Review

A Seven-Component Anatomy-Guided Literature Review Framework for Chronic Respiratory Disease and Medical Imaging

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A Seven-Component Anatomy-Guided Literature Review Framework for Chronic Respiratory Disease and Medical Imaging

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Abstract

Most computational studies in medical imaging are conducted by researchers with IT or engineering backgrounds, who may lack the clinical and anatomical expertise of medical experts. As a result, important anatomical details, clinically relevant features, and medical context are often underrepresented. This highlights the need for anatomy-guided literature reviews that integrate clinical insight with technical requirements to support the development of more generalizable and clinically meaningful methods. To address this gap, we propose a novel seven-component anatomy-guided literature review framework that links anatomical and clinical relevance with the technical aspects required to develop robust computational methods (3D) tailored to specific diseases and imaging modalities for the extraction of clinically important anatomical features. We apply the framework to Chronic Respiratory Diseases (CRDs), which cause progressive and irreversible lung damage and are a major contributor to respiratory failure and mortality in adults. Importantly, many adult CRDs are recognized to originate early in life during critical phases of lung growth and development in children. Despite this, most computational studies related to CRDs are dominated by adult cohorts, with limited focus on pediatric populations, particularly Indigenous children. The framework is demonstrated using key clinically relevant features of adult bronchiectasis (airway dilatation) and pediatric bronchiectasis (lower-lobe airway dilatation), which is highly prevalent among indigenous children. The framework integrates 3 core computational methods (airway tree extraction, artery-vein separation and extraction, and lobar and segmental localization), approx. 10 key technical aspects (branch detection, tree-length detection, leakage control, completeness and connectivity, mean-surface distance, etc.), and literature from the past decade (7 sources, approx. 20 keywords, approx. 52 publications reviewed, and 15 selected). This process enabled the identification of key limitations and 30 overall research gaps, anatomically and clinically grounded across the selected CRDs and features. Overall, the proposed framework provides a novel way for developing robust, clinically meaningful computational methods applicable to children and anatomically diverse populations across CRDs and other diseases.

Keywords: anatomy-guided framework; chronic respiratory diseases; bronchiectasis; 3D reconstruction; airway tree; artery-vein separation; lobar and segmental localization; HRCT; adult imaging; pediatric imaging; medical imaging

1. Introduction

Over the years, medical imaging and computational studies have relied on a variety of literature review approaches, including narrative, systematic, scoping, technical, integrative, and critical, each offering a particular way of organizing, analyzing, and interpreting prior work. A simple literature search on Google Scholar using general keywords such as *airway segmentation review, CT deep learning*

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review, medical AI review, radiology AI review, 3D medical imaging, and clinical imaging AI review, shows that most identified studies focus primarily on summarizing existing methods and neural network architectures, benchmarking their performance on common datasets, and mapping research trends and future directions [1,2]. Importantly, no studies were found across multiple databases that conducted literature reviews using anatomical or clinically grounded criteria, an important gap this research specifically aims to address [3]. This can assist future researchers in developing both generalizable methods and task-specific (non-generalizable) independent methods that maintain efficiency while accounting for anatomical diversity across different population groups, age groups, and geographic regions. To fill this gap, this study introduces a novel literature review (LR) framework for the medical-imaging domain that can be applied to any disease or condition.

The proposed framework integrates seven components (see Figure 1):

- Clinical anatomical requirements of the disease.
- Anatomical features visible/partially visible/not visible in the medical-imaging data.
- Technical aspects/methods that computational researchers focused on for robust extraction of the features from the data.
- Evaluation metrics used to assess the performance of technical methods, along with comparisons between relevant existing computational studies.
- Limitations identified for each technical aspect in terms of evaluation metrics.
- Anatomy-based limitations to identify the clinical anatomical structures that are missed by the existing computational methods.
- Overall research gaps from both computational and anatomical perspectives.

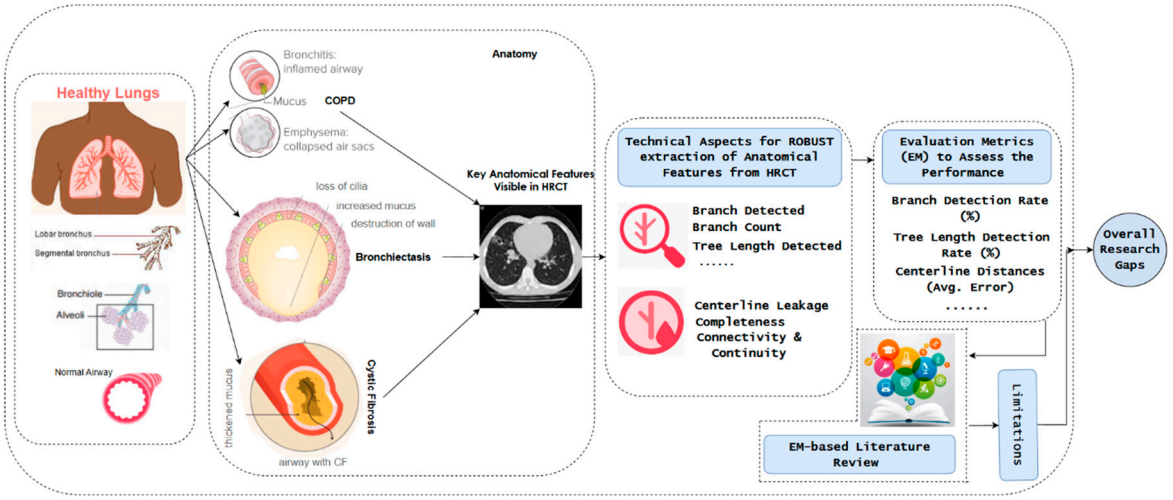

Figure 1. Seven-Component LR Framework.

1.1. Chronic Respiratory Diseases (CRDs)

For this study, CRDs were chosen as the domain for implementing the proposed LR framework. This is because CRDs have imparted a huge global disease and economic burden [4,5], with indigenous people and low-income groups (LIGs) in high-income countries (HICs: Australia, New Zealand, United States, Canada, and Others), as well as populations in many low- and middle-income countries (LMICs), experiencing disproportionately higher prevalence and elevated risks of morbidity, disability, and mortality [6,7]. It is also evident that the anatomical structures relevant to CRDs vary across population groups, age groups, and gender groups, both within and among countries. These variations arise not only from current risk factors [8,9], such as smoking, exposure to dry and cold climates, prematurity, low birthweight, poor nutrition, air pollution, high burden of infections, poverty, poor access to appropriate diagnosis and care, remoteness, socio-economic disadvantage, and genetic influences [10], but also from the enduring consequences of historical events that have resulted in generational trauma. Furthermore, most computational studies relevant

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to CRDs have relied predominantly on adult cohorts, with comparatively limited attention given to pediatric and indigenous cohorts [11,12]. These clear and persistent disparities make CRDs an ideal domain for implementing the proposed LR framework, enabling computational researchers to identify the key factors needed to develop both generalizable and population- or age-specific independent methods.

Many CRDs require the extraction and analysis of airways, arteries, vessels, and lung lobe/segmental anatomy to detect and quantify various anatomical/structural features, which can be time-consuming and subject to inter-rater variability [13]. Other CRDs also require information such as spirometry, parenchymal assessments, and physiological measures to provide a complete diagnostic picture [14]. Based on our literature review, we identified that most researchers have approached the extraction and analysis of airways and other anatomical structures primarily from a computational mindset, rather than an anatomy-informed mindset, resulting in methods that are often non-generalizable. Multiple studies [15–17] have shown that applying the same computational methods to different medical-imaging datasets of airways produces varied performance metrics, as shown in the Table 1.

Table 1. Branch Detection Rate (BD%) and Tree Length Detection Rate (TD%) on Different Datasets.

Studies	Performance Metrics of the Proposed Method
Yanan Wu et al. (2023) [15]	ISICDM'21 Dataset **BD(%) – 93.96 ± 4.54** TD(%) - 92.06 ± 6.83 EXACT'09 Dataset: **BD(%) – 81.4 ± 12.2** **TD(%) – 79.6 ± 11.0** BAS Dataset: BD(%) – 92.4 ± 6.0 **TD(%) - 94.9 ± 3.4** ATM'22 Dataset: BD(%) – 90.97 ± 10.41 TD(%) – 86.67 ± 13.09
Puyang Wang et al. (2024) [16]	BAS Dataset: BD(%) – **99.1 ± 1.0** TD(%) – **98.0 ± 2.2** ATM'22 Dataset: BD(%) – 97.9 ± 2.3 TD(%) – 97.1 ± 3.4 EXACT'09 Dataset: **BD(%) – 86.5 ± 9.3** TD(%) – 87.1 ± 6.7 PLCD: BD(%) – 87.1 ± 7.9 **TD(%) – 74.3 ± 8.5**

The studies listed in the table have implemented their proposed methods on medical imaging datasets of the airways from 4 different sources and obtained the performance metrics for branch

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detection rate (BD %) and tree length detection rate (TD %). In the first study [15], a higher BD of 93.96 ± 4.54% is noticed for the ISICDM'21 dataset, and a lower BD of 81.4 ± 4.54% for the EXACT'09 dataset, using the same method. Similar variation is observed in the second study [16], where the BAS dataset achieved a higher TD of 98.0 ± 2.2% and a lower TD of 74.3 ± 8.5% for a private lung cancer dataset (PLCD). PLCD represents the real-world clinical scenario, whereas all the other datasets are publicly available. It is also evident that achieving higher metrics across multiple public datasets doesn't always yield the same results in private datasets. This variation is also observed among public datasets, where the same method produces different results, as listed in the Table 1. This is due to developing methods that are non-generalizable. Most existing studies have primarily focused on technical/computational aspects, such as branch detection, tree reconstruction, leakage avoidance, improved connectivity, and others, without sufficient attention to clinical anatomical requirements and structural variability.

1.2. Importance of Digital Equity and Access

HICs have advanced surveillance systems to monitor disease trends and population health through nationwide programs [18], better diagnostic and treatment facilities, and well-funded research environments [19]. These resources enable them to conduct thousands of studies each year by age group and local health needs, which helps create diagnostic criteria, treatment methods, and mitigation strategies that account for varied biological traits, risk factors, and social determinants across population groups.

Despite having those advantages, evidence clearly shows a higher risk of respiratory disease between indigenous vs non-indigenous adults and children, LIGs [20] vs HIGs, and Humans from a diverse range of identities and expression of gender vs cisgender females and males [21]. Most current guidelines, thresholds, and scoring systems for CRDs were historically developed from datasets that predominantly consisted of non-indigenous (white) adults from the U.S., Australia, and Europe. These frameworks have rarely been validated in Indigenous populations, LMIC populations, or children from diverse ethnic backgrounds [22]. As a result, they do not fully represent the differences in lung size, airway geometry, anatomical disease patterns, early-life exposures, and growth trajectories across these groups.

It is essential [23] to develop population-specific, evidence-based guidelines for diagnosis, resource prioritization (management), and targeted prevention, particularly in LMIRs, where mortality is substantially higher. However, due to a lack of robust healthcare and research infrastructure [24] in many LMICs, data collection is often incomplete or inconsistent, limiting the number and quality of locally conducted studies needed to generate population-specific evidence. This further contributes to ongoing gaps that worsen existing inequalities [25].

These challenges highlight the need to develop computational methods and digital technologies that enable comprehensive and objective assessment of CRDs by analyzing diverse data modalities, such as high-resolution and multi-detector computed tomography (HRCT/MDCT), low-dose CT (LDCT), chest X-ray, CT angiography, spirometry, and other sources spanning medical imaging, physiological signals, clinical records, and omics data. Such technologies can automate large-scale analyses and allow researchers to conduct numerous studies efficiently and remotely, facilitating global collaborations beyond geographical and resource limitations.

1.3. Importance of Pediatric Studies for Indigenous and Non-Indigenous

Automated analysis and computer-based research related to CRDs have predominantly focused on adult data [25], largely because stable, mature anatomical structures make algorithm development, training, and validation easier. Pediatric data, in contrast, saw less research, despite strong evidence underscoring the importance of early diagnosis, timely intervention, and reversal of disease during critical stages of lung growth and development [26]. Pediatric imaging and physiological data pose unique challenges: lung anatomical structures vary significantly across pediatric age groups – from infants to adolescents – and are often underdeveloped or highly variable

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[27]. This highlights the clear need to do more research using pediatric data, especially including indigenous children from remote regions such as Northern Australia.

CRDs such as Chronic Obstructive Pulmonary Disease (COPD), Asthma, Bronchiectasis, Cystic Fibrosis (CF), Pulmonary Hypertension (PH), Post-Tuberculosis Lung (PTLD), Interstitial Lung Disease (ILD), and Chronic Bronchitis (CB) often cause progressive and irreversible structural, and functional damage to the lung tissue, which can lead to respiratory failure and increased mortality in adults [28,29]. Many cases of adult CRDs are recognized to originate early in life during critical phases of lung growth and development. Evidence also suggests that childhood respiratory health and adverse lung function trajectories are inextricably linked to adult respiratory health and cardiovascular events, as well as all-cause mortality. Despite the imperative to address global inequity, research focused on strengthening respiratory health in indigenous children and those living in LMICs and HICs is lacking [30]. Research related to CRDs also receives substantially less funding than other chronic disorders [31].

1.4. Generalized Research Gaps

This section provides the rationale for proposing the anatomy-guided framework and explains how it will benefit researchers in developing robust computational methods for both adult- and pediatric-centric medical imaging data. We have identified a handful of generalized research gaps related to CRDs and bronchiectasis.

- Most computational studies on CRDs and bronchiectasis rely on adult-centric data, largely due to the limited availability of pediatric datasets from diverse geographic locations in public repositories and greater anatomical variability across pediatric age groups compared with adults.
- To account for anatomical variability, we argue that identifying anatomically and clinically grounded research gaps, and linking them with the required technical aspects, can support the development of robust computational methods (3D) tailored to specific diseases and imaging modalities.
- Identifying research gaps only in terms of neural networks, 3D methods, and image processing methods or curated common datasets is insufficient for developing computational tools that work reliably in real-world settings, where such datasets are often unavailable.
- Although the lung anatomy can vary with geographic location, socio-economic factors, and other influences, the fundamental structural information, such as large, medium, and small distal airways and arteries, as well as lobes and broncho-pulmonary segments, remains the same.

These gaps are among the primary reasons for proposing an anatomy-guided literature review framework in this research, which has the potential to support the development of robust computational methods applicable to subjects/patients across diverse population groups.

1.5. Research Aim

This study is organized into two main aims (see Figure 2):

Aim 1 - Identify one key anatomical feature for each selected CRD. We have selected one adult CRD and one pediatric CRD, each represented by a single meaningful feature (see AIM 1 in Figure 2). These CRDs were selected because their anatomical features can be visualized, detected, or quantified from HRCT through the extraction and analysis of airways, arteries, vessels, and lobe/segment labelling. To establish the computational landscape (technical aspects and evaluation metrics) relevant to these features, a structured LR is conducted across four domains. The first domain comprises 3D computational studies of the airway tree in adults, which are essential for CRDs such as bronchiectasis, asthma, and airway-predominant COPD, where airway structure is the primary feature of interest. The second domain includes 3D computational studies of the arterial tree in adults, which are important for CRDs such as post-TB lung disease and bronchiectasis that depend

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on airway-artery relationships. The third domain encompasses 3D studies of lobar and segmental labelling, which are crucial for CRDs with region-specific involvement, including paediatric bronchiectasis, chronic suppurative lung disease, and cystic fibrosis[]. The fourth domain focuses on 3D paediatric-based computational methods of the airway and arterial trees. Together, these four LR domains provide the technical foundation required to support AIM 2.

Aim 2 - The second aim represents the core contribution of this research, as it integrates the selected clinical anatomical features (see Figure 2) of each CRD with existing 3D-based computational methods by linking each feature to the relevant technical aspects and evaluation metrics (from AIM 1). This integration enables the systematic identification of both technical and anatomy-based limitations and supports the synthesis of the overall research gap for each clinical feature. AIM 2 in Figure 2 describes the workflow in the proposed Seven-Component LR framework.

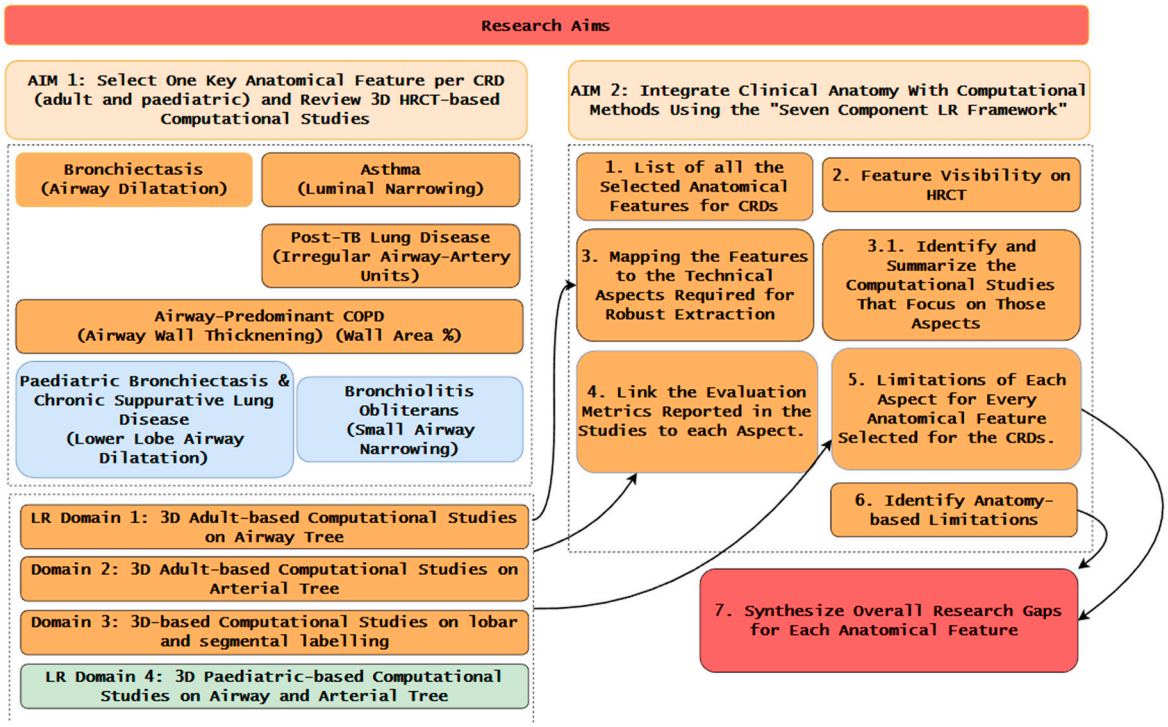

Figure 2. Research Aims.

2. Methods

2.1. Stage 1 - Identification of CRDs, Anatomical Features, and Literature Sources

1) CRD and Feature Selection

CRDs were selected using the following criteria:

(i) The CRD must have at least one clinically recognized anatomical feature that is detectable or quantifiable on HRCT.

(ii) The feature must require extraction or analysis of airways, arteries, vessels, or lobar/segmental structures.

(iii) Peer-reviewed computational studies must exist to support downstream analysis.

One adult CRD and one pediatric CRD were selected. For each disease, one key anatomical feature was identified.

2) Literature Sources and Domains

Four computational domains were defined for extracting relevant studies:

(i) 3D adult-based computational studies on the airway tree.

(ii) 3D adult-based computational studies on the arterial tree.

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(iii) 3D computational studies on lobar and segmental labelling.
(iv) 3D paediatric-based computational studies of the airway and arterial trees.

3) Search Strategy

(i) Databases: Searches were conducted in PubMed, IEEE Xplore, Scopus, Google Scholar, and ScienceDirect, supplemented by manual screening of reference lists from key publications.
(ii) Time Window: The search was restricted to literature published from 2015 to 2025 to capture the most current and relevant studies.
(iii) Keywords: airway tree reconstruction deep learning/NN; airway tree modelling deep learning/NN; airway tree extraction; lung airway tree; 3D reconstruction pulmonary artery; automated methods bronchial trees; airway tree reconstruction graph; automated 3D airway tree paediatric; 3D airway tree children; artery–vein separation; automatic artery–vein separation; artery lung segmentation; lung vessel segmentation, and related terms.

4) Inclusion and Exclusion Criteria for 3D-based Computational Studies

(i) Inclusion Criteria: 3D HRCT-based methods, quantitative evaluation metrics (e.g., BD, TD, connectivity indices), studies addressing airways, arteries, vessels, and lobe/segment labelling, clinically relevant anatomical features, and peer-reviewed journal and conference publications.
(ii) Exclusion Criteria: studies on 2D-only methods, non-HRCT modalities, E.M for Branch Detection Rate (BD%) > 90%, Tree Length Detection Rate (TD%) > 85%, and similar performance for other metrics.

After applying the inclusion criteria, 52 studies were selected as important studies. Each study was thoroughly analyzed to extract key information, including year of publication and first author, study objective, dataset source and size, proposed methodology, key outcomes and evaluation metrics, and code availability in the *public domain.*

Exclusion criteria are applied to the 52 studies, and 15 are selected as primary studies for inclusion in this research. Limitations from an anatomical and technical perspective are identified for each of those 15 studies, which are later synthesized into 30 overall anatomy-guided research gaps.

2.2. Stage 2 – Seven-Component Literature Review Framework

The following steps were applied to the selected anatomical feature of a CRD.

(i) Anatomical Feature and its clinical definition.
(ii) HRCT Visibility Assessment: Important structural information that should be extracted from HRCT for each anatomical feature, along with its visibility on HRCT, categorized as fully visible, partially visible, indirectly visible, or not visible.
(iii) Technical Aspect (TA) Requirement Mapping: The feature is decomposed into the technical aspects necessary for its extraction, including branch detection, leakage control, segmentation completeness, and others.
    - Evidence Extraction from Four LR Domains: Studies identified in Stage 1 are mapped to the corresponding technical aspect.
(iv) Metric Compilation: Collected evaluation metrics such as branch detection rate, tree length detection rate, connectivity indices, completeness ratios, leakage scores, and others.
(v) Technical Limitation Analysis: Technical limitations are identified by comparing the reported performance of TAs against clinical anatomical requirements.
(vi) Anatomy-Based Limitation Analysis: Identified structural regions, patterns, or features not captured by existing computational methods.
(vii) Overall Research Gaps: The outputs of these six components were synthesized into feature-specific research gaps.

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3. Results

Results of the Seven-Component Literature Review for Selected CRDs

1) Bronchiectasis

(i) Airway Dilatation (AD): For diagnosing bronchiectasis, AD is the key feature among several others. On CT, AD is considered present when the internal diameter of a bronchus is greater than the accompanying pulmonary artery (increased broncho-arterial ratio) [].

(ii) HRCT Visibility: To detect AD in adult-HRCTs, the computational methods should extract structural information such as large (fully visible), medium (fully visible), small distal (partially visible), and peripheral (indirectly visible) airways and arteries, artery-vein separation, labelling of lobes and broncho-pulmonary segments (fully visible). Existing works are assessed based on how well they extract the information.

(iii) Technical Aspects (TA), Evaluation Metrics (EM), Literature Review (LR), Limitations (Technical & Anatomical):

Table 1. Airway Segmentation. Technical Aspects (TA). Branch Detection & Tree Length Detection. Branch Detection Rate (BD %); Tree Length Detection Rate (TD %).

LR-TA & LR-EM	Limitations
Minghui Zhang et al. 2023 [17] ATM'22 CT scans BD: 94.729 ± 6.38 TD: 95.92 ± 2.27 Noisy COVID-19 CT scans BD: 92.05 ± 4.9 TD: 94.251 ± 3.54 (Team Timi – best out of 30)	1. Precision declined to 87.928% (lower than the average) for ATM'22 due to unintentional over-segmentation of the airway, making them appear wider than they actually are, particularly in distal regions and near vessels. 3. Aggressive breakage reconnection introduces false-positive branches. 4. Models trained on ATM'22 are difficult to be generalized to the noisy CTs. 5. The method favors completeness over anatomical specificity, especially in small and peripheral airways. 6. Over-emphasizing topological completeness compromised topological correctness.
Puyang Wang et al. 2024 [16] (deeptree_damo) BAS: BD:99.1 ± 1.0 TD:98.0 ± 2.2 ATM'22: BD:97.9 ± 2.3 TD:97.1 ± 3.4 EXACT'09: BD:86.5 ± 9.3 TD:87.1 ± 6.7 PLCD: BD:87.1 ± 7.9 TD:74.3 ± 8.5	1. BAS has higher BD and TD using original reference labels, but lower precision (84.5 ± 5.5) due to incomplete labelling issues. 2. EXACT'09 has lower BD and TD due to high noise, low contrast, weak peripheral airway visibility, and incomplete annotations. 3. Most false positives belong to unannotated distal branches. (EXACT'09). 4. False positives in BAS and PLCD appear at local regions that exhibit similar patterns of lumen + wall, often located near the junctions of branches or adjacent to branches. 5. On public datasets (BAS, ATM'22), most branches and tree-length are detected, whereas on the private (PLCD) dataset, the method mainly captures central airways, missing distal branches, and shows continuity breakages, leading to missed terminal bronchi and shortened trees.

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Hao Zheng et al. 2021 [32] BAS: BD:88.7 ± 7.9 TD:92.5 ± 4.5 EXACT'09: BD:80.5 ± 12.5 TD:79 ± 11.1	1. For BAS, gradient erosion and dilation can appear in both large and small airways, but their impact is more serious in the distal branches. 2. For BAS, when the gradient ratio is reduced, the baseline method is prone to gradient erosion, resulting in a higher number of undetected peripheral branches. 3. For BAS, the highest number of FPs occurs at the indistinct borders between the airway lumen and the airway wall. 4. For BAS, branches with inhomogeneous wall intensity (bright-blurry) may go undetected. These FNs cause breakages, leading to the extraction of only the largest connected domain while discarding the remaining branch segments. 5. The network fails to capture sufficient long-range features needed for maintaining connectivity in thin bronchi.
Yan Hu et al. 2025 [33] BAS: BD:91.5% TD: 95% ATM'22: BD:97.3% TD:97.6%	1. Confidence maps show high certainty in central airways but much lower confidence in thin branches with less distinct boundaries. 2. Low confidence regions are more susceptible to segmentation errors, such as missed detections and minor leakages. 3. Segmentation errors frequently occur at thin terminal branches and branch bifurcations.
Yanan Wu et al. 2023 [15] ISICDM'21: BD: 93.96 ± 4.54 TD: 92.06 ± 6.83 EXACT'09 Dataset: BD: 81.4 ± 12.2 TD: 79.6 ± 11.0 BAS Dataset: BD: 92.4 ± 6.0 TD: 94.9 ± 3.4 ATM'22 Dataset: BD: 90.97 ± 10.41 TD: 86.67 ± 13.09	1. Higher rates of FPs noticed in ISICDM'21 are likely to be due to annotation errors arising from missed terminal branches in the reference standard. 2. Airway segmentation performance varies between healthy subjects and patients with different diseases. 3. In COPD patients, reduced branch count and shorter detected tree length are particularly evident in the peripheral airways. 4. Most FNs occur near the trachea and main airway margins, where manual annotation is difficult, and connectivity is challenging to maintain. As a result, unannotated pixels lead to over-segmentation.
Yi Xu et al. 2025 [34] ATM'22: BD: 96.1 ± 5.5 TD: 97.5 ± 2.8 AeroPath: BD: 94.5 ± 3.9 TD: 95 ± 3.8 Parse22:	1. The precision (%) of 78.8 ± 8.7 and 81.9 ± 8.6 indicates difficulties in the precise and complete labelling of thin bronchi, resulting in high FPs when extracting unannotated peripheral bronchi. 2. Due to uneven airway wall intensity and disease-induced morphological changes, some airway structures may be broken or omitted, resulting in FNs. 3. The study focuses solely on airway shapes and skeletons, without fully exploring other morphological features, such as varying airway diameters across generations.

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BD: 83.5 ± 8.5 TD: 87.9 ± 4.9	4. A significant scale difference is noticed between the low-generation airway and the distal segmental bronchi due to intra-class imbalance, which increases the difficulty of extracting small bronchi.

Table 2. Airway Segmentation. Technical Aspects (TA). Leakage Control, Connectivity and Continuity.

LR-TA & LR-EM	Limitations
Jihye Yun et al. 2024 [35] Own Test Dataset: Mean Leakage Volume (MLV in mm^3): 8791.8 EXACT'09: Mean Leakage Count (MLC): 94.1 Mean LV: 726.4	1. On own data, the method achieved a higher average spatial overlap of 0.90 ± 0.09, though performance declined in severe COPD cases. large low-attenuation areas (regions of damaged lung tissue). 2. Lower DSC (spatial overlap) (~ 0.79-0.83) is noticed among patients with higher emphysema index (43.4 - 47.5), reflecting degraded branch and tree detection performance. 3. For EXACT'09, high sensitivity was obtained at the expense of an increased FPR due to the sub-ideal quality of the reference standards given. 4. Tuning the parameters that influence the tree length, and the number of leakages is difficult and time-consuming, and dependent on CT scan quality. 5. Reducing leakages often leads to fewer detected small bronchi, limiting distal airway recovery.
Hong Wei Yang et al. 2024 [36] ATM'22: Leakage (%): 17.11 ± 9.17 Detected Tree Length Ratio (DLR): 92.99 ± 2.84% Detected Branch Ratio (DBR): 89.08 ± 6.31%	1. The best existing method (nnU-Net) reports a leakage of 6.1%, indicating higher false positives for the proposed method due to over-segmentation beyond true airway boundaries and the generation of spurious branches. 2. The proposed method achieves lower Intersection of Union (IoU %), Dice (%), and precision (%) compared to nnU-Net, but shows higher DLR and DBR, indicating a sacrifice of overall accuracy for completeness. 3. Evaluation metrics are impacted due to incomplete reference labels in training and validation sets from ATM'22.

Table 3. Artery-Vein Segmentation. Technical Aspects (TA) – Accuracy, F1-Score, Sensitivity, Specificity, and DSC.

LR-TA & LR-EM	Limitations
Pietro Nardelli et al. 2018 [37] COPDGene: Non-Contrast CT Accuracy (%): 93.6 ± 4.9 Sensitivity (%): 97.3 ± 2.5 Specificity (%): 89.5 ± 9.2 CTEPH Dataset: Contrast CT Accuracy (%): 89.1 ± 5.9 Sensitivity (%): 93.4 ± 3.5 Specificity (%): 83.9 ± 9.9	1. On non-contrast CT in the COPDGene dataset, the method performs best on medium-sized vessels (Accuracy: 95.2%), while showing reduced accuracy for large vessels (88.9%) and a modest decline for small vessels (93.4%), likely due to insufficient capture of contextual information for wider structures. 2. A higher number of false positives is observed for small vessels (specificity: 88.9%) and large vessels (74%), likely due to lower contrast, vessel-scale imbalance in the training data (richer in medium-size (COPDGene)), and local misclassifications from incorrect labels. 3. Accuracy is higher in control subjects than in CTEPH patients for A-V classification, where disease-induced vascular distortions increase false positives. 4. The dataset contains significantly more arteries than veins, biasing classification toward arterial labels.

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	5. The training dataset doesn't include contrast-enhanced CT scans (CTEPH dataset), which could have improved performance.
Jiantao Pu et al. 2022 [38] LIDC-IDRI Dataset – Non-Contrast Chest CT Extrapulmonary Artery & Vein Segmentation: (DSC) Vein: 0.919 ± 0.017 Artery: 0.907 ± 0.012 Hilum Vessels: 0.924 ± 0.011 Mediastinal Vessels: 0.913 ± 0.007 Intrapulmonary Vessel Detection (Branch-Level): Average Detected Branch Count (Computer): Veins: 1459.6 ± 620.9 Arteries: 1414.5 ± 779.5 Intrapulmonary Vessels Artery-Vein Labeling: Sensitivity (%) Veins: 98.3 ± 1.0 Arteries: 98.1 ± 1.1	1. In peripheral and hilar regions, an average of 43.2 ± 23.0 vein branches mislabeled as arteries and 39.3 ± 28.4 artery branches mislabeled as veins per scan, due to artery-vein intertwining and fusion leading to vessel continuity in non-contrast CT. 2. Geometric assumptions of cylindrical vessel morphology break down near bifurcations, hilum regions, and in diseased lungs, where vessels appear blob-like, flattened, or irregular. 3. Skeleton-based tracing is sensitive to bifurcations, overlaps, and discontinuities, where local vessel fusion and noisy skeleton fragments lead to incorrect branch continuation, limiting perfect artery–vein separation even though overall labeling accuracy after expert review remains ~97%. 4. High inter-subject anatomical variability and image resolution effects cause large fluctuations in detected vessel complexity, with computer-identified intrapulmonary branches averaging 1459.6 ± 620.9 (veins) and 1414.5 ± 779.5 (arteries) per scan, far exceeding manual annotations (~300–350 branches), indicating difficulty in defining complete anatomical ground truth. 5. Absence of explicit anatomical priors (airways, lobar or segmental context) limits region-aware consistency, particularly for small peripheral vessels that are strongly affected by slice thickness, where detected branch counts drop from approximately 1900–2000 (0.625 mm) to 700–800 (1.5 mm) slices.
Lin Pan et al. 2023 [39] Contrast-Enhanced CT scans from Affiliated Union Hospital of Fujian Medical University Artery-Vein Separation (with Trunk) (Mean, %) Accuracy: 97.7% Precision: 85.1 ± 6.9 TPR: 85.1 ± 6.2 Artery-Vein Separation (without Trunk) (Mean, %) Accuracy: 98 Precision: 80.5 ± 8.6 TPR: 84.8 ± 7.7	1. Although the method achieves 97.7% accuracy, the Dice Score remains lower at 84.9%, indicating challenges in peripheral and central regions where vessels that run parallel and blob-like vessel shapes lead to inaccurate centerline extraction. 2. Despite multi-scale and multi-view feature aggregation, the precision and TPR remained lower at 85.1%, likely due to persistent fragmentation and topological inconsistencies in small and distal vessels. 3. The proposed method is sensitive to bifurcation-dense and overlapping regions, resulting in complicated centerline tracing, ambiguous branch continuity, and labelling errors along anatomically incorrect branches. 4. Dilation can artificially widen vessels, merge nearby parallel vessels, and suppress fine-scale AV differences. 5. The lack of airway, lobar, and segmental anatomical information, together with reliance on multi-view voting, can reduce region-aware consistency and suppress anatomically correct branches visible in only one view.
Jean-Paul Charbonnier et al. 2016[40] Dutch-Belgium lung cancer screening study (NELSON): low-dose CT	1. Geometric graph separation relies on angle-based pruning to detect artery–vein attachments, which can misidentify normal bifurcations as attachments in anatomically variable or densely branching regions. 2. Periphery matching assumes one-to-one artery–vein proximity near alveolar regions, which may fail in dense,

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Automatic Method vs Reference Standard: Mean Accuracy: 88% Cohen's κ (CK): 0.76 Sensitivity: 88%, Specificity: 89% Performance on CT Scans with Fully Annotated Vasculature Mean Accuracy (MA): 92% Manual Classification of Linked Subtrees vs Reference Standard: 90% (MA): 0.80 (CK) vs Consensus Set: 91% (MA); 0.81 (CK)	asymmetric, or diseased anatomy, leading to incorrect subtree linking and class propagation errors. 3. Separation quality estimation assumes peripheral leaf-node matching, but complex local anatomy may leave true attachments undetected, requiring sensitive reanalysis that can over-detect candidate nodes and introduce anatomical ambiguity. 4. Volume-based classification assumes veins have a larger total volume than arteries, which may fail in anatomically atypical or diseased lungs, leaving small, weakly connected subtrees unlabeled or inconsistently classified. 5. Complex vascular anatomy produces many small subtrees (≈444 per scan), where segmentation errors and diseased lung regions reduce peripheral matching, lowering accuracy to 88–92% in difficult cases. 6. The method is sensitive to disease-related vessel segmentation errors, particularly in peripheral lung regions, where false positives disrupt subtree matching, leading to reduced accuracy (<80%) in 5 of 55 scans despite an overall median accuracy of 94%.

Table 4. Lobar and Segmental Localization. Technical Aspects (TA) – DSC, MSD.

LR-TA & LR-EM	Limitations
Zhi Chen et al. 2024 [41] LUNA16 Dataset: For Training and Validation VIA/I-ELCAP Dataset (low-dose CT): For Evaluation. Lobe Segmentation DSC – 0.94 ± 0.06 Pulmonary Segments Segmentation DSC – 0.73 ± 0.11 Mean Surface Distance (MSD) – 6.1 ± 2.9 mm Avg. Maximum Airway Tree Generations: 8.5 ± 1.3	1. Peripheral airway segmentation is uncertain, as small distal bronchi were segmented using a pretrained BronchiNet without manual validation, making anatomical completeness sensitive to 1 mm resampling and disease-related airway loss. 2. Airway branch labeling depends on skeletonization and distal endpoints, which can fail in anatomical variants (e.g., trifurcations or shared branches), requiring manual correction in 17% of lobes, particularly in middle-lobe segments with shorter airway trees (≈40–52 mm). 3. Pulmonary segment boundaries are approximated using bronchial distance and virtual branches, which may not reflect true inter-segmental anatomy when bronchi are incompletely segmented or deviate from anatomical planes, resulting in limited scores (DSC: 0.73, MSD: 6.1 mm), particularly in the right middle lobe (DSC: 0.66, MSD: 8.0 mm). 4. Right Middle Lobe (RML) segmentation is less reliable for both validation (DSC: 0.86 ± 0.09) and evaluation datasets (DSC: 0.91 ± 0.05) due to poorly visible fissures, leading to higher boundary errors (MSD: 1.49 ± 0.99 mm and 1.24 ± 0.54 mm). 5. The bronchial tree (BT) based segmentation is sensitive to anatomical airway variability and incomplete BT extraction, requiring manual corrections in 64% of patients and yielding lower accuracy (DSC = 0.73 ± 0.11, MSD = 6.1 ± 2.9 mm) than pulmonary arteries (PA) based methods.
Weihao Yu et al. 2023 [42] Shanghai Chest CT Dataset Lobar:	1. The proposed architecture may struggle to generalize to routine clinical scans, as it was developed on carefully selected high-quality thin-slice CT data and may be sensitive to severe anatomical variability, overlapping subtree distributions, and incomplete airway topology.

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Accuracy (%) – 98.6 ± 0.7 Precision (%) - 98.4 ± 0.8 Recall (%) – 96.4 ± 1.7 F1 (%) - 97.4 ± 1.1 Segmental: Accuracy (%) – 93.6 ± 3.6 Precision (%) - 93.0 ± 4.2 Recall (%) - 93.6 ± 3.3 F1 (%) - 93.3 ± 3.3 Subsegmental: Accuracy (%) – 82.0 ± 6.3 Precision (%) - 76.9 ± 6.2 Recall (%) - 79.7 ± 5.8 F1 (%) - 78.2 ± 5.9	2. Compared with existing methods, TNN improves segmental accuracy from 89.2% to 93.6% with approximately 10% subsegmental gains, but shows reduced performance at the lobar level, where hyperedge averaging and intra-class feature compaction can misclassify main bronchi as lobar nodes, lowering Recall near bronchial–lobar boundaries. 3. The model remains sensitive to overlapping feature distributions and subtree similarity, particularly at the segmental and subsegmental levels, where severe class imbalance and limited airway generations (only a dozen from CT) constrain the effectiveness of graph- and hypergraph-based message passing. 4. The multi-stage framework is susceptible to error accumulation, particularly at the subsegmental level, where inaccuracies from earlier stages propagate and degrade performance; this effect is exacerbated by overlapping feature distributions and anatomical variability, especially in anatomically complex regions such as the left and right-lower lobes. 5. The method is sensitive to pathological airway abnormalities, where missing distal branches disrupt anatomical cues needed to distinguish combined branches (a+b) from individual subsegments, leading to misclassifications that human experts can resolve but the network cannot.

Methods that do not adequately address one or more of these components—such as incomplete distal branch detection, inaccurate centerline geometry, poor leakage control, unreliable airway–vein separation, or lack of regional localization—are likely to produce measurements that are not generalizable across datasets, age groups, or population groups.

2) Pediatric Bronchiectasis

(i) Lower-Lobe Airway Dilatation (LLAD):

(ii) HRCT Visibility: To detect LLAD in Children-HRCTs, the computational methods should extract structural information such as large (fully visible), medium (fully visible), small distal (partially visible), and peripheral (indirectly visible) airways and arteries, artery-vein separation, labelling of lobes and broncho-pulmonary segments (fully visible). Existing works are assessed based on how well they extract the information.

(iii) Technical Aspects, Literature Review, Limitations (Technical & Anatomical):

Table 5. Airway Segmentation. Technical Aspects (TA). Tree Length Detection, Leakage Control, Connectivity, and Continuity. Tree Length (TL), Centerline Leakage (CL), Dice Similarity (DSC).

LR-TA & LR-EM	Limitations
Antonio Garcia-Uceda et al. 2021 [43] Children-CF-CT: TL: 83.5 (80.7–87.1) %, $p < 0.001$ CL: 6.09(4.41–13.6) %, $p = 0.021$ DSC: 0.876(0.854–0.883), $p < 0.001$	1. The proposed method shows higher airway completeness in pediatric cystic fibrosis (CF)-CT data (TL: 83.5%) than adult datasets (TL: 81.5% and 70.3%), and despite similar TL and CL between pediatric controls and CF subjects (TL: 84.1% vs 83.5%; CL: 5.74 vs 6.45), CF scans exhibited substantially higher total tree length (146 vs 263), likely due to CF-related airway widening that makes peripheral bronchi appear bigger and easier to detect. 2. The performance on CF scans may not generalize to children without bronchiectasis or to anatomically normal pediatric lungs, where peripheral airways are less dilated.

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Adult-DLCST: TL (%): 81.5(79.2–84.1), $p = 0.19$ CL (%): 8.25(6.26–9.58), $p < 0.001$ DSC: 0.916(0.909–0.924), $p < 0.001$ Adult-EXACT'09: TL (%): 70.3 FPR (%): 2.74	3. On adult DLCST data, the Leakage-Optimization Path (LOP) method achieved a higher TL (96.8%) than the proposed U-Net (81.5%) by aggressively extending peripheral branches to maximize airway completeness, at the cost of increased false positives and leakage, whereas U-Net favors anatomical correctness with fewer false positives and less leakage. 4. On adult EXACT'09 data, reduced airway completeness (TL: 70.3) is observed, primarily because anatomically valid distal and subsegmental airway branches are misclassified as false positives due to incomplete reference segmentations. 5. The method does not account for age-dependent airway development in children, where airway caliber, branching geometry, and generation depth change with lung growth, potentially reducing robustness across pediatric age groups.

Most computational studies of pediatric data have focused on airway–artery quantification to assess airway wall thickness, broncho-arterial ratio, and disease severity, particularly in pediatric bronchiectasis [44] and asthma [45]. Earlier work largely relied on two-dimensional (2D) image analysis methods, which demonstrated reasonable agreement with human readers but were inherently limited in capturing the complex three-dimensional airway–vascular anatomy of the pediatric lung [11,12]. These approaches employed a range of techniques, including region growing and morphological operations [46,47], full-width-half-maximum and phase-congruency methods [48–50], pixel-level intensity analysis [51,52], and edge-radius-symmetry transforms [53], as well as artificial intelligence-based segmentation models [56,57].

The limitations identified in adult-based studies, together with their anatomy-driven research gaps, can inform the development of more robust computational methods for pediatric data. Despite differences in geographic location, age, and anatomical variability, all human subjects share the same fundamental pulmonary structures, including large and distal airways, arteries and veins, lung lobes, and bronchopulmonary segments. Systematically identifying research gaps across a large body of adult studies by explicitly linking anatomical structures with technical limitations can further support the adaptation and development of methods tailored to pediatric imaging data.

3) Other CRDs

The proposed framework is not limited to adult bronchiectasis and pediatric bronchiectasis but can also be applied to other CRDs and their anatomical features with similar airway-dominant characteristics, as discussed in the previous sections. For example, CRDs such as Asthma in adults and Bronchiolitis Obliterans in children require the extraction of anatomical features, such as luminal narrowing (adults) and small airway narrowing (children), from HRCT scans.

As identified in the previous section, reliable extraction of features such as airway dilatation and lower lobe airway dilatation requires computational researchers to focus on airway tree extraction, artery-vein separation and extraction, lobar and segmental localization, so that the methods can localize the features anatomically and interpret them clinically. In addition, researchers should address key technical aspects, including branch detection, tree-length detection, leakage control, completeness and connectivity, mean-surface distance, and others, for robust feature extraction from axial HRCT scans (see Table 6).

The same challenges are encountered when analyzing luminal narrowing (adults) and small airway narrowing (Children). Consequently, computational methods developed for adult airway dilatation and pediatric lower lobe airway dilatation are directly applicable to airway narrowing in adults and children, as listed in the Table 6.

For CRDs such as Emphysema-predominant COPD and pulmonary hypertension, extracting information related to airway + vessels and airway-vein separation is insufficient. They require additional computational methods and technical aspects for robust extraction of the relevant features

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from HRCT scans, as listed in the Table 6. Similarly, different CRDs and their features require different computational methods and technical aspects. By applying the proposed seven-component framework, researchers can identify relevant 3D computational studies, their limitations, and existing research gaps, thereby guiding the development of robust and clinically meaningful methods tailored to specific CRDs and their key features.

Table 6. Computational Methods and Technical Aspects Required for Other CRDs According to the Proposed Framework.

CRD & Anatomical Feature (AF)	Computation Methods for Robust Extraction of AF	Technical Aspects
Adult & Pediatric Bronchiectasis – Airway Dilatation & Lower-lobe airway dilatation	(a) Airway Tree Extraction (b) Artery-Vein Separation & Extraction. (c) Lobar and Segmental Localization	(a) Tree Length Detection (b) Branch Length Detection (c) Leakage Control (d) Connectivity & Completeness (e) Mean Surface Distance
Adult Asthma & Pediatric Bronchiolitis Obliterans – Luminal Narrowing & Small Airway Narrowing	(a) Airway Tree Extraction (b) Artery-Vein Separation & Extraction. (c) Lobar and Segmental Localization	(a) Tree Length Detection (b) Branch Length Detection (c) Leakage Control (d) Connectivity & Completeness (e) Mean Surface Distance
Emphysema-predominant COPD	(a), (b), (c) from above, along with (d) Vascular Pruning Analysis (e) Low Attenuation Area (LAA%) (f) Airway-parenchyma interaction metrics	(a), (b), (c), (d), (e) from above, along with (h) Estimated Vessel Caliber (i) Vessel Density Ratios (j) Spatial Coupling (k) Regional Correlation (l) Voxel-wise attenuation
Pulmonary Hypertension	(b), (c) from above, along with (d) Vessel Caliber Tapering (e) Vascular Pruning (f) Central-peripheral vessel ratios (g) Right Heart-Lung Interaction Markers	(a), (b), (c), (d), (e) from above, along with (d) Vessel Radius Estimation Along Centerlines (e) Caliber Profiling Across Branching Generations (f) Density Distribution Across Lung Regions (g) Region-wise Vessel Density peripheral vessel ratios (h) Right Heart-Lung Interaction Markers (i) Artery Trunk & Branch Caliber Estimation

4. Discussions

Overall Research Gaps

(a) Most literature reviews in the medical imaging domain focus on summarizing the neural network architectures, algorithms, datasets, and performance metrics, with little emphasis on anatomy and clinical relevance.
(b) Evaluation metrics across studies show that the methods developed on a specific dataset often fail to achieve comparable performance on other datasets, due to a lack of generalizability.
(c) Studies have primarily focused on methodological generalization and performance benchmarking on common datasets.

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(d) Existing studies offer limited guidance on how algorithms perform across anatomically diverse populations, including variations due to age, ethnicity, and geographic context (low-to-middle-income countries, high-income countries, indigenous, etc.).
(e) HRCT studies almost never report the centerline extraction metrics. Although the extraction is part of their pipeline. HRCT datasets rarely include manually annotated ground-truth centerlines for comparison.
(f) AD measurement requires computing diameters perpendicular to the local airway centerline. Even an average centerline distance (CD) error (mm) of 1-2 mm can produce overestimated lumen diameter, underestimated wall thickness, and incorrect BAR measurements.
(g) Leakage creates false airways and enlarges lumen masks, producing artificial airway dilatation, inflated broncho-arterial ratio (BAR), and incorrect wall thickness calculations.
(h) Leakage should be near zero for accurate quantification of AD. Only one study included leakage count and volume, which is not good. Reducing leakages often leads to fewer small bronchi being detected, limiting distal airway recovery.
(i) More studies should include methods for leakage control, especially in children, where bronchi are thin and easily distorted, and can be affected by even small leakages.
(j) Methods for aggressive breakage reconnection in airway and artery tree reconstruction introduce false-positive branches. And an overemphasis on topological completeness can compromise overall topological correctness.
(k) Most segmentation errors arise from annotation limitations rather than algorithm capability. False positives are mostly associated with unannotated distal branches near branch junctions, while false negatives occur around the trachea and main airway margins, where manual annotation and connectivity preservation are challenging.
(l) Current methods are sensitive to gradient erosion/dilation and wall intensity inhomogeneity, particularly in distal airways, leading to false negatives, branch breakages, and extraction biased toward only the largest connected airway segments.
(m) Segmentation accuracy degrades in low-confidence regions of confidence maps, particularly at thin terminal branches and bifurcations, resulting in frequent missed detections and minor leakages that remain insufficiently addressed by existing methods.
(n) Existing airway segmentation methods show inconsistent performance between healthy subjects and patients with different respiratory diseases, indicating limited disease robustness and generalizability.
(o) Segmentation of small and large vessels produces high false positives, driven by low contrast, vessel-size imbalance in training data dominated by medium vessels, and errors from incorrect local labels.
(p) Artery–vein classification remains unreliable, with frequent mislabeling in peripheral and hilar regions due to vessel intertwining in non-contrast CT. Simplified geometric assumptions fail near bifurcations, the hilum, and in diseased lungs where vessels have irregular shapes.
(q) Skeleton-based tracing is vulnerable at bifurcations and discontinuities, where vessel overlap and noisy skeletons cause incorrect branch continuation, limiting reliable artery–vein separation despite high overall accuracy after expert review.
(r) Evaluation metrics are impacted due to incomplete labels and imbalanced datasets, where arteries greatly outnumber veins and bias classification. In addition, training data rarely includes both contrast and non-contrast CT scans, limiting model generalizability across different datasets.
(s) Large anatomical variability and image resolution strongly affect vessel detection, producing highly inconsistent branch counts and far exceeding manual annotations, making complete ground truth difficult to define. The lack of explicit anatomical priors (airways, lobes, segments) further reduces region-aware consistency, especially for small peripheral vessels that are highly sensitive to slice thickness.

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(t) Despite multi-scale and multi-view aggregation, fragmentation and topological errors occur in the small distal vessels. The absence of airway, lobar, and segmental context reduces region-aware consistency and can suppress anatomically correct branches visible in only a single view.

(u) Peripheral artery–vein matching relies on simplified one-to-one proximity assumptions that break down in dense or diseased anatomy, causing incorrect subtree linking and error propagation.

(v) Volume-based classification relies on the assumption that veins are larger than arteries, which do not hold in anatomically atypical or diseased lungs. This leads to unstable labeling of small or weakly connected subtrees, with complex vascular anatomy and disease-related segmentation errors—especially in peripheral regions—disrupting subtree matching and reducing classification reliability.

(w) Airway branch and segment labeling relies on skeletonization and simplified anatomical assumptions, which fail in anatomical variants and incomplete segmentations, leading to frequent manual correction and inaccurate pulmonary segment boundaries, particularly in the right middle lobe.

(x) Right middle lobe segmentation is less reliable due to unclear fissures and sensitivity to anatomical variability, often requiring manual correction and yielding lower accuracy than artery-based approaches.

(y) While graph-based models improve fine-level airway labeling, they remain limited at lobar boundaries due to feature averaging, class imbalance, and overlapping subtree characteristics, reducing robustness across airway hierarchies.

(z) Higher airway completeness in pediatric cystic fibrosis CT likely reflects disease-related airway widening that makes peripheral bronchi easier to detect, rather than true method/algorithm robustness. Consequently, performance on CF scans may not generalize to children without bronchiectasis or to anatomically normal pediatric lungs with narrower peripheral airways.

(aa) Current methods trade airway completeness for anatomical correctness, with aggressive strategies increasing false positives and methods/algorithms missing valid distal branches due to incomplete reference labels. Additionally, the lack of age-aware airway modeling limits robustness across pediatric development stages.

5. Conclusions

Existing literature reviews in medical imaging summarize methods and trends but lack anatomical and clinical grounding. This is a critical gap for diseases shaped by anatomical variability, age, and population differences. To address this gap, we propose a seven-component anatomy-guided framework that integrates anatomy, clinical context, and technical requirements to support robust, clinically meaningful 3D computational methods across diseases and imaging modalities. Although demonstrated in adult and pediatric bronchiectasis, the framework readily extends to other airway-dominant CRDs, such as adult asthma and pediatric bronchiolitis obliterans, which face similar HRCT challenges in analysing airway narrowing. For CRDs such as emphysema-predominant COPD and pulmonary hypertension, airway and vessel extraction alone is insufficient, and the proposed framework systematically identifies disease-specific limitations and gaps to guide the development of robust, anatomy-aware, and clinically meaningful computational methods across CRDs and beyond.

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