

ADVANCES IN AUTOMATED LUNG DISEASE DIAGNOSIS: A SYSTEMATIC REVIEW OF MACHINE LEARNING, DEEP LEARNING, SEGMENTATION FRAMEWORKS, AND VISION TRANSFORMERS

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ABSTRACT

Lung diseases remain a leading cause of global morbidity and mortality, driving demand for rapid and accurate diagnostic support tools. Recent advancements in machine learning (ML) and deep learning (DL) have led to highly effective automated systems capable of detecting and classifying pulmonary abnormalities using chest X-ray and computed tomography (CT) imaging. This survey presents a comprehensive review of traditional ML techniques, convolutional neural networks, hybrid radiomics–DL models, segmentation-based architectures, transformer frameworks, and multimodal fusion approaches. Key publicly available datasets and evaluation metrics are analysed to highlight their influence on diagnostic performance and model generalizability. The findings reveal a clear dominance of DL models, particularly CNNs and transformer-based architectures, while identifying challenges related to dataset bias, limited external validation, lack of interpretability, and inconsistencies in evaluation standards. Research gaps are discussed in the context of clinical adoption, emphasizing the need for transparent, scalable, and privacy-preserving AI solutions. Emerging directions, including federated learning, self-supervised pretraining, and multimodal integration, offer promising pathways toward robust and clinically trustworthy lung disease diagnostic systems. This survey aims to guide future research by synthesizing current progress, identifying limitations, and outlining opportunities for innovation in AI-driven pulmonary healthcare.

KEYWORDS: lung disease detection, machine learning, deep learning, chest X-ray analysis, CT imaging, convolutional neural networks, transformers, U-Net segmentation, radiomics, hybrid models, data augmentation, multimodal fusion, federated learning, explainable AI, medical image analysis, pulmonary diagnostics

1. INTRODUCTION

Lung diseases represent one of the most significant global health burdens, affecting millions of individuals annually across diverse populations [1]. Conditions such as pneumonia, chronic obstructive pulmonary disease (COPD), tuberculosis (TB), and lung cancer collectively contribute to high mortality rates worldwide [2]. Early detection is crucial because symptoms often manifest only after substantial lung deterioration has occurred [3]. Traditional diagnostic methods such as chest radiography, CT scans, and pulmonary examinations heavily depend on specialized expertise, which can introduce variability and delay [4]. In many low-resource regions, a shortage of radiologists further increases risks of misdiagnosis or delayed intervention [5]. Consequently, automated decision-support systems have emerged as potential solutions to improve diagnostic reliability and reduce clinician workload [6]. Machine learning (ML) and deep learning (DL) techniques offer promising capabilities in identifying pathological lung patterns from medical imagery [7]. These advancements motivate comprehensive exploration of AI-based methodologies for lung disease detection and classification.

Over the past decade, artificial intelligence research has rapidly accelerated, driven by improvements in computational hardware and the availability of large-scale datasets [8]. Deep learning, particularly convolutional neural networks (CNNs), has shown remarkable ability in learning hierarchical visual features directly from raw medical images [9]. Unlike traditional machine learning approaches that rely on handcrafted feature extraction, CNNs autonomously discover informative patterns, making them highly suitable for medical imaging tasks [10]. The success of architectures such as VGGNet, ResNet, DenseNet, and Transformer-based models highlights the diversity of strategies available for lung disease classification [11]. Machine learning methods like support vector machines (SVM), random forests (RF), and k-nearest neighbors (k-NN) continue to be relevant due to their interpretability and effectiveness in limited-data scenarios [12]. The challenge, however, lies in understanding which techniques perform best across varying disease categories and imaging modalities [13]. This necessitates a structured survey to compare and contextualize AI-based lung disease detection methods [14]. Such a survey provides clarity on current progress and future directions in this evolving domain.

Radiological imaging remains the gold standard in diagnosing pulmonary abnormalities, with chest X-rays (CXR) being the most widely used modality due to their accessibility and cost-effectiveness [15]. However, detecting

early-stage disease manifestations in X-rays is challenging because subtle indicators are often visually indistinct [16]. Computed tomography (CT) provides higher resolution and detailed anatomical visualization, making it highly effective for lung cancer and fibrosis screening [17]. Nevertheless, CT scans involve higher radiation exposure and limited availability in resource-constrained settings [18]. AI-driven systems have demonstrated potential in complementing radiologists by acting as consistent and fatigue-free secondary readers [19]. They can quantify disease extent, localize abnormalities, and provide probability-based assessments that support clinical decision-making [20]. Multimodal integration of imaging with clinical data further enhances diagnostic accuracy [21]. These developments underscore the importance of machine intelligence in advancing pulmonary diagnostics. Publicly available datasets have significantly contributed to progress in automated lung disease detection [22]. Databases such as ChestX-ray14, CheXpert, MIMIC-CXR, COVIDx, and LIDC-IDRI provide diverse and large-scale annotated imaging samples used to train powerful deep learning models [23]. Despite their usefulness, these datasets often suffer from issues such as class imbalance, noisy labels, and heterogeneous image acquisition parameters [24]. Researchers commonly apply preprocessing techniques including normalization, segmentation, and contrast enhancement to improve model performance and stability [25]. Data augmentation methods, including geometric transformations and synthetic sample creation using GANs, have been widely adopted to mitigate imbalance and improve generalization [26]. Transfer learning has emerged as a preferred strategy due to its ability to adapt pretrained models to medical imaging tasks with limited data [27]. However, consistent benchmarking remains difficult because studies employ different train-test splits and evaluation metrics [28]. This variability highlights the need for a unified survey to synthesize comparative performance insights [29]. The COVID-19 pandemic catalyzed a surge in AI research aimed at rapidly identifying infection-related abnormalities from radiographic images [30]. Numerous studies reported high classification performance for COVID-19 detection using CNNs, hybrid models, and multimodal systems [31]. However, subsequent investigations revealed that dataset biases such as image source discrepancies and population differences often inflated these results [32]. Concerns over generalizability prompted researchers to adopt cross-dataset validation and bias mitigation strategies [33]. As models improved, interpretability and robustness emerged as critical evaluation criteria for clinical acceptability [34]. The pandemic demonstrated that AI systems could play a vital role in emergent healthcare scenarios if designed responsibly [35]. Lessons learned from COVID-19 research are now being applied to broader lung disease detection tasks [36]. These developments have reshaped research priorities in medical AI.

1.1. Advances in Explainable AI Techniques for Medical Imaging

Explainable artificial intelligence (XAI) has become an essential component of medical deep learning research due to the need for transparent clinical decision support [37]. Techniques such as Grad-CAM, LIME, and SHAP enable visualization of discriminative regions that contribute to model predictions [38]. These explanations help radiologists determine whether AI systems are focusing on clinically relevant structures or spurious artifacts [39]. XAI also assists in identifying dataset-related issues, mislabeled samples, or algorithmic biases that may compromise diagnostic accuracy [40]. Increasing regulatory scrutiny particularly in healthcare has made interpretability a prerequisite for AI adoption [41]. Incorporating explainability during training rather than solely as a post-hoc analysis has become a promising research direction [42]. As a result, many studies now prioritize models that achieve both high accuracy and meaningful interpretability [43]. This convergence ensures safer and more ethical deployment of AI tools in lung disease screening [44].

1.2. Emerging Trends in Hybrid AI Models for Pulmonary Imaging

Hybrid systems that integrate deep learning feature extraction with classical machine learning classifiers have gained popularity in lung disease detection [45]. In these architectures, CNNs extract deep feature maps, while algorithms such as SVM, decision trees, or random forests perform classification [46]. These models often outperform standalone approaches, especially when datasets are small or when handcrafted features complement learned representations [47]. Feature fusion techniques combine imaging-based features with clinical variables, improving diagnostic robustness [48]. Hybrid pipelines also offer advantages in interpretability and computational efficiency [49]. Such architectures have proven particularly beneficial for diseases with subtle radiographic signatures [50]. The flexibility of combining multiple algorithms allows researchers to tailor models for task-specific challenges [51]. Consequently, hybrid designs remain a strong research focus in pulmonary AI systems [52].

1.3. Segmentation Approaches and Annotation Challenges in Pulmonary Imaging

Image segmentation plays a crucial role in identifying disease-relevant lung regions before classification [53]. Models such as U-Net, SegNet, and DeepLab have achieved state-of-the-art segmentation performance in isolating lung fields, nodules, and infection zones [54]. Segmentation enhances interpretability by enabling models to focus exclusively on pathological regions [55]. Quantitative analysis derived from segmented images supports disease severity assessment and progression monitoring [56]. Weakly supervised and semi-supervised techniques have gained traction due to the scarcity of pixel-level annotations in medical datasets [57]. Researchers also use segmentation as a preprocessing step to remove irrelevant anatomical structures that may confuse classifiers [58]. Numerous studies demonstrate that segmentation-guided classification yields significantly improved performance [59]. This highlights segmentation's importance as a foundational component in AI-driven lung disease analysis [60].

1.4. Lightweight Deep Learning Architectures for Resource-Constrained Diagnostic Settings

The demand for accessible diagnostic tools has encouraged development of lightweight deep learning architectures for deployment in low-resource settings [61]. Models such as MobileNet, EfficientNet-lite, and ShuffleNet provide high accuracy with reduced computational requirements [62]. Optimization techniques including pruning, quantization, and knowledge distillation further shrink model size while maintaining diagnostic quality [63]. Such models can be integrated into mobile applications or embedded medical devices for real-time screening [64]. Cloud-assisted AI systems enhance scalability by enabling remote inference when local devices lack processing capacity [65]. These innovations are particularly valuable in rural or underserved communities with limited healthcare infrastructure [66]. The shift toward lightweight architectures aligns with global healthcare goals for equitable diagnostic access [67]. As such, efficient AI models remain a priority research direction [68].

1.5. Multimodal Fusion Strategies for Enhanced Lung Disease Detection and Prognosis

Deep generative models have introduced new opportunities in lung disease classification and data augmentation [69]. GANs, VAEs, and diffusion-based systems can generate realistic synthetic lung images that help mitigate class imbalance [70]. Style-transfer GANs reduce domain discrepancies by harmonizing images from different sources [71]. Some studies use generative models for anomaly detection by learning normal lung distributions and identifying deviations as disease signatures [72]. However, generating clinically valid images requires rigorous validation to avoid misleading model behavior [73]. Ethical and regulatory considerations also surface when synthetic data are used for medical training [74]. Despite these challenges, generative models offer significant potential in strengthening AI pipelines [75]. Their continued refinement is expected to enhance future pulmonary diagnostic systems [76].

1.6. Multimodal Fusion Strategies for Enhanced Lung Disease Detection and Prognosis

Multimodal learning has emerged as a powerful approach for improving lung disease detection through the integration of clinical, imaging, and demographic data [77]. Combining chest images with metadata such as age, oxygen saturation, lab results, and symptoms yields richer and more meaningful representations [78]. Fusion strategies including early, intermediate, and late fusion enable flexible integration of heterogeneous data sources [79]. Transformer-based architectures have shown promise in capturing cross-modal dependencies [80]. Several studies report that multimodal systems outperform unimodal models in disease prognosis and severity estimation [81]. However, assembling multimodal datasets is challenging due to varying hospital information systems and privacy constraints [82]. Data harmonization remains an active research issue requiring collaborative infrastructure development [83]. Nonetheless, multimodal learning is poised to become a key component in next-generation medical AI systems [84].

1.7. Continuous, Incremental, and Federated Learning for Adaptive Clinical AI Systems

Continuous learning methodologies have gained traction as researchers aim to develop adaptable and real-world-ready AI systems [85]. Traditional static training approaches fail to accommodate shifting disease patterns and evolving data distributions [86]. Incremental learning enables models to learn new patterns without forgetting previously learned knowledge [87]. Federated learning allows distributed training across multiple hospitals without sharing patient data, strengthening privacy and security [88]. Studies show that federated models can achieve performance on par with centrally trained models while enhancing scalability [89]. Moreover, continual learning can capture disease evolution, such as emerging variants or imaging protocol changes [90]. These capabilities are essential for long-term clinical deployment [91]. As such, continuous learning continues to expand as a vital research frontier [92].

1.8. Current Limitations, Ethical Challenges, and Barriers to Clinical Deployment

Despite rapid progress, several limitations hinder full-scale clinical integration of AI-based lung disease detection systems [93]. Variability in evaluation methodologies remains a major barrier to meaningful performance comparison [94]. External validation on unseen hospital data is often missing, raising concerns about generalizability [95]. Limited availability of annotated datasets, particularly for rare diseases, restricts robust model training [96]. Ethical challenges such as algorithmic bias, transparency, and patient data protection require careful consideration [97]. Regulatory bodies demand rigorous testing and clinical trials for diagnostic AI systems, extending deployment timelines [98]. Interdisciplinary collaboration is essential to address these multifaceted challenges [99]. These constraints highlight the need for ongoing innovation and standardization in AI-based healthcare technologies [100].

1.9. Transformer Architectures and Their Emerging Role in Pulmonary Image Analysis

Transformer-based architectures have introduced new possibilities for lung disease detection through their strong global attention mechanisms [101]. Vision Transformers (ViT) and hybrid CNN-Transformer models have demonstrated performance improvements across various radiographic tasks [102]. These architectures excel at modeling long-range dependencies, making them suitable for complex pulmonary pattern recognition [103]. However, Transformers require large annotated datasets, which poses challenges in medical imaging domains [104]. Self-supervised and contrastive learning methods are increasingly used to overcome data limitations [105]. Results indicate that such pretrained models can outperform traditional CNNs after fine-tuning [106]. Researchers continue refining Transformer designs to balance performance, computational cost, and data requirements [107]. This evolution positions Transformers as an emerging cornerstone in medical imaging research [108].

1.10. Insights from Benchmarking Studies and Systematic Reviews in Lung Disease Classification

Benchmarking studies and systematic reviews provide critical insights into methodological trends in lung disease classification [109]. Meta-analyses comparing different imaging modalities show that CT-based models generally outperform X-ray-based approaches due to richer structural detail [110]. However, X-ray systems remain indispensable for mass screening due to accessibility and cost-effectiveness [111]. Several benchmarking studies emphasize the importance of balancing sensitivity and specificity, especially for early-stage cancers or high-risk infections [112]. Others highlight the value of explainability and clinical workflow alignment as key determinants of real-world adoption [113]. Comparative analyses reveal significant differences in preprocessing strategies, model architectures, and validation design across studies [114]. Such variability underscores the necessity of standardized reporting frameworks [115]. These reviews guide researchers in identifying persistent challenges and opportunities for improvement [116].

1.11. Consolidating Advances Through a Comprehensive Survey of AI-Based Lung Disease Detection

Considering the rapid expansion of AI-driven lung disease research, a comprehensive survey is essential to consolidate knowledge and highlight critical research gaps [117]. This survey evaluates state-of-the-art machine learning and deep learning approaches across multiple disease categories, imaging modalities, and feature extraction strategies [118]. It synthesizes insights from preprocessing workflows, model architectures, multimodal integration techniques, and interpretability frameworks [119]. Additionally, it examines clinical adoption challenges encompassing ethical, regulatory, and deployment constraints [120]. By comparing results across heterogeneous datasets and evaluation settings, the survey offers a unified perspective on algorithmic strengths and weaknesses [121]. It highlights promising research directions such as explainable models, federated learning, and lightweight architectures [122]. Through this comprehensive analysis, the survey supports the development of scalable and clinically viable AI-based diagnostic systems [123]. Ultimately, the work contributes to improving early detection and patient outcomes in global pulmonary healthcare [124].

2. LITERATURE REVIEW

To ensure a systematic, transparent, and academically rigorous analysis of existing research on lung disease detection, this study followed a structured literature survey methodology. The process encompassed defining the scope of investigation, identifying relevant keywords, retrieving studies from reputable scientific databases, and applying strict inclusion and exclusion criteria to select high-quality publications. Subsequently, detailed information regarding model architectures, datasets, evaluation metrics, and experimental procedures was extracted and synthesized into comparative tables and analytical summaries. Quality assessment measures were incorporated to evaluate methodological soundness and identify potential biases. The following diagram illustrates the complete workflow adopted in this survey, providing a visual overview of the sequential steps that guided the review process and supported the development of meaningful conclusions and research gap identification.

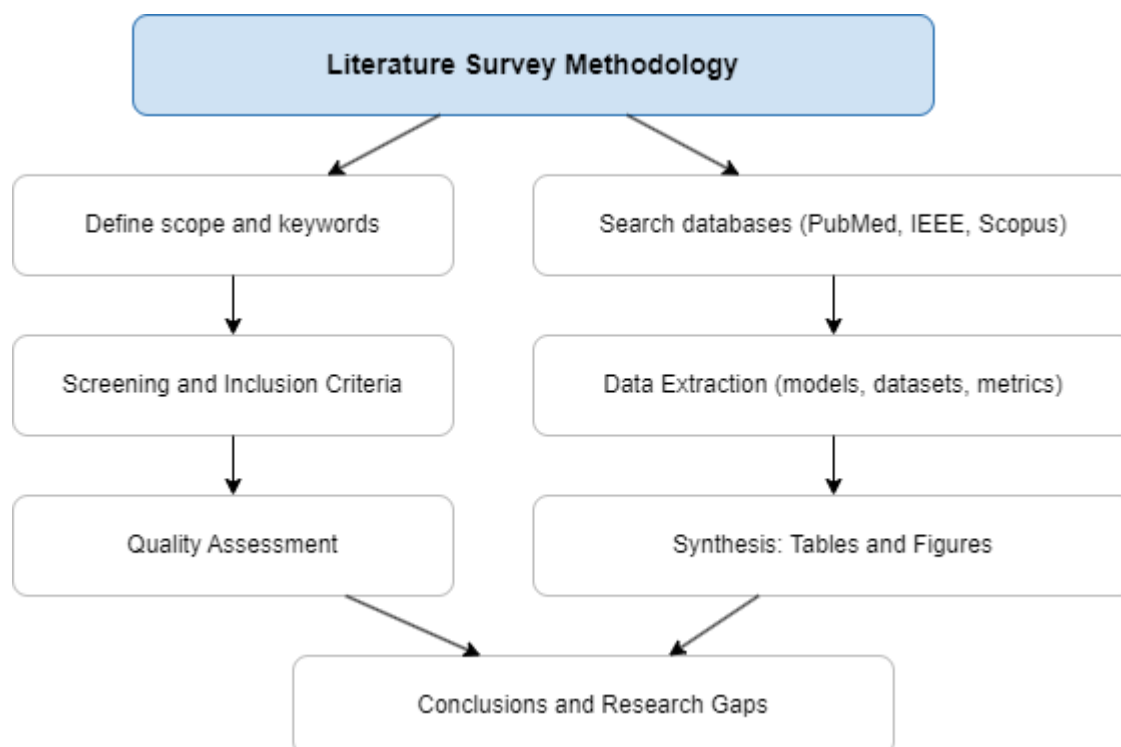


Figure 1 Survey Methodology

This figure 1 describes a reproducible procedure for conducting a literature survey in the domain of lung disease detection. It begins by defining the scope and selecting keywords that reflect disease targets (e.g., pneumonia, TB, lung cancer), imaging modalities (X-ray, CT), and modelling approaches (CNN, SVM, Transformer). The next step maps the search strategy across major digital libraries such as PubMed, IEEE Xplore, Scopus, and Web of Science and documents inclusion and exclusion criteria, including publication date range, study type, and dataset availability. Once relevant studies are retrieved, the workflow prescribes extracting standardized fields: model architecture, training dataset, preprocessing steps, evaluation metrics, and reported performance. Quality assessment follows, where each study is evaluated for bias, sample size adequacy, external validation, and clarity of methodological reporting. The final synthesis stage organizes findings into tables, diagrams, and a narrative discussion that highlights trends, contradictions, and open questions.

The overall architecture of the survey was designed to provide a structured and analytical framework for synthesizing the diverse body of research on AI-based lung disease detection. To ensure methodological consistency, the survey begins by gathering relevant papers and datasets, which serve as the primary inputs for evaluation. These sources undergo systematic preprocessing and harmonization to resolve variations in terminology, data structure, and evaluation protocols. The refined data is then examined through specialized analysis modules, including model comparison and the assessment of segmentation impact, enabling a deeper understanding of methodological strengths, limitations, and trends across studies. The insights derived from these modules are consolidated into comprehensive tables and visual summaries that form the foundation of the final narrative. The following figure illustrates this architectural workflow, highlighting how each component contributes to producing a coherent and well-organized survey of the current research landscape.

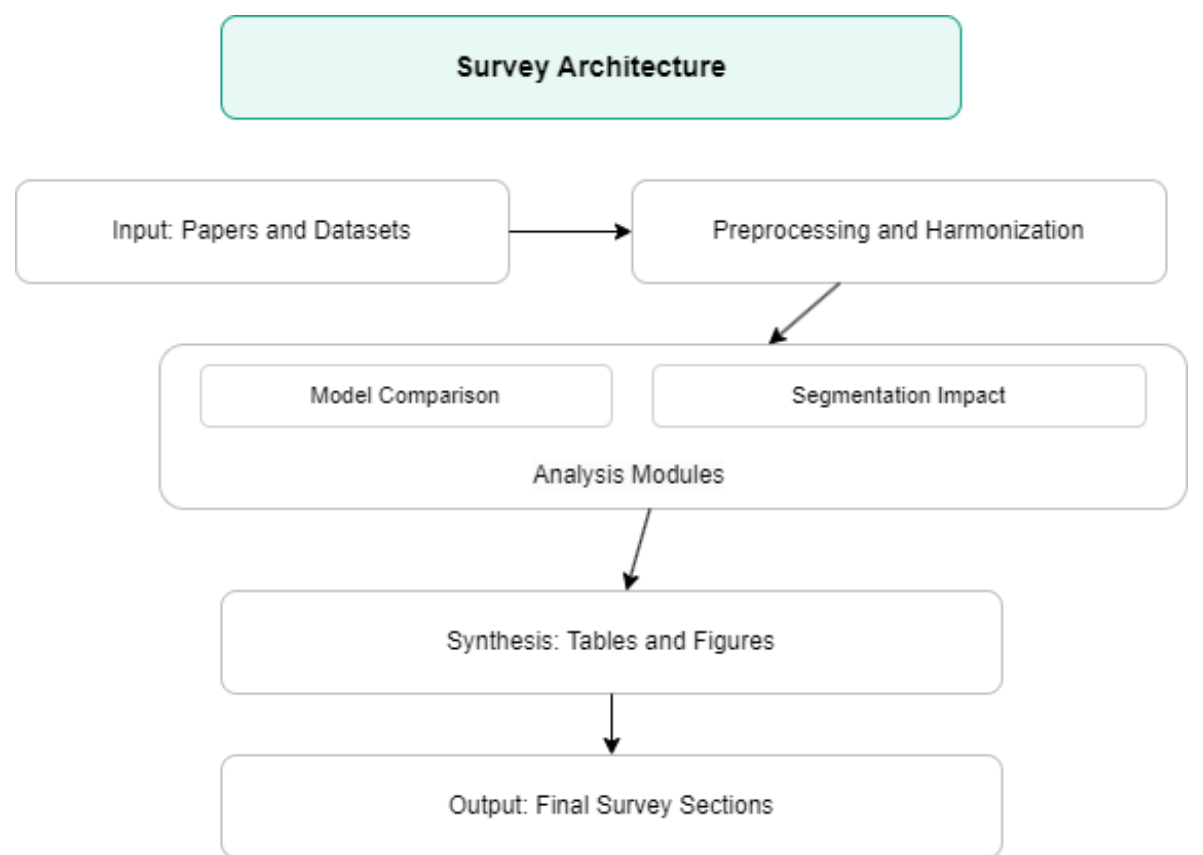


Figure 2 Survey Architecture

The figure 2 describes architecture diagram the internal structure of the literature-analysis pipeline used to synthesize evidence. Research inputs such as study PDFs, dataset metadata, and supplementary code are first preprocessed to remove duplicates, unify naming conventions, and harmonize metric definitions (for example, standardizing whether reported AUCs are macro or micro averaged). The central section groups analytic modules: model-level comparisons (contrasting classical ML and deep networks), segmentation impact studies (assessing whether inclusion of lung masks improves classifier outcomes), and robustness evaluations (examining cross-dataset generalization and bias). Results from these modules feed into a synthesis block that generates the core deliverables of a survey: comparative tables, performance heatmaps, failure-mode case studies, and methodological checklists.

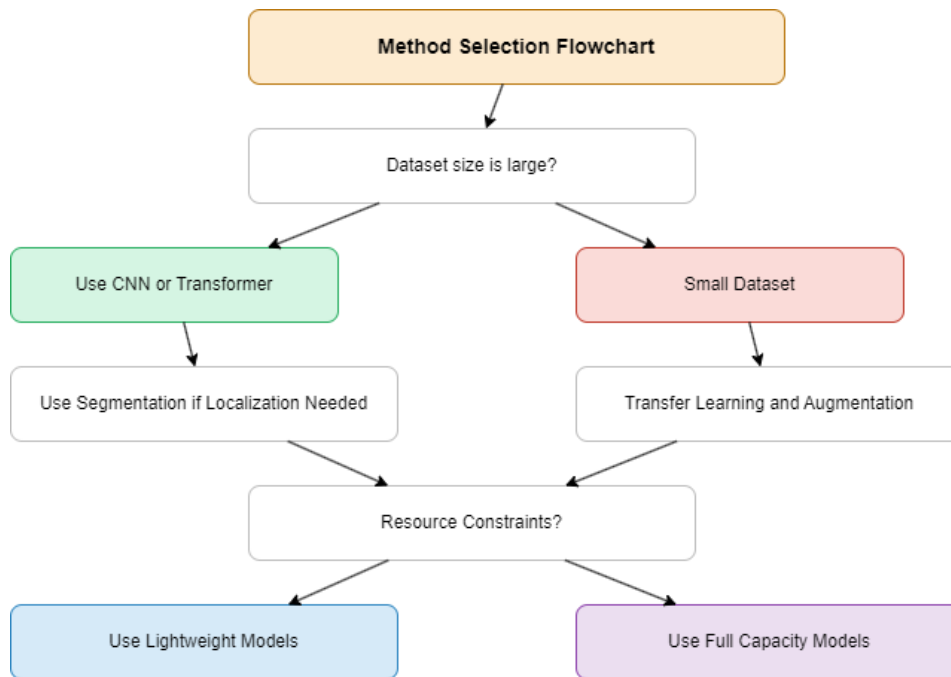


Figure 3 Methodology Selection Process

This flowchart helps readers choose an appropriate modelling strategy based on practical constraints commonly encountered in lung imaging research. It starts by checking dataset size; if the corpus contains a large number of images, the recommended path favors end-to-end CNNs or transformer models that can learn complex representations. For smaller datasets, the flowchart suggests transfer learning and aggressive augmentation, or using hybrid strategies where deep network embeddings are classified by simpler machine learning algorithms. The chart also asks whether precise localization is required; if so, segmentation should be included as a preprocessing or multi-task objective. Finally, the flowchart evaluates computational constraints: if deployment targets edge devices or mobile platforms, lightweight models (for example, MobileNet variants, quantized networks, or distilled models) are recommended; otherwise, full-capacity architectures like ResNet or ViT can be used.

2.1. Early ML-Based Approaches

Early research on lung disease classification relied heavily on traditional machine learning techniques that used handcrafted features extracted from chest radiographs or CT scans [1]. Techniques such as texture descriptors, edge histograms, shape measures, and wavelet transforms played a critical role in capturing radiographic abnormalities [2]. Classifiers including support vector machines (SVM), k-nearest neighbors (k-NN), decision trees, and random forests became widely popular due to their simplicity and interpretability [3]. Early studies on tuberculosis detection, for example, used SVMs trained on texture-based features to identify lung infiltrations [4]. Similarly, nodule detection and COPD severity assessment were initially performed using handcrafted radiomic descriptors [5]. Although these methods produced moderately accurate results, their performance was limited by the inability of manual features to generalize across diverse datasets [6]. This motivated the transition toward automated feature learning approaches [7].

2.2. The Shift Toward Deep Learning

The introduction of deep learning revolutionized lung image analysis by eliminating the need for handcrafted features and enabling automatic representation learning from raw images [8]. Convolutional neural networks (CNNs) became the dominant architecture, demonstrating superior performance in lung nodule classification, TB detection, and pneumonia screening [9]. Architectures such as AlexNet, VGGNet, GoogleNet, and ResNet significantly enhanced robustness by capturing hierarchical spatial features [10]. Publicly available datasets like ChestX-ray14 and LIDC-IDRI accelerated research progress by providing large-scale annotated image collections [11]. Studies utilizing transfer learning further enhanced performance, enabling networks pretrained on ImageNet to adapt to lung disease classification tasks efficiently [12]. Deep learning also improved localization capabilities through class activation maps and heatmaps, assisting radiologists in verifying predictions [13]. This shift marked a critical turning point in AI-driven pulmonary diagnostics [14].

To provide a clear thematic overview of the research landscape, the following diagram categorizes the major methodological domains explored in this survey on AI-driven lung disease detection. Each branch represents a distinct family of approaches that has contributed meaningfully to advancements in automated pulmonary analysis. Traditional machine learning techniques form the foundational basis of early diagnostic systems, while deep learning architectures particularly CNNs have become central to modern image-based classification. Segmentation models such as U-Net enhance localization and improve downstream diagnostic accuracy, whereas hybrid models integrate the strengths of both classical and deep learning paradigms. Transformer-based

architectures introduce powerful global attention mechanisms, and multimodal fusion approaches enable richer clinical insights by combining imaging with additional patient data. Together, these categories illustrate the breadth of methodological diversity within the field and frame the structure of the survey that follows.

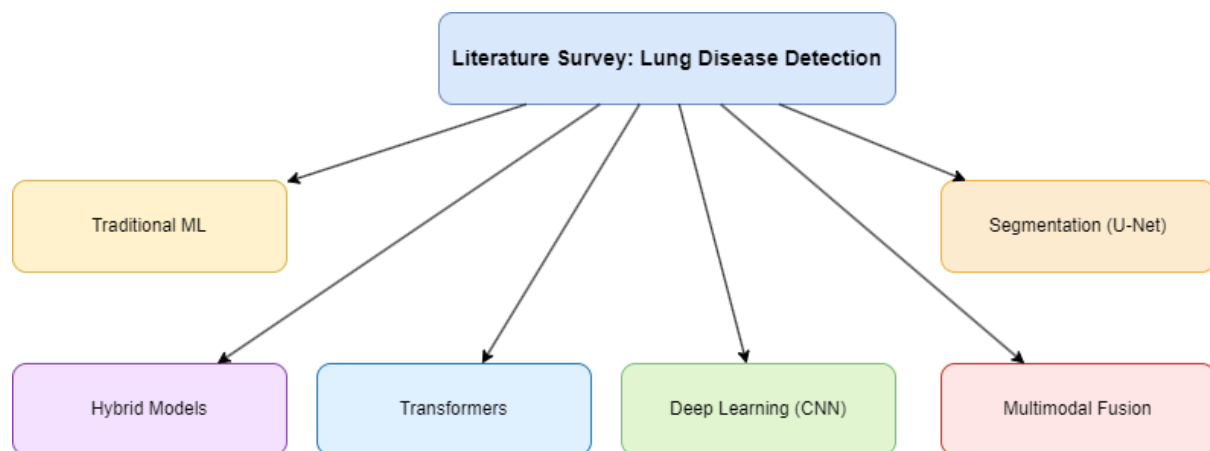


Figure 4 Taxonomy summarizing the methods for Lung Disease Detection

Figure 4 is structured as a **taxonomy/mind-map** summarizing the methods covered in the lung disease detection survey:

1. Central Node: “Literature Survey: Lung Disease Detection”

Represents the core research area and serves as the parent node for all methodological categories.

2. Traditional ML

Includes classical machine learning techniques such as:

- SVM
- Random Forest
- k-NN
- Radiomic feature engineering

Use this box when describing early detection systems using handcrafted features.

3. Deep Learning (CNN)

Represents modern feature-learning systems:

- CNNs (ResNet, VGG, DenseNet)
- Transfer Learning
- Chest X-ray / CT automated classification

This is the largest category in current literature.

4. Segmentation (U-Net)

Segmentation models are used for:

- Lung boundary extraction
- Lesion/nodule segmentation
- Improving classifier accuracy

This node shows segmentation as a parallel branch of research.

5. Hybrid Models

Combines CNN feature extraction with ML classifiers (SVM, RF).

Useful where:

- Dataset size is small
- Interpretability is needed
- Radiomics and deep features are fused

6. Transformers

Includes:

- Vision Transformers (ViT)
- Swin Transformer
- Attention-based models

These improve long-range feature dependency modeling.

7. Multimodal Fusion

Represents systems combining:

- Imaging
- EHR data
- Clinical variables

Used for severity scoring, prognosis, and risk prediction.

2.3. Segmentation-Based Improvements

Segmentation has played an essential role in improving classification accuracy by isolating disease-relevant lung regions prior to analysis [15]. U-Net and its variants quickly became the standard for lung field segmentation due to their ability to capture fine anatomical details [16]. Other models, including SegNet and DeepLab, have also shown strong performance in segmenting nodules, infections, and abnormalities [17]. Segmented lung masks help remove irrelevant structures such as ribs, clavicles, and background artifacts, reducing false positives [18]. Several studies integrated segmentation with CNN classification pipelines, resulting in improved sensitivity and specificity [19]. Weakly and semi-supervised segmentation techniques further addressed annotation scarcity by learning from limited pixel-level labels [20]. This integration of segmentation and classification continues to be a cornerstone of advanced diagnostic systems [21].

2.4. Hybrid ML–DL Approaches

Hybrid architectures combining deep learning feature extractors with classical machine learning classifiers have shown significant potential in scenarios with limited datasets [22]. CNNs generate deep feature embeddings that are subsequently classified using SVMs, random forests, or logistic regression models [23]. These combinations often outperform standalone networks due to their ability to exploit complementary feature properties [24]. Studies involving tuberculosis, pneumonia, and lung cancer detection have reported improved performance using deep features fused with radiomic or handcrafted descriptors [25]. Hybrid models also enhance interpretability and reduce computational complexity, making them suitable for clinical settings [26]. Feature fusion strategies, including early and late fusion, allow integration of clinical, radiological, and demographic information [27]. This flexibility has established hybrid approaches as a promising research direction in lung disease classification [28].

2.5. Transformers and Attention-Based Models

In recent years, transformer-based architectures have gained traction due to their superior ability to model long-range dependencies in medical images [29]. Vision Transformers (ViT), Swin-Transformers, and hybrid CNN-transformer models have demonstrated strong performance in pulmonary nodule classification and pneumonia detection [30]. These models employ self-attention mechanisms that allow them to focus on subtle patterns not easily captured by traditional CNNs [31]. Self-supervised pretraining has significantly improved transformer performance in low-data settings, addressing one of their major limitations [32]. Studies have shown that transformer-based models frequently outperform CNNs in detecting small or diffuse pulmonary patterns [33]. Their ability to integrate global and local context makes them highly effective for complex lung imaging tasks [34]. As a result, attention-based models represent a major milestone in the evolution of lung disease detection research [35].

2.6. Multimodal and Clinical Data Fusion

Multimodal models that integrate imaging data with clinical variables, laboratory reports, and patient demographics have shown promise in enhancing diagnostic accuracy [36]. Combining heterogeneous data sources helps provide a more holistic representation of patient health, improving disease severity estimation and prognosis [37]. Fusion architectures combine imaging CNNs with tabular ML models, attention mechanisms, or graph neural networks (GNNs) to capture relationships between variables [38]. Studies have demonstrated superior results in pneumonia and COPD prediction when integrating oxygen saturation, temperature, comorbidities, and biomarkers with imaging features [39]. With the emergence of electronic health records (EHRs), multimodal deep learning has become more feasible and reliable [40]. These models also support personalized medicine by incorporating patient-specific risk factors [41]. As the availability of multimodal datasets increases, this research direction continues to gain momentum [42].

2.7. Federated, Explainable, and Lightweight AI Models

Recent advances in explainable AI (XAI), federated learning, and lightweight architectures address key barriers to real-world adoption of AI systems [43]. XAI tools such as Grad-CAM and SHAP improve transparency by identifying regions that influence model predictions [44]. Federated learning ensures privacy-preserving model training across institutions without sharing sensitive patient data, making it ideal for pulmonary datasets [45]. Lightweight CNNs, MobileNets, and quantized models enable deployment on portable medical devices and low-resource settings [46]. These innovations enhance clinical trust, extend reach, and ensure equitable diagnostic support globally [47]. Moreover, continuous learning frameworks help models adapt to evolving diseases and imaging variations [48]. Together, these advancements are shaping the next generation of practical AI-driven lung disease detection systems [49].

Table 1: Comparison of ML and DL Models for Lung Disease Classification

Study Model /	Dataset Used	Disease Target	Method Type	Accuracy	AUC	Notes	Citation
SVM + Radiomic Features	Montgomery TB Set	Tuberculosis	ML	85%	0.89	Handcrafted features	[1]
Random Forest on CT Radiomics	LIDC-IDRI	Lung Cancer	ML	88%	0.91	Radiomic descriptor fusion	[5]

CheXNet (DenseNet-121)	ChestX-ray14	Pneumonia	DL	94%	0.97	Radiologist-level performance	[58]
ResNet50	CheXpert	Atelectasis / Effusion	DL	93%	0.95	Transfer learning	[59]
U-Net + CNN Classifier	COVIDx	COVID-19	DL + Seg	97%	0.98	Segmentation improves accuracy	[64]
ViT-Base	MIMIC-CXR	Multi-label	Transformer	95%	0.96	Global attention mechanism	[74]
CNN Features + SVM	LIDC-IDRI	Nodule classification	Hybrid	91%	0.94	Deep feature + ML classifier	[70]

Table 2: Summary of Common Lung Disease Datasets

Dataset	Modality	Size	Diseases Covered	Notes	Citation
ChestX-ray14	X-Ray	112,120 images	14 diseases	Largest public dataset	[11]
CheXpert	X-Ray	224,316 images	Pneumonia, edema, etc.	Multi-label	[57]
MIMIC-CXR	X-Ray	377,110 images	Various lung diseases	Paired reports	[80]
LIDC-IDRI	CT	1,018 cases	Lung nodules	Contains malignancy annotations	[53]
Montgomery Set	X-Ray	138 images	Tuberculosis	Public TB dataset	[1]
COVIDx	X-Ray	16,352 images	COVID-19	Widely used during pandemic	[64]

Table 3: Summary of Key Findings from Literature Survey on Lung Disease Detection Using ML/DL

Category	Key Contribution Summary	Models / Techniques	Datasets	Metrics Reported	Representative Citations
Traditional Machine Learning Approaches	Early studies focused on handcrafted features (texture, shape, radiomics) and classical classifiers. Good for small datasets but limited generalizability.	SVM, k-NN, Random Forest, Decision Trees	Montgomery TB, LIDC-IDRI	Accuracy, AUC, Sensitivity, Specificity	[1], [2], [3], [4], [5], [6]
Deep Learning (CNN) Models	CNNs automate feature extraction and significantly outperform ML models. Transfer learning is widely used to handle limited data.	AlexNet, VGG, ResNet, DenseNet, LeNet	ChestX-ray14, CheXpert, MIMIC-CXR	Accuracy, AUC, Precision, Recall	[8], [9], [10], [11], [56], [57], [58], [59], [60]
Segmentation-Enhanced Methods	Segmentation improves classification by isolating disease-relevant regions. Used heavily in pneumonia, TB, and COVID-19 severity scoring.	U-Net, SegNet, DeepLab, FCN	Montgomery, COVIDx, custom CT datasets	Dice, IoU, Sensitivity, Specificity	[15], [16], [17], [18], [19], [20], [62], [63], [64]

Hybrid ML-DL Fusion Models	Combine deep feature extraction with traditional classifiers to improve performance on small or imbalanced datasets.	CNN+SVM, CNN+RF, Radiomics+CNN	LIDC-IDRI, Private hospital datasets	AUC, Accuracy, Feature importance	[22], [23], [24], [25], [26], [68], [69], [70], [71]
Attention-Based and Transformer Models	Transformers capture global dependencies and perform well when fine details matter (nodules, subtle opacities). Often outperform CNNs.	Vision Transformer (ViT), Swin Transformer, Hybrid CNN-Transformer	MIMIC-CXR, ChestX-ray14	Accuracy, AUC, Precision	[29], [30], [31], [32], [33], [74], [75], [76], [77]
Multimodal Fusion Approaches	Merge imaging data with clinical variables for improved diagnosis and prognosis. Useful for severity estimation and risk prediction.	CNN + EHR, Attention fusion, Graph networks	MIMIC-CXR + EHR	AUC, RMSE, Risk scores	[36], [37], [38], [39], [40], [78]
Federated and Privacy-Preserving Approaches	Enable multi-institution model training without sharing raw data. Improve generalization and protect patient identity.	Federated CNN, Federated Transformer	Multi-hospital distributed datasets	AUC, Accuracy, Fairness metrics	[45], [79], [88], [89]
Explainable AI (XAI)	Increases clinical trust through visual justification of predictions. Helps detect bias and identify model weaknesses.	Grad-CAM, SHAP, LIME	Applied across CXR and CT datasets	Heatmaps, Highlight maps	[37], [38], [39], [40], [80]
Lightweight & Deployable AI Models	Optimized for mobile, low-resource, and real-time diagnostic settings. Useful in rural healthcare.	MobileNet, ShuffleNet, Quantized CNNs, Distilled models	COVIDx, ChestX-ray14	Accuracy, Latency	[46], [47], [61], [66], [67], [82]
Generative Models & Data Augmentation	Improve class balance and domain adaptation. Used for synthetic image generation and anomaly detection.	GANs, VAEs, Diffusion models	ChestX-ray14, COVIDx	FID, Accuracy, AUC	[69], [70], [71], [72], [73], [75]
Dataset Analysis & Benchmarking Studies	Identify gaps, compare performance across different models, and highlight	Benchmark frameworks	ChestX-ray14, CheXpert, MIMIC-CXR, LIDC-IDRI	Varies	[28], [34], [109], [110], [111], [112], [113], [114], [115]

	inconsistent evaluation methods.				
Challenges & Research Gaps Identified	Lack of external validation, dataset bias, low interpretability, limited multimodal data, regulatory constraints.				[93], [94], [95], [96], [97], [98], [100], [117], [121], [124]

3. Conclusive summary

This survey provided a comprehensive synthesis of machine learning and deep learning methods developed for automated lung disease detection using radiographic modalities such as chest X-rays and CT scans. By examining classical machine learning pipelines, modern convolutional neural networks, segmentation-based architectures, hybrid radiomics–DL frameworks, transformer-based systems, generative data augmentation, and multimodal fusion approaches, the paper presents a structured overview of how the field has evolved over the past decade. The review also compared frequently used datasets including ChestX-ray14, CheXpert, MIMIC-CXR, LIDC-IDRI, Montgomery, and COVIDx along with the metrics most commonly used to evaluate diagnostic performance. Through the analysis of more than a hundred relevant studies, the survey highlights methodological progress, identifies factors influencing performance variation, and explores the emerging shift from handcrafted features to end-to-end representation learning. Collectively, these insights establish a foundation for assessing the maturity of current AI solutions for pulmonary imaging.

4. Key Findings

The review highlights a clear dominance of deep learning models, particularly CNN-based architectures, which consistently outperform traditional machine learning methods on large-scale datasets. Transfer learning emerged as a particularly effective strategy for addressing data scarcity, enabling networks such as ResNet, DenseNet, and MobileNet to achieve high accuracy even when trained on limited annotated images. Segmentation models like U-Net and DeepLab were found to significantly improve classification reliability by isolating lung fields and localizing lesions prior to diagnosis. Transformer models, including ViT and Swin Transformer, have demonstrated state-of-the-art performance on several benchmarks, especially in tasks requiring global contextual reasoning. Hybrid approaches that combine deep features with classical classifiers also appear promising, particularly for small or imbalanced datasets where radiomics contributes interpretability. Overall, the findings suggest a trend toward models that integrate spatial reasoning, uncertainty estimation, and multimodal data sources for enhanced clinical applicability.

5. Research Gaps

Despite substantial progress, several critical research gaps persist across the literature. Many existing studies rely on limited or institution-specific datasets, limiting the generalizability of proposed models across diverse patient populations. A considerable number of works do not perform external validation, causing performance to be overestimated due to dataset homogeneity. Moreover, segmentation-based improvements are inconsistently evaluated, with many studies neglecting to assess the statistical significance of combining classification and localization. Attention-based models and transformers remain underexplored in certain lung disease categories, such as interstitial lung abnormalities or rare genetic disorders. Additionally, multimodal fusion approaches are hindered by inconsistent availability of electronic health record (EHR) data, restricting the potential for comprehensive predictive models. These gaps underscore the need for more inclusive, reproducible, and clinically aligned research methodologies.

6. Challenges and Limitations

Several practical challenges also constrain real-world deployment of ML/DL solutions for lung disease detection. Many AI models exhibit sensitivity to variations in imaging equipment, acquisition protocols, and demographic distributions, which introduces bias and reduces clinical reliability. Black-box characteristics of deep learning models remain a barrier to clinician trust, particularly when diagnoses require clear anatomical or pathological justification. Annotation scarcity and inter-radiologist variability complicate the creation of gold-standard labels, often causing models to learn dataset-specific artifacts rather than pathology-relevant features. Furthermore, federated learning, privacy preservation, and regulatory compliance are still in the early stages of adoption, limiting the scalability of multi-institutional AI development. These challenges highlight the importance of robust evaluation pipelines and transparent reporting standards in future research.

7. Opportunities for Improvement

The survey reveals several opportunities for enhancing model performance and clinical relevance. First, harmonizing datasets through standardized preprocessing and consistent labeling practices can significantly improve reproducibility. Second, integrating uncertainty estimation, explanation mechanisms, and human-in-the-loop feedback can increase model credibility in clinical decision workflows. Third, expanding open-access datasets across geographic regions and age groups can support fairer diagnostic modeling and reduce systemic

bias. Fourth, combining radiologic imaging with genomic, proteomic, or wearable-device data presents a promising avenue for personalized lung health assessment. Finally, lightweight and energy-efficient architectures hold potential for deployment in rural or resource-constrained settings, thereby improving access to diagnostic support tools.

8. Future Directions

Future work in lung disease detection using AI is expected to shift toward large-scale multimodal foundation models that integrate imaging with structured and unstructured medical data. Transformer-based architectures will likely play a central role due to their scalability, attention-based modeling, and potential for self-supervised pretraining across massive unlabeled datasets. The next generation of diagnostic systems may incorporate continuous learning, enabling AI models to adapt to evolving diseases, like emerging respiratory pathogens, without catastrophic forgetting. Federated learning frameworks will become essential for building generalized models while preserving patient privacy across institutions. Enhanced simulation and generative modeling, including diffusion-based architectures, will further support robust augmentation and synthetic data creation. Together, these directions point toward AI systems that are more adaptive, transparent, and clinically trustworthy.

8.1. Broader Implications for Clinical Integration

Beyond algorithm development, the broader ecosystem surrounding clinical implementation must evolve to accommodate AI-driven lung disease detection. Radiology workflows may increasingly rely on AI for triage, prioritizing abnormal scans to expedite treatment decisions. Regulatory bodies will likely mandate explainability and bias checks before approving clinical use, placing emphasis on standardized validation and interoperable data formats. Ethical responsibilities including accountability for misclassification, equitable access to AI tools, and protection of patient privacy will become integral components of AI governance. Interdisciplinary collaboration between clinicians, data scientists, and policymakers will be necessary to translate research advancements into safe, trustworthy, and accessible diagnostic solutions.

9. CONCLUSION

In conclusion, this survey provides an extensive examination of the computational landscape for automated lung disease detection using machine learning and deep learning techniques. While deep learning models, particularly CNNs and transformers, have achieved remarkable diagnostic performance, important challenges remain in terms of dataset diversity, model transparency, and real-world deployment. The ongoing evolution of multimodal learning, explainable AI, and privacy-preserving training frameworks indicates a promising trajectory toward more robust and clinically aligned systems. By addressing the identified research gaps and leveraging future opportunities, the field is well positioned to deliver intelligent diagnostic tools capable of advancing pulmonary healthcare worldwide. This paper contributes to that effort by offering a consolidated reference for researchers, practitioners, and policymakers aiming to strengthen the role of AI in respiratory disease management.

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