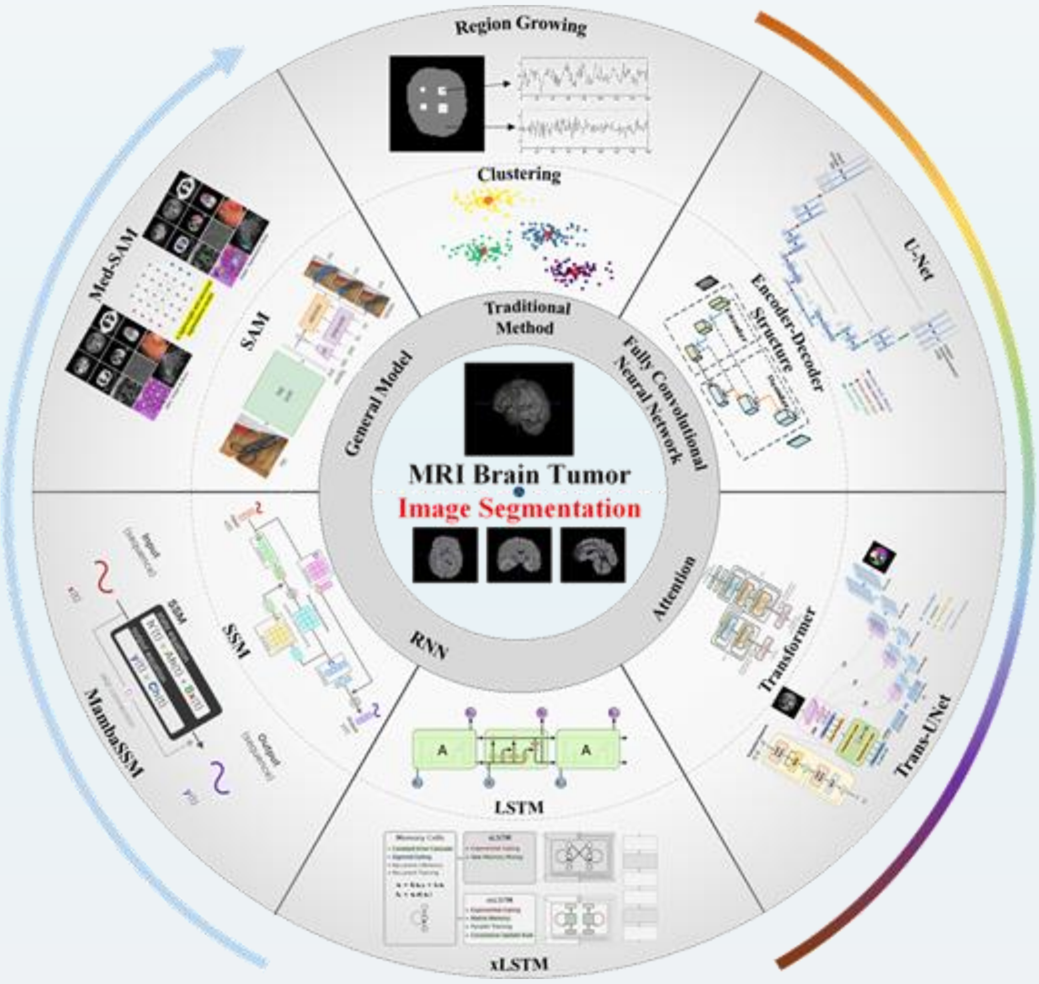


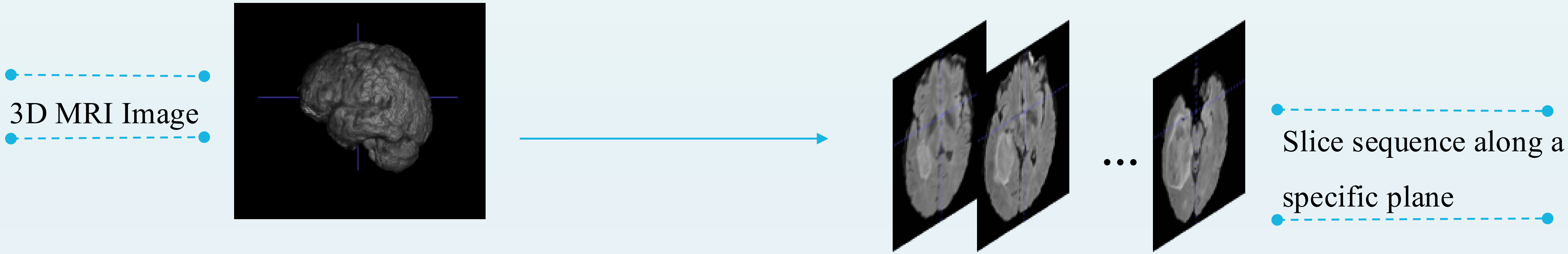
Illustration of Development Trends
in Brain Tumor MRI Segmentation Methods

- Q1: However, existing 2D algorithms suffer from low accuracy, while 3D algorithms incur high computational costs. What causes this gap?

- A1: There exist sequential correlations among MRI slices! 2D algorithms struggle to capture them, while 3D algorithms require extensive computation.

02 M-Net Brain Tumor MRI Sequential Segmentation Framework

2 Brain MRI Slice Sequence Modeling Strategies



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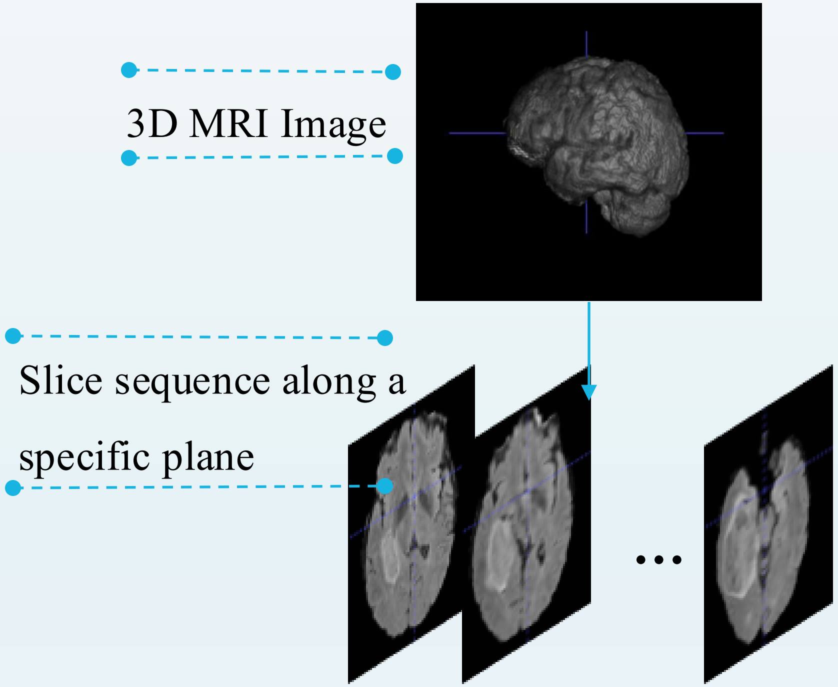
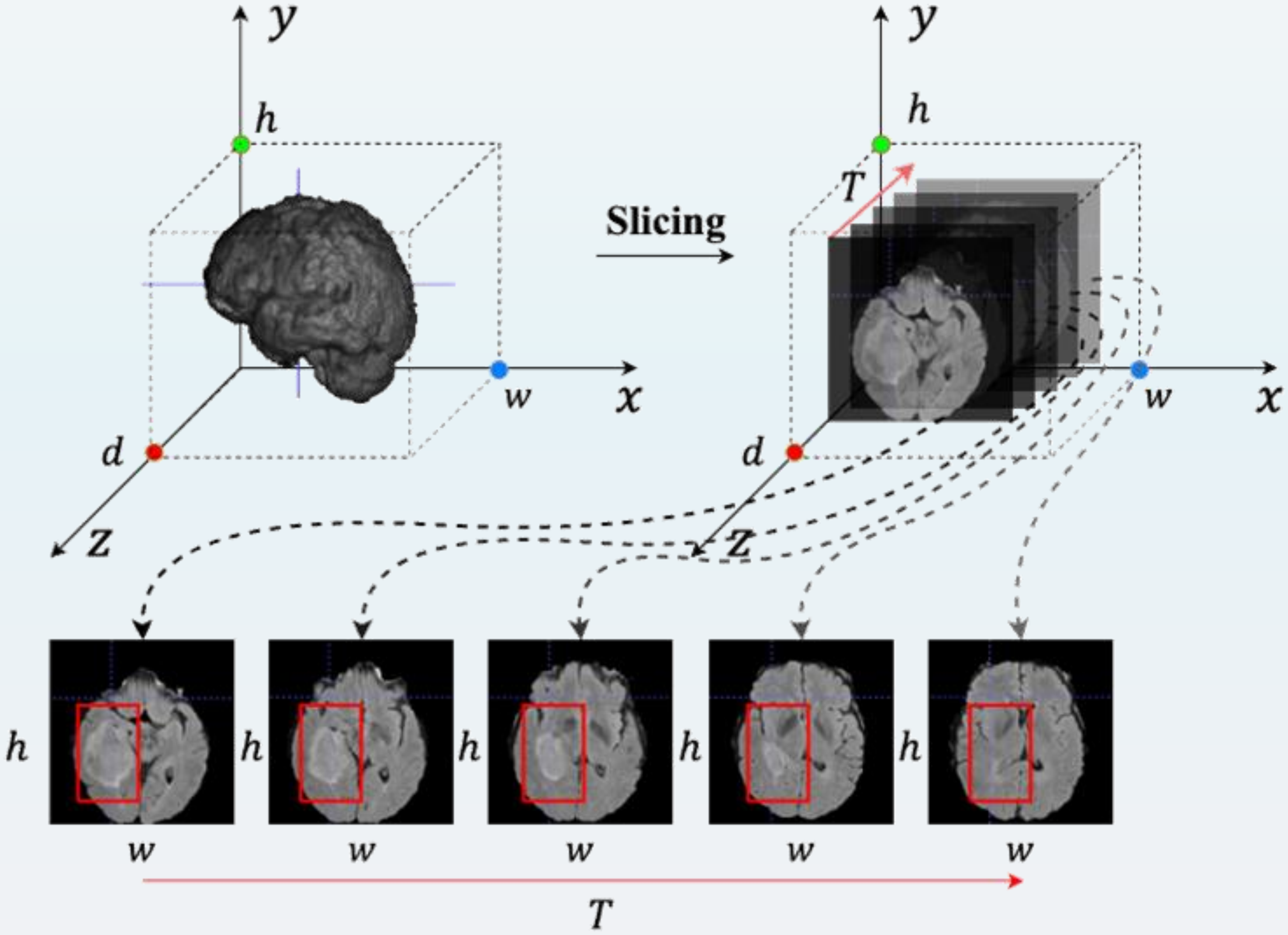


- There exists spatial correlation among MRI slices as a "temporal-like" sequence.
- The position and size of lesions vary continuously across slices due to spatial continuity.



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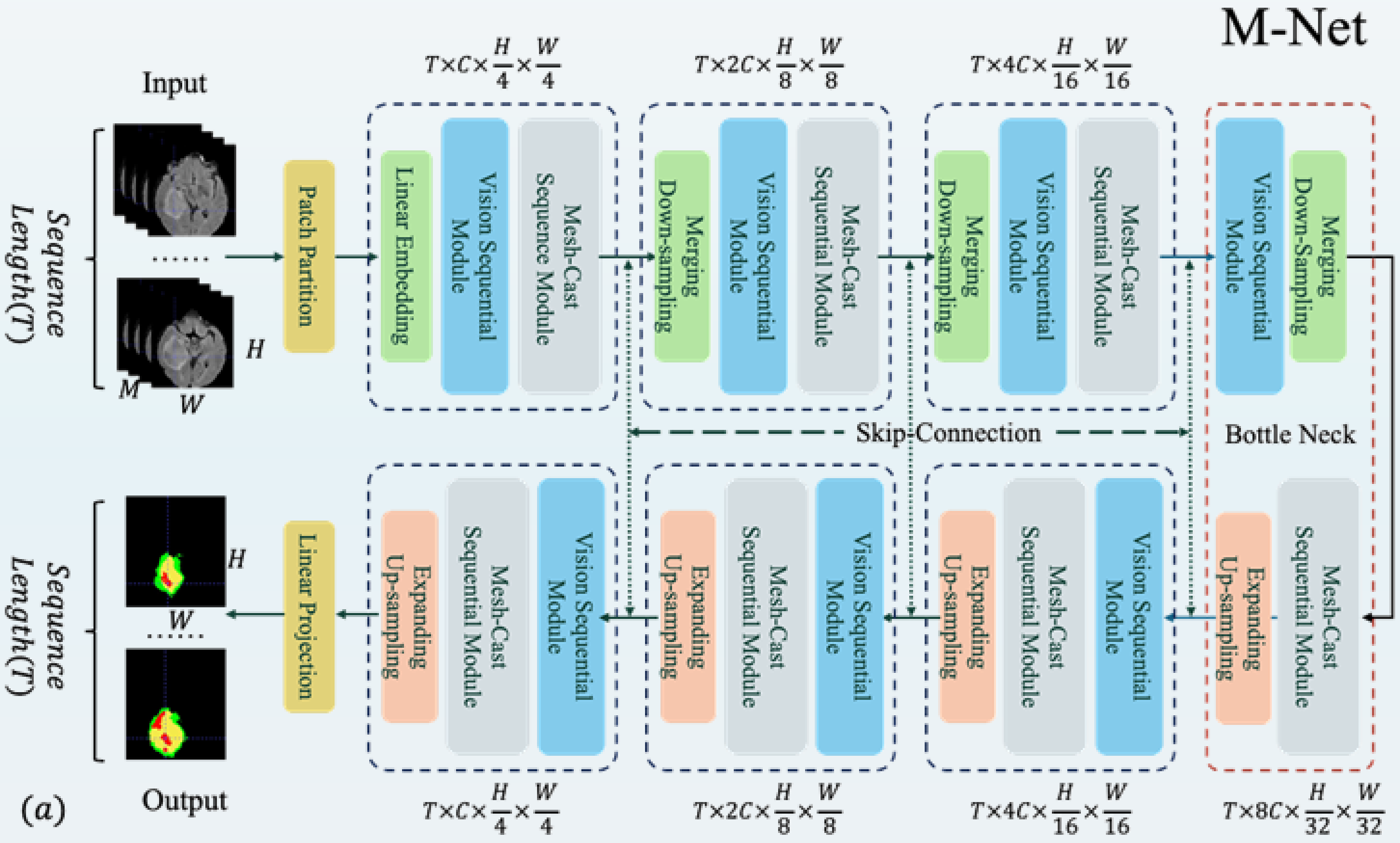
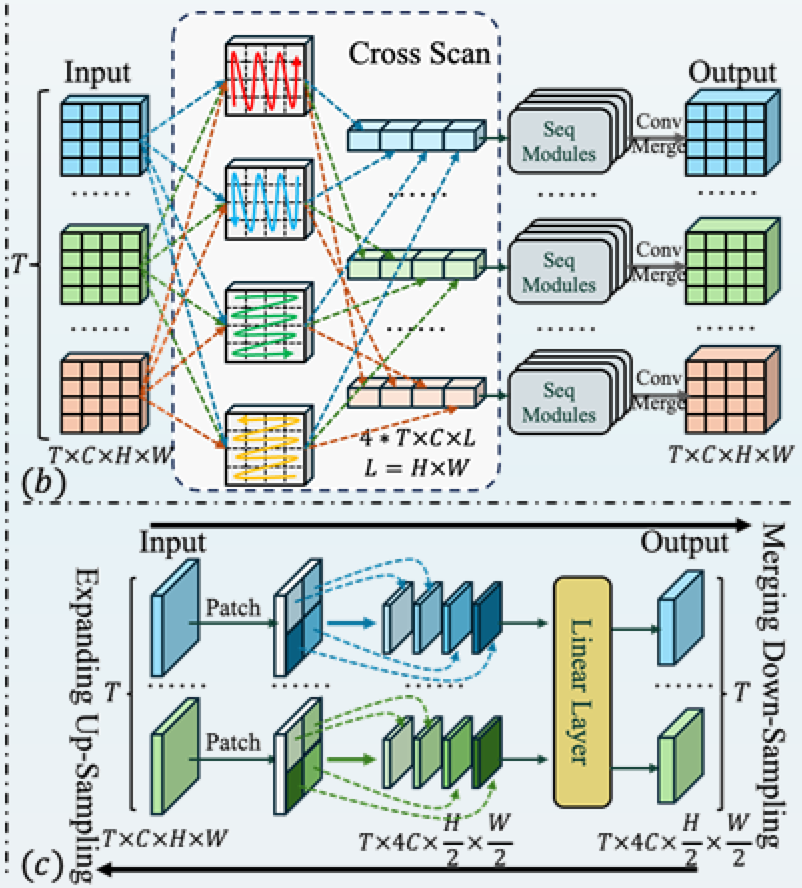
2 M-Net MRI Sequential Segmentation Network



(a) M-Net Architecture



(b)(c) M-Net Basic Visual Backbone

*Lu J, Ding H, Zhang S, et al.

M-Net: MRI Brain Tumor Sequential Segmentation Network via Mesh-Cast[J]. arXiv preprint arXiv:2507.20582, 2025.

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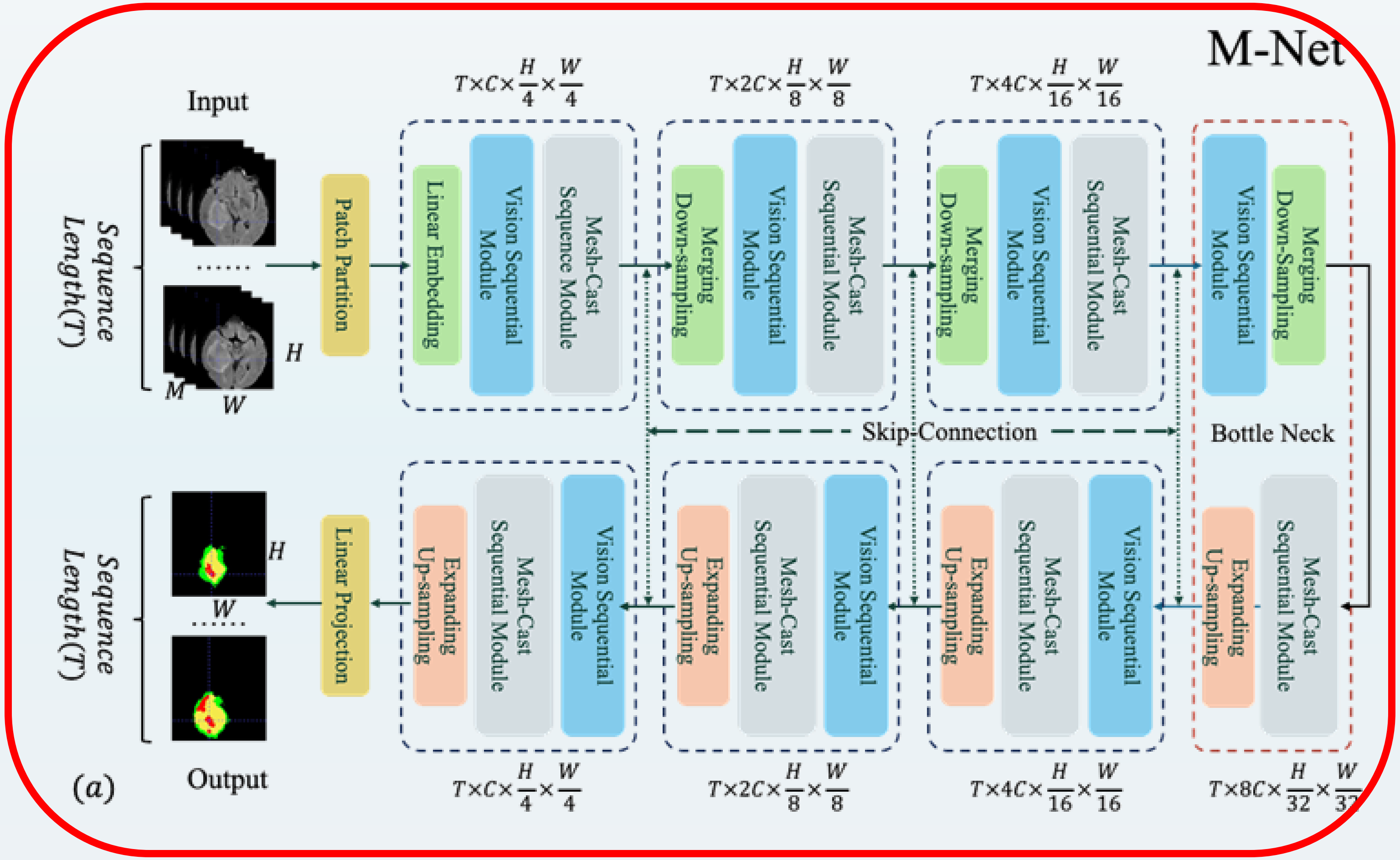

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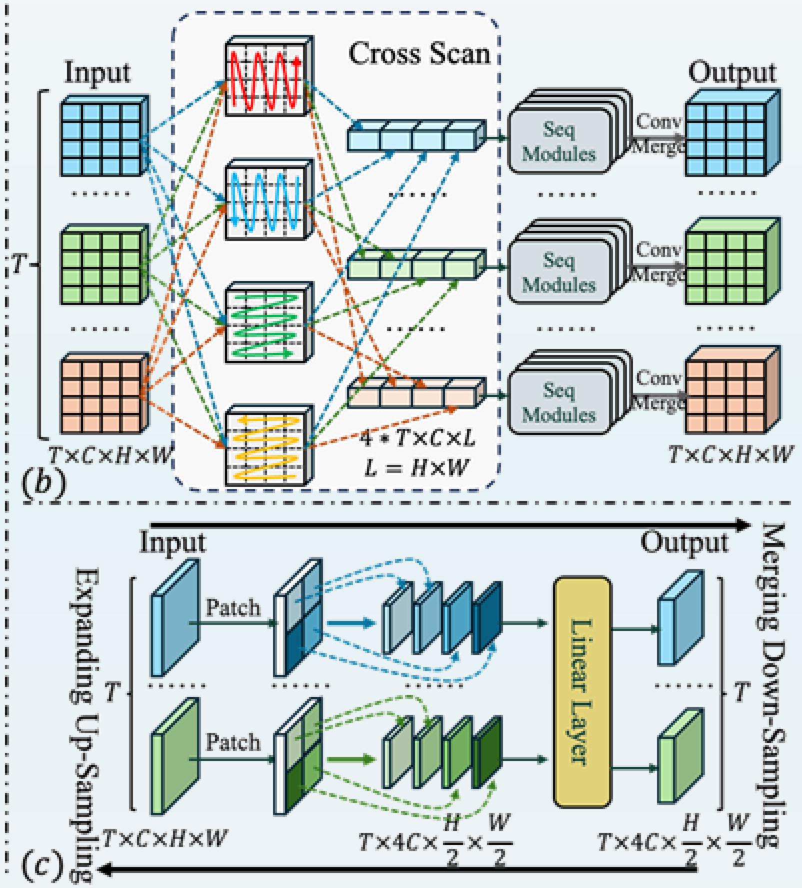

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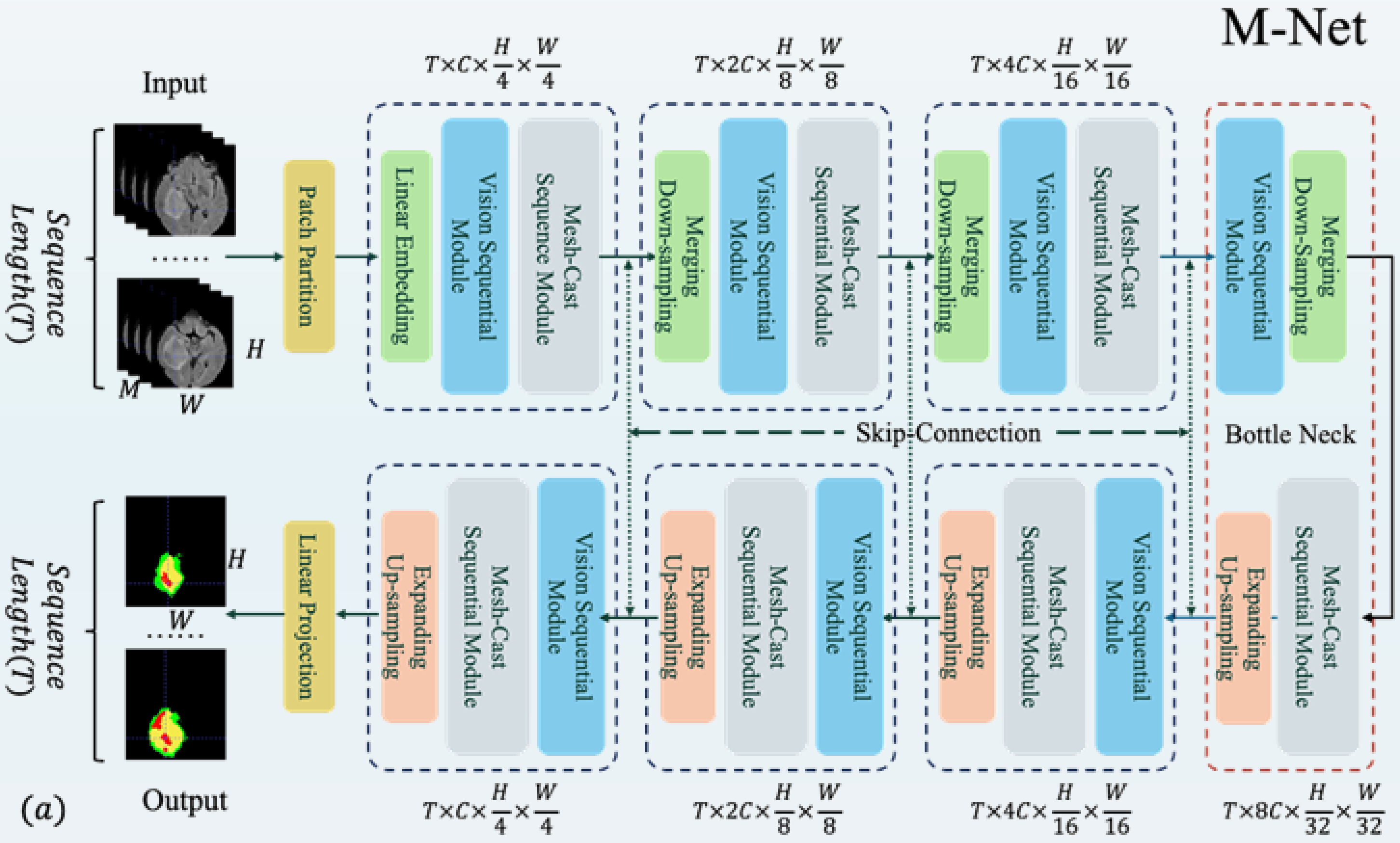

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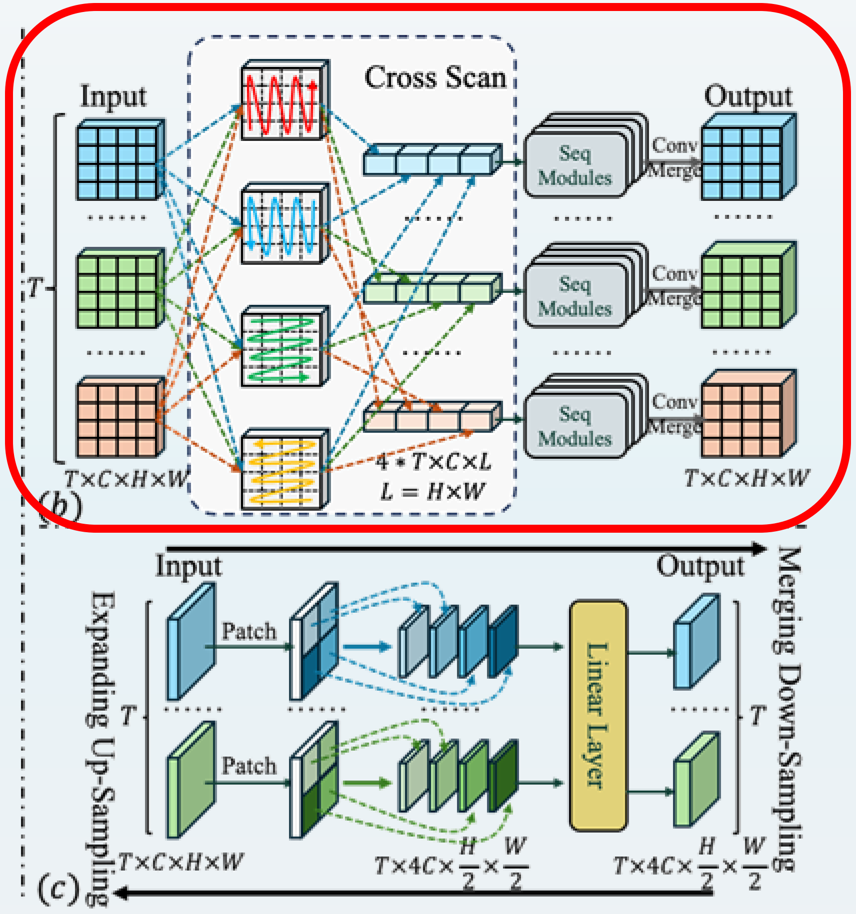

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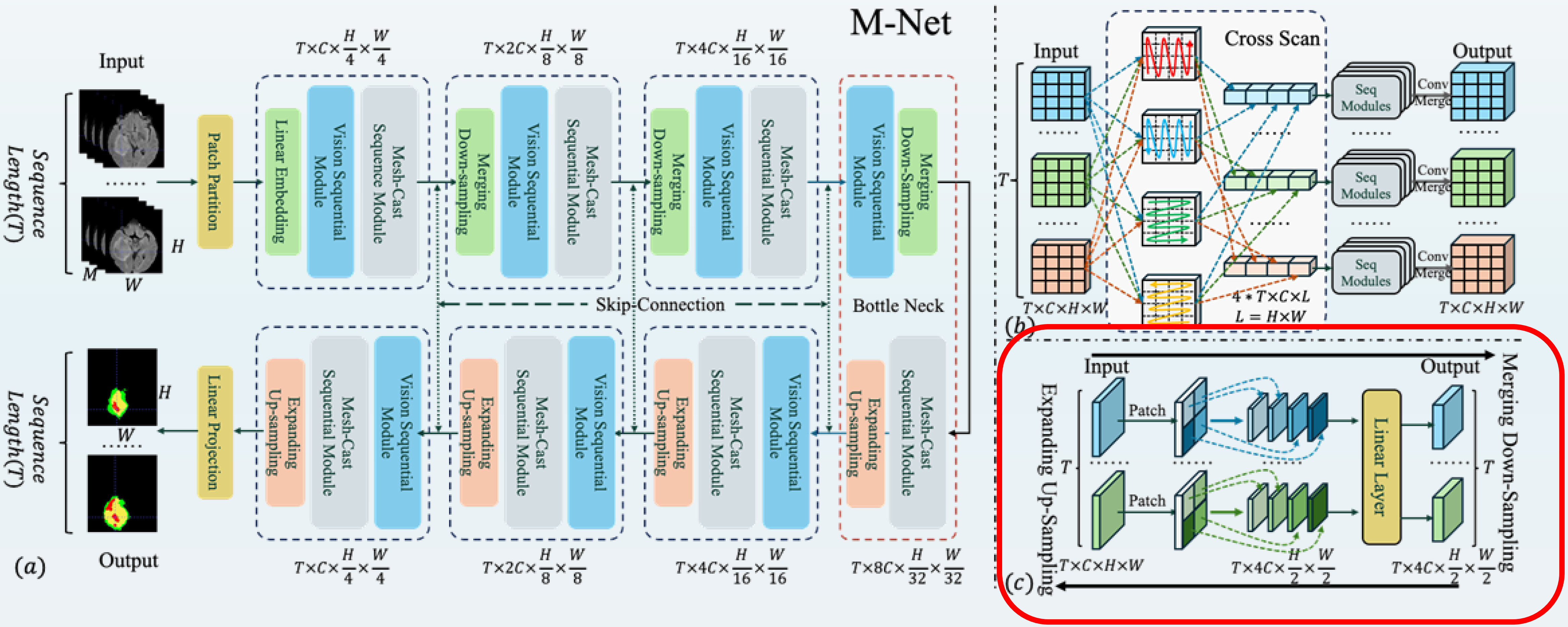

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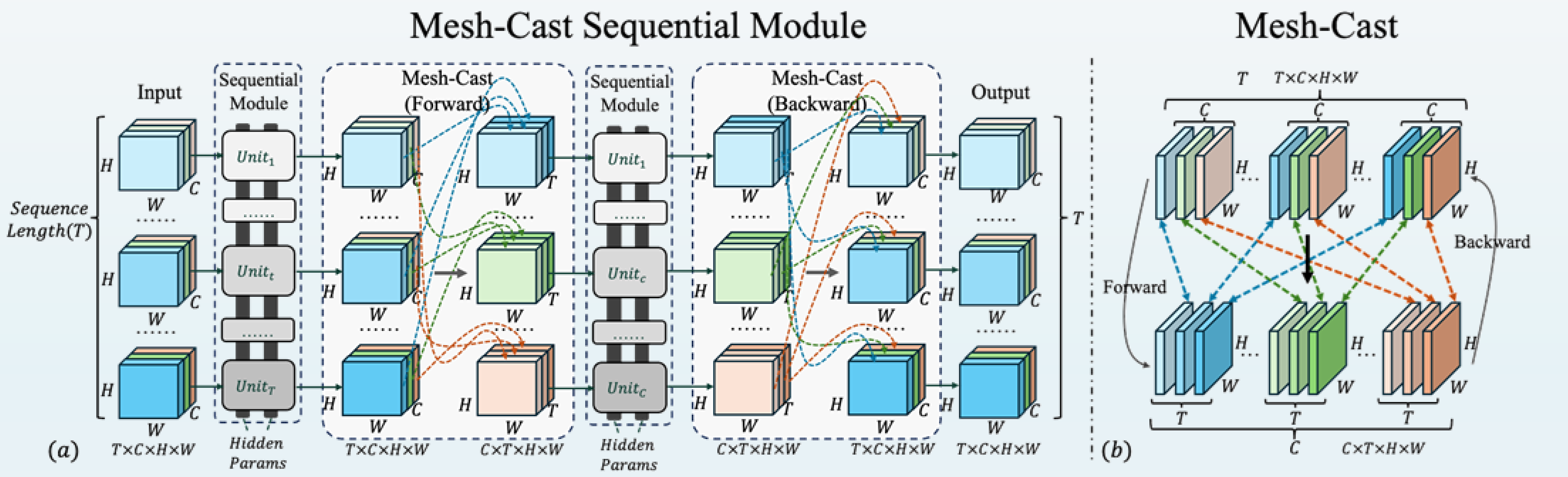

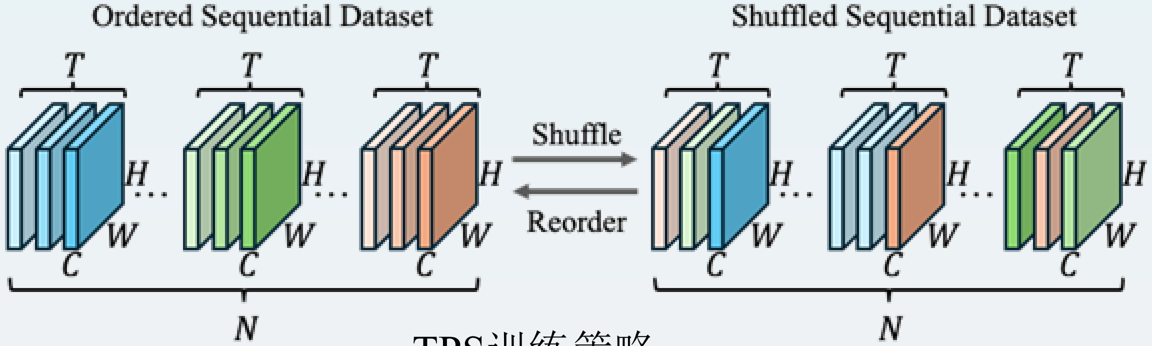

TPS训练策略

- M-Net alternately captures temporal and modality correlations in multi-modal MRI sequences through the proposed Mesh-Cast mechanism.
- To improve training efficiency, a Two-Phase Shuffling (TPS) strategy is designed, which feeds data in a “shuffle-then-order” manner.

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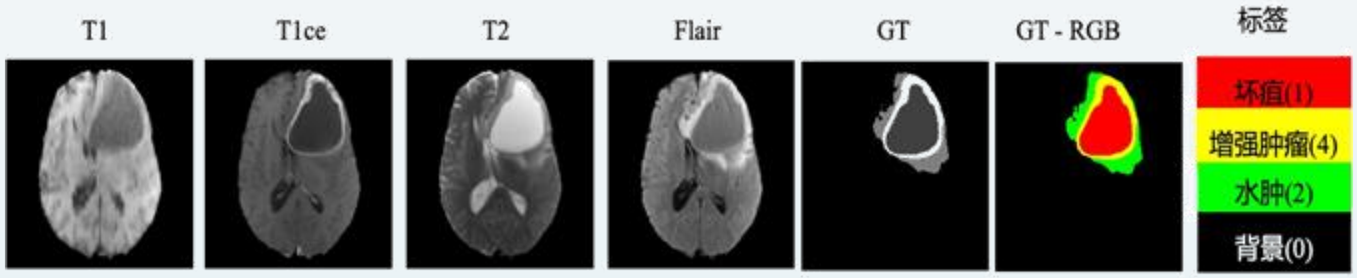
03 Experiments and Analysis

3 Datasets and Evaluation Metrics



Examples of Brain MRI Slices from BraTS 2019 and BraTS 2023

Dataset	Method	Training Sets		Testing Sets
		Training	Valuation	Testing
BraTS 2019	Sequences Data	2483	275	702
	Slices Data	37246	4139	10540
BraTS 2023	Sequences Data	11250	3750	3763
	Slices Data	116250	38750	38905

Table 1. Data Number on BraTS 2019 and BraTS 2023 Datasets.

- **Dice Score**

$$Dice = \frac{2TP}{FP + 2TP + FN}$$

- TP: True Positive TN: True Negative
- FP: False Positive FN: False Negative

- **Hausdorff Distance (HD)**

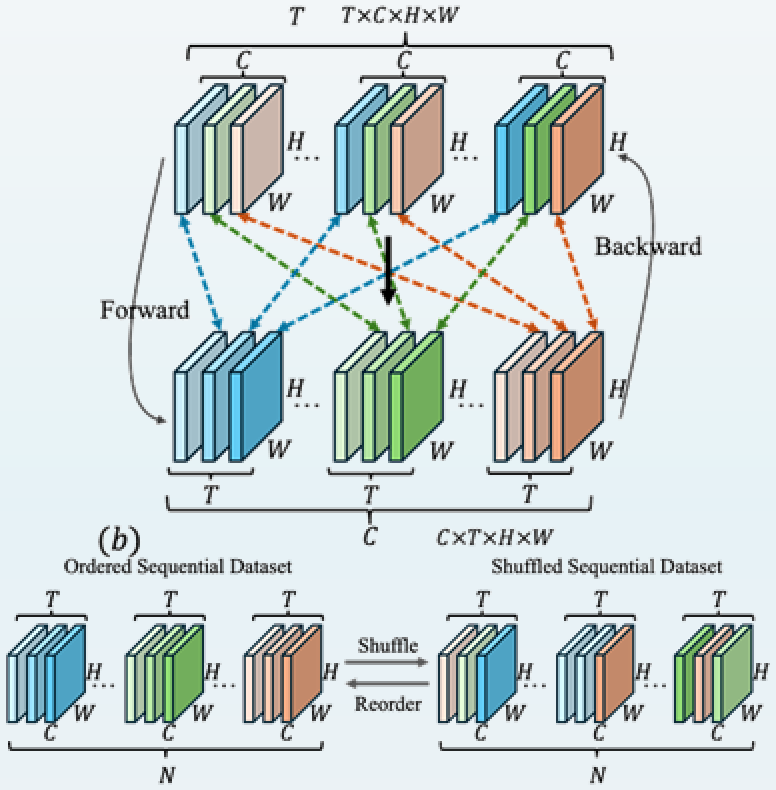
$$Haus(A,B) = \max\left(\max_{S_A \epsilon S(A)}\left(d\left(S_A, S(B)\right)\right), \max_{S_B \epsilon S(B)}\left(d\left(S_B, S(A)\right)\right)\right)$$

- Each processed MRI volume has a size of 155 × 160 × 160, which is then divided into 155 two-dimensional slices of 160 × 160 pixels.
- For each case, 15 consecutive slices are combined into a sequence, including the target slice and its neighboring slices.

3 Ablation Study

Module and Method	FLOPs↓	Dice_score(%)			Hausdorff95		
		WT↑	TC↑	ET↑	WT↓	TC↓	ET↓
Backbone(Slices)	72.44G	87.17	89.29	90.41	1.3710	0.8875	0.7093
Transformer(Slices)	97.45G	87.24	89.30	90.29	1.3641	0.8791	0.6983
Transformer(TPS)		87.56	89.96	90.79	1.3270	0.8354	0.6776
LSTM(Slices)	106.65G	87.59	89.78	90.56	1.3059	0.8454	0.6775
LSTM(TPS)		88.06	89.97	90.73	1.2968	0.8340	0.6701
ConvLSTM(Slices)	132.31G	87.74	89.92	90.68	**1.3290**	**0.8480**	0.6905
ConvLSTM(TPS)		88.19	**90.22**	90.79	1.3071	0.8358	0.6883
xLSTM(Slices)	93.56G	87.92	89.60	90.77	1.3090	0.8707	0.6717
xLSTM(TPS)		**88.19**	90.00	**90.93**	1.3040	0.8552	**0.6689**
Mamba SSM(Slices)	91.29G	88.05	90.21	90.65	1.3332	0.8465	0.7064
Mamba SSM(TPS)		**88.38**	**90.52**	**91.43**	**1.2869**	**0.8154**	**0.6571**

Table 2. Ablation Study of M-Net with Different Sequential Models on BraTS 2019 DATASET.



In horizontal comparisons, all variants of the Mesh-Cast module and TPS training strategy contribute to significant performance improvements.

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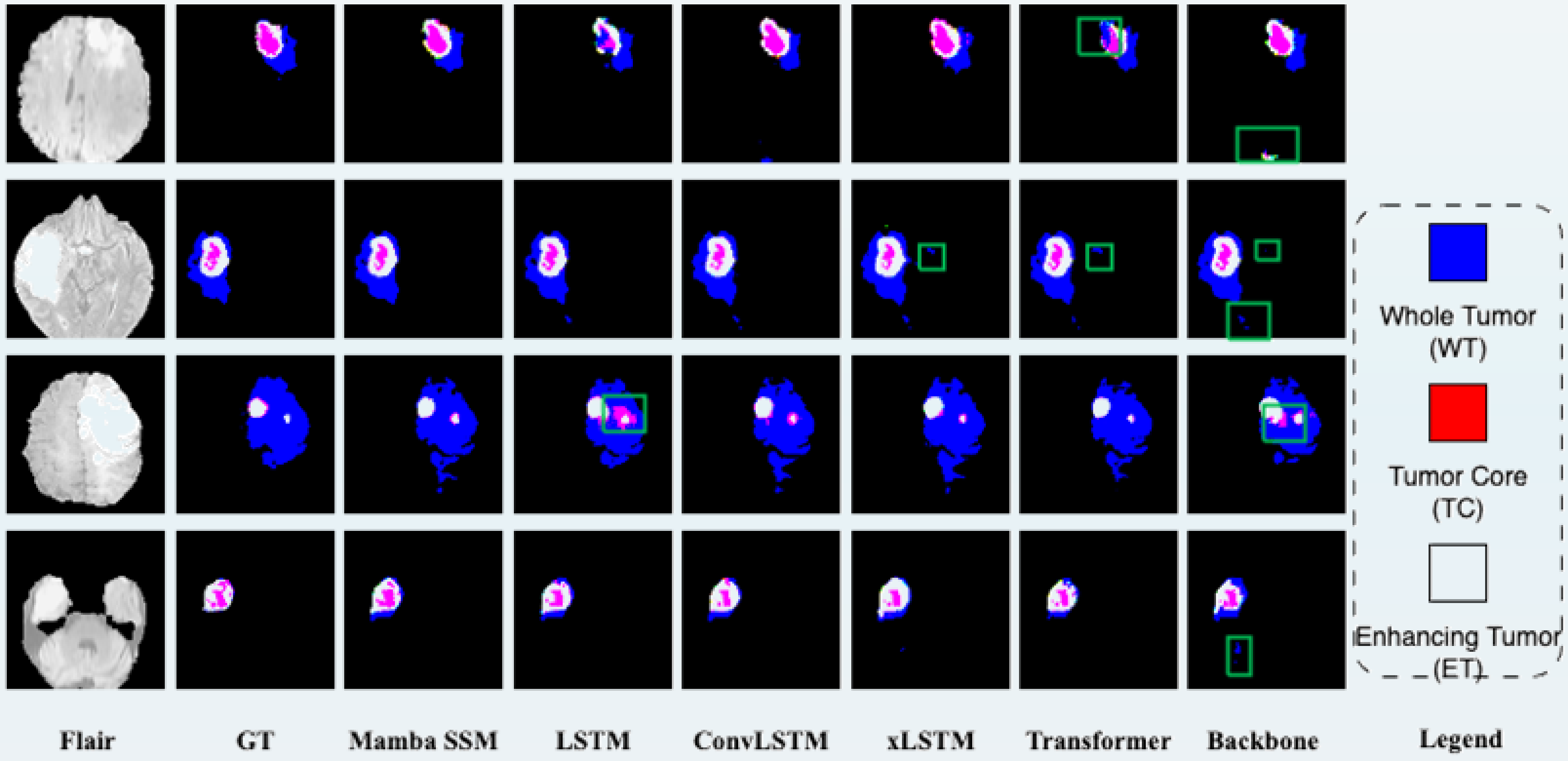

Examples of Multi-sequential Module (TPS) segmentation results in the ablation study. From left to right: Flair modality, input image, Ground Truth (GT), and segmentation results of different M-Net configurations.

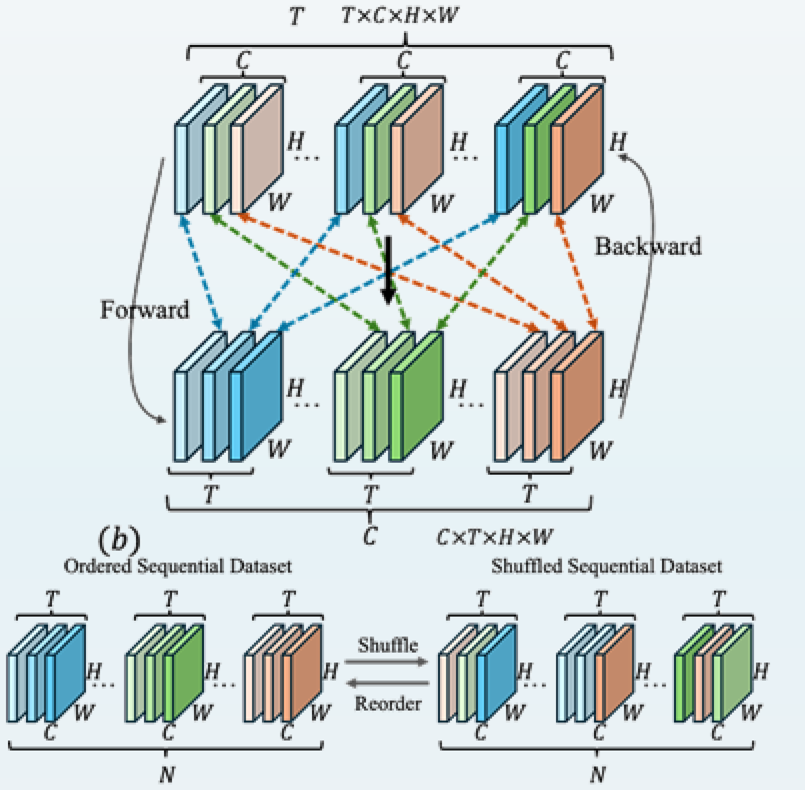

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Table 2. Ablation Study of M-Net with Different Sequential Models on BraTS 2019 DATASET.

Model	Dice_score(%)		
	WT	TC	ET
Backbone (Ordered)	87.17	89.29	90.41
M-Net (T, Ordered)	87.86	89.28	90.93
M-Net (T+C, Ordered)	88.05	90.21	90.65
Backbone (Shuffled)	**88.21**	90.11	90.86
M-Net (T+C, Shuffled)	88.07	**90.32**	91.05
M-Net (T+C, Ordered+Shuffled)	88.10	90.27	**91.29**
M-Net (T+C, TPS)	**88.38**	**90.52**	**91.43**

Table 3. Ablation study about TPS training strategy and Mesh-Cast Sequential Module on BraTS 2019 DATASET.

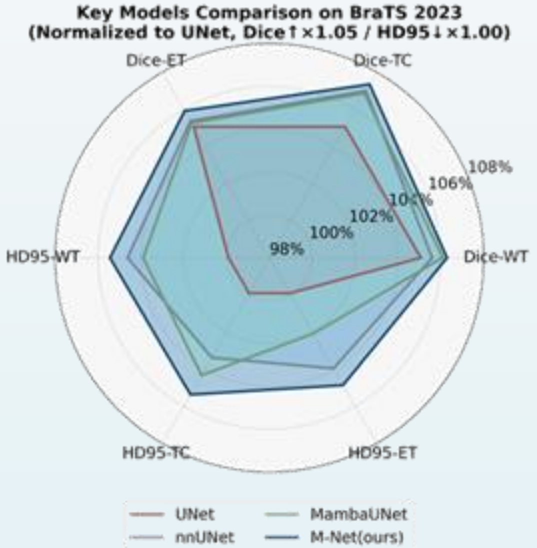
In horizontal comparisons, all variants of the Mesh-Cast module and TPS training strategy contribute to significant performance improvements.

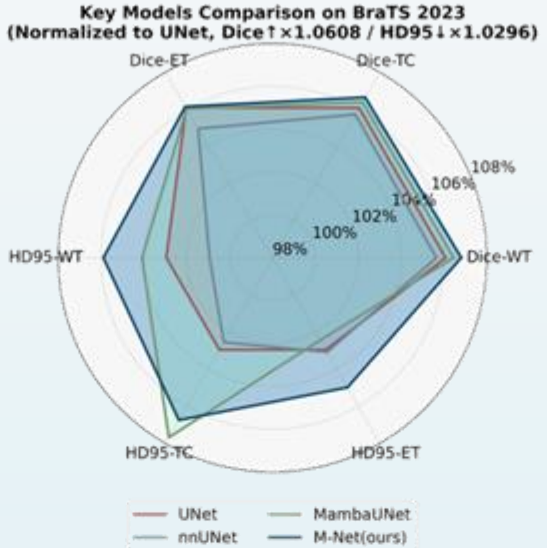
3 Comparison With Mainstream Algorithms

Model	Year	FLOPs↓	Inf Time(min)↓	Dice_score(%)			Hausdorff95		
				WT↑	TC↑	ET↑	WT↓	TC↓	ET↓
UNet	2015	321.19G	12:32	87.36/90.71	88.59/93.05	90.69/**93.36**	1.3582/1.1863	0.9076/0.7329	0.6897/0.6730
SegResNet	2019	5.98G	10:54	87.89/90.55	89.58/92.99	91.14/92.65	1.2977/1.1987	0.8403/0.7282	0.6649/0.7118
TransUNet	2021	237.83G	11:02	84.50/90.71	86.72/92.52	88.39/92.92	1.3911/1.1810	0.9300/0.7276	0.7396/0.6869
nnUNet	2021	82.00G	97:67	87.81/90.34	**90.23**/92.74	90.96/92.37	**1.2970**/1.2100	0.8311/0.7358	0.6628/0.6722
Transnorm	2022	253.25G	12:11	86.56/87.97	87.88/91.82	89.28/91.49	1.3414/1.2226	0.8952/0.7299	0.7102/0.7247
UNETR	2022	150.71	18:31	85.29/88.35	87.16/89.16	89.54/91.43	1.3831/1.2427	0.9504/0.8926	0.7042/0.7211
Swin UNETR	2022	136.80	21:33	88.16/**91.11**	88.85/93.20	90.86/**93.42**	1.3077/**1.1629**	0.9119/0.7088	0.6814/**0.6631**
MedNeXt	2023	1.98G	29:42	87.55/89.91	89.18/92.82	90.45/92.85	1.3330/1.2160	0.8800/0.7303	0.6958/0.6953
SLf-UNet	2024	534.73G	17:26	87.55/90.81	88.21/93.18	90.38/93.30	1.3273/1.1748	0.9032/0.7100	0.6871/0.6709
MedSAM	2024	166.55G	30:19	85.39/88.55	87.90/91.55	88.20/90.30	1.4409/1.3155	0.9224/0.8003	0.7667/0.8153
Mamba UNet	2024	72.44G	14:12	**88.21**/91.03	90.11/**93.32**	90.86/93.31	1.3061/1.1734	**0.8235**/**0.7008**	0.6750/0.6764
UKAN	2024	62.21G	19:43	87.39/90.64	89.50/93.04	**91.20**/93.14	1.2989/1.1862	0.8415/0.7234	**0.6585**/0.6824
M-Net	ours	91.29G	15:33	**88.38/91.33**	**90.52/93.55**	**91.43/93.42**	**1.2869/1.1534**	**0.8154/0.7069**	**0.6571/0.6600**

Table 4. Comparison with The SOTA Methods on BRATS 2019 and BraTS-2023 Datasets.

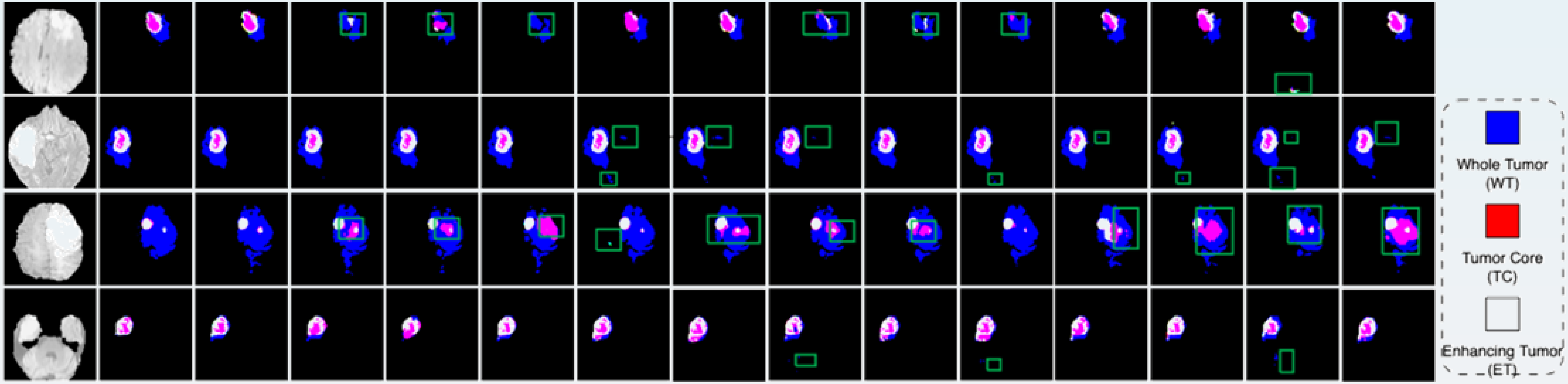
3 Comparison With Mainstream Algorithms





- Radar charts comparing M-Net with various mainstream models on the BraTS 2023 and 2019 datasets demonstrate its nearly comprehensive performance superiority.

- Combining qualitative and quantitative analyses, M-Net achieves a well-balanced trade-off between accuracy and efficiency, validating the effectiveness of sequence-based MRI tumor segmentation.

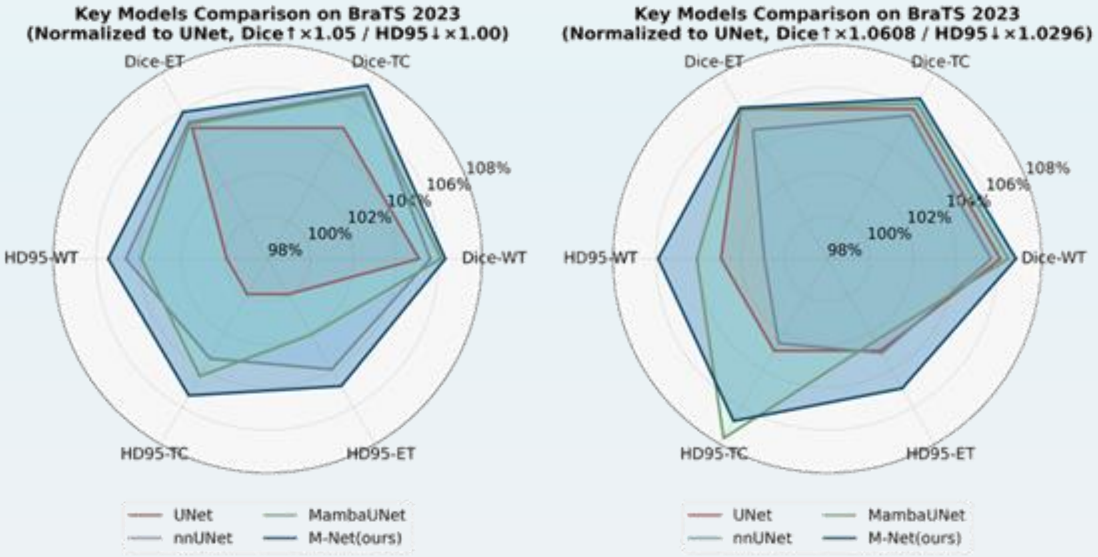


Flair GT M-Net(ours) UNet TransUNet Transnorm SegResNet nnUNet UNETR Swin UNETR MedNeXt SLf-UNet MedSAM Mamba UNet UKAN Legend

04 Conclusion and Outlook

4 Conclusion

M-Net introduces a new sequential perspective to brain MRI segmentation tasks.



- **Addressing** the neglect of inter-slice correlations in existing brain tumor MRI segmentation algorithms.
- **Proposing** the M-Net sequential segmentation framework, which treats multi-modal MRI slices as 'temporal-like' inputs.
- **Introduces** the Mesh-Cast module and TPS strategy specifically designed for sequential segmentation.
- **Experiments show** that M-Net achieves state-of-the-art performance on the BraTS 2019 and BraTS 2023 datasets.

4 M-Net in ICCV 2025

Poster

M-Net: MRI Brain Tumor Sequential Segmentation Network via Mesh-Cast

Jiacheng Lu · Hui Ding · Shiyu Zhang · Guoping Huo

#1852

[Abstract]

Thu 23 Oct 11:15 a.m. HST — 1:15 p.m. HST (Bookmark)

- arXiv preprint：
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M-Net: MRI Brain Tumor Sequential Segmentation Network via Mesh-Cast

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Abstract

MRI tumor segmentation remains a critical challenge in medical imaging, where volumetric analysis faces unique computational demands due to the complexity of 3D data. The spatially sequential arrangement of adjacent MRI slices provides valuable information that enhances segmentation continuity and accuracy, yet this characteristic remains underutilized in many existing models. The spatial correlations between adjacent MRI slices can be regarded as "temporal-like" data, similar to frame sequences in video segmentation tasks. To bridge this gap, we propose M-Net, a flexible framework specifically designed for sequential image segmentation. M-Net introduces the novel Mesh-Cast mechanism, which seamlessly integrates arbitrary sequential models into the processing of both channel and temporal information, thereby systematically capturing the inherent "temporal-like" spatial correlations between MRI slices. Additionally, we define an MRI sequential input pattern and design a Two-Phase Sequential (TPS) training strategy, which first focuses on learning common patterns across sequences before refining slice-specific feature extraction. This approach leverages temporal modeling techniques to preserve volumetric contextual information while avoiding the high computational cost of full 3D convolutions, thereby enhancing the generalizability and robustness of M-Net in sequential segmentation tasks. Experiments on the BraTS2019 and BraTS2023 datasets demonstrate that M-Net outperforms existing methods across all key metrics, establishing itself as a robust solution for temporally-aware MRI tumor segmentation. Code is available at https://github.com/CNU-MedAI-Lab/M-Net.

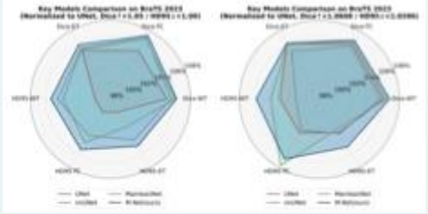

Figure 1. Performance radar charts of M-Net and several mainstream models on BraTS 2023/2019. The values in the charts are rescaled, with larger values indicating better performance.

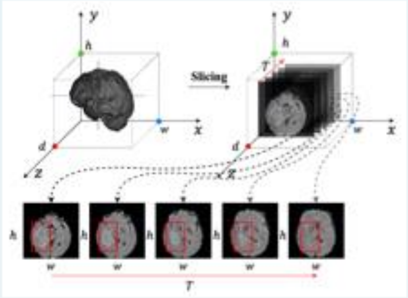

Figure 2. "Temporal-like" spatial correlations in MRI. For an MRI slice sequence, the position and size of the lesion change with spatial continuity through the sequence of slices.

1. Introduction

Accurate brain tumor segmentation is essential for disease diagnosis and treatment planning in medical imaging[22, 32]. However, brain tumor MRI images pose significant challenges due to irregular tumor boundaries, varying locations, complex textures, inconsistent grayscale levels, and low interclass contrast. In recent years, deep learning[11] has achieved remarkable results in medical image segmentation. A key milestone was the UNet[29], a 2015 encoder-decoder segmentation network proposed by O. Ronneberger et al. Many subsequent studies have introduced improvements, such as CANet[14] and MIRAU-Net[1] with convolutional attention, UKAN[20] with knowledge-aware net-

4 M-Net in ICCV 2025

M-Net: MRI Brain Tumor Sequential Segmentation Network via Mesh-Cast

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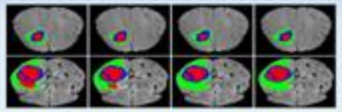
1 College of Information Engineering, Capital Normal University, 2 School of Artificial Intelligence, China University of Mining and Technology-Beijing

Background

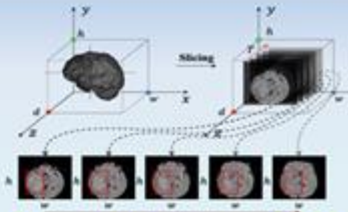


• What?

Accurate brain tumor segmentation is crucial.

- To address issues such as irregular boundaries and variable locations in MRI images, deep learning–based segmentation methods are widely used.

Motivation



• Why?

The "temporal-like" spatial correlations is overlooked.

- Most approaches rely on either 2D or 3D models: 2D models fail to capture inter-slice dependencies, while 3D models demand excessive computational resources, making it difficult to balance accuracy and efficiency.

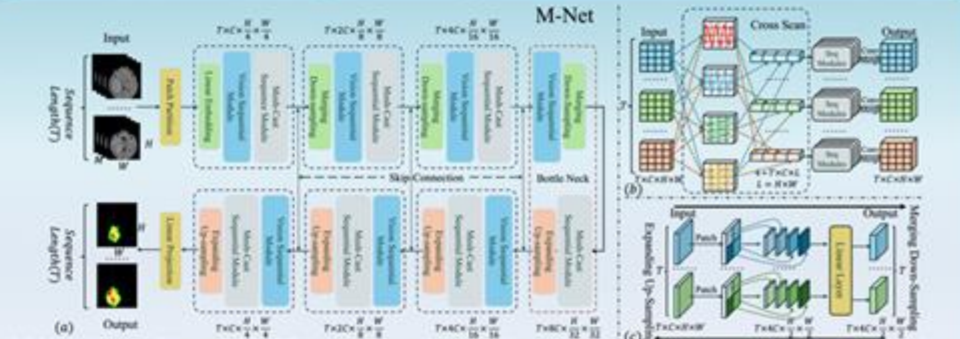
Approach

• How?

We propose a **sequence** segmentation model, **M-Net**.

- M-Net treats MRI slices as sequential inputs and employs a temporal module to capture inter-slice dependencies.

M-Net Sequential Segmentation Framework



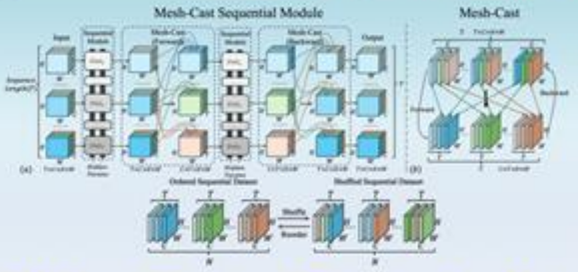
M-Net takes **multi-modal MRI sequences** as input and can incorporate any temporal modeling module.

- It adopts an encoder–decoder architecture with VMamba as the visual backbone, enabling joint modeling across both channel and sequence dimensions.

$$X = \{x_1, x_2, \dots, x_T\}$$

- Here, $x_t \in \mathbb{R}^{H\times W\times C}$ represents a single multi-modal MRI slice, where $t \in [1, T]$ denotes the frame index within the slice sequence (i.e., the sequence length).

Mesh-Cast Sequential Module and TPS Strategy



Ablation Study of M-Net with Different Sequential Models on BraTS 2019 DATASET.

Module and Method	FLOPs↓	Dice score(%)			Hausdorff95		
		WT↑	TC↑	ET↑	WT↓	TC↓	ET↓
Backbone(Slices)	72.44G	87.17	89.29	90.41	1.3710	0.8875	0.7093
Transformer(Slices)	97.45G	87.24	89.30	90.29	1.3641	0.8791	0.6983
Transformer(TPS)		87.56	89.96	90.79	1.3270	0.8354	0.6776
LSTM(Slices)	106.65G	87.59	89.78	90.56	1.3059	0.8454	0.6775
LSTM(TPS)		88.06	89.97	90.73	1.2968	0.8340	0.6701
ConvLSTM(Slices)	132.31G	87.74	89.92	90.68	**1.3290**	**0.8480**	0.6905
ConvLSTM(TPS)		88.19	**90.22**	90.79	1.3071	0.8358	0.6883
xLSTM(Slices)	93.56G	87.92	89.60	90.77	1.3090	0.8707	0.6717
xLSTM(TPS)		**88.19**	90.00	**90.93**	1.3040	0.8552	**0.6689**
Mamba SSM(Slices)	91.29G	88.05	90.21	90.65	1.3332	0.8465	0.7064
Mamba SSM(TPS)		88.38	90.52	91.43	1.2869	0.8154	0.6571

Mesh-Cast and TPS interleave **different temporal modules** for multi-modal sequence modeling.

- The Mesh-Cast Sequential Module models the input sequences along both temporal and channel dimensions.

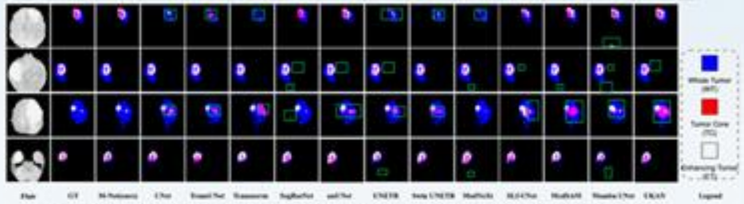
$$X_{channel} = Transpose_{forward}(X'_{seq}, (0, 1)), \quad X_{seq} = Transpose_{backward}(X'_{channel}, (0, 1))$$

- While the TPS strategy facilitates sequence learning through a "disordered(shuffled)-to-ordered" training scheme.

Results on BraTS 2019 and BraTS 2923

Comparison with The SOTA Methods on BRATS 2019 and BraTS-2023 Datasets.

Model	Year	FLOPs↓	Inf Time(min)↓	Dice score(%)			Hausdorff95		
				WT↑	TC↑	ET↑	WT↓	TC↓	ET↓
UNet	2015	321.19G	12:32	87.36/90.71	88.59/93.05	90.69/**93.36**	1.3582/1.1863	0.9076/0.7329	0.6897/0.6730
SegResNet	2019	5.98G	10:54	87.89/90.55	89.58/92.99	91.14/92.65	1.2977/1.1987	0.8403/0.7282	0.6649/0.7118
TransUNet	2021	237.83G	11:02	84.50/90.71	86.72/92.52	88.39/92.92	1.3911/1.1810	0.9300/0.7276	0.7396/0.6869
nnUNet	2021	82.00G	97:67	87.81/90.34	**90.23**/92.74	90.96/92.37	**1.2970**/1.2100	0.8311/0.7358	0.6628/0.6722
Transnorm	2022	253.25G	12:11	86.56/87.97	87.88/91.82	89.28/91.49	1.3414/1.2226	0.8952/0.7299	0.7102/0.7247
UNETR	2022	150.71	18:31	85.29/88.35	87.16/89.16	89.54/91.43	1.3831/1.2427	0.9504/0.8926	0.7042/0.7211
Swin UNETR	2022	136.80	21:33	88.16/**91.11**	88.85/93.20	90.86/93.42	1.3077/**1.1629**	0.9119/0.7088	0.6814/**0.6631**
MedNeXt	2023	1.98G	29:42	87.55/89.91	89.18/92.82	90.45/92.85	1.3330/1.2160	0.8800/0.7303	0.6958/0.6953
SLf-UNet	2024	534.73G	17:26	87.55/90.81	88.21/93.18	90.38/93.30	1.3273/1.1748	0.9032/0.7100	0.6871/0.6709
MedSAM	2024	166.55G	30:19	85.39/88.55	87.90/91.55	88.20/90.30	1.4409/1.3155	0.9224/0.8003	0.7667/0.8153
Mamba UNet	2024	72.44G	14:12	**88.21**/91.03	90.11/**93.32**	90.86/93.31	1.3061/1.1734	**0.8235**/0.7008	0.6750/0.6764
UKAN	2024	62.21G	19:43	87.39/90.64	89.50/93.04	**91.20**/93.14	1.2989/1.1862	0.8415/0.7234	**0.6585**/0.6824
M-Net	ours	91.29G	15:33	88.38/91.33	90.52/93.55	91.43/93.42	1.2869/1.1534	0.8154/**0.7069**	0.6571/0.6600

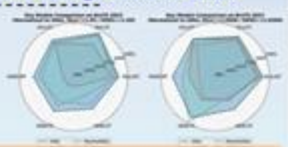


Examples of segmentation results from multiple methods. From left to right: Flair modality input image, Ground Truth (GT), the proposed M-Net, and segmentation results from various comparison algorithms.

Conclusion

M-Net introduces a new **sequential** perspective to brain MRI segmentation tasks.

- **Addressing** the neglect of inter-slice correlations in existing brain tumor MRI segmentation algorithms.
- **Proposing** the M-Net sequential segmentation framework, which treats multi-modal MRI slices as 'temporal-like' inputs.
- **Introduces** the Mesh-Cast module and TPS strategy specifically designed for sequential segmentation.
- **Experiments show** that M-Net achieves state-of-the-art performance on the BraTS 2019 and BraTS 2023 datasets.



Contact Us

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- Hui Ding: dhui@cnu.edu.cn

4 Outlook

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M-Net (T, Ordered)	87.86	89.28	90.93
M-Net (T+C, Ordered)	88.05	90.21	90.65
Backbone (Shuffled)	**88.21**	90.11	90.86
M-Net (T+C, Shuffled)	88.07	**90.32**	91.05
M-Net (T+C, Ordered+Shuffled)	88.10	90.27	**91.29**
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Table 3. Ablation study about TPS training strategy and Mesh-Cast Sequential Module on BraTS 2019 DATASET.

In horizontal comparisons, all variants of the Mesh-Cast module and TPS training strategy contribute to significant performance improvements.

4 Outlook

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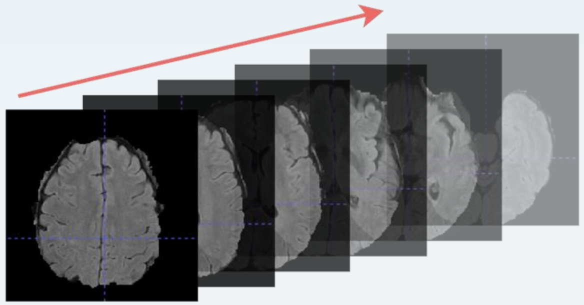
- **It seems that Shuffle performs better than Ordered**
- **— so why do we still use the Ordered setting?**

In horizontal comparisons, all variants of the Mesh-Cast module and TPS training strategy contribute to significant performance improvements.

4 Outlook

- Q2: It seems that Shuffle performs better than Ordered
- — so why do we still use the Ordered setting?

- A2: The frequency characteristics of sequential images determine that each approach — Shuffle and Ordered — has its own advantages and disadvantages!



Our future work will illustrate the reason.

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