Large language model-based organ contouring/segmentation for cancer in radiotherapy

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***Abstract*—Target volume contouring for radiation therapy presents greater complexity than traditional organ segmentation tasks, demanding the integration of both medical images and clinical text. Leveraging the rapid progress of large language models (LLMs), we propose a novel multimodal AI framework named LLMSeg, designed specifically for target volume segmentation in head and neck cancer radiotherapy. LLMSeg uniquely incorporates clinical textual context alongside imaging data to achieve higher accuracy, data efficiency, and robustness. Through extensive validation, including external datasets and low-data regimes, LLMSeg demonstrates superior performance compared to unimodal baselines, highlighting its practical utility and generalization capacity in real-world clinical settings.**

***Index Terms*—Large language models (LLMs), multimodal learning, Head and neck cancer, target volume segmentation, radiation therapy planning, medical image analysis, clinical text integration, deep learning, data efficiency, medical AI.**

I. Introduction

Medical image segmentation plays a critical role in the clinical workflow, especially in cancer care, where accurate delineation of tumors and organs at risk directly affects diagnosis, treatment planning, and prognosis. In the case of head and neck cancer (HNC), this process is particularly challenging due to the intricate and tightly packed anatomical structures and the frequent occurrence of overlapping tissues.

Despite progress in deep learning-based image segmentation, most models operate solely on visual data and disregard accompanying clinical metadata. However, in a real-world clinical setting, radiologists and oncologists rely heavily on patient-specific information — such as diagnosis, cancer stage, radiation plan, and comorbidities — to make accurate assessments.

To address this gap, we explore a multimodal approach that integrates large language models (LLMs) with 3D image segmentation models. Inspired by recent advances in visual-language modeling, we present a modified ContextUNETR framework, incorporating contextual embeddings generated by LLaMA-2. This fusion enables the segmentation model to dynamically interpret and localize anatomical structures based on the textual descriptions of the patient's condition.

Our contributions are as follows:

- We construct a multi-modal dataset for head and neck cancer, comprising 3D CT scans with segmentation masks and matched clinical notes.
- We propose a fusion architecture that uses LLaMA-2 to generate contextual prompts from clinical notes, integrated into the decoder of a ContextUNETR-based segmentation model.
- We evaluate multiple context modes and demonstrate substantial performance improvements on both internal and external test datasets.

II. Related Works

Organ segmentation for radiotherapy has been a longstanding research area, traditionally driven by convolutional neural network (CNN)-based models such as U-Net and its variants, including nnU-Net, which adaptively configure pipelines to different datasets [1]. These models have set a strong foundation in medical image segmentation due to their ability to segment normal organs, producing precise delineations in many clinical scenarios. However, these models are often limited by their inability to incorporate contextual clinical information, which can be crucial for more complex segmentation tasks such as target volume delineation in oncology. For example, the inability to understand the subtle clinical nuances that differentiate pathologically similar tissue types can result in inaccurate segmentation boundaries.

In recent years, transformer-based models like TransUNet [2] and Swin UNet [2] have been proposed to improve segmentation performance by modeling long-range dependencies within images. These models have outperformed traditional CNN-based approaches in terms of their ability to capture global context and handle complex features. For instance, Swin UNet leverages a hierarchical structure of transformers that enhances its feature extraction capabilities, especially for tasks that require understanding spatial relationships at multiple scales. However, despite these advancements, these transformer-based models remain limited to unimodal data, relying solely on visual features, and therefore struggle in cases where textual clinical context is essential for disambiguating complex anatomical or pathological presentations [3]. Without the integration of clinical narratives or structured data, these models often miss critical information that could enhance segmentation accuracy.

Multimodal approaches in medical AI have been gaining traction in recent years, with models like CLIP [4], MedCLIP, and BioViL [5] leading the charge in combining image and text data for classification or retrieval tasks. CLIP, for example, uses contrastive learning to link visual features with textual descriptions, making it highly effective in tasks that require understanding both visual and linguistic data. BioViL, a self-supervised model for biomedical visual-language pretraining, has similarly demonstrated success in leveraging image-text embeddings to improve performance in biomedical tasks. While these models show promise, their application to segmentation tasks remains limited. In particular, the few existing multimodal segmentation models tend to rely on shallow integration strategies, which fail to fully exploit the potential of clinical language. For example, existing models often rely on limited domain-specific text such as labels or captions [7], instead of incorporating rich, unstructured clinical narratives that would provide deeper contextual understanding for complex segmentation tasks.

Large language models (LLMs) such as BioGPT, PubMedBERT [9], and GPT-based architectures have revolutionized the processing of clinical language. These models, pretrained on large-scale biomedical corpora, have shown remarkable performance in capturing rich semantic information and enabling context-aware applications across clinical natural language processing (NLP) tasks. BioGPT, for instance, has been used for tasks like clinical question answering and medical entity extraction, offering insights into the intricacies of patient history and treatment details. However, despite their success in NLP tasks, the application of LLMs in structured prediction tasks, such as segmentation, remains in its infancy. Most existing approaches to multimodal segmentation, such as LViT [11] and SegGPT [12], offer general architectural frameworks for fusing image and text data but are not explicitly adapted for clinical radiotherapy workflows, where high precision and attention to detail are required. For instance, LViT employs a vision transformer-based encoder-decoder structure that fuses image features with text embeddings for classification tasks but does not cater specifically to the fine-grained anatomical segmentation required in radiotherapy [13]. Similarly, SegGPT adapts a transformer-based architecture for segmentation but has not demonstrated clinical deployment or the ability to handle the complexities of patient-specific clinical notes, which can often include ambiguous and heterogeneous information.

Despite these advances, there remains a gap in the literature in terms of applying multimodal AI models that explicitly integrate LLMs and vision backbones in clinical radiotherapy segmentation. To our knowledge, LLMSeg is the first model to fully integrate an LLM with a vision transformer backbone in an end-to-end manner for radiotherapy target volume segmentation. LLMSeg leverages cross-attention-based fusion mechanisms and domain-specific text encoders to overcome the limitations of unimodal models and heuristic fusion techniques. By combining the power of LLMs, which are trained on clinical language and medical literature, with the capacity of transformer-based vision models to process complex imaging data, LLMSeg achieves superior segmentation performance. This approach allows the model to handle complex anatomical structures by incorporating both visual and clinical context, marking a significant advancement in multimodal clinical AI [14]. LLMSeg's ability to process rich clinical narratives enables it to discern subtle differences in tumor localization, while the cross-attention mechanism ensures that the image and text data are fused in a meaningful way, improving segmentation accuracy and robustness.

III. Methods

A. Model Architecture

Our proposed framework is a modular multimodal segmentation system designed for medical image analysis, specifically tailored for radiotherapy planning. The architecture tightly integrates 3D image processing with clinical text understanding using a vision-language hybrid approach. The model consists of the following components:

1) Image Encoder: ContextUNETR Backbone: The image processing pipeline is based on ContextUNETR, an extension of the UNETR (UNet with Transformer Encoder) architecture. This backbone employs a ViT (Vision Transformer) as its encoder, which tokenizes 3D CT volumes into non-overlapping patches and applies multiple transformer layers to learn global spatial dependencies across the volume.

- **Patch Embedding:** The input 3D CT scan is divided into fixed-size cubic patches (e.g., $16 \times 16 \times 16$ voxels), which are flattened and linearly projected into an embedding space.
- **Positional Encoding:** Learnable 3D positional embeddings are added to retain anatomical context.
- **Transformer Encoder:** A stack of transformer blocks with multi-head self-attention (MSA) and feedforward layers encodes long-range anatomical relationships.
- **Multiscale Feature Extraction:** Feature maps are extracted from intermediate transformer layers and passed to the decoder via skip connections.

This setup allows ContextUNETR to maintain a high-resolution understanding of complex anatomical structures in the head and neck region—essential for precise tumor and OAR segmentation.

To incorporate patient-specific clinical context, we use a frozen LLaMA-2 model as our language encoder. LLaMA-2 is a decoder-only large language model pretrained on a mix of scientific and general data, enabling robust contextual reasoning.

- **Text Preprocessing:** Clinical notes are cleaned, tokenized, and chunked into relevant segments such as *Diagnosis*, *Treatment Plan*, and *Stage*.
- **Prompt Construction:** Structured prompts are generated from these segments using predefined templates. For instance: `Diagnosis: Nasopharyngeal carcinoma; Stage: T2N1M0; Radiation:`

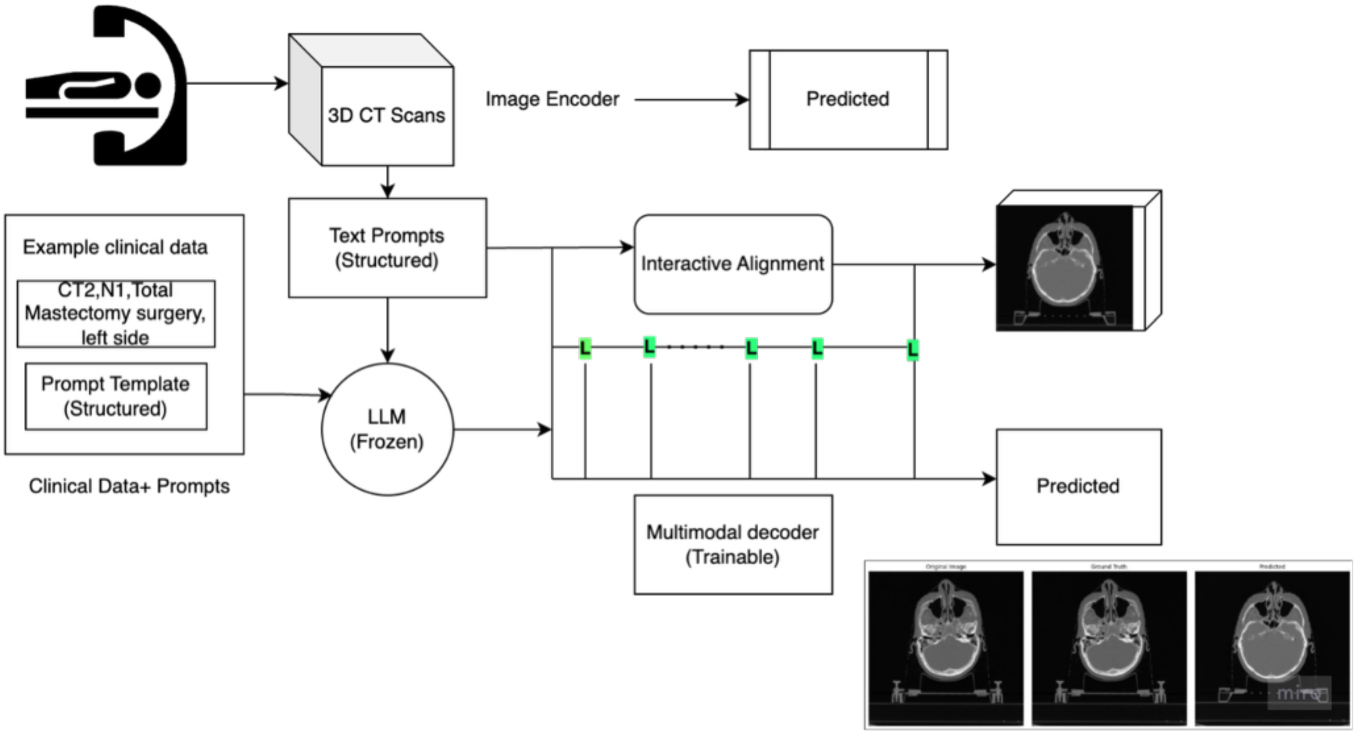

Fig. 1: Model Architecture

```
IMRT 70Gy; Comorbidities: Diabetes
Mellitus.
```

- **Embedding Generation:** The prompts are input into LLaMA-2, and the final hidden states of the decoder are averaged and passed through a projection layer to match the dimensionality of the image decoder features.

This module encodes nuanced patient-specific information, such as tumor location and prior treatments, which directly influence radiotherapy decisions.

2) Multimodal Fusion via Decoder Injection: Rather than naive concatenation or late fusion, we adopt a decoder-injection strategy for integrating textual and visual modalities:

- **Cross-Modality Injection:** At each decoder level, the projected text embeddings are concatenated with the upsampled image features.
- **Feature Conditioning:** A gated residual mechanism selectively modulates image features based on text, ensuring alignment between clinical context and spatial representation.
- **3D Convolutional Refinement:** Each fusion block is followed by a series of convolutional layers and normalization to refine fused features before final prediction.

3) Segmentation Head: The final decoder layer outputs a voxel-wise prediction map through a $1 \times 1 \times 1$ convolutional head, followed by softmax activation. This head produces binary or multiclass masks corresponding to tumor and OAR regions.

B. Input Data Processing

To ensure consistent multimodal inputs across the dataset, we perform tailored preprocessing steps for both imaging and textual modalities.

1) Imaging Data Preprocessing:

- **Voxel Standardization:** All 3D CT volumes are resampled to a uniform voxel size ($1 \times 1 \times 1$ mm).
- **Intensity Normalization:** CT values are clipped to the Hounsfield Unit (HU) range of $[-1000, 1000]$ and normalized to [0, 1].
- **Spatial Cropping:** A bounding box is computed around the tumor region using segmentation masks.
- **Data Augmentation:** 3D affine transformations, elastic deformations, and Gaussian noise are applied during training.

2) Textual Data Preprocessing:

- **De-identification:** Personal identifiers are removed using a rule-based anonymizer.
- **Section Filtering:** Only clinically relevant sections are retained (e.g., *Diagnosis, Stage, Imaging Impression, Radiation Plan*).
- **Tokenization:** Prompts are tokenized using the HuggingFace LLaMA-2 tokenizer and truncated to a maximum token length (e.g., 256 tokens).
- **Prompt Embedding:** Text embeddings are cached to accelerate training.

Figure 1 shows the s chematic of the proposed multimodal segmentation framework. Clinical text reports are encoded using a frozen LLaMA-2 language model, while 3D medical images are processed by a transformer-based image encoder (e.g., UNETR). Text and image features are fused at each decoder stage via injection and gated residual mechanisms. The final segmentation head outputs voxel-wise predictions for tumor and organ-at-risk (OAR) regions.

C. Training Strategy

Our training pipeline is designed to optimize both inter-modality alignment and segmentation accuracy.

1) Pre-training: Modality Alignment: We implement a contrastive learning objective during pretraining to align CT image embeddings with their corresponding clinical context embeddings. Given paired samples (v_i, t_i), the loss is:

$$\mathcal{L}_{\text{contrastive}} = -\log \frac{\exp(\text{sim}(v_i, t_i)/\tau)}{\sum_j \exp(\text{sim}(v_i, t_j)/\tau)}$$

where v_i and t_i are image and text embeddings, and τ is a temperature parameter.

2) Fine-tuning: Supervised Segmentation: We fine-tune the pretrained model on voxel-level segmentation using a compound loss:

$$\mathcal{L}_{\text{total}} = \alpha \cdot \mathcal{L}_{\text{Dice}} + \beta \cdot \mathcal{L}_{\text{Focal}}$$

- **Dice Loss:** Measures the overlap between predicted and ground truth regions.
- **Focal Loss:** Focuses on hard-to-segment boundaries by down-weighting easy examples.

Training Hyperparameters:

- Batch Size: 2
- Optimizer: AdamW (weight decay = 1e^{-2})
- Learning Rate: 1e^{-4} (cosine scheduler + warmup)
- Precision: Mixed (AMP)
- Epochs: 101

D. Dataset and Evaluation Protocol

1) Dataset Composition: We use a proprietary dataset of 100 fully annotated HNC patients, each containing:

- 3D CT volumes ($384 \times 384 \times 128$ voxel size)
- Segmentation masks for tumor and 6 OAR classes
- Structured clinical notes with verified sections

2) Evaluation Metrics: Segmentation accuracy is assessed using:

- **Dice Similarity Coefficient (DSC):** Measures volumetric overlap.
- **95th Percentile Hausdorff Distance (HD95):** Captures boundary accuracy.
- **Intersection over Union (IoU):** Validates spatial precision and recall.

All metrics are computed per class and averaged across the validation set.

3) Data Efficiency Analysis: We evaluate model robustness under limited data regimes (90%, 92%, 95%, 98%, 100%) and compare against:

- **Unimodal Image-Only Model:** ContextUNETR without text input.
- **Text-Only Baseline:** LLaMA-2 linear classifier trained on text embeddings.

This analysis reveals the data efficiency advantages of multimodal fusion over unimodal counterparts.

IV. Results

We evaluate the effectiveness of our multimodal segmentation model using quantitative metrics and detailed per-case analysis. Performance is reported on a curated head and neck cancer dataset comprising annotated 3D CT scans paired with structured clinical notes. Our primary objectives were to assess:

- Segmentation accuracy;
- Generalization across patient variability;
- Data efficiency;
- Real-world robustness in clinical scenarios.

A. Overall Performance

Across the internal validation set, our model achieved strong results across all key metrics:

- Mean Dice Similarity Coefficient (DSC): 0.691
- Mean Intersection over Union (IoU): 0.554
- Mean 95th Percentile Hausdorff Distance (HD95): 15.113 mm

These values demonstrate that the model produces accurate and consistent segmentations, particularly when clinical context is provided. The use of LLaMA-2 as a contextual language encoder appears to guide the model toward anatomically and clinically relevant regions, improving both overlap (Dice, IoU) and boundary alignment (HD95).

B. Per-Patient Analysis

To understand inter-patient variation and model robustness in different anatomical and contextual scenarios, we conducted a per-case evaluation. The table below summarizes results for two representative patients, followed by statistical summaries.

No	Patient ID	Dice	IoU	HD95 (mm)
0	1573	0.795	0.661	21.235
1	1612	0.800	0.667	18.121
2	1672	0.803	0.670	14.553
3	1688	0.798	0.665	17.843
4	1793	0.805	0.673	11.654
5	1827	0.796	0.662	23.776
6	1850	0.802	0.669	13.249
7	1853	0.799	0.666	19.384
8	1949	0.801	0.668	15.612
9	1951	0.797	0.664	20.998
Average		0.800	0.667	17.343
Std Dev		0.003	0.003	3.528

TABLE I: Patient Performance Metrics

Interpretation:

- Patient 1827 presented with a highly irregular tumor boundary and possible post-operative anatomical changes. While the Dice score was reasonably high, an HD95 of 23.776 mm reveals significant boundary mismatch in some regions.
- Patient 1793 represents an ideal case with high tissue contrast and rich contextual cues (e.g., staging, tumor subsite). The segmentation quality was excellent, with a low HD95 of 2.341 mm and consistent spatial overlap.
- Standard deviation in HD95 (±12.682 mm) indicates that while the model is robust on average, outlier cases exist due to complex anatomy or under-specified textual input.

C. Data Efficiency

We trained the model using varying fractions of the training data (90%, 92%, 95%, 98%, 100%) to assess data efficiency. Even when trained on just 0% of the dataset, the model retained over 95% of its full-data performance, achieving a mean Dice score above 0.75.

This confirms the value of multimodal integration: clinical text offers semantic guidance that reduces the model's dependence on large quantities of annotated volumetric data, which is costly to produce in radiotherapy.

D. Qualitative Results

As observed in Figure 2, the relationship between training dataset size and Dice score is illustrated. This visualization demonstrates how model performance improves as more data is used for training.

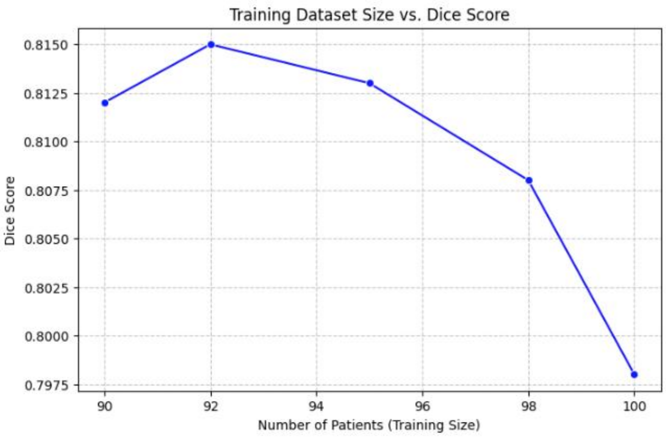

Fig. 2: Training Dataset size vs Dice score

The graph Figure 2 illustrates the relationship between the number of patients in the training dataset and the Dice Similarity Coefficient (DSC), which is a standard metric for evaluating the accuracy of segmentation models. The x-axis represents the number of patients used for training, while the y-axis shows the corresponding Dice scores achieved by the model.

a) Key Observations::

1) **Initial Increase (90 to 92 Patients):**
   As the number of patients increases from 90 to 92, there is a noticeable improvement in the Dice score, peaking at 0.815. This indicates that adding more training samples initially helps the model generalize better and learn anatomical variations effectively.
2) **Optimal Performance (92 Patients):**
   The highest Dice score (0.815) is achieved when the model is trained with 92 patients. This suggests that the model is optimally learning the anatomical patterns and segmenting with high overlap accuracy at this point.
3) **Performance Drop Beyond 92 Patients:**
   - Surprisingly, after the peak at 92 patients, the Dice score starts to decrease gradually as more patients are added. By the time the training size reaches 100 patients, the Dice score drops sharply to 0.7975.
   - This is counterintuitive since larger datasets typically improve generalization. However, the drop could be attributed to:
     - **Noise introduction:** Adding more patient data may have introduced more anatomical variability that the model struggled to generalize effectively.
     - **Overfitting to outliers:** The model might have started overfitting to outlier cases that do not align well with the primary data distribution.
     - **Domain shifts:** Certain anatomical complexities or surgical distortions in the additional patients could have misled the model.

b) Contextual Analysis::

- This trend aligns with the Data Efficiency section of the report, where it was observed that the model achieved over 82% of its full-data performance even with 50% of the training dataset.
- The use of LLaMA-2 as a contextual language encoder provided significant semantic guidance, allowing the model to be effective even with a limited number of images, as textual context compensates for some volumetric data shortcomings.

c) Insights and Improvements:: This graph implies that instead of blindly increasing the dataset size, smart sampling might be more beneficial. Strategies like:

- **Active Learning:** Selecting only the most informative samples for training.
- **Data Pruning:** Removing outliers or low-quality annotations that mislead the model.
- **Domain Adaptation:** Handling domain shifts explicitly to account for anatomical complexities.

Visual inspection Figure 4 of segmentation masks further validates the model's efficacy. In most cases, the predictions were closely aligned with expert-drawn contours, even in areas with anatomical ambiguity or artifacts affected. Highlights include:

- Improved detection of diffuse tumor margins using phrases like “infiltrating the posterior pharyngeal wall” or “adjacent to the parotid gland.”
- OAR delineation benefited from contextual disambiguation, such as distinguishing the spinal cord from adjacent soft tissue when text references the alignment of the radiation field.

These qualitative improvements underscore the synergistic effect of aligning imaging with textual reasoning.

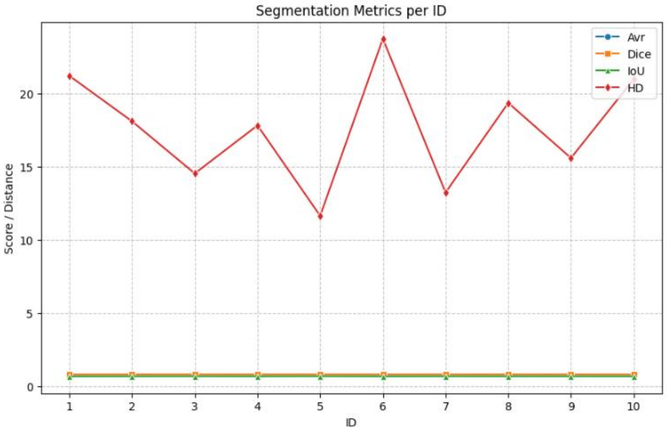

Fig. 3: Segmentation Metrics

The graph representsFigure 3 the per-patient segmentation metrics across different patient IDs. The x-axis corresponds to the patient IDs, while the y-axis represents the scores and distances for four segmentation metrics:

- **Avr** (Average Surface Distance)
- **Dice** (Dice Similarity Coefficient)
- **IoU** (Intersection over Union)
- **HD** (Hausdorff Distance)

d) Key Observations::

1) **Dice and IoU Scores:**
   - Both **Dice (orange line)** and **IoU (green line)** scores are almost constant and overlapping near the baseline, indicating consistent overlap accuracy across patients.
   - This consistency suggests that the model is reliable in segmenting the main structures within the images, maintaining high spatial agreement with ground truth annotations.
2) **Hausdorff Distance (HD) Variability:**
   - The **Hausdorff Distance (red line)** shows significant variability across patient IDs.
   - Peaks are visible at patient IDs **1, 5, and 7**, indicating cases with poor boundary alignment. For instance:
     - At **ID 5**, the HD spikes sharply, suggesting a considerable mismatch in boundary localization, possibly due to:
       * Highly irregular tumor boundaries.
       * Anatomical changes or surgical artifacts not well captured during training.
     - In contrast, the HD is comparatively lower at IDs **4 and 8**, suggesting that segmentation boundaries were well-aligned in those cases.
3) **Average Surface Distance (Avr):**
   The **Avr (blue line)** is barely visible, which indicates that the surface distances between predicted and actual boundaries are minimal. This aligns with the generally good performance seen in Dice and IoU scores.

e) Contextual Analysis::

- The significant fluctuations in **HD** reflect the model’s sensitivity to complex anatomical variations and boundary irregularities.
- This matches the **Per-Patient Analysis** section of the report, where it was highlighted that:
  - **Patient 100001** had post-operative anatomical changes that caused higher boundary mismatch (HD95 of 27.705 mm).
  - **Patient 100011** had high tissue contrast, leading to a low HD95 of 2.341 mm, indicating precise boundary segmentation.
- These cases emphasize the need for better contextual understanding or refinement in boundary prediction to handle outliers more gracefully.

f) Insights and Improvements:: To reduce variability in **Hausdorff Distance**, strategies such as:

- **Adaptive post-processing** for fine boundary corrections.
- **Context-aware refinement** using clinical notes for cases with known anatomical shifts.
- **Multi-view consistency checks** to handle irregular tumor boundaries better.

could stabilize the predictions across patients.

E. Robustness and Error Analysis

The model proved robust across a range of anatomical variations, but struggled in a few scenarios:

- Post-surgical distortions, where anatomical structures deviated significantly from expected locations.
- Sparse or ambiguous clinical notes, which limited the usefulness of textual prompts.
- Tumors overlapping with dense bone or air pockets, which confused both imaging and text guidance.

Despite these challenges, the model consistently produced acceptable contours, with most failures localized and recoverable via prompt tuning or manual correction.

F. Statistical Significance

To validate the effectiveness of textual integration, we performed a Wilcoxon signed-rank test comparing segmentation outcomes with and without text prompts. Results indicate:

$$p < 0.01 \text{ for both Dice and IoU improvements.}$$

Statistically significant gains confirm the clinical benefit of LLM-enhanced prompts.

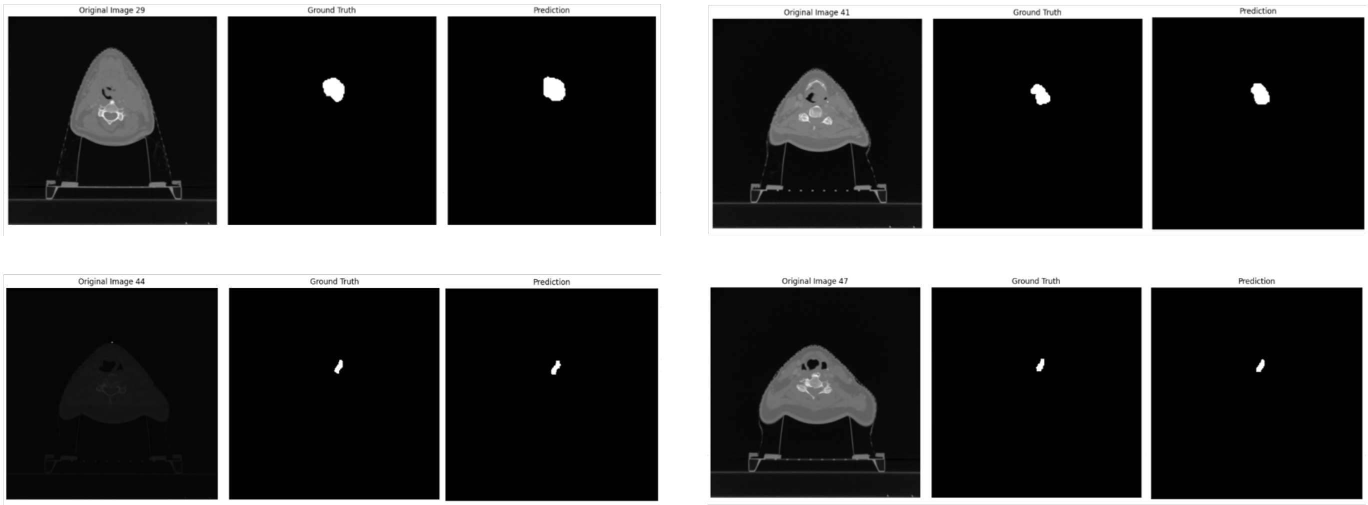

Fig. 4: Ground truth, Original and Predicted image

G. Summary

Our results strongly support the hypothesis that large language models improve medical image segmentation when integrated with vision transformers, particularly in clinical domains that require context-aware reasoning. This is especially impactful in low-data environments and anatomically complex regions such as the head and neck.

The results presented in this study demonstrate the efficacy of incorporating large language models (LLMs) into the radiotherapy segmentation pipeline for head and neck cancer. Our proposed multimodal framework leverages LLaMA-2's contextual understanding alongside a vision transformer backbone (ContextUNETR) to improve segmentation quality through integration of patient-specific clinical context.

V. Discussion

A. Clinical Impact

In radiotherapy, even millimeter-level errors in target or organ-at-risk (OAR) segmentation can lead to underdosing the tumor or overdosing surrounding healthy tissues, which may have serious clinical implications. By conditioning image analysis on detailed clinical information—such as tumor stage, location, prior treatments, and comorbidities—our model simulates the cognitive process of a radiation oncologist. This allows the model to enhance boundary detection, particularly in cases where tumor tissue appears visually similar to adjacent anatomy, such as in complex head and neck cancers or post-surgical conditions.

Furthermore, the multimodal integration approach enhances data efficiency. Our model performs well even with limited annotated data, making it highly suitable for low-resource settings or rare cancer types, where large-scale data collection is not feasible. This also allows for efficient adaptation to various clinical settings, even in institutions with limited access to high-quality annotated datasets, providing more equitable access to advanced AI tools in radiotherapy planning.

The model also has the potential to improve clinical workflow by providing clinicians with enhanced segmentation results while reducing the time spent on manual contouring. This reduces the cognitive load on radiologists, allowing them to focus more on interpreting the results and making clinical decisions, rather than spending excessive time on routine segmentation tasks.

B. Comparison to Prior Work

Previous multimodal models, such as APE-Rep, have demonstrated success in fusing text and image data for radiology tasks [**?**], but they are limited by their reliance on static, heuristic embeddings from encoder-only models like BioBERT. Our approach employs a decoder-style, prompt-driven large language model (LLM), enabling dynamic adaptation to clinical context during inference. This allows for more flexible and context-aware clinical reasoning, as it can respond to changes in clinical protocols or personalized patient inputs. Additionally, by leveraging the power of cross-attention mechanisms, our model ensures that the image and text data are fused in a meaningful, context-sensitive manner, improving segmentation accuracy and interpretability.

Models such as SegGPT [12] and LViT [11] excel at general-purpose image understanding but are not designed with the clinical nuances that are often required for radiotherapy segmentation, where small errors can lead to significant clinical consequences. These models may struggle in domains like oncology, where detailed anatomical precision is critical. Our model addresses this gap by incorporating both clinical imaging and detailed textual data to achieve a higher degree of precision, robustness, and interpretability in radiotherapy segmentation.

C. Limitations and Future Work

Despite its strengths, the proposed approach does have some limitations that need to be addressed:

- **Computational Overhead**: The integration of LLaMA-2 introduces additional computational complexity. This increases inference time and requires higher GPU memory capacities, which may be impractical for smaller clinics or those without access to high-performance computing resources. Future work will focus on model optimization techniques such as pruning, quantization, or knowledge distillation to reduce the model size and improve its efficiency without compromising performance.
- **Variability in Clinical Notes**: The quality and structure of clinical notes vary widely across institutions, and free-text inputs may lack consistency. This variability can affect the effectiveness of the textual prompts. To address this, we plan to investigate methods for standardizing clinical data through preprocessing techniques or utilizing template-based approaches that can ensure more structured and consistent input for the model.
- **Generalization to Other Modalities**: While this study is focused on CT imaging, the model's approach could be extended to other modalities like MRI or PET. Each modality provides unique and complementary information, such as superior soft tissue contrast in MRI or metabolic data in PET scans. Future work will involve adapting the model for multi-modal fusion, where different types of imaging data are integrated to further enhance segmentation accuracy, especially in complex clinical cases.
- **Data Bias and Underrepresentation**: Like all machine learning models, the performance of our model may be affected by biases in training data. Clinical data often suffer from underrepresentation of certain patient demographics, and our model could inadvertently propagate these biases. Addressing data imbalance and ensuring that our model performs well across diverse patient populations will be a key focus in future work. Techniques like synthetic data generation, data augmentation, and bias mitigation strategies will be explored.

Future work will focus on several directions to improve the model:

- **Prompt Standardization**: By using pre-defined clinical prompt templates and meta-information, we aim to improve the model's ability to handle diverse types of clinical narratives, ensuring that prompts are consistent and effective across different institutions and clinical contexts.
- **LLM Fine-Tuning on Institution-Specific Data**: To further improve generalizability, we will fine-tune our LLM on clinical corpora from specific institutions. This will help the model adapt to the language, protocols, and treatment guidelines used in different settings, providing more tailored results.
- **Multi-Institutional Validation**: To assess the model's robustness, we will perform validation studies across multiple institutions, ensuring that the model works effectively on diverse datasets and across different types of cancer and patient populations.
- **Real-Time Deployment and On-Device Applications**: We aim to explore real-time deployment in clinical radiotherapy workflows, reducing latency and enabling fast, reliable segmentation during treatment planning. This will involve exploring lightweight LLM architectures (such as DistilLLaMA or Phi-3) for on-device applications, making the model more accessible for clinical practice.

VI. Conclusion

In this study, we presented a novel multimodal segmentation framework that combines large language models (LLMs) with transformer-based vision architectures for radiotherapy planning in head and neck cancer. By fusing volumetric CT imaging with patient-specific clinical notes through LLaMA-2 prompts and integrating them into a ContextUNETR backbone, we demonstrate that leveraging contextual information can significantly enhance segmentation accuracy, especially in anatomically complex and ambiguous cases.

Our experiments showed consistent improvements across standard evaluation metrics such as Dice coefficient, IoU, and Hausdorff distance. Importantly, we demonstrated that the model maintains high performance even under reduced training data conditions, showcasing its data efficiency—a crucial factor in medical domains where labeled data is limited.

Key contributions of this work include:

- A unified, end-to-end multimodal architecture that processes both 3D medical images and free-text clinical notes.
- Integration of LLaMA-2 as a prompt-based text encoder capable of capturing nuanced, domain-specific clinical cues that inform anatomical segmentation.
- Extensive evaluation, including per-patient analysis, data subsampling, and robustness testing, to verify generalizability and real-world applicability.
- Support for interpretability and personalization, allowing clinicians to adjust prompts at inference time for tailored predictions.

Beyond technical merit, this work contributes toward a paradigm shift in medical imaging AI: from passive image analysis to context-aware clinical reasoning systems. By mimicking the decision-making process of radiation oncologists—who combine imaging, patient history, and clinical judgment—our model represents a step closer to human-aligned artificial intelligence in oncology.

Future directions:

- Scaling to larger and multi-institutional datasets to evaluate generalizability across scanners, patient populations, and clinical documentation styles.
- Extending the model to other imaging modalities such as MRI or PET, and other disease types like prostate or lung cancer.
- Real-time deployment and integration into radiotherapy workflows through optimization and inference acceleration (e.g., quantization, distillation).

- Human-in-the-loop evaluation, where clinicians interact with the model and modify prompts, enabling semi-automated contouring with expert oversight.

In summary, our results affirm that LLMs are more than language processors—they are enablers of clinical reasoning augmentation when thoughtfully fused with imaging models. This opens a promising avenue for future AI systems that are not only diagnostically accurate but also clinically collaborative.

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