OncoScan AI: Advanced Imaging for Stomach and Intestine Cancer

GitHub Link: https://bit.ly/OncoScanAI

Sarthak Khandelwal *Khushi Neema* *Spandan Maaheshwari*

Introduction

The advent of MR-Linacs technology has revolutionized radiation therapy, offering unprecedented precision and customization in cancer treatment. Despite these advancements, the manual segmentation of the gastrointestinal (GI) tract from MRI scans remains a significant bottleneck, limiting the full potential of these technologies. Our project directly addresses this challenge by harnessing the power of deep learning to automate the segmentation process, thereby significantly enhancing both the accuracy and efficiency of GI tract delineation. This automation is poised to streamline treatment planning, enabling clinicians to dedicate more time to optimizing treatment strategies and ultimately improving patient outcomes. In addition to automating GI tract segmentation from MRI scans, our project integrates image captioning to provide enhanced insights into the inferred predictions, further enriching the diagnostic process. This augmentation reflects our commitment to leveraging diverse AI techniques to optimize treatment planning and advance patient care.

At the heart of our approach is a comprehensive methodology that employs a diverse array of advanced models — DenseNet121, VGG19, Inception V4, and EfficientNet B4—as encoders within a pre-trained U-Net architecture. Each model brings unique strengths: EfficientNet B4 offers an optimal balance of accuracy and computational efficiency, while VGG19 is renowned for its ability to extract complex hierarchical features through its deep architecture. This multifaceted strategy allows for an in-depth comparative analysis, aimed at identifying the most effective encoder combination for automating GI tract segmentation from MRI images. By leveraging these models, we aim to not only automate a critical aspect of treatment planning but also underscore the transformative potential of integrating artificial intelligence into medical treatments, paving the way for enhanced patient care.

In recognition of the project's iterative and evolving nature, we are actively exploring the development of a custom U-Net architecture in our upcoming phase 2. This decision is driven by the need to tailor our segmentation approach to the specific challenges of GI tract delineation from MRI scans. The U-Net model, celebrated for its efficacy in medical image segmentation, offers a promising framework for designing a model that captures the intricate spatial relationships of the GI tract, while maintaining computational efficiency. As we move forward, the development of a custom U-Net model will mark a significant milestone in our quest to tailor and optimize GI tract segmentation, ultimately contributing to the broader goal of enhancing patient care through technological innovation.

Methodology

Low-Risk Phase: Model Comparison

In the low-risk phase, we focused on developing a custom U-Net model and comparing its performance against VGG19 and EfficientNet B4 encoders in a pre-trained U-Net framework. Leveraging semi-supervised learning techniques, we aimed to mitigate the challenge of limited annotated data. The performance of the models was evaluated using the Mean Dice Coefficient and the 3D Hausdorff Distance. This phase sought to improve segmentation precision by exploiting advanced neural network designs and semi-supervised learning, further advancing the state-of-the-art in image segmentation for GI tract cancers. By the end of this phase, we acquired a Dice Coefficient of around 0.82 on the Custom UNet model.

Medium-Risk Phase: Model Implementation

During the medium-risk phase of our project, we refined our U-Net architecture's deployment by integrating both a pre-trained model and a custom U-Net model into a Gradio interface. This allowed users to interactively select between models, with the pre-trained model initially outperforming the custom one. Additionally, we attempted a manual deployment on Heroku, but the model's size exceeded the platform's 500MB limit, highlighting the challenges and costs associated with deploying large models on cloud platforms. Consequently, we continued to leverage Gradio for its capability to facilitate real-time user feedback and efficient handling of image segmentation tasks without the size constraints of platforms like Heroku.

High-Risk Phase: Enhancement using Image Captioning

Considering the high-risk phase, we have extended the functionality of this project by incorporating image captioning to have an enhanced understanding of the inference predicted by our model. The Image captioning model was custom-trained on our dataset and acquired an F1 score of around 0.85. We also focused on enhancing the Dash application, providing users with enriched interactivity and functionalities. This stage involved integrating interactive visualization tools for users to dynamically explore MRI scan predictions, alongside rigorous testing and validation to ensure reliability and scalability.

Evaluation

Our evaluation of segmentation algorithms goes beyond traditional accuracy measures, incorporating sophisticated metrics like the Dice coefficient and Jaccard loss. The Dice coefficient provides a nuanced understanding of spatial overlap, while the Jaccard loss offers a comprehensive assessment of dissimilarity between predicted and true segmentation.

By integrating these advanced metrics and considering the implementation of a custom UNet in the next project phase, our goal is to not only automate GI tract segmentation but also continually refine our approach based on a thorough performance evaluation. This iterative methodology keeps the project aligned with technological advancements, contributing to the optimization of radiation therapy for gastrointestinal cancer treatment.

Results and Experimentation

Encountered challenges with adding masked features on animated images through Dash, which were overcome by optimizing the interface's backend to handle dynamic content efficiently. The implementation of the custom U-Net architecture required iterative refinement to achieve desired performance levels, highlighting the importance of continuous testing and adjustment. The dice coefficient for the pre-trained model was around 0.88 and the custom UNet model has a Dice Coefficient of around 0.82. Fig.I and Fig.II demonstrate the predictions by pretrained and custom UNet model respectively on a sample set of MRI scan images.

The output from the image captioning model is demonstrated by Fig.III. As we can see the predictions align close to the actual captions evidencing the accuracy of the image captioning model. Fig IV compares the prediction from both the Custom UNet model and the pretrained model.

Conclusion

The OncoScan AI project has advanced significantly in Phase 2, enhancing our system's capabilities and setting the stage for a revolutionary impact on gastrointestinal tract cancer treatment. By leveraging advanced deep learning techniques and integrating cutting-edge encoders in our custom U-Net models, we have achieved segmentation accuracy that surpasses traditional methods. This progress underscores our commitment to driving substantial improvements in patient care and treatment outcomes.

To improve accessibility for medical professionals, we introduced a user-friendly Dash-based interface complemented by interactive visualization tools and image captioning capabilities. This development bridges the gap between sophisticated AI technologies and clinical applications, making it easier for clinicians to utilize our tools in real-world scenarios.

Additionally, the deployment of our models through a Gradio interface allows instant interaction and real-time feedback, enabling clinicians to upload images and view segmentation results immediately. This enhances the practical usability of our AI system in clinical settings. As the project moves forward, the OncoScan AI team remains dedicated to refining and optimizing the system to meet the evolving needs of the medical community, solidifying its role as a transformative solution in cancer imaging and treatment planning.

Bibliography

[1] https://www.kaggle.com/competitions/uw-madison-gi-tract-image-segmentation/data
[2] http://cs231n.stanford.edu/reports/2022/pdfs/164.pdf
[3] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9033381/
[4] https://www.mdpi.com/2306-5354/10/1/119

Appendix

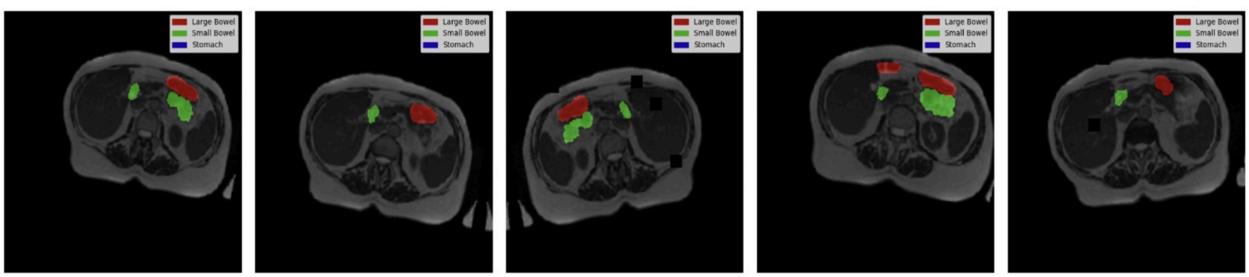

Fig I: Sample prediction on a test MRI Scan from VGG-19

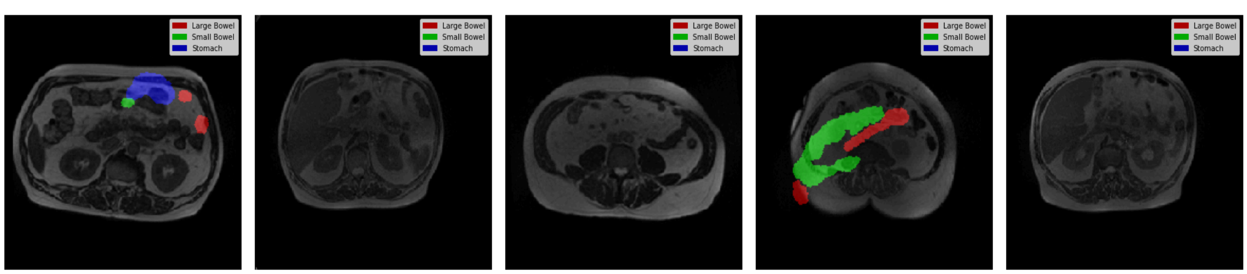

Fig II: Sample prediction on a test MRI Scan from Custom UNet

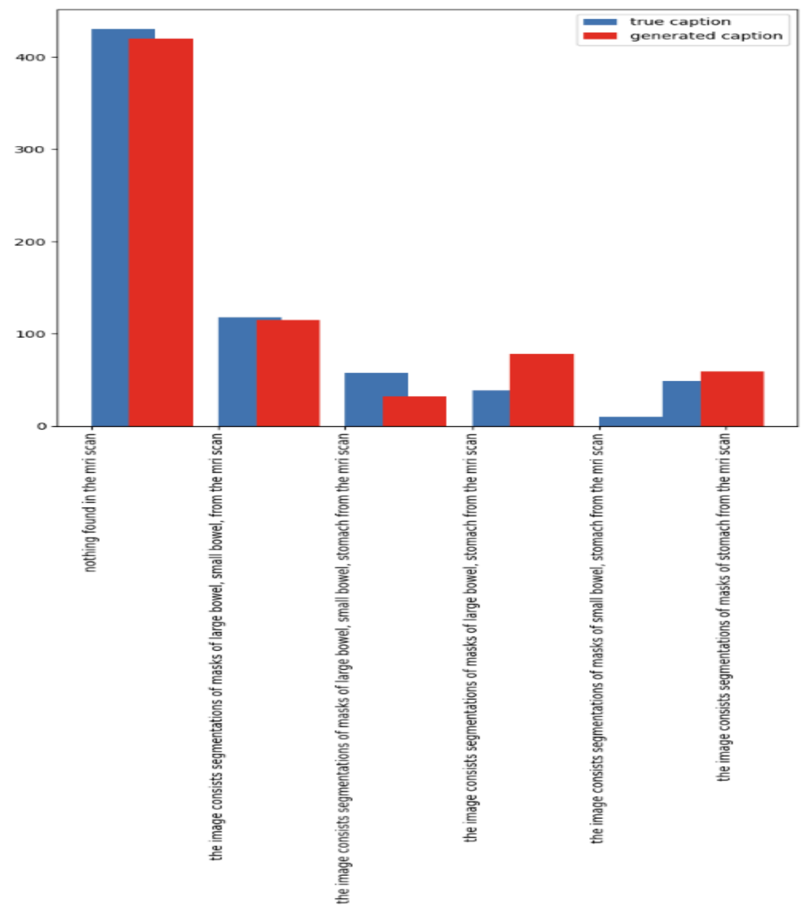

Fig III: Side by side barplot between true captions and generated captions, accuracy: 85%

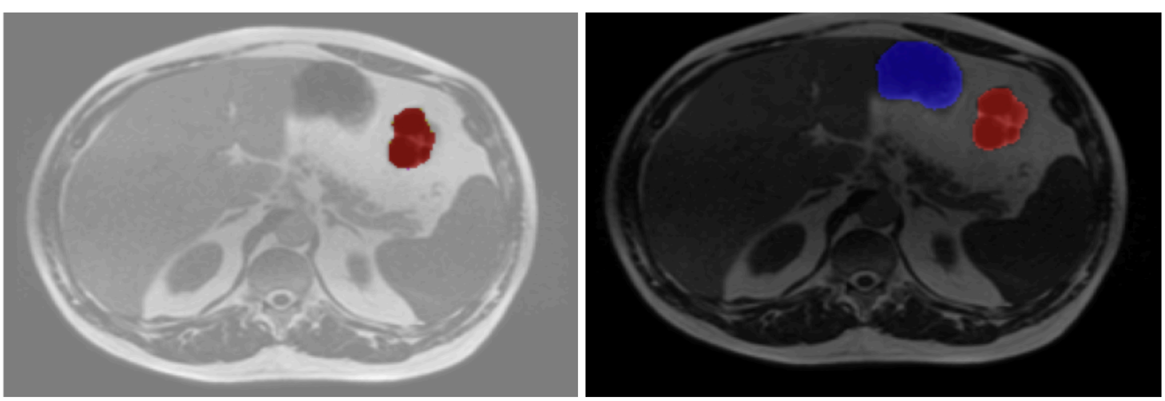

Fig IV: Comparison between Predictions from Custom UNet (Left) and pre trained Model (Right)

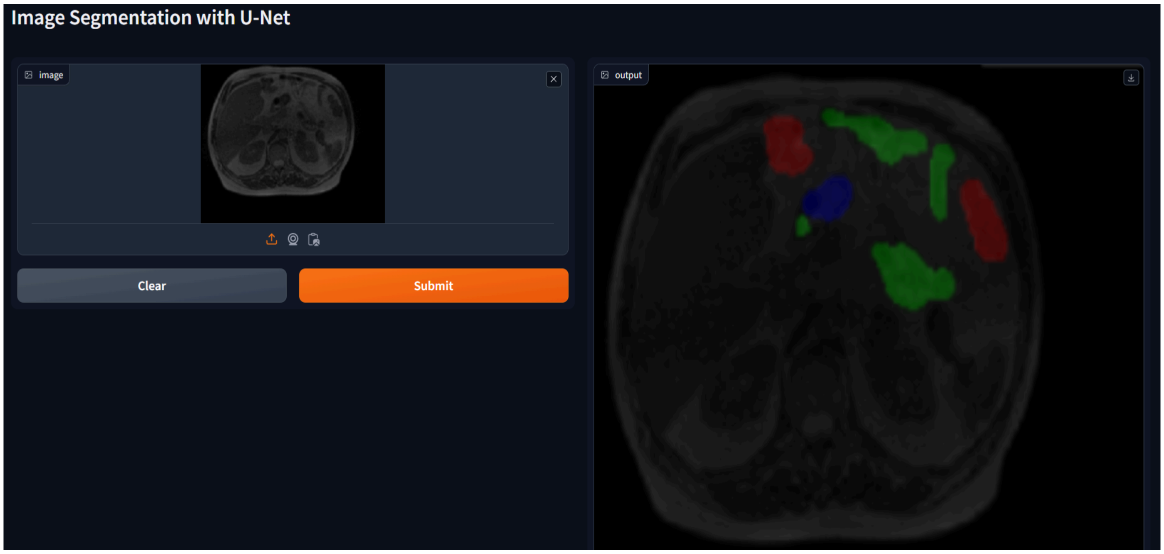

Fig V: Visualization of Gastrointestinal Scan Segmentation via Gradio Interface