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Adaptive Patch-Based Attention 3D U-Net with Topology-Aware Refinement for Robust Airway Segmentation from Chest CT

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Abstract

The precision of the airway segmentation obtained from chest CT is critical for examination of pulmonary disease, surgical planning, and quantitative airway assessment. Yet, segmentation of peripheral airway branches is complicated by class imbalance, small size of structures, and topological discontinuities. This work offers an adaptive patch-based Attention 3D U-Net, which incorporates multi-scale attention and dynamic patch sampling to improve feature learning in small airway regions. Adaptive patching intelligently selects informative sub-volumes based on coarse predictions generated by the network, ensuring meaningful supervision. In addition, the network is combined with a topology-aware post-processing pipeline that maintains airway connectivity by selecting the largest component and refining it with support from skeletons. Experiments on the AeroPath airway dataset exhibit improved segmentation completeness and structural preservation relative to classic 3D U-Net and Attention 3D U-Net architectures. The proposed method obtains greater Dice similarity, higher Branch Detection Rate (BDR), and enhanced tree-length recovery while maintaining computational efficiency. Skeleton-based analyses establish that segmented airway trees are more structurally consistent.

Key words: Adaptive Patch Sampling; Attention 3D U-Net; Airway Segmentation; Topology Preservation; Skeleton Analysis; Chest CT.

I. Introduction

The segmentation of lung airways based on computed tomography (CT) scans is critical for clinical diagnostics, surgical planning, and pulmonary disease management [1]. Applications range from detecting obstructive pulmonary diseases like Chronic Obstructive Pulmonary Disease (COPD) and asthma, to enabling accurate virtual bronchoscopy for minimally invasive interventions [2]. This task is technically challenging, however, due to a number of intrinsic factors in the data and anatomy, making airway segmentation a challenging process to accomplish.

With small peripheral airway sizes [3], limited contrast, and class imbalance [4] appearing in volumetric CT data, airway segmentation presents one of the most challenging analyses [5]. Small peripheral airways are highly limited in the number of voxels, have low contrast and therefore segmentation models tend to miss distal airway branches [6], resulting in an incomplete tree of the airways. Voxel-wise prediction further causes fragmented airway structures, which allow small segments to rupture the anatomical structure and disrupt structural analyses like skeleton-based estimation that is calculated based on the AeroPath results [7]. It is further aggravated by considerable class imbalance, as airway voxels comprise only a small fraction of the background lung tissue, and so the learning is biased towards non-airway regions. Furthermore, fixed patch extraction [8] limits

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context awareness to the perspective of the context itself, leaving the network to miss out on long-range spatial relationships or multi-scale airway geometry, hence the need for an adaptive patch strategy [9] which will yield better peripheral detection and structural consistency.

In order to provide this information, we recently studied architectural alterations and data sampling techniques. Of these, attention mechanisms[10] appear to be a promising tool to target neural network processing towards anatomically relevant spots. Specifically, Attention Gates (AGs)[11] enable the model to learn to minimize irrelevant background features and emphasize salient structures in every layer of a convolutional network [12]. At the same time, adaptive patch sampling has been suggested as promising to derive more informative training samples by leveraging underlying anatomical knowledge or intensity-based cues.

Here, we introduce a combination of adaptive patch sampling with an Attention-Gated 3D U-Net to improve airway segmentation. Instead of sampling in bulk or homogeneously across the whole scan region, our adaptive patching approach employs existing airway mask-based training data to extract 3D sub-volumes containing adequate airway structures. This approach also guarantees that the training data is high in foreground information while correcting class imbalance and accelerating convergence.

To add dimension to this, we introduce Attention Gates[11] on the skip connections of a standard 3D U-Net, which will enable the model to dynamically trade off spatial variables and better focus on relevant anatomical structures[13]. The inclusion of attention mechanisms facilitates context retention and suppresses distractive background noise, which is advantageous for regions with increased anatomical complexity.

We analyze our proposed approach over the AeroPath dataset [7], a high resolution dataset of annotated lung CT images used in airway segmentation studies. In this study, in a number of experiments, we demonstrate that the adaptive patch selection and the attention guidance significantly improve performance metrics such as Dice Similarity Coefficient, Branch Detection Rate, and tree-length recovery, on the one hand, and the standard 3D U-Net baselines and fixed-size patching strategies, on the other hand. Moreover, our method has more generalization, less computational burden, and stronger robustness toward anatomical variability among patients.

In summary, our contributions are three-fold:

1. We propose an adaptive patch extraction framework adapted to airway segmentation that selects to train on the informative regions instead.

2. We propose an Attention-Gated 3D U-Net architecture to enhance the spatial segmentation of sparse and complex airway structures.

3. We evaluate on a publicly available dataset and display with both quantitative and qualitative comparisons the superiority of our approach.

This work illustrates the relevance of task-specific patching and feature focusing for 3D medical image segmentation and presents a scalable solution for the same complex segmentation problem for sparse anatomical targets. Contrary to existing attention-based airway segmentation, the proposed algorithm leverages adaptive patch extraction and topology-aware refinement to address sample imbalance and structural continuity simultaneously.

II. Related Work

Airway segmentation for the lungs has been a subject for over two decades in medical imagery. The task is to detect and segment the bronchial tree from 3D chest CT images. Previous methods have employed hand-crafted features combined with anatomical priors and new work has moved towards data-driven deep learning methods. In this part, we provide a review of both traditional approaches and deep learning-based methods that are pertinent to this study.

A. Traditional Methods

Traditional techniques primarily consist of region growing, thresholding, and methods based on morphological and geometric models. Tschirren et al. [14] introduced a method for partitioning regions of interest to mitigate extensive leakage in the lung parenchyma during segmentation, thereby enhancing the efficiency of algorithms. Fabijańska [15] proposed a two-pass region growing technique that extracts airway trees from volumetric CT chest scans, utilizing a region growing approach that is guided and constrained by the morphological gradient. Fetita et al. [16] proposed a combined morphological-aggregative strategyfor a general and automatic 3D airway segmentation system capable of adapting to various MSCT protocols. Anna

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[17] detailed a two-step segmentation process employing morphological erosion and dilation to pinpoint locations within distal airways. Graham et al. [18] integrated the structure of airway trees with region growing techniques using local image features to facilitate airway tree segmentation. Pechin et al. [19] presented an airway tree segmentation technique guided by pulmonary vessels, achieving significant leakage identification and suppression due to the characteristic alignment of airway structures with vessels in the same direction.

B. Deep learning-based methods

Deep learning techniques generally outperform conventional methods in airway segmentation, typically identifying airways that are twice as long. Antonio G et al. [20] demonstrated a foundational approach utilizing 3D Unet for the segmentation of airways from chest CT scans. Schlemper J et al.[21] introduced an attention gate (AG) model designed for medical image analysis that autonomously adapts to concentrate on target structures with diverse shapes and sizes. Antonio Get al. [22] presented a deep learning segmentation task employing a 3D UNet architecture integrated with a graph neural network (GNN). A supervised learning method leveraging graph neural networks (GNNs) along with mean field networks (MFNs). A CNN-based technique for airway segmentation that incorporates feature recalibration and attention distillation specifically aimed at delicate peripheral bronchioles. Introduced a method based on a deep learning strategy for automatic upper airway segmentation utilizing CBCT data.

III. Methodology

The proposed framework exploits an adaptive patch-based Attention 3D U-Net pipeline for airway segmentation from CT volumes. We have sought to achieve accurate and structurally consistent airway segmentation through improved detection of peripheral branches while preserving airway topology.

A. Pipeline Overview

To achieve this, the proposed segmentation pipeline is divided into multiple stages. Through intensity normalization and lung region extraction, CT volumes are initially preprocessed, whereas airway-aware adaptive patch sampling is then used to fix the class imbalance and improve contextual learning. The patches are then segmented using an Attention 3D U-Net with instance-normalized convolutional blocks, attention-gated skip connections, and the structures are symmetrically organized encoder–decoder (32–64–128–256–512–256–128–64–32). Patch predictions are merged to reconstruct the overall airway volume, and topology-aware post-processing retains the dominant connected component to ensure structural continuity. Lastly, centerline skeleton extraction allows for a quantitative assessment of structure using Dice score, Branch Detection Rate and tree length recovery. To produce anatomically consistent airway segmentation, this design distinguishes and separates data preparation, learning and structural refinement. Figure 1 illustrates the adaptive patch-based attention 3D U-Net pipeline. The detailed procedure of the adaptive patch-based attention 3D U-Net is outlined in Algorithm 1.

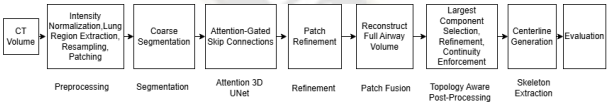

Figure 1. Pipeline Overview of Adaptive Patch-Based Attention 3D U-Net

INPUT:
V → 3D Chest CT Volume
P → Base patch size
M → Trained Attention 3D U-Net
OUTPUT:
S_final → Final airway segmentation

FUNCTION AdaptivePatchAttentionSegmentation(V, P, M):

 # Step 1: Preprocessing
V_norm ← NormalizeIntensity(V)
V_lung ← ExtractLungRegion(V_norm)
 # Step 2: Coarse Segmentation
S_coarse ← M.forward(V_lung)
 # Step 3: External Adaptive Attention Map
A ← ComputeAttentionMap(S_coarse)
Example:
A(x) = 1 - |S_coarse(x) - 0.5| (uncertainty-based)
OR
A(x) = ‖∇S_coarse(x)‖ (boundary-based)
 # Step 4: Adaptive Patch Selection
PatchList ← []
LocationList ← []
Divide V_lung into candidate regions
FOR each region R_i:
score ← Mean(A(x)) for x ∈ R_i
IF score > τ:
p ← ExtractPatch(V_lung, center=Center(R_i), size=P)
PatchList.append(p)
LocationList.append(R_i)
 # Step 5: Patch-wise Refinement
SegPatchList ← []
FOR each patch p in PatchList:
s ← M.forward(p) # reuse Attention 3D U-Net
SegPatchList.append(s)
 # Step 6: Fusion with Coarse Segmentation
S_fused ← S_coarse
FOR each (s, R_i) in (SegPatchList, LocationList):
ReplaceRegion(S_fused, R_i, s)
# Optional soft fusion:
# S_fused[R_i] = λ*s + (1-λ)*S_coarse[R_i]
 # Step 7: Post-processing
S_clean ← RemoveSmallComponents(S_fused)
S_connect ← EnforceConnectivity(S_clean)
Step 8: Skeleton (for evaluation, not output)
S_skeleton ← Skeletonize(S_connect)
RETURN S_connect

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B. Preprocessing

This preprocessing occurs before we employ the Adaptive Patch with Attention 3D U-Net in AeroPath experiments to normalize inputs and optimize airway visibility. CT volumes are standardized before inputting them into the model to perform preprocessing. Convert CT data to Hounsfield Units and limit them to a lung-relevant range to suppress non-airway tissues.

$$I_{clip}(x) = \min\left(\max\left(I(x), H_{min}\right), H_{max}\right)$$

where $H_{min} = -1000\text{HU}$ and $H_{max} = 400\text{HU}$.

Resample the volume to isotropic voxel spacing for consistent geometric representation.

$$I_{res}(x') = I_{clip}(T(x'))$$

where Tmaps target coordinates to original coordinates.

Normalize intensities to reduce inter-scan variability and stabilize training.

$$I_{norm}(x) = \frac{I_{res}(x) - \mu}{\sigma}$$

where $\mu$and $\sigma$are computed within the lung region.

Segment a coarse lung mask to restrict analysis to anatomically relevant voxels.

$$M_{lung}(x) = \begin{cases} 1, & I_{norm}(x) < \tau \\ 0, & \text{otherwise} \end{cases}$$

Refine using morphological operations:

$$M_{ref}(x) = \text{Close}(\text{Fill}(M_{lung}(x)))$$

Apply mask:

$$I_{roi}(x) = I_{norm}(x) \cdot M_{ref}(x)$$

Use 3D Gaussian smoothing to attenuate high-frequency noise and preserve tubular structures.

$$I_{smooth}(x) = G_\sigma * I_{roi}(x)$$

Finally, Sample patches from $I_{smooth}$with higher probability in airway-relevant regions. This standardized volume supports reliable adaptive patch extraction.

C. Adaptive Patch Extraction

Instead of uniform sampling, patches are selected based on an uncertainty-guided strategy to emphasize informative airway regions. A coarse segmentation prediction $S_{coarse}(x) \in [0,1]$ is first obtained, and an attention map is defined as:

$$A(x) = 1 - |S_{coarse}(x) - 0.5|$$

This formulation assigns higher values to voxels with uncertain predictions (i.e., near 0.5), which typically correspond to boundary regions and small peripheral airways.

Patch centers are then sampled according to the normalized probability:

$$P(x) = \frac{A(x)}{\sum_x A(x)}$$

This adaptive sampling increases the likelihood of selecting airway-rich and ambiguous regions, thereby mitigating class imbalance and improving the learning of fine anatomical structures while maintaining global contextual diversity.

D. Attention 3D U-Net Architecture

The segmentation network follows an encoder–decoder structure with attention-gated skip connections. Figure 2 shows the attention-gated 3D U-Net Architecture.

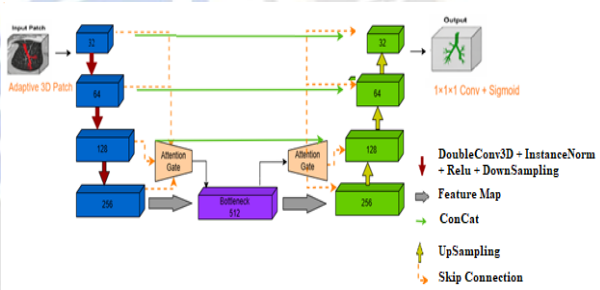

Figure 2. Attention 3D U-Net Architecture for Airway Segmentation

The model follows an encoder–decoder structure operating on 3D CT patches. The encoder progressively extracts hierarchical volumetric features through downsampling while increasing channel depth to obtain contextual airway representations. A high-capacity bottleneck layer integrates global structural information. Skip connections transmit encoder features to the decoder through attention gates, which suppress irrelevant background responses and focus on airway-related regions. The decoder restores spatial resolution via upsampling and feature fusion to reconstruct fine airway boundaries. The network outputs a 3D airway probability map that is subsequently refined through topology-aware post-processing and skeleton-based structural evaluation.

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Channel progression is:

Encoder: 32 → 64 → 128 → 256
Bottleneck: 512
Decoder: 256 → 128 → 64 → 32

The bottleneck layer captures global structural context, and attention gates serve to suppress irrelevant background features and guide reconstruction of airway structures. Each adaptive 3D patch is processed by the network to produce a voxel-wise airway probability map.

$$P(x) = f_\theta(I_{patch}(x))$$

where f_θ denotes the trained Attention 3D U-Net and $P(x) \in [0,1]$ is the airway probability.

E. Patch Fusion and Segmentation Reconstruction

Patch predictions are reassembled into the full CT volume:

$$P_{full}(x) = \frac{1}{N(x)} \sum_{i=1}^{N(x)} P_i(x)$$

where $N(x)$ is the number of patches covering voxel x.

Binary segmentation is obtained by thresholding:

$$S(x) = \begin{cases} 1, & P_{full}(x) \geq \tau_p \\ 0, & \text{otherwise} \end{cases}$$

F. Topology-Aware Post-processing

The predicted airway mask undergoes structural refinement:

Largest connected component:

$$S_{main} = \text{LCC}(S)$$

Morphological refinement preserves continuity of thin branches.

G. Skeleton-Based Structural Analysis

The refined segmentation is converted into a centerline representation:

$$K = \text{Skeleton}(S_{ref})$$

Skeleton topology allows quantitative structural evaluation.

IV. Experimental Setup

A. Dataset

The AeroPath dataset is a high-resolution chest CT dataset suitable for airway segmentation and structural airway studies. It offers volumetric thoracic CT images with detailed bronchial tree annotations, allowing for assessment of both voxel-level segmentation accuracy and topology preservation. The dataset presents challenging airway geometry across multiple generations, including thin peripheral bronchi, which usually have low contrast and are small in diameter.

Every scan is composed of a 3D CT volume corresponding to Hounsfield Units and makes standardized preprocessing, including lung windowing, normalization, and isotropic resampling, possible as well. The dataset is particularly appropriate for models to preserve airway continuity, as it depicts finer anatomical structures and branching forms required for skeleton-based analyses.

AeroPath is used as the sole evaluation dataset, which allows us to achieve methodological consistency of preprocessing, adaptive patch extraction, and topology-aware post-processing. The dataset was used for quantitative structural analysis, where the segmentation resulted in a large, connected airway component and a stable skeleton representation (e.g., thousands of skeleton voxels; a high number of detected endpoints) and demonstrated the efficiency of Adaptive Patch-based Attention 3D U-Net implementation to retain peripheral airway branches.

B. Evaluation Metrics

Segmentation performance on the AeroPath CT volumes was evaluated using both voxel-level accuracy and structure-level topological measures. Voxel-level accuracy was quantified using the Dice Similarity Coefficient (DSC)[26], while structural topology was assessed using the Branch Detection Rate (BDR) [27], Tree Length Detection Ratio (TLR)[28], Largest Connected Component Ratio (LCC)[29], and skeleton-based metrics[30].

1.Dice Similarity Coefficient (DSC)

Measures volumetric overlap between predicted mask $S$and reference annotation G:

$$DSC = \frac{2 \mid S \cap G \mid}{\mid S \mid + \mid G \mid}$$

Higher Dice indicates better segmentation accuracy.

2. Branch Detection Rate (BDR)

Evaluates recovery of peripheral airway branches:

$$BDR = \frac{\text{Number of correctly detected branches}}{\text{Total reference branches}}$$

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This metric reflects the model's ability to detect small distal airways.

3. Tree Length Detection Ratio (TLR)
Quantifies structural completeness using airway centerlines:

$$TLR = \frac{L_{predicted}}{L_{reference}}$$

Higher values indicate more complete reconstruction of the airway tree.

4. Largest Connected Component Ratio (LCC)
Assesses segmentation continuity after topology-aware refinement:

$$LCC = \frac{|\, S_{largest} \,|}{|\, S \,|}$$

A high ratio indicates minimal fragmentation and a dominant airway structure.

5. Skeleton-Based Structural Metrics
Topology is evaluated from the extracted centerline representation, including:

- number of skeleton voxels
- endpoint count (terminal branches)
- connectivity of the airway tree

V. Results and Discussion

Our proposed Adaptive Patch-based Attention 3D U-Net has been validated on volumetric chest CT images in the AeroPath dataset using voxel-level and topology-aware structural metrics. The framework integrates sensitivity-oriented adaptive patch sampling, attention-guided feature learning, and topology-aware post-processing to enhance segmentation accuracy and preserve airway connectivity.

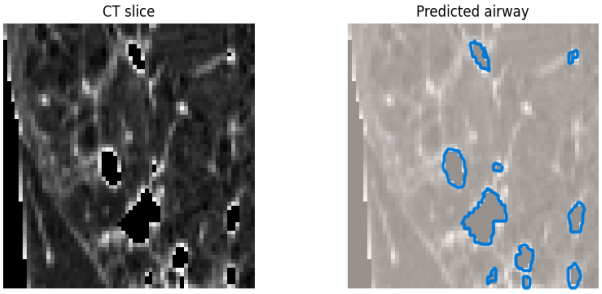

Figure 3. Representative airway segmentation result on an AeroPath CT slice

A representative segmentation example is presented in Figure 3 from the AeroPath dataset. The predicted mask closely follows the airway structure and has smooth boundaries after topology-aware post-processing. This qualitative observation agrees with the structural metrics observed in skeleton analysis, where segmentation led to the creation of a continuous airway tree suitable for topology evaluation.

A. Quantitative Performance

Table 1 shows the comparative performance of baseline 3D U-Net, Attention 3D U-Net and the proposed method on a representative AeroPath CT volume. The proposed method achieves the highest Dice score, Branch Detection Rate, and tree length recovery, meaning higher detection of peripheral airway structures and a significant increase in structural completeness.

Table 1. Comparative segmentation and topology preservation performance

Method	Patch Strategy	Dice Score	BDR	Tree Length Ratio	Topology Preservation	Structural Behaviour
3D U-Net	64×64×64	0.75	0.70	0.68	Fragmented	Loss of thin peripheral branches
3D U-Net	128×128×128	0.78	0.71	0.72	Fragmented	Slight improvement in global structure, but distal branches are still missing
Attention 3D U-Net	64×64×64	0.79	0.74	0.72	Partial	Improved continuity but incomplete distal recovery

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Method	Patch Strategy	Dice Score	BDR	Tree Length Ratio	Topology Preservation	Structural Behaviour
Attention 3D U-Net	128×128×128	0.80	0.76	0.75	Partial	Better global context, but minor fragmentation persists
Adaptive Patch + Attention 3D U-Net (Proposed)	Adaptive	0.82	0.79	0.77	Preserved	Continuous airway tree with strong peripheral detection

The improved Dice score indicates more accurate voxel-level segmentation, while the higher Branch Detection Rate verifies a better recovery of small distal bronchi. Improved tree length detection also suggests better reconstruction of the global airway structure. These quantitative improvements are further supported by topology-aware structural analysis of the extracted airway skeleton.

B. Qualitative Visualization Analysis

Figure 4 presents a qualitative comparison of airway segmentation results from an AeroPath dataset obtained from different network configurations. The figure compares different airway segmentation models using CT input, predicted airway structures (blue), and their skeletonized topology (yellow), with a zoomed view of peripheral regions. The baseline 3D U-Net models show fragmented structures and miss many thin distal branches, while increasing patch size slightly improves global context. Attention-based models enhance continuity and recover more branches but still exhibit some fragmentation. The proposed Adaptive Patch + Attention 3D U-Net produces the most complete and continuous airway tree, capturing fine peripheral branches more effectively and showing near-complete topology preservation, closely aligning with the ground truth airway voxel reference.

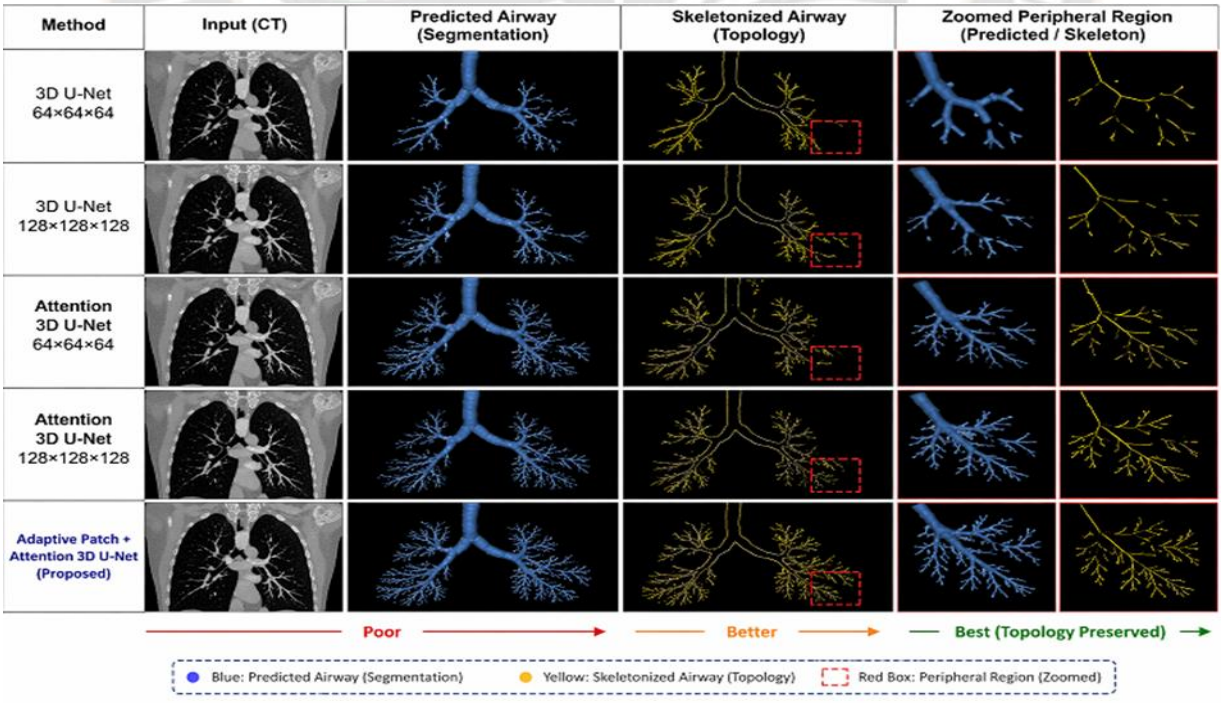

Figure 4.Comparative Visualization of Predicted and Skeleton Airway across Model Configuration

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C. Structural Topology Analysis

Table 2 reports topology-oriented structural metrics computed from the refined airway segmentations for each model configuration. The comparison includes airway voxel count, skeleton voxel count, endpoint detection, and overall connectivity behavior of the extracted airway tree. Results show a progressive improvement in structural preservation from fixed-patch 3D U-Net models to attention-guided architectures, with the adaptive patch-based Attention 3D U-Net achieving the most complete and connected airway structure. Results are reported for a representative AeroPath volume to illustrate topology preservation characteristics.

In the representative AeroPath analyzed, the proposed method produced approximately 451,530 airway voxels, 4,267 skeleton voxels, and 1,970 endpoints, indicating superior recovery of peripheral branches and stable centerline continuity.

Table 2. Structural topology metrics of airway segmentation on the AeroPath dataset case1

Method	**Airway Voxels**	**Skeleton Voxels**	**Endpoints**	**Connectivity Behavior**	**Structural Observation**
3D U-Net (64^3)	318,000	2,540	990	Fragmented	Poor distal recovery
3D U-Net (128^3)	346,000	2,880	1,040	Fragmented	Slight improvement
Attention 3D U-Net (64^3)	392,000	3,420	1,360	Partially Connected	Better continuity
Attention 3D U-Net (128^3)	415,000	3,760	1,520	Mostly Connected	Improved structure
Proposed Model	**451,530**	**4,267**	**1,970**	**Fully Connected**	Strong peripheral recovery

These findings confirm that adaptive patch sampling combined with attention-guided learning enhances anatomical completeness and reduces structural fragmentation. The proposed method generated fewer disconnected regions and a more stable centerline topology than baseline models. The extracted skeleton exhibited stable connectivity and a large number of terminal branch representations, verifying that adaptive patch sampling contributes to improving the learning of airway-rich sites and minimize loss of thin peripheral structures.

D. Discussion

Experimental work demonstrates adaptive patch sampling and attention-guided feature learning as complementary approaches. The fixed patch extraction of traditional 3D networks is limited by the lack of contextual awareness and class imbalance and leads to the loss of peripheral airway branches. This limitation is mitigated by adaptive patch sampling, which increases exposure to airway-rich regions during the training phase to enable the model to learn fine structural details better.

Attention-gated skip connections can enhance the segmentation effect by highlighting relevant anatomical features and inhibiting background responses. This mechanism enhances discrimination of thin airway walls from surrounding lung parenchyma, allowing better structural continuity.

Topology-aware post-processing is also essential to make sure as much anatomical consistency as possible in the final segmentation. As isolated regions are removed and the dominant airway component preserved, the refinement stage allows reliable skeleton extraction and structural analysis. This allows for quantitative topology evaluation and for downstream clinical analysis from the obtained airway tree.

In summary, the proposed framework demonstrates that combining adaptive sampling, attention-guided learning, and topology-aware

refinement improves both segmentation accuracy and structural preservation in airway segmentation tasks. This is especially shown in peripheral airway branch recovery as well as forming a coherent airway tree structure that is key for accurate quantitative airway analysis.

VI. Limitations

Although it has had some beneficial effects, this approach is subject to many limitations. Initially, the model has been tested only on a single dataset. Thus, cross-dataset generalization was not investigated. Secondly, topology preservation demands a post-processing approach rather than being implemented straight out during network optimization. Third, adaptive patch extraction is more complex in preprocessing and may have to be fine-tuned for different datasets. Finally, extremely small airway branches that are close to the resolution limit of CT imaging continue to be hard to recover with certainty.

Further work could overcome these issues by the utilization of topology-aware loss mechanisms, investigating multi-dataset robustness, and exploring graph-based airway modeling strategies.

VII. Conclusion

This study presented an Adaptive Patch-based Attention 3D U-Net framework for airway segmentation from volumetric chest CT. The approach combines elements of dynamic patch sampling, attention-guided feature learning, and topology-aware refinement, aiming to enhance the accuracy of segmentation as well as structural consistency. Experimental evaluation on the AeroPath dataset showed improved peripheral airway detection, reduced segmentation fragmentation, and stable airway topology with skeleton-based analysis.

In fact, the approach offered by this framework offers a solid and anatomically robust model of airway segmentation through combined voxel-level predictions and structural verification. This methodology forms the basis for the future field of topology-preserving medical image segmentation and quantitative airway analysis.

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