Can Frozen Transformer in Large Language Model Help with Medical Image Segmentation?

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Abstract

Transformer models shine in medical image segmentation by harnessing their self-attention mechanism to capture global information, thus boosting segmentation accuracy. Recent research has unveiled that large language models (LLMs), trained solely on text, surprisingly excel at visual tasks even without language, through a simple strategy: integrating a frozen transformer block from pre-trained LLMs as a direct visual token processor. This paper applies this approach to medical image segmentation by combining frozen transformer blocks with Trans-UNet. Experiments are conducted on BTCV, ACDC, ISIC 2017, CVC-ClinicDB, CVC-ColonDB and BUSI datasets, demonstrating some improvements.

Keywords: Medical image segmentation, Large Language Models, Frozen transformers, Trans-UNet

1. Introduction

Segmentation in medical imaging refers to the process of partitioning medical images into meaningful regions or structures, which plays a crucial role in various medical applications. By accurately delineating organs, tissues, tumors, and other anatomical structures, segmentation facilitates quantitative analysis, patient-specific modeling, and personalized healthcare delivery. UNet-like (Ronneberger et al., 2015) architecture holds a prominent position in image segmentation due to its combination of encoder-decoder structure and skip connections, effectively capturing multiscale features, thereby enhancing segmentation accuracy and preserving details. Transformer-based UNet variants such as Trans-UNet (Chen et al., 2021), Swin-UNet (Cao et al., 2022) and Ds-transunet (Lin et al., 2022) exhibit remarkable capabilities in medical image segmentation owing to their overall architectures with self-attention mechanism, which adeptly captures global information and have stronger visual encoding capabilities.

Recent research (Pang et al., 2023) unveils the surprising effectiveness of large language models (LLMs), trained solely on text, as potent encoders for pure visual tasks by leveraging a frozen transformer block from pre-trained LLMs and another research (Lai et al., 2024) show that the LLM transformer block with global residual connections can boost medical image classification. This paper applies this method in medical image segmentation tasks, adding two frozen transformer blocks from LLaMA-7B to the encoder of Trans-UNet. Experiments on BTCV (Landman et al., 2015), ACDC (Bernard et al., 2018), ISIC 2017 (Codella et al., 2018), CVC-ClinicDB (Bernal et al., 2015), CVC-ColonDB (Bernal et al., 2012) and BUSI (Al-Dhabyani et al., 2020) datasets show that this method can lead to some improvements.

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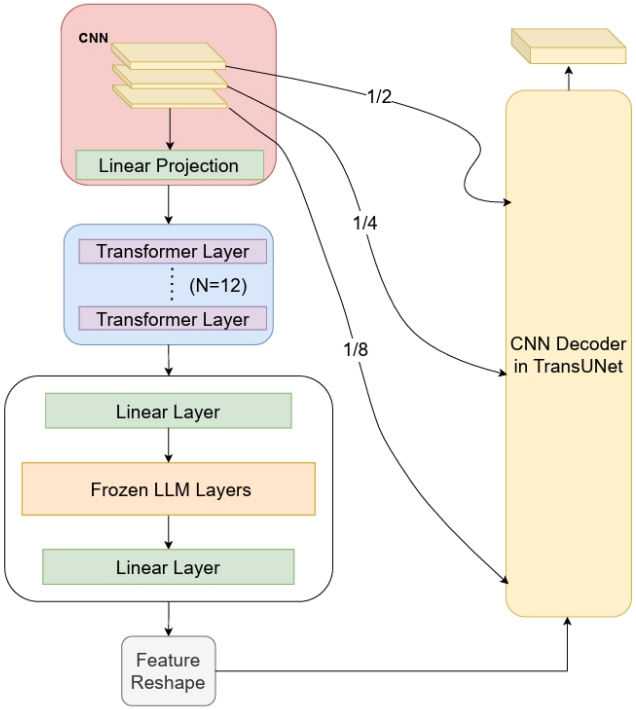

Figure 1: The architecture of Trans-UNet with frozen Transformer blocks in LLMs (LLM-TransUNet)

2. Method

The architecture of Trans-UNet with frozen Transformer blocks in LLMs (LLM-TransUNet) can be seen in Figure 1. Two pre-trained transformer blocks from LLaMA-7B (Touvron et al., 2023) are inserted after Transformer layers in the encoder of Trans-UNet. As the feature dimensions are different between the original transformers in Trans-UNet and the language transformer, two linear layers are used to align the dimensionality just like the design in (Pang et al., 2023).

3. Experiments

3.1. Implementation Details

All experiments are conducted on Tesla PG500-216 GPU platform with 32G RAM. The resolution of input images is 224×224. For ISIC 2017 (Codella et al., 2018), CVC-ClinicDB (Bernal et al., 2015), CVC-ColonDB (Bernal et al., 2012) and BUSI (Al-Dhabyani et al., 2020), the total training epochs are 200, and the batch size in training, validation and testing is 8. The optimizer used is ADAM (Kingma and Ba, 2017). The initial learning rate is 0.0001 while the minimum learning rate is 0.00001. A CosineAnnealingLR (Loshchilov and Hutter, 2016) scheduler is utilized. Rotation by 90 degrees clockwise for random times, random flipping and normalization methods are applied. The evaluation metrics in validation are

IOU of the lesions. The loss function used is a mixed loss combining binary cross entropy loss and dice loss (Milletari et al., 2016):$\mathcal{L} = 0.5BCE(\hat{y}, y) + Dice(\hat{y}, y)$. For CVC-ClinicDB, CVC-ColonDB and BUSI, the testing sets are split from datasets with a ratio of 0.2. Then the validation sets are split from the training set with a ratio of 0.2. The random states for splitting are all 41. For BTCV (Landman et al., 2015) and ACDC(Bernard et al., 2018), All settings except for the device specification, including the dataset preprocessing methods and the training details, are aligned with the configuration detailed in (Chen et al., 2021).

3.2. Results

The experimental results are shown in Table 2, which show that the frozen transformer layers in LLM can lead to improvement and the method is still effective in medical image segmentation tasks. The explanation may be as the hypothesis in (Pang et al., 2023) mentioned – the incorporated LLM blocks may distinguish the informative tokens and amplify their effect. We also conduct experiments to evaluate the methods in (Lai et al., 2024), applying global residual connections to added frozen transformers. However, the experiments show that it fails to improve the segmentation performance.

Table 1: Comparison Experimental Results on ISIC 2017, BUSI, CVC-ClinicDB, CVC-ColonDB, BTCV and ACDC datasets

Methods	ISIC 2017		BUSI		CVC-ClinicDB		CVC-ColonDB		BTCV	ACDC
	IoU	Dice	IoU	Dice	IoU	Dice	IoU	Dice	mDice	mDice
Trans-UNet	0.7487	0.8532	0.5964	0.7327	0.8498	0.9171	0.8159	0.8907	0.7722	0.8946
LLM-Trans-UNet	**0.7691**	**0.8667**	**0.6238**	**0.7562**	**0.8582**	**0.9219**	**0.8284**	**0.8991**	**0.7780**	**0.8985**

Table 2: Comparison Experimental Results of w/o global residual connections

Methods	BTCV	ACDC
	mDice	mDice
LLM-Trans-UNet	**0.7780**	**0.8985**
Res-LLM-Trans-UNet	0.7519	0.8964

4. Conclusion

This paper explores integrating frozen transformer blocks from large language models (LLMs) into the Trans-UNet architecture for medical image segmentation. Experimental results demonstrate some improvements compared to the baseline, further proving that the LLM layers can be useful in visual recognition tasks. The designed module has the potential to become a plug-and-play component in medical image segmentation tasks. However, the BUSI, CVC-ClinicDB and CVC-ColonDB are quite small, thus the way of splitting datasets has a significant impact on the final results. More experiments are needed to demonstrate the block can truly lead to improvements. Also, more baselines like Swin-UNet and Ds-transunet can be used for experiments.

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