Appendix A.2 (AY24-25)

Proposal for a Mode A Project

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Title of Proposed Project: Medical-SAM2 Framework for Enhancing Medical Image Segmentation and Improving Diagnostic Accuracy

Brief Description:

Medical image segmentation is crucial for improving diagnostic accuracy and supporting clinical decision-making. Recent advancements have highlighted the need for robust segmentation models that can handle the complex structures and diverse characteristics of medical images[5]. Although the Segment Anything Model 2 has shown promising results in natural image segmentation, its performance on medical images, such as mammograms, remains suboptimal due to domain-specific challenges posed by medical imaging data[3]. These challenges include high resolution, complexity, and the subtle differences of breast masses within normal glandular tissue, which make automated segmentation tasks particularly difficult[6].

Additionally, the variability in image quality, diverse imaging modalities, and anatomical differences across patient populations further complicate the segmentation tasks in medical imaging[2].Moreover, the presence of artifacts such as noise, blurring, and low contrast in medical images can significantly impact the performance of segmentation models, necessitating more sophisticated approaches to model design and fine-tuning[4].Finally, the limited availability of annotated medical datasets poses another challenge, often requiring the use of data augmentation and weak supervision techniques to enhance learning efficiency and model performance[8]

This project proposes to develop an innovative framework called Medical-SAM2, aimed at enhancing the segmentation performance of SAM2 in medical imaging tasks. The framework will focus on fine-tuning SAM2 to meet the unique requirements of medical image analysis. By leveraging domain-specific pre-trained models, Medical-SAM2 is expected to better understand the unique features of medical images, such as textures, shapes, and contrast patterns associated with various pathological changes. The integration of multi-scale feature adapters and a redesigned decoder architecture is anticipated to further improve the model's ability to accurately and efficiently segment complex medical images.

The framework also aims to address several challenges in medical image segmentation, including limited annotated data, high resolution, and the complexity of medical images. By incorporating weak supervision and data augmentation techniques, the framework intends to enhance the model's learning efficiency and segmentation performance. These techniques are expected to include using image-level labels, partially labeled data, and data augmentation strategies such as rotation, flipping, scaling, and contrast adjustment. These methods are projected to be crucial for overcoming the difficulties associated with limited labeled data and the high computational cost of obtaining pixel-perfect annotations in medical imaging[7, 1].Additionally, the framework plans to utilize semi-supervised and self-supervised learning methods, effectively leveraging both labeled and unlabeled data to boost the model's generalization capabilities. Techniques such as mutual consistency learning, adversarial training, and self-training are anticipated to demonstrate promising results in enhancing segmentation accuracy under low-data scenarios, making them particularly useful in medical applications where annota

By addressing these challenges through advanced model design and training strategies, Medical-SAM2 is expected to significantly improve upon existing models, providing a robust tool for accurate and efficient segmentation in medical image analysis. This innovative approach is projected not only to enhance diagnostic accuracy but also to support clinical decision-making, making it a valuable contribution to the field of medical imaging.

Experiments will be conducted on various medical imaging datasets, including MRI, CT, and polyp images, to test the performance of the Medical-SAM2 framework. Performance metrics such as Dice coefficient, Intersection over Union (IoU), precision, and recall will be used to evaluate the accuracy and efficiency of segmentation. Additionally, cross-dataset validation and robustness testing will be employed to assess the model's adaptability and generalization capabilities under different medical imaging conditions.

Does this project involve a collaboration with any organisation outside of the XJTLU?
NO

Name of collaborating organization (if any):

Name of contact person at this organisation:

Telephone number: **E-mail:**

Signature of Student:

Signature of Supervisor:

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