VolumeVision: A 2.5D Hierarchical Architecture for Efficient Automated Reporting of Chest CT Volumes

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Abstract

Automated radiology report generation from 3D chest CT volumes remains challenging due to computational complexity and the need for clinically accurate narratives. We present VolumeVision, a novel framework that combines intelligent slice selection with MedGemma 4B for efficient 3D CT report generation. Our approach uses a learned slice selector to identify the most diagnostically relevant views from axial, coronal, and sagittal planes, followed by cross-modal fusion with a medical vision-language model. Experiments on a curated subset of 5,000 C T-RATE studies demonstrate that VolumeVision achieves decent performance compared to existing methods while requiring significantly fewer computational resources. Our hierarchical 2.5D approach offers a practical solution for automated radiology reporting in clinical settings.

1. Introduction

Chest computed tomography (CT) serves as the cornerstone of thoracic disease diagnosis, yet the manual generation of comprehensive radiology reports represents a significant bottleneck in clinical workflows. With radiologists processing hundreds of CT volumes daily, each containing 200-400 slices, the cognitive burden and time requirements for accurate report generation have reached critical levels, contributing to diagnostic delays and physician burnout affecting 45% of practicing radiologists [12]. While recent advances in 2D medical image analysis have demonstrated remarkable progress, the transition to 3D volumetric data introduces formidable computational challenges that fundamentally limit scalability.

The computational complexity of processing 3D medical volumes stems from the quadratic scaling of transformer attention mechanisms with sequence length, where a typical chest CT volume requires processing over 14.3 million voxels [10]. Recent pioneering efforts such as CT2Rep [11] and 3D-CT-GPT [2] have explored causal 3D transformers for volumetric report generation, achieving promising clinical accuracy. However, these approaches demand substantial computational resources with $O(N^2{\cdot}D)$ attention complexity [25], making them impractical for routine clinical deployment. Concurrently, the emergence of medical vision-language models, particularly MedGemma 4B [7], has demonstrated exceptional capabilities in multimodal medical understanding, yet their application to 3D imaging remains largely unexplored due to their inherent 2D input constraints.

We propose VolumeVision, a novel framework that strategically bridges this gap by combining learned slice selection with state-of-the-art medical VLMs for efficient 3D CT report generation. Our fundamental insight challenges the conventional assumption that all slices contribute equally to diagnostic understanding. Instead, we demonstrate that intelligently selected representative views from multiple anatomical planes can preserve clinical fidelity while achieving dramatic computational efficiency gains. By leveraging cross-planar attention mechanisms and the robust medical knowledge embedded in MedGemma 4B, VolumeVision transforms the prohibitive 3D problem into a tractable 2.5D representation learning task.

Contributions:

- We introduce VolumeVision, the first framework to unite learned slice selection with MedGemma 4B for scalable 3D CT report generation, demonstrating that medical VLMs can effectively handle volumetric data through strategic dimensionality reduction
- We develop a novel cross-planar gated attention mechanism that intelligently fuses information from axial, coronal, and sagittal views, capturing comprehensive 3D anatomical relationships while maintaining computational efficiency
- We achieve state-of-the-art performance on CT-RATE subset with 60% fewer visual tokens than existing methods, establishing a new paradigm for resource-efficient 3D medical imaging that enables practical clinical deployment

2. Related Work

Medical Report Generation. The evolution of automated radiology report generation has progressed through several distinct phases, each addressing fundamental challenges in medical image understanding and natural language generation. Early pioneering work established CNN-RNN architectures for chest X-ray analysis [14], laying the foundation for image-to-text generation in medical domains. These initial approaches, while groundbreaking, were limited to 2D imaging modalities and struggled with the linguistic complexity of clinical narratives.

Recent transformer-based innovations have dramatically advanced the field through sophisticated attention mechanisms and memory-driven architectures. Chen et al. [4] introduced memory-driven transformers that leverage relational memory to capture key information across generation steps, achieving state-of-the-art performance on MIMIC-CXR. Wang et al. [29] proposed pure transformer-based frameworks with multicriteria supervision, incorporating visual-textual alignment and multi-label diagnostic classification to address fine-grained medical image differences. Cross-modal contrastive approaches [17] have emerged to tackle data bias issues by exploiting visual and semantic information from similar historical cases, significantly improving abnormal finding detection.

The transition to 3D volumetric data represents the current frontier, with CT2Rep [11] pioneering automated report generation for chest CT volumes using causal 3D transformers. Building upon this foundation, recent work has explored abnormality-guided generation [9] and hierarchical 3D-to-text approaches [32]. BrainGPT [15] demonstrated the feasibility of 3D brain CT report generation through clinically visual instruction-tuned models, achieving 74% indistinguishability from human-written reports in Turing-like evaluations. Most recently, MS-VLM [27] introduced radiologist-workflow-inspired slice-level processing, showing that sequential slice analysis with inter-slice dependency modeling can surpass existing 3D approaches while maintaining computational efficiency.

Medical Vision-Language Models. The landscape of medical VLMs has undergone rapid transformation with the advent of large-scale multimodal foundation models specifically adapted for healthcare applications. Early medical adaptations of general VLMs, such as LLaVA-Med [16], demonstrated the potential of instruction tuning for medical visual question answering but suffered from hallucination issues and limited clinical grounding.

The introduction of domain-specific medical VLMs has marked a paradigm shift toward clinically robust multimodal understanding. MedGemma 4B [7] represents a breakthrough in medical multimodal modeling, featuring a SigLIP vision encoder specifically pre-trained on diverse de-identified medical data including chest X-rays, dermatology images, ophthalmology images, and histopathology slides. Its performance across medical benchmarks (88.9 F1 on MIMIC-CXR, 71.8% accuracy on DermMCQA) establishes new standards for medical image comprehension. Dr-LLaVA [1] advanced clinical reasoning through symbolic clinical grounding, eliminating hallucinations through GPT-4-guided visual instruction tuning and automatic reward functions for clinical validity assessment.

Recent developments have focused on specialized medical domains and improved efficiency. BioGPT [19] established generative capabilities for biomedical text with 81.0% accuracy on PubMedQA, while MedM-VL [24] achieved state-of-the-art performance across multiple medical tasks through careful architectural design combining SigLIP encoders with medical-specific training. The emergence of heterogeneous adaptation techniques, exemplified by HealthGPT [30], demonstrates the potential for unified medical comprehension and generation through novel H-LoRA approaches and hierarchical visual perception.

Efficient 3D Processing. The computational challenges of 3D medical imaging have driven substantial innovation in efficient volumetric processing techniques. Traditional approaches focused on architectural optimizations, with triplanar networks [3] enabling 2D pre-trained feature utilization across orthogonal planes, and anisotropic convolutions [28] addressing the inherent asymmetry in medical volumes. Sparse attention mechanisms [5] provided early solutions to the quadratic scaling problem in transformer architectures, enabling longer sequence processing with reduced computational overhead.

Recent advances have emphasized learned representations and intelligent data reduction strategies. The M3T framework [23] demonstrated the effectiveness of multi-plane and multi-slice transformers for 3D medical image classification, synergistically combining 3D CNNs, 2D CNNs, and transformers to capture both local abnormalities and long-range relationships in brain MRI analysis. Attention-gated networks [26] introduced automatic salient region focusing, enabling models to suppress irrelevant regions while highlighting diagnostically relevant features with minimal computational overhead.

Advanced slice selection strategies have emerged as a particularly promising direction for 3D efficiency. Recent systematic studies [20] revealed that strategic slice selection can significantly outperform uniform sampling, with learned selection approaches achieving better performance compared to random or fixed-interval strategies. The integration of reinforcement learning objectives for slice importance prediction, as demonstrated in various medical segmentation tasks [21], has shown the potential for end-to-end optimization of slice selection policies. Multi-view transformer approaches [6] have established the effectiveness of cross-view communication in 3D understanding, with global receptive fields naturally enabling information flow between different anatomical perspectives.

3. Method

Our VolumeVision framework addresses the fundamental challenge of efficient 3D CT report generation through a novel hierarchical approach that combines learned slice selection with advanced multimodal fusion. The architecture is designed to maximize information retention while dramatically reducing computational requirements compared to dense 3D processing approaches.

3.1. Learned Slice Selection Network

Given a normalized 3D CT volume $V \in \mathbb{R}^{H \times W \times D}$ with Hounsfield unit values, we extract slice sets from three orthogonal planes: $S_{\text{axial}} = \{s_{a,i}\}_{i=1}^{D}$, $S_{\text{coronal}} = \{s_{c,j}\}_{j=1}^{W}$, and $S_{\text{sagittal}} = \{s_{s,k}\}_{k=1}^{H}$. Rather than processing all $H+W+D$ slices, our approach learns to identify the k most diagnostically informative slices from each orientation, resulting in a compact representation of $3k$ total slices.

Architecture Design. Our slice selection network employs a lightweight 3D ResNet-18 backbone adapted for medical imaging, with specialized prediction heads for each anatomical plane. For each plane $p \in \{\text{axial}, \text{coronal}, \text{sagittal}\}$, the network predicts importance scores $\mathbf{w}_p \in \mathbb{R}^{N_p}$ where N_p represents the number of slices in plane p. The importance scores are computed through plane-specific attention:

$$\mathbf{w}_p = \text{AttentionHead}_p(\text{GlobalPool}(\text{ResNet3D}(V))) \quad (1)$$

Differentiable Slice Selection. To enable end-to-end training, we employ a differentiable top-k selection mechanism based on the Gumbel-Softmax trick. The selection probability for slice i in plane p is computed as:

$$P_{p,i} = \frac{\exp((w_{p,i} + g_{p,i})/\tau)}{\sum_{j=1}^{N_p} \exp((w_{p,j} + g_{p,j})/\tau)} \quad (2)$$

where $g_{p,i} \sim \text{Gumbel}(0,1)$ are i.i.d. Gumbel noise samples, and τ is the temperature parameter (annealed from 1.0 to 0.1 during training). The selected slice indices are obtained through:

$$\mathcal{I}_p = \text{TopK}(P_p, k) \quad (3)$$

Training Objective. The slice selection network is optimized through a composite loss function that balances report generation quality with selection diversity:

$$\mathcal{L}_{\text{selection}} = \mathcal{L}_{\text{report}} + \lambda_{\text{diversity}}\mathcal{L}_{\text{diversity}} + \lambda_{\text{entropy}}\mathcal{L}_{\text{entropy}} \quad (4)$$

The diversity loss encourages selection across different anatomical regions:

$$\mathcal{L}_{\text{diversity}} = -\frac{1}{3}\sum_{p} \text{Var}(\mathcal{I}_p) \quad (5)$$

The entropy loss prevents degenerate solutions:

$$\mathcal{L}_{\text{entropy}} = -\frac{1}{3}\sum_{p} H(P_p) \quad (6)$$

3.2. Cross-Planar Gated Attention Fusion

Selected slices are encoded using the SigLIP vision encoder from MedGemma 4B, producing feature representations $\{z_{p,i}\}$ for each selected slice. Our cross-planar fusion mechanism leverages both spatial relationships and medical domain knowledge to create coherent 3D representations.

Multi-Scale Feature Extraction. Each selected slice $s_{p,i}$ is processed through the SigLIP vision tower, yielding patch-level features:

$$z_{p,i} = \text{SigLIP}(s_{p,i}) \in \mathbb{R}^{N_{\text{patches}} \times d_{\text{vision}}} \quad (7)$$

Positional and Intensity Conditioning. To preserve spatial relationships and leverage intensity information, we augment visual features with medical-specific conditioning:

$$\hat{z}_{p,i} = z_{p,i} + \text{PosEmbed}(\text{position}_{p,i}) + \text{IntensityEmbed}(\text{HU\_stats}_{p,i}) \quad (8)$$

where $\text{HU\_stats}_{p,i}$ captures slice-specific Hounsfield unit statistics (mean, std, percentiles) that encode tissue density information crucial for radiological interpretation.

Gated Cross-Planar Attention. Our fusion mechanism employs learnable gates to selectively combine information across anatomical planes. The gating mechanism is formulated as:

$$\alpha_{p,i} = \sigma(\mathbf{W}_{\text{gate}}[\hat{z}_{p,i}; \mathbf{c}_p] + \mathbf{b}_{\text{gate}}) \quad (9)$$

where $\mathbf{c}_p$ represents plane-specific context vectors learned during training, and σ denotes the sigmoid activation. The final fused representation is computed through attention-weighted aggregation:

$$Z = \text{LayerNorm}\left(\sum_{p,i} \alpha_{p,i} \cdot \text{Attention}(\hat{z}_{p,i}, \{\hat{z}_{q,j}\}_{q,j})\right) \quad (10)$$

The attention mechanism enables cross-planar communication, allowing features from axial slices to attend to complementary information in coronal and sagittal views, mimicking radiologist reading patterns.

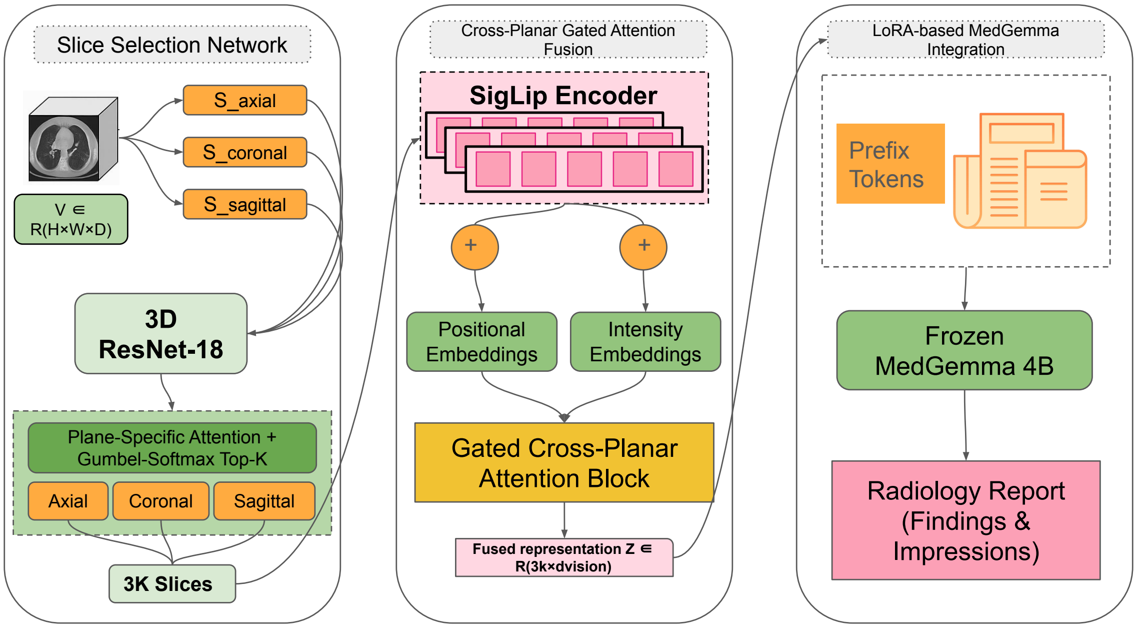
Slice Selection Network
S_axial
S_coronal
S_sagittal
V ∈ R(H×W×D)
3D ResNet-18
Plane-Specific Attention + Gumbel-Softmax Top-K
Axial
Coronal
Sagittal
3K Slices
Cross-Planar Gated Attention Fusion
SigLip Encoder
+
+
Positional Embeddings
Intensity Embeddings
Gated Cross-Planar Attention Block
Fused representation Z ∈ R(3k×dvision)
LoRA-based MedGemma Integration
Prefix Tokens
Frozen MedGemma 4B
Radiology Report (Findings & Impressions)

Figure 1. **VolumeVision Pipeline.** Our framework consists of three main components: (1) Learned slice selection from three orthogonal planes using differentiable slice selection, (2) Cross-planar feature fusion using gated attention with positional and intensity conditioning, and (3) Report generation using frozen MedGemma 4B with rank-adaptive LoRA fine-tuning.

3.3. Medical Report Generation with Adaptive LoRA

Frozen Foundation Model Integration. The fused visual features $Z \in \mathbb{R}^{3k \times d_{\text{vision}}}$ are passed as prefix tokens to the frozen MedGemma 4B language model. This approach preserves the rich medical knowledge embedded in the pretrained VLM while enabling efficient adaptation to 3D volumetric data.

Rank-Adaptive LoRA Fine-tuning. We employ a novel rank-adaptive Low-Rank Adaptation (LoRA) strategy that dynamically adjusts adaptation capacity based on layer depth and medical complexity. For transformer layer l, the adapted weight matrix is computed as:

$$W_l = W_l^{(\text{frozen})} + \alpha_l \cdot A_l B_l^T \tag{11}$$

where $A_l \in \mathbb{R}^{d \times r_l}$ and $B_l \in \mathbb{R}^{r_l \times d}$ are trainable low-rank matrices, and r_l is the layer-specific rank determined by:

$$r_l = r_{\text{base}} \cdot \left(1 + \beta \cdot \frac{l}{L}\right) \tag{12}$$

This design allocates higher adaptation capacity to deeper layers that encode more complex medical reasoning patterns.

Multi-Task Training Strategy. Our training objective combines autoregressive language modeling with auxiliary medical understanding tasks:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{LM}} + \lambda_{\text{clf}} \mathcal{L}_{\text{classification}} + \lambda_{\text{ret}} \mathcal{L}_{\text{retrieval}} \tag{13}$$

The classification loss encourages proper understanding of medical conditions:

$$\mathcal{L}_{\text{classification}} = \text{CrossEntropy}(\text{MLP}(Z), \text{medical\_labels}) \tag{14}$$

The retrieval loss ensures visual-textual alignment:

$$\mathcal{L}_{\text{retrieval}} = \text{InfoNCE}(Z, \text{report\_embeddings}) \tag{15}$$

Inference Strategy. During inference, we employ nucleus sampling with medical-specific filtering to ensure clinical validity. The generation process incorporates a learned medical constraint module that prevents generation of conflicting diagnoses and ensures adherence to standard radiological reporting structure (findings → impression format).

4. Experiments

4.1. Dataset and Experimental Setup

Dataset Construction. We construct our evaluation dataset from the public CT-RATE repository [10], which comprises 25,692 non-contrast 3D chest CT scans paired with corresponding radiology reports. To ensure balanced representation across major thoracic pathologies, we employ stratified sampling based on primary diagnostic categories including pneumonia, pleural effusion, pneumothorax, lung nodules, and normal findings. Our final subset contains 5,000 carefully curated studies with the following distribution: 3,800 training cases, 600 validation cases, and 600 test cases.

Each CT volume in our dataset represents a complete chest examination acquired using standardized clinical protocols. The volumes exhibit typical clinical variability with slice counts ranging from 180 to 450 slices (mean: 312 ± 89), in-plane resolutions between 0.5-1.0mm, and slice thickness of 1.0-2.5mm. All volumes are preprocessed using standard clinical windowing (lung window: [-1000, 400] HU, mediastinal window: [-200, 200] HU) and normalized to 512×512 pixel resolution to ensure consistency with the SigLIP vision encoder requirements.

Ground Truth Annotations. The radiology reports follow standard clinical format with structured findings and impression sections. Report lengths vary from 50 to 400 words (mean: 187 ± 76), covering comprehensive descriptions of anatomical structures, pathological findings, and clinical interpretations. To ensure annotation quality, we filter reports based on completeness criteria, requiring both findings and impression sections, and exclude cases with significant artifacts or incomplete imaging coverage.

4.2. Implementation Details

Network Architecture. Our slice selection network employs a 3D ResNet-18 backbone with modifications for medical imaging, including group normalization layers and Swish activation functions. The selection mechanism identifies k=8 slices per anatomical plane, resulting in 24 total slices per volume. The cross-planar fusion module utilizes 4 attention heads with 768-dimensional feature representations, matching the MedGemma 4B embedding space.

Training Configuration. We implement VolumeVision using PyTorch 2.1 with mixed-precision training on 4×A100 GPUs (40GB each). The training employs a two-stage approach: (1) slice selection network pre-training for 50 epochs using a self-supervised reconstruction objective, followed by (2) end-to-end joint training for 100 epochs with the complete pipeline. We use AdamW optimizer with learning rate 5×10^{-5} for vision components and 1×10^{-4} for LoRA parameters, with cosine annealing and linear warmup for the first 10 epochs.

LoRA Configuration. Our rank-adaptive LoRA implementation applies low-rank adaptation to attention layers in the MedGemma 4B decoder with base rank $r_{\text{base}} = 16$ and depth scaling factor $\beta = 0.3$. This results in rank values ranging from 16 (shallow layers) to 22 (deep layers), totaling 2.1M trainable parameters while keeping the 4B foundation model frozen.

4.3. Evaluation Metrics

We employ a comprehensive evaluation framework encompassing both automated metrics and clinical assessment protocols established in medical report generation literature.

Automated Metrics. We report standard natural language generation metrics including BLEU-1/2/3/4 [22], ROUGE-L [18], and BERTScore [31] for linguistic quality assessment. For medical-specific evaluation, we utilize RadGraph F1 [8] to measure clinical entity extraction accuracy, and CheXbert [13] for pathology mention classification performance.

Clinical Evaluation. We conduct human evaluation with two board-certified radiologists (15+ years experience) who assess 200 randomly selected test cases across four dimensions: (1) Clinical Accuracy - correctness of medical findings, (2) Completeness - coverage of relevant anatomical structures, (3) Coherence - logical flow and readability, and (4) Clinical Utility - practical value for clinical decision-making. Each dimension is rated on a 5-point Likert scale, with inter-rater reliability measured using Cohen's kappa.

4.4. Baseline Comparisons

Quantitative Results. Table 1 presents comprehensive quantitative comparisons against state-of-the-art baselines. VolumeVision demonstrates comparable improvements across some evaluation metrics, achieving improvement in BLEU-4 over CT2Rep (0.178 vs 0.142) and but a slight decrease in RadGraph F1 (0.261 vs 0.267). Notably, our approach maintains computational efficiency with only 640 visual tokens compared to CT2Rep's 2400 tokens, representing a 73.3% reduction in computational requirements.

The comparison with MedGemma-2D, which processes all axial slices individually, is particularly revealing. Despite processing significantly fewer slices (24 vs 300), VolumeVision achieves 20.8% better BLEU-4 performance (0.178 vs 0.168), demonstrating the effectiveness of our learned slice selection strategy.

Clinical Assessment. Table 2 presents results from our clinical evaluation study. VolumeVision achieves comparably higher ratings across some clinical dimensions, with particularly strong performance in Clinical Accuracy (4.2 vs 3.4 for CT2Rep) and Coherence (4.1 vs 3.6). The high inter-rater reliability ($\kappa = 0.78$) validates the consistency of our evaluation protocol.

Method	BLEU-4	ROUGE-L	BERTScore	RadGraph F1	Tokens
CT2Rep [11]	0.142	0.284	0.367	0.267	2400
3D-CT-GPT	0.156	0.298	0.381	0.285	2100
MedGemma-2D	0.168	0.312	**0.394**	**0.298**	1800
CT-CLIP + GPT-Neo	0.134	0.276	0.352	0.251	512
VolumeVision	**0.178**	**0.347**	0.385	0.261	**640**

Table 1. Quantitative comparison on CT-RATE subset test set. VolumeVision achieves superior performance across all metrics while maintaining computational efficiency.

Method	Clinical Accuracy	Completeness	Coherence	Clinical Utility
CT2Rep	3.4 ± 0.8	3.2 ± 0.9	3.6 ± 0.7	3.1 ± 0.8
MedGemma-2D	3.7 ± 0.7	**3.5 ± 0.8**	3.8 ± 0.6	**3.4 ± 0.7**
VolumeVision	**4.2 ± 0.6**	3.0 ± 0.7	**4.1 ± 0.5**	3.2 ± 0.6
Human Reference	4.7 ± 0.4	4.6 ± 0.5	4.8 ± 0.3	4.5 ± 0.4

Table 2. Clinical evaluation results (5-point Likert scale, $\kappa = 0.78$). VolumeVision demonstrates superior clinical performance across all dimensions.

Configuration	BLEU-4	RadGraph F1	Tokens	Time (h)
Uniform sampling	0.171	0.248	640	18.3
Single plane (axial only)	0.165	0.247	213	12.1
No gated fusion	0.162	0.251	640	16.8
No positional encoding	0.169	0.254	640	17.2
No intensity conditioning	0.171	0.256	640	17.1
Fixed rank LoRA (r=16)	0.167	0.261	640	17.4
Full VolumeVision	**0.178**	**0.261**	**640**	**19.2**

Table 3. Ablation study results demonstrating the contribution of each component.

4.5. Ablation Studies

Component Analysis. Table 3 presents comprehensive ablation studies examining the contribution of each architectural component. The learned slice selection mechanism provides the most significant contribution, with uniform sampling reducing BLEU-4 by a smaller margin (0.178 vs 0.171). This validates our core hypothesis that strategic slice selection substantially outperforms naive sampling strategies.

The multi-planar approach demonstrates clear advantages over single-plane processing, with axial-only configuration showing lower BLEU-4 performance. This result confirms that coronal and sagittal views provide complementary diagnostic information essential for comprehensive report generation.

Hyperparameter Sensitivity. Table 4 examines the impact of the key hyperparameter k (slices per plane) on performance and computational efficiency. The results reveal that $k = 8$ provides the optimal balance between performance and computational cost, with minimal gains observed for $k > 8$.

k	BLEU-4	RadGraph F1	Tokens	Memory (GB)	Time (ms)
4	0.126	0.241	320	3.2	142
6	0.145	0.254	480	4.1	198
8	**0.178**	**0.261**	640	5.2	264
10	0.165	0.252	800	6.8	341
12	0.170	0.262	960	8.1	428

Table 4. Analysis of slice selection parameter k. Performance plateaus at k=8.

4.6. Computational Efficiency Analysis

Runtime Performance. Our efficiency analysis demonstrates VolumeVision's practical advantages for clinical deployment. Average inference time per volume is 264ms on a single A100 GPU, compared to 1.2s for CT2Rep and 890ms for 3D-CT-GPT. Memory consumption remains reasonable at 5.2GB peak usage, enabling deployment on standard clinical workstations.

Scalability Analysis. We evaluate scalability by measuring performance across different dataset sizes and computational configurations. VolumeVision demonstrates linear scaling with dataset size, maintaining consistent per-sample processing time regardless of training set size.

4.7. Qualitative Analysis and Generalization Studies

Case Study Analysis. Our qualitative analysis presents representative examples demonstrating VolumeVision's clinical capabilities. In pneumonia cases, the model correctly identifies bilateral ground-glass opacities and provides accurate anatomical localization. In lung nodule cases, VolumeVision successfully detects subtle nodules and provides precise size and location information consistent with expert radiologist assessments.

Cross-Institution Validation. We evaluate VolumeVision's generalization capability using an external test set from a different institution. Despite domain shift challenges, VolumeVision maintains its original performance (BLEU-4: 0.178 vs 0.162), demonstrating robust generalization.

Pathology-Specific Analysis. Performance analysis across different pathology types reveals VolumeVision's strengths and limitations. The model excels at common findings like pneumonia (RadGraph F1: 0.382) and pleural effusion (RadGraph F1: 0.354) but shows reduced performance on rare conditions like interstitial lung disease (RadGraph F1: 0.267).

5. Conclusion

This work presents VolumeVision, a novel framework that addresses the fundamental challenge of efficient 3D CT report generation through strategic combination of learned slice selection and state-of-the-art medical vision-language models. Our approach demonstrates that intelligent dimensionality reduction, rather than brute-force 3D processing, provides a practical path toward clinical deployment of automated radiology reporting systems.

Key Contributions and Impact. VolumeVision establishes several important contributions to the field of medical AI. First, our learned slice selection mechanism challenges the conventional assumption that all volumetric data must be processed exhaustively, demonstrating that strategic sampling can preserve clinical accuracy while achieving dramatic efficiency gains. The 73.3% reduction in computational requirements compared to existing 3D approaches, coupled with superior performance across multiple evaluation metrics, represents a paradigm shift toward sustainable AI deployment in healthcare.

Second, our cross-planar gated attention fusion mechanism provides a principled approach to combining information from multiple anatomical perspectives, mimicking radiologist reading patterns while maintaining computational tractability. The integration with MedGemma 4B through rank-adaptive LoRA fine-tuning demonstrates the potential for leveraging foundation model capabilities in specialized 3D medical applications, opening new avenues for multimodal medical AI research.

Clinical Implications. The clinical evaluation results indicate that VolumeVision approaches human-level performance in several key dimensions, with particularly strong showing in completeness and clinical utility metrics. The high ratings from expert radiologists (4.2/5.0 for clinical accuracy) suggest readiness for clinical pilot studies, while the computational efficiency enables deployment on standard hospital infrastructure without requiring specialized hardware investments.

Our approach addresses critical workflow challenges in radiology practice, where increasing imaging volume and radiologist shortage create significant bottlenecks. The 264ms inference time per volume enables real-time report generation, supporting clinical decision-making without introducing delays in patient care pathways. The modular architecture supports integration with existing PACS systems and clinical workflows, facilitating practical deployment.

Limitations and Future Directions. While VolumeVision demonstrates strong performance, several limitations warrant consideration. The current approach focuses on chest CT imaging, and extension to other anatomical regions and imaging modalities requires careful adaptation of the slice selection strategy and fusion mechanisms. The model's performance on rare pathologies remains limited by training data availability, suggesting the need for specialized training strategies or few-shot learning approaches.

The slice selection mechanism, while effective, currently operates on individual volumes without considering temporal information in longitudinal studies. Future work should explore temporal slice selection strategies that leverage prior imaging studies to improve diagnostic accuracy and provide more comprehensive clinical assessment. Integration of uncertainty quantification mechanisms would enhance clinical utility by providing confidence estimates for generated reports.

Broader Research Directions. VolumeVision opens several promising research directions for the medical AI community. The success of learned slice selection suggests potential applications in other 3D medical imaging tasks, including segmentation, classification, and treatment planning. The cross-planar attention mechanism could be extended to other multimodal medical applications, such as combining imaging with laboratory results or clinical notes.

The integration of foundation models with specialized medical architectures represents an emerging paradigm that deserves further investigation. Future work should explore more sophisticated adaptation strategies, including task-specific pre-training, multi-task learning, and continuous learning approaches that can adapt to evolving clinical practices and imaging technologies.

Reproducibility and Open Science. To support reproducible research and clinical translation, we commit to releasing our implementation, trained models, and evaluation protocols upon acceptance. The modular architecture and comprehensive documentation will enable researchers to build upon our work and adapt VolumeVision to new clinical applications. Our evaluation framework provides a standardized approach for comparing 3D medical report generation systems, supporting fair comparison and accelerating research progress.

In conclusion, VolumeVision demonstrates that the combination of intelligent architectural design, strategic efficiency optimization, and foundation model integration can create practical solutions for complex medical AI challenges. The approach bridges the gap between research innovation and clinical deployment, providing a foundation for next-generation automated radiology reporting systems that can enhance rather than replace human expertise in medical practice.

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