SegMed: Implementation of MedSAM for medical Imaging and enhancement with FeatUp and GAFL

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***Abstract*—In this study, we present SegMed, a comprehensive framework for the implementation and enhancement of MedSAM, a state-of-the-art medical imaging segmentation algorithm. Leveraging the capabilities of FeatUp, an advanced feature upsampling technique, and GAFL (Genetic Algorithm Feature Learning), our framework significantly improves the accuracy and efficiency of medical image segmentation. MedSAM, originally designed for robust and precise segmentation of medical images, faces challenges in processing high-resolution data with intricate anatomical details. By integrating FeatUp, we achieve superior spatial resolution and feature representation, which enhances the segmentation performance of MedSAM. Additionally, the application of GAFL optimizes feature extraction and selection processes, further refining the segmentation accuracy. Through extensive experimentation using the LGG Segmentation Dataset, we demonstrate that SegMed outperforms existing methods in terms of segmentation quality**

***Index Terms*—Computer Vision, Medical Imaging, Image Segmentation, Feature Upsampling**

I. Introduction

Brain tumors critically affect patient health, survival, and quality of life. Manual segmentation of tumors from MRI images, essential for treatment planning, is both slow and prone to errors [1]. Our project aims to automate this process with advanced deep learning techniques, focusing on the development of the MedSAM model, a specialized adaptation of the Segment Anything Model (SAM) for medical imaging. By enhancing the accuracy and efficiency of tumor segmentation, we seek to support more informed clinical decisions, optimize treatment strategies, and ultimately improve patient outcomes.

A. Problem Statement

The problem we are addressing is the manual segmentation of brain tumors from MRI images. This process is critical for treatment planning but is often slow and prone to errors. Our goal is to automate this process using the MedSAM model and enhance it with FeatUp and GAFL techniques. By doing so, we aim to improve the efficiency and accuracy of tumor segmentation.

B. Dataset description

In our project we used the LGG Segmentation Dataset. The LGG Segmentation Dataset is an integral part of the Brain Tumor Segmentation (BraTS) Challenge, aimed at advancing research in automatic brain tumor segmentation from MRI scans [2] [3]. It's a dataset consists of MRI brain images paired with FLAIR abnormality segmentation masks derived from The Cancer Imaging Archive (TCIA). It includes 110 cases from The Cancer Genome Atlas (TCGA), featuring lowergrade glioma patients. Each case includes pre-contrast, FLAIR, and post-contrast sequences, with segmentation masks provided as binary, single-channel images. The dataset is partitioned into training, testing, and validation sets, with 2828, 393, and 708 samples, respectively.

II. Related Work

Medical image segmentation has been an area of extensive research due to its critical role in clinical diagnosis and treatment planning. Several approaches have been developed to enhance the accuracy and efficiency of segmentation algorithms.

A. Baselines

1) DeepLabV3+: DeepLabV3+ is an advanced version of the DeepLab series that incorporates atrous convolution and a decoder module to refine the segmentation results at object boundaries. This model has been widely used in various medical image segmentation tasks, including MRI. Its ability to capture multi-scale context and fine-grain details makes it suitable for delineating complex structures in MRI scans [4].

2) U-Net: U-Net is one of the most popular architectures in medical image segmentation. It features a symmetric encoder-decoder structure with skip connections that facilitate the preservation of spatial information. U-Net's effectiveness in MRI segmentation has been validated through numerous studies, showing robust performance in segmenting different types of tissues and lesions [5].

3) U-Net++: U-Net++ is an extension of the U-Net architecture, introducing nested and dense skip connections to improve feature propagation and gradient flow. This model aims to address the limitations of U-Net by providing better segmentation accuracy and reduced computational complexity. U-Net++ has shown superior performance in MRI segmentation tasks, particularly in handling complex and small structures [6].

4) DeepLabV3: DeepLabV3 employs atrous convolution to control the resolution of feature responses, which is particularly useful for segmenting images with objects at multiple scales. In the context of MRI segmentation, DeepLabV3 has been effective in capturing fine details and improving the segmentation quality of various anatomical structures [7].

5) Pyramid Attention Network (PAN): PAN introduces a pyramid attention mechanism that enhances feature representation by capturing global context and refining feature maps at multiple scales. This model has demonstrated promising results in medical image segmentation, including MRI, by providing precise and detailed segmentation outputs [8].

6) Comparison of Models: Each of these models brings unique strengths to MRI segmentation. DeepLabV3+ excels in boundary refinement, U-Net and U-Net++ are renowned for their robustness and accuracy, DeepLabV3 is noted for its multi-scale feature extraction, and PAN offers enhanced attention mechanisms. Combining these models with advanced techniques like FeatUp and GAFL, as explored in this study, can further improve segmentation performance and clinical applicability.

B. Deep Learning in Medical Imaging

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical imaging tasks. U-Net [5] and its variants have become the backbone of many segmentation frameworks due to their ability to capture both local and global features. The success of U-Net inspired numerous modifications and extensions tailored to various medical imaging applications.

C. Attention Mechanisms

Attention mechanisms have been incorporated into segmentation networks to improve feature representation and model performance. The attention U-Net [9] integrates attention gates into the U-Net architecture, allowing the network to focus on relevant features while suppressing irrelevant information. These attention-based methods have demonstrated improved segmentation accuracy in medical images.

D. Self-Attention and Transformer Models

Recently, transformer models have gained popularity in medical imaging for their ability to capture long-range dependencies. The TransUNet [10] combines transformers with the U-Net architecture, leveraging self-attention to enhance feature extraction. This approach has shown significant improvements in tasks like organ segmentation from CT scans.

E. Few-Shot and Meta-Learning Approaches

Few-shot learning aims to tackle the data scarcity issue in medical imaging by learning from a limited number of annotated examples. Models like MedSAM [11] utilize few-shot learning techniques to perform accurate segmentation with minimal training data. These methods are particularly beneficial in medical domains where obtaining large annotated datasets is challenging.

F. Feature Enhancement Techniques

Enhancement of feature representations is crucial for improving model performance in medical imaging. FeatUp [12] is a notable technique that enhances feature maps by dynamically adjusting their scales and biases, leading to better segmentation results. Incorporating such enhancement methods can significantly boost the performance of baseline segmentation models.

G. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have been employed to enhance medical image segmentation by generating synthetic data and improving feature learning. The use of GAN-based Feature Learning (GAFL) [13] has shown promise in various medical imaging tasks by providing realistic data augmentation and refining segmentation boundaries.

III. Methodology and Approach

A. Baseline Models

- Implemented baseline models: DeepLabV3+, U-Net, U-Net++, DeepLabV3, and Pyramid Attention Network (PAN).
- Best performing model: DeepLabV3+ with an IoU of 0.87

B. Preprocessing

Segmentation

- Data Acquisition: MRI scans with corresponding segmentation masks are downloaded from Kaggle.
- One-hot Encoding and Reverse Encoding: Segmentation labels are one-hot encoded for compatibility with neural network models.
- Custom Dataset Class: The LGGDataset class handles image loading, one-hot encoding, and augmentations.
- Image Size Divisibility by 32: Ensuring image dimensions are divisible by 32 for proper alignment of encoder and decoder features.
- Data Augmentation: Techniques include RandomCrop, HorizontalFlip, VerticalFlip, RandomRotate90, CLAHE, RandomBrightnessContrast, RandomGamma, and Normalize.

Training

- Encoder: EfficientNetB5
- Segmentation Models: SAM, U-Net, U-Net++, Pyramid Attention Network (PAN), and DeepLabV3+.
- Loss Function: For SAM Focal loss, for baseline models: Combined Dice loss and Binary Cross-Entropy (BCE) loss.
- Training: Conducted about 5-7 epochs on a CUDA-enabled device, used T4 GPU.

C. Preliminary Results of base models

Implemented baseline models DeepLabV3+, Unet, Unet++, Deeplabv3, PAN.

The models' performances are evaluated using the Intersection over Union (IoU) metric. The results are as follows:

DeepLabV3+ emerges as the top-performing model, indicating its superior capability in segmenting brain tumors from MRI images. The choice of models, loss functions, and evaluation metrics is driven by the objective to achieve high-precision segmentation, which is critical for the accurate diagnosis and treatment of brain tumors. The experimental setup and

TABLE I
SEGMENTATION PERFORMANCE

Model	Train loss	Valid Loss	IOU
DeepLabV3+	1.6634	1.6662	0.8741
UNET	1.6691	1.6712	0.8517
UNET++	1.6730	1.6750	0.8268
DeepLabV3	1.6646	1.6700	0.7986
PAN	1.6656	1.6683	0.7970

results contribute valuable insights into the application of deep learning for medical image segmentation, with potential implications for enhancing clinical workflows and patient care.

D. Performance Metrics of baseline models

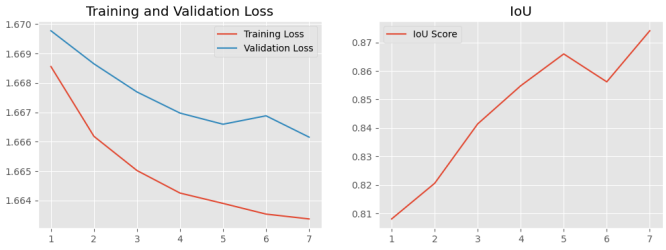

Fig. 1. DeepLabV3+-Result

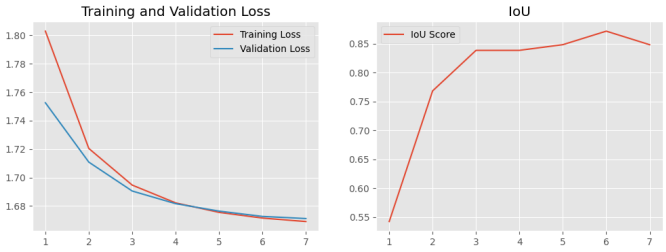

Fig. 2. UNet-Results

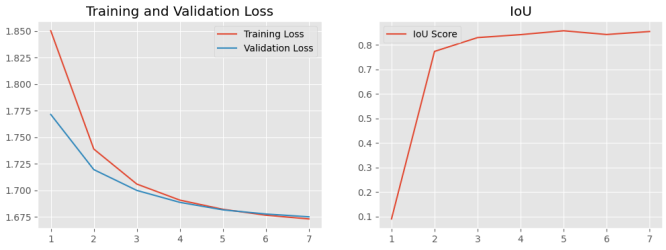

Fig. 3. UNET++-Results

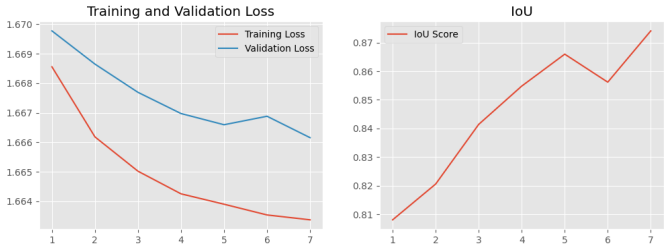

Fig. 4. Deeplabv3

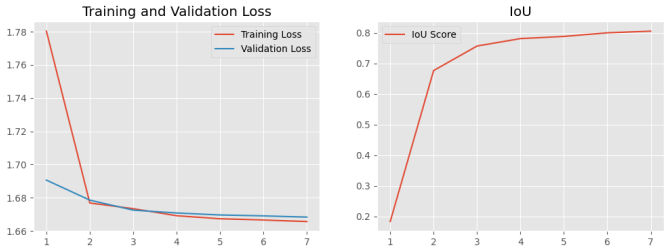

Fig. 5. PAN-Results

IV. SEGMENT ANYTHING MODEL

SAM is a foundation model for image segmentation that leverages a vision transformer-based architecture. It consists of three main components:
Image Encoder: Extracts image features and computes an image embedding.
Prompt Encoder: Embeds prompts (such as points, bounding boxes, or text) and incorporates user interactions.
Mask Decoder: Combines the embeddings from the image and prompt encoders to generate segmentation masks.

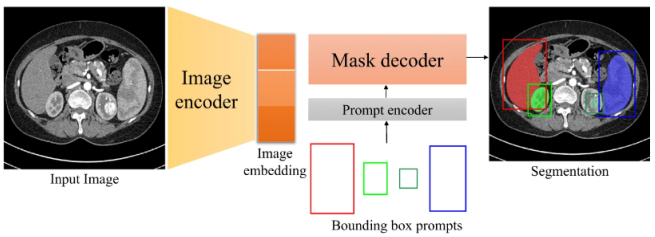

Fig. 6. SAM

Model Configuration

1) Pre-trained Weights::

- The model is initialized with pre-trained weights from the "facebook/sam-vit-base" model. These weights have been trained on a large dataset, providing a strong starting point for further fine-tuning on the specific segmentation task.

2) Frozen Parameters::

- During training, the parameters of the vision encoder and prompt encoder are frozen. This approach ensures that the pre-trained features are retained, and only the mask decoder is fine-tuned. This strategy helps in leveraging

the robust pre-trained features while adapting the decoder to the specific characteristics of the new dataset.

Training Setup

A. Optimizer:

- The Adam optimizer is used for training, configured with a learning rate of 0.001 and no weight decay. Adam is chosen for its effectiveness in handling sparse gradients and adaptive learning rates

B. Loss Function:

- The focal loss function from the MONAI library is used to address class imbalance during training. Focal loss places more focus on hard-to-classify examples, improving the model's ability to handle imbalanced datasets.

C. FeatUp: A Model-Agnostic Framework for Features at Any Resolution

SAM Model Integration with FeatUp

The Segment Anything Model (SAM) is a powerful model designed for image segmentation tasks. By integrating FeatUp, a tool for upsampling feature representations, the SAM model's performance can be further enhanced. This integration allows for improved visualization and analysis of feature maps, contributing to better segmentation accuracy and understanding of the model's internal workings.

1) Upsampler Initialization::

- FeatUp's upsampler, specifically the 'dino16' model, is loaded using Torch Hub. This upsampler is configured with normalization enabled to ensure consistency in feature representation.

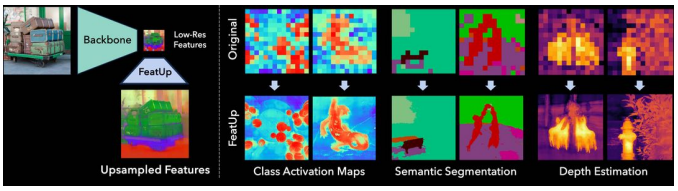

Fig. 7. FeatUp

Load and Setup SAM Model

2) Model Loading::

- The SAM model is loaded from pre-trained weights available on the Hugging Face model hub.
- The parameters of the vision and prompt encoders are frozen to retain their pre-trained features, ensuring that only the mask decoder is fine-tuned during training.

3) Optimizer and Loss Function::

- The Adam optimizer is configured with a specified learning rate and weight decay.
- The focal loss function from MONAI is used to handle class imbalance during training.

Featup Integration and Visualization

4) Image Enhancement::

- A utility function 'enhance-image' is defined to improve the contrast and brightness of images, making visualizations clearer and more informative.

5) Feature Visualization::

- The 'visualize-featup' function is created to visualize the original and upsampled features extracted by FeatUp.
- This function enhances the input image, extracts high-resolution (HR) and low-resolution (LR) features, and plots them for comparison.
- The visualization function is applied to images from the test dataset.
- Various channels and colormaps are used to explore different aspects of the feature maps, providing deeper insights into the model's behavior.

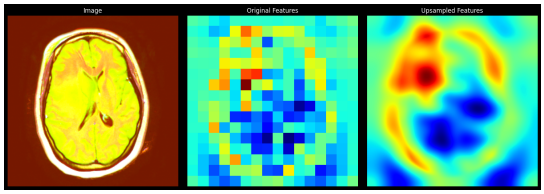

Fig. 8. Visualizing with channel 0 and colormap jet

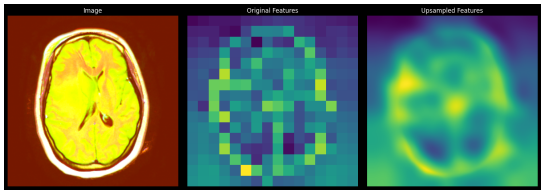

Fig. 9. Visualizing with channel 1 and colormap viridis

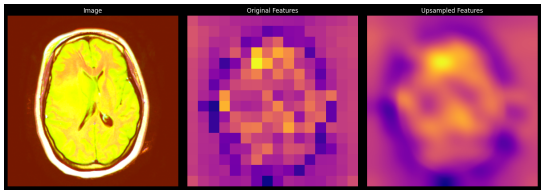

Fig. 10. Visualizing with channel 2 and colormap plasma

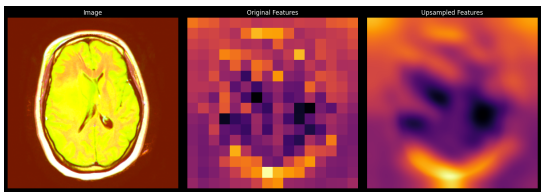

Fig. 11. Visualizing with channel 3 and colormap inferno

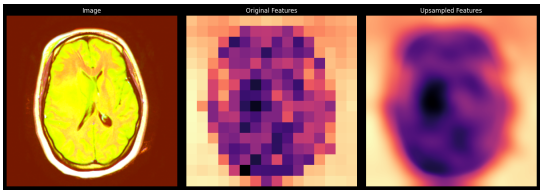

Fig. 12. Visualizing with channel 4 and colormap magma

TABLE II
RESULTS COMPARISON OF SAM/SAM+FEATUP WITH REDUCED IMAGE SIZE

Models	SAM	SAM+Featup
Mean Loss	0.0442	0.0159
Mean IoU	0.8095	0.8537
Mean Accuracy	0.9721	0.9762
Mean Precision	0.5089	0.5728
Mean Recall	0.2857	0.4258
Mean F1 Score	0.2947	0.4351
Mean Dice Score	0.2870	0.3395

D. GAFL: Global Adaptive Filtering Layer for Computer Vision

Integration with SAM Model

The GAFL architecture is integrated into the Segment Anything Model (SAM) to enhance its performance in segmentation tasks. This integration involves the following key aspects:

Spectral Domain Adjustments:
Before the images are processed by the SAM model, they are passed through the GAFL layers, which adjust their features in the spectral domain. This preprocessing step enhances the feature representation, making it easier for the SAM model to segment the images accurately.
Layer Configuration:
The integration allows for the use of different types of GAFL layers, such as spectrum, spectrum_log, phase, or general_spectrum, providing flexibility to select the most appropriate spectral adjustment technique for the task at hand.

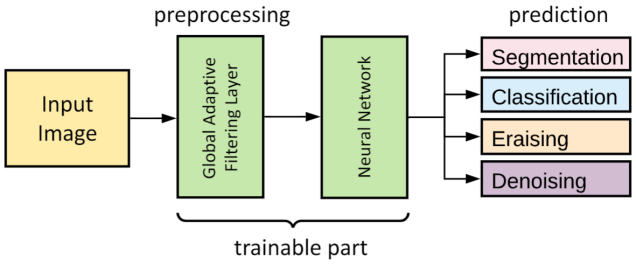

Fig. 13. GAFL

Implementation of Architecture

The implementation of the GAFL architecture involves the following layers:

1) Vision Encoder::

- The vision encoder processes input images through a series of convolutional and transformer layers to extract high-level features. These features are crucial for understanding the content and context of the images.

2) Prompt Encoder::

- The prompt encoder encodes spatial prompts, such as bounding boxes, which guide the segmentation process. This helps the model focus on specific regions of the image that are of interest.

3) Mask Decoder::

- The mask decoder combines the features from the vision and prompt encoders to generate segmentation masks. This decoder is optimized to produce accurate masks that align with the provided prompts.

4) Adaptive Layer::

- The adaptive layer, which is part of the GAFL architecture, applies spectral domain adjustments to the input images. This layer is crucial for enhancing the feature representation before the images are fed into the vision encoder.

TABLE III
SAM/SAM+GAFL COMPARISON

Models	SAM	SAM+GAFL
Mean Loss	0.0052	0.0062
Mean IoU	0.6757	0.9245
Mean Accuracy	0.9919	0.9698
Mean Precision	0.8609	0.9468
Mean Recall	0.8344	0.9289
Mean F1 Score	0.8348	0.9176
Mean Dice Score	0.7786	0.8124

We compare SAM and SAM+GAFL. The second one significantly enhances performance in these metrics, demonstrating the effectiveness of the Global Adaptive Filtering Layer. Mean IoU increased on 25%, mean precision improved on 8%, mean recall improved on 9%, mean F1 score higher on 8% and mean Dice score better on 4%.

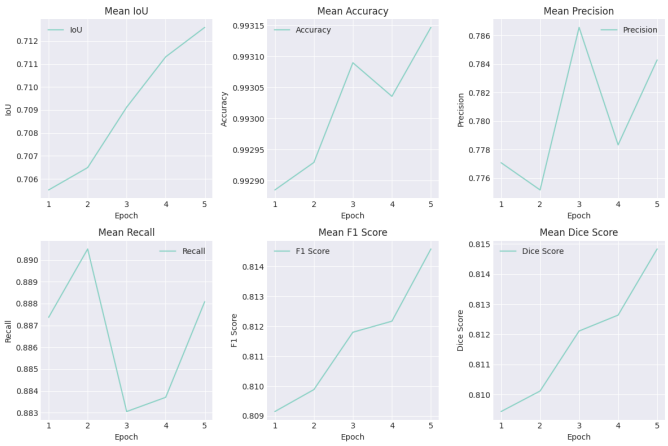

Fig. 14. Test Performance Metrics of GAFL

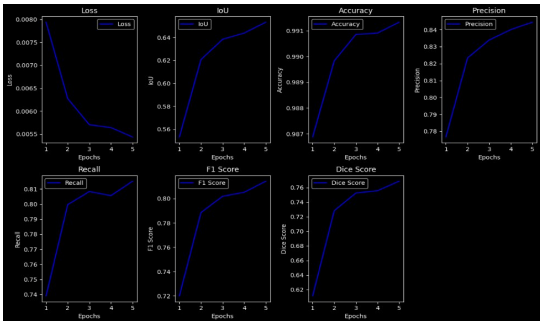

Fig. 15. Test Performance Metrics of SAM

E. Results of Comparison models

TABLE IV
RESULTS COMPARISON OF MODELS

Models	**SAM**	**SAM+FeatUP**	**SAM+GAFL**
Mean Loss	0.0052	0.0159	0.7004
Mean IoU	0.6757	0.8537	0.7004
Mean Accuracy	0.9919	0.9762	0.9926
Mean Precision	0.8609	0.5728	0.7704
Mean Recall	0.8344	0.4258	0.8901
Mean F1 Score	0.8348	0.4351	0.8043
Mean Dice Score	0.7786	0.3395	0.8045

If we compare FeatUP framework and GAFL, we can see the following picture. The average loss of FeatUp is lower than that of GAFL, IoU is 15% more. But precision of GAFL is better than FeatUp by 20%, in recall it is higher than 47%, F1 score is higher by 37%, mean Dice score is higher by 46%.

V. CONCLUSION

When comparing the enhanced models (SAM+FeatUp and SAM+GAFL) with the base SAM model, significant improvements are observed, particularly in the IoU and Dice Score metrics, which are critical for assessing segmentation accuracy:

SAM+FeatUp:

- **Mean IoU**: 0.8537
- **Mean Dice Score**: 0.3395

SAM+GAFL:

- **Mean IoU**: 0.9245
- **Mean Dice Score**: 0.8124

The integration of FeatUp and GAFL not only improves the spatial resolution and feature representation but also enhances the segmentation performance by optimizing feature extraction and selection processes.

The study shows that the SegMed framework, by leveraging FeatUp and GAFL, significantly advances the capabilities of MedSAM for medical image segmentation. The improved performance metrics demonstrate its potential to enhance clinical workflows, providing more accurate and reliable segmentation results essential for treatment planning and patient care.

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