

MULTIMODAL EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR COPD DIAGNOSIS: A PRISMA-BASED SYSTEMATIC REVIEW

N. Malathy and V. Vijaya Samundeeswari
Department of Computer Science, Women's Christian College, India

Abstract

Chronic Obstructive Pulmonary Disease (COPD) remains critically under-diagnosed globally, contributing disproportionately to global respiratory morbidity and mortality. Development in deep learning modalities like multimodal data fusion and Explainable Artificial Intelligence (XAI) automates COPD diagnosis. This literature review uses PRISMA to systematically examine the COPD diagnosis studies from 2007 to 2026, which were collected from Scopus and PubMed. Final 84 studies were analyzed with modals includes CT and CXR-based deep learning models, multimodal integration strategies, and XAI techniques like Grad-CAM, SHAP and LIME. The result shows that CT-based systems dominate the literature, whereas CXR, Spirometry, and clinical data were used in very limited studies. Explainable artificial intelligence (XAI) and clinical informatics are absent in the majority of the studies. This review identifies major research gaps and proposes a Hybrid Multimodal Explainable AI (HMX-COPD) framework by integrating Chest X-rays, Spirometry, and clinical data, providing scalability within a single interpretable architecture for COPD diagnosis.

Keywords:
COPD Diagnosis, Explainable AI, Deep Learning, SHAP, LIME

1. INTRODUCTION

COPD ranks among the most life-threatening non-communicable respiratory disorders, marked by incompletely reversible progressive and irreversible obstruction of airflow. Early diagnosis of the disease can reduce severity and mortality but it remains systematically underdiagnosed in resource-constrained settings where access to clinical diagnostic infrastructure remains scarce. Advancements in deep learning have transformed applications in radiological interpretation and health informatics. Deep neural architectures particularly CNNs like ResNet, DenseNet and Vision transformers (ViTs) have improved radiologist-level performance across models. Natural language processing (NLP) has enabled the automated extraction of unstructured data like electronic health records. This development supports promising improvements in clinical decision support.

Automated COPD diagnosis faces several limitations like majority of studies rely on CT images and lack integration of multiple clinical modalities like CXR, Spirometry and EHR clinical data within a unified architectural framework. The absence of explainability in most deep learning studies creates opacity of modal decision making like a “black-box” problem. Explainable AI(XAI) addresses these challenges by improving interpretability in diagnosis. This review identifies the major gap in the current literature and proposes a novel Hybrid Multimodal Explainable AI(HMX-COPD) framework that integrates Chest X-rays, spirometry, and clinical notes within a single interpretable diagnostic system.

2. REVIEW METHODOLOGY

2.1 PRISMA PROTOCOL

The review uses the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [1], ensuring rigour, transparency, and reproducibility (Fig.1). Four sequential phases structured the review protocol: Identification, Screening, Eligibility Assessment and Inclusion.

2.2 DATABASE SELECTION

Two complementary databases were searched: Scopus, for engineering and multidisciplinary breadth and PubMed for biomedical depth. Their combination balances the computational and clinical literatures essential to a topic spanning both.

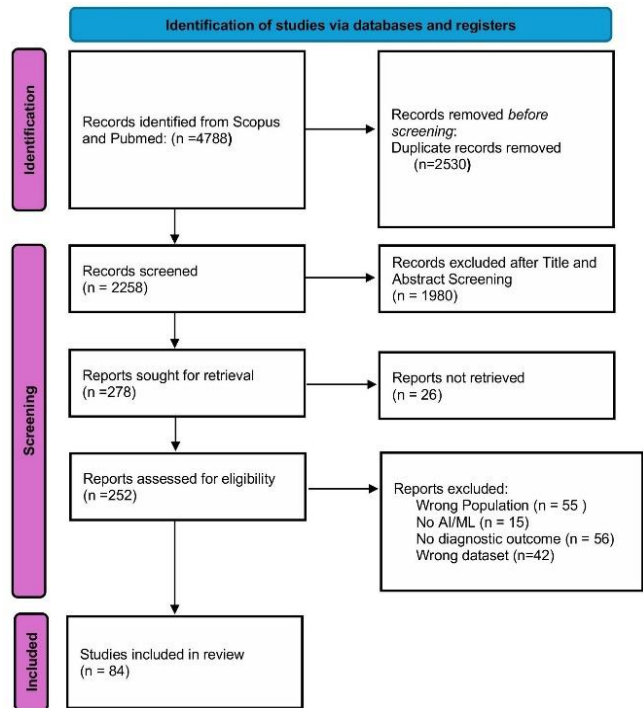


Fig.1. Flow diagram based on PRISMA 2020 illustrating the stepwise study selection process from database searches through final inclusion

2.3 LITERATURE SEARCH STRATEGY

Controlled vocabulary terms were combined with free-text keywords to construct the search string covering publications from 2007 to 2026 as detailed below:

“COPD” OR “chronic obstructive pulmonary disease”) AND (“deep learning” OR “machine learning” OR “convolutional neural network” OR “CNN” OR “transformer” OR “artificial

intelligence” OR “neural network”) AND (“chest X-ray” OR “CXR” OR “chest radiograph” OR “CT” OR “spirometry” OR “pulmonary function test” OR “electronic health record” OR “EHR” OR “clinical narratives”) AND (“explainability” OR “XAI” OR “model interpretability” OR “Grad-CAM” OR “SHAP values” OR “LIME” OR “attention mechanism” OR “visualization”)

2.4 INCLUSION CRITERIA

Studies were included if they are concerned COPD as the primary condition employed AI, ML or DL as the core method, addressed COPD diagnosis or prediction and used Chest X-rays, CT Spirometry or Clinical records (Table 1).

2.5 EXCLUSION CRITERIA

Studies were excluded if they targeted diseases other than COPD, did not employ AL/ML methods, addressed treatments rather than diagnosis or used non-clinical datasets (Table.1).

Table.1. Inclusion and Exclusion criteria governing study selection throughout the review process

Inclusion criteria	Exclusion criteria
Exclusively concerned with COPD as the primary condition of interest	Studies targeting diseases other than COPD
Employs AI, ML or DL as the core analytical methodology	Did not employ AI/ML methods
Addressed COPD diagnosis or prediction	Addressed COPD treatment rather than diagnosis
Uses chest X-rays, CT scans, spirometry or clinical records	Used non-clinical datasets

2.6 STUDY SELECTION PROCESS

Initial database searches retrieved 4788 records from Scopus and PubMed. Following automated deduplication 2258 unique records underwent title and abstract screening of which 278 were selected for full-text review, 26 of those could not be retrieved. Full-text eligibility assessment was guided by PICO framework considering COPD patients (Population), model Intervention and diagnostic or predictive Outcome related to COPD. A final corpus of 84 studies was retained for data extraction and analysis.

2.7 DATA EXTRACTION

For each study we extracted bibliometric metadata, data modality (CXR, CT, Spirometry, Clinical/EHR or multimodal), modal architecture, explainability method, datasets, and performance metrics. All study-level content in this review derives from this extraction.

3. BIBLIOMETRIC ANALYSIS

Bibliometric analysis was conducted using Biblioshiny (R Bibliometrix package) on the 84 included documents, which were published across 72 unique sources spanning 2007 to 2026 with an annual growth rate of 7.57% and a mean document age of 3.54 years. The corpus comprised 484 unique authors, yielding an

average co-authorship rate of 6.56 authors per document, reflecting the inherently interdisciplinary nature of healthcare AI research. International co-authorships accounted for 21.43% of all documents, underscoring the global character of this research community.

3.1 PUBLICATION TRENDS ANALYSIS

The annual publication trend indicates steady growth in AI-based COPD diagnosis over the period of years (Fig.2). Very few publications appeared between 2007 and 2019, and from 2021 onward output increased rapidly with a sharp rise between 2023 and 2025 reflecting growing momentum behind deep learning and multimodal AI in respiratory healthcare. The inclination in 2026 reflects incomplete indexing of recently submitted works rather than a genuine contraction in research activity.

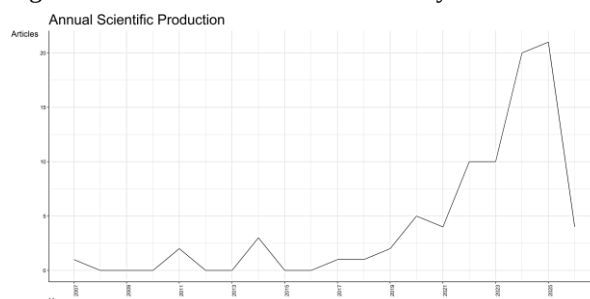


Fig.2. Annual publication trends in AI-based COPD diagnosis

3.2 KEYWORD CO-OCCURRENCE ANALYSIS

In co-occurrence network (Fig.3) the red cluster is controlled by Clinical and spirometry terms including “forced expiratory volume” “forced vital capacity” and “sensitivity and specificity” highlighting clinical diagnostic orientation. The blue cluster captures AI-driven imaging approaches like “deep learning”, “computer-aided design” and “convolutional neural networks”. The green group consists of diagnostic imaging and computed tomographs. These networks reflect how clinical respiratory diagnostics and advanced AI methodologies merge for diagnostic purposes.

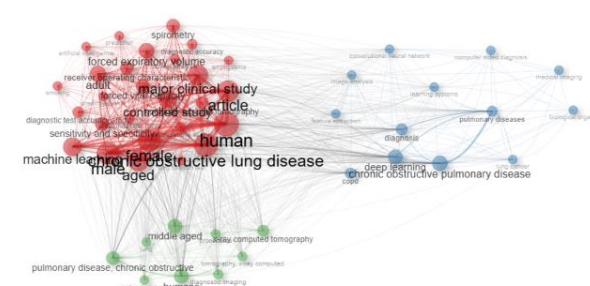


Fig.3. Keyword co-occurrence network for COPD diagnosis

4. SYSTEMATIC LITERATURE REVIEW

4.1 AI ARCHITECTURES FOR COPD DIAGNOSIS

4.1.1 Convolutional Neural Networks and Residual Architecture:

CNNs are the dominant architectural paradigm across the reviewed literature, appearing in 58% of studies either as

standalone classifiers or as feature extraction backbones. ResNet variants (ResNet-18, ResNet-50) are the most widely adopted pretrained architectures. Ho et al. [2] demonstrated that “3D-CNN combined with CT-based Parametric Response Mapping” achieving an accuracy of 89.3% with an AUC of 0.937 for COPD classification, while Sun et al. [3] reported an AUC of 0.934 for weekly supervised COPD detection using ResNet-18 on a multi-centre dataset of 1,393 participants. DenseNet architectures featured by dense inter-layer connectivity enabling feature reuse appear in several CXR-based studies. Jabbour et al. [4] employed DenseNet-121 for diagnosing acute respiratory failure, COPD achieves an AUROC of 0.88 for COPD classification when combined multimodally with EHR data.

Efficient and lightweight CNN variants have attracted increasing interest in resource-constrained deployment contexts. Yang et al. [5] proposed CAR-MLNet, a lightweight model incorporating multimodal shuffling and mixed spatial-channel attention for CT-based COPD diagnosis, achieving 93.69% accuracy with low computational overhead. Jeon et al. [6] introduced a multi-task framework using ConvNeXt-Large with slot attention mechanisms on CXR images, simultaneously classifying COPD severity and estimating the FEV1/FVC ratio with 91.07% classification accuracy demonstrating that CXR-based systems can approximate spirometric functional estimation.

4.1.2 Transformer-based and Attention-Enhanced Architectures:

Transformer architectures and self-attention mechanisms represent the most rapidly growing architectural trend in the 2023-2026 period. Curiale and San Jose Estepar [7] introduced LobTe, a lobe-based tissue distribution achieving an RMSE of 1.73 g/L-yr and explaining 35% of variability in emphysema progression. Yi et al. [8] introduced COPD-MMDDxNet the first multimodal deep learning diagnostic tool using electronic medical records combining a pretrained BERT model for text feature extraction with Gated Cross-Attention mechanisms and achieving 81.76% accuracy without requiring spirometry data.

Attention-guided Multiple Instance Learning (MIL) framework have been specifically adapted to COPD classification from CT scans where pixel-level annotation is impractical. Wu et al. [9] presented an attention-guided MIL framework that fuses CT intensity features with 3D airway tree morphological descriptors, achieving 95.8% accuracy on a primary dataset. Lee et al. [10] showed that 3d Residual Attention CNN applied to single-phase CT combined with clinical data yielding within-one-stage diagnostic accuracy of 83.5-84.1% comparable to multi-phase CT models with clinical data integration improving the intraclass correlation coefficient (ICC) for staging to 0.72-0.78.

Table.2. Comparative analysis of selected high-priority studies in AI based COPD diagnosis

Reference	Model	XAI method	Modality	Key metric	limitation
Ho et al.[2]	3D-CNN + PRM	Grad-CAM	CT	Acc 89.3%, AUC 0.937	Multi-scanner variance; no EHR integration
Sun et al.[3]	ResNet-18 + attention mechanism	Grad-CAM +attention heat maps	CT	AUC 0.934 (internal), 0.866 (external)	Diagnostic Criteria, Sample Size, Clinical Utility
Jabbour et al.[4]	DenseNet-121(CXR) + LR/NN (EHR)	Grad-CAM + Permutation	CXR + EHR	AUC 0.88 (COPD); macro-0.82	Simple concatenation; imperfect retrospective labels
Ikechukwu and Murali[11]	ResNet-50 + Xception (ensemble, TL)	Grad-CAM + SHAP	CXR	Acc 93%, recall 96.5%	PA view only; no prospective validation
Wang et al. [12]	CatBoost + NRSBoundary-SMOTE	SHAP + PDP	Clinical(tabular)	AUC 0.727 (external)	Questionnaire-only predictors; no spirometry
Kor et al. [13]	GBM (XGBOOST)	SHAP	Clinical + Spirometry	AUC 0.836	Single healthcare system; no imaging
Mei et al. [14]	DeepSpiro (Net1D + Bi-LSTM + CatBoost)	Volume attention +SHAP	Spirometry + clinical demographic information	AUROC 0.8328	Low AUPRC for short-term predictions
Yi et al. [8]	COPD-MMDxNET (BERT + gated cross-attention)	Attention Mechanism	Multimodal (EMR)	Acc 81.76%, F1-score 78.32	Single-centre; no CXR; no spirometry waveforms
Deng et al. [15]	MMDF-Net (ResNet-50 + MLP + C-GAN	Dynamic gating mechanism (Modal weights)	CT+pulmonary function indicators + environmental exposure data	AUC 0.92	Single dataset; high computational requirements
Shaikat et al. [16]	XGBoost + RF (ML ensemble)	SHAP +LIME	Clinical + Spirometry	Acc 99.55% (XGB)	Very small dataset; limited generalisability

To provide a concise comparison of the most influential AI-based COPD diagnosis studies Table.2 summarizes the representative literature included in this review. The comparison highlights the deep learning architectures, explainability techniques, data modality, key metrics and major limitations of each study. This comparative analysis facilitates the identification of current research trends and unresolved challenges in explainable multimodal COPD diagnosis.

4.2 MEDICAL IMAGING - BASED COPD DIAGNOSIS

4.2.1 Chest X-Ray Approaches:

CXR studies are comparatively few (9/84) but strategically important. Ikechukwu [11] developed a ResNet-50/Xception ensemble with Grad-CAM and SHAP on VinDr-CXR (93.0% accuracy, 96.5% recall); multi-site radiograph screening across CheXpert, MIMIC-CXR, and Emory-CXR reported external AUC around 0.76 and, importantly, documented Grad-CAM instability across acquisition sites.

4.2.2 CT-Based Approaches:

CT dominates (19/84 single-modality plus most multimodal work). Lightweight shuffling networks, weakly-supervised ResNet-with-attention, and quantitative-CT plus texture-radiomics models with SHAP achieve accuracies in the high-80s to mid-90s; the recurring caveat is degradation under external validation and reliance on smoker-enriched cohorts.

4.2.3 Comparative Analysis of Imaging Modalities:

CT yields the highest reported accuracies but at the cost of dose, expense, and limited reach; CXR trails modestly in headline

metrics yet aligns far better with population-scale deployment. The literature thus exhibits an inverse relationship between reported performance and clinical deployability, arguing for a strategic reorientation toward CXR and CXR-plus-text systems (Table.3).

4.3 MULTIMODAL FUSION APPROACHES

Feature-level fusion strategies dominate the multimodal literature. Zhang et al. [25] proposed a dual-input multimodal CNN architecture (RFEbNet + FCNet) processing paired inspiratory and expiratory chest CT images alongside clinical variables achieving an AUC of 0.930 on internal validation. Lin et al. [26] introduced AutoCOPD an XGBoost-based model detecting COPD from ten quantitative CT features with AUCs of 0.860-0.915 across internal and external cohorts. Deng et al. [15] proposed MMDF-Net a multimodal dynamic fusion framework combining ResNet-50 for CT imaging an MLP for clinical text encoding and a C-GAN for missing modality attaining an AUC of 0.92 on the COPDGene dataset.

Spirometry-CXR fusion represents a particularly relevant archetype for the proposed research direction. Krishnaveni et al. [27] introduced MultimodNet, a DenseNet-121-based architecture fusing CXR images with pulmonary function test (PFT) parameters notably FEV1, FVC and the FEV1/FVC ratio achieving greater than 94% accuracy across all COPD staging categories. Jabbour et al. [4] combined DenseNet-121 CXR features with EHR clinical variables demonstrating that multimodal models achieve a macro-average AUROC of 0.82 compared with 0.78 for image-only models providing quantitative evidence for the additive diagnostic value of modality fusion.

Table.3. Representative CNN and Residual-Architecture Studies for AI-Based COPD Diagnosis

Study	Modality	AI Architecture	XAI	Performance
Ho et al. [2]	CT	3D-CNN	Grad-CAM	89.3% accuracy, 88.3% sensitivity, 93.6% specificity, 0.937 AUC
Sugimori et al. [17]	CT	CNN, ResNet50 and Xception models	None	AUC of 0.68 accuracy of 0.74
Khade et al. [18]	Chest X-rays + breathing patterns	CNN	None	Accuracy 0.98 Precision 0.99 Recall 0.98 F1-score 0.98
Chawla et al. [19]	Chest X-ray	ResNet-50 and SVM	None	accuracy of 93%, precision of 94%, recall of 92.8%, and an F1-Score of 93.3%
Heyman et al. [20]	Clinical	CareNet	Attention Mechanism	AUROC of 87.0%
Zhang et al. [21]	CT	EDLNet	Attention Mechanism	accuracy 93.13% AUROC 99.08%
Jayadharshini et al. [22]	Chest X-ray + Spirometry	ACGAN (augmentation), CNNs (image classification), and ML models (severity grading)	None	InceptionV3 (92.85% accuracy) for detection, and XGBoost (90% accuracy) for severity grading
Bigolin Lanfredi [23]	Chest X-ray + Spirometry	Generative Adversarial Network	VR-GAN	normalized cross-correlation 0.127±0.017
Saad et al. [24]	Chest CT + Spirometry + Clinical data	Deep learning CNNs	None	AUC of 0.860

4.4 EXPLAINABLE AI TECHNIQUES

4.4.1 Gradient-based Visualization (GRAD-CAM):

Grad-CAM is the most frequently applied XAI technique in the reviewed literature appearing in 12 of 84 studies. It generates heatmaps by backpropagating classification gradients to the final convolutional layer, highlighting image regions most strongly influence the prediction. Ikechukwu and Murali [11] developed an ensemble model combining ResNet-50 and Xception architectures with Grad-CAM and SHAP for CXR-based COPD diagnosis achieving 96.5% recall and 93.0% accuracy on the VinDR-CXR validation set. Wang et al. [28] applied Grad-CAM alongside permutation importance for multi-site multimodal COPD screening across “CheXpert, MIMIC-CXR and Emory-CXR” datasets achieving an AUC of 0.76 on external testing though the authors notes variability in Grad-CAM robustness across acquisition sites.

4.4.2 SHAP-Based Explainability:

SHAP (Shapley Additive exPlanations) was based on game theory provides global and local feature importance attributions satisfying the properties of consistency, efficiency and linearity. In the COPD literature SHAP is primarily applied to tabular clinical and spirometry models. Wang et al. [12] applied SHAP to a CatBoost model for COPD risk prediction in smokers revealed that older age, higher COPD Assessment Test (CAT) scores, and gross annual income as the principal risk factors with an AUC of 0.727 on external validation. Kor et al. [13] integrated SHAP with a Gradient Boosting Machine for AECOPD exacerbation prediction achieving an AUC of 0.836 and enabling individualized feature attribution visualizations for clinicians.

In spirometry-focused models SHAP has demonstrated particular translational potential. Mei et al [14] incorporated SHAP analysis and volume attention within DeepSpiro a custom architecture for early COPD detection from spirogram sequences, achieving an AUROC of 0.8328 and demonstrating predictive the disease 1 to 5 years in advance. Makimoto et al. [29] applied SHAP to multivariate models combining texture-based CT radiomic features with demographic variables on the CanCOLD dataset achieving AUC of 0.87 for COPD classification while identifying CT texture features as dominant contributors beyond conventional quantitative metrics.

4.4.3 LIME And Attention-Based Explainability:

Shaikat et al. [16] employs LIME with SHAP for COPD severity classification and quality-of-life assessment in a 101-patient clinical dataset using XGBoost achieving 99.55% classification accuracy. LIME’s model-agnostic design offers architectural flexibility, its reliance on local linear approximations and random perturbations introduces instability for high-dimensional imaging inputs, limiting its utility relative to Grad-CAM in medical imaging contexts.

Attention mechanism-based explainability offers a structurally integrated alternative to post-hoc attribution methods. Heyman et al. [20] developed CareNet an clinical attention-based recurrent encoder network using bidirectional GRUs for dyspnoea diagnosis in emergency departments achieving a median micro-AUROC of 87.0% while generating patient-level attention plots that weight individual clinical variables for each prediction. Cai et al. [30] introduced a “local-to-global CT based COPD

diagnostic framework” employing ConvNeXt with multi-head attention and BiLSTM attaining 96.08% accuracy with inherent attention-based spatial interpretability.

4.5 DATASET USED

CT-based studies mostly utilize the COPDGene study cohort, which is a longitudinal, multicenter dataset with standardized CT protocols and spirometric ground truth. The National Lung Screening Trial (NLST) serves as a frequent external validation source. CXR-based studies rely heavily on the NIH Chest X-ray dataset, followed by VinDR-CXR or Indiana University CXR for fine-tuning and validation. No reviewed study employed a dataset integrating CXR images, full-waveform spirometry and free-text clinical notes from the same patient cohort, precisely the data combination required for the proposed hybrid framework.

5. RESEARCH GAPS AND CHALLENGES

The AI COPD diagnosis faces several challenges from data limitations to regulatory considerations. The major consequential problem is that there most studies rely on small, single-centre, private datasets, and no public cohort jointly integrates CXR images, spirometry waveforms, and clinical informatics within a single explainable AI architecture. The current research remains heavily CT-focused while low-cost, widely accessible Chest X-rays are comparatively underutilized. Explainable techniques are applied inconsistently and are not very often integrated across multiple modalities. Most studies rely on small, single-centre private datasets, limiting the generalizability of current AI models in clinical validation. Most medical AI isn’t built to handle real-world challenges like missing data, limited hardware, or busy hospital workflows. Even worse, these tools are rarely tested on actual patients before being deployed. Breaking this cycle requires coordinated investment in shared, multimodally-linked cohorts and in standardised explanation-fidelity evaluation, not merely incremental architectural novelty.

6. PROPOSED FUTURE DIRECTION

To address the gaps above we propose the Hybrid Multimodal Explainable AI(HMX-COPD) framework which unifies Chest X-ray images, spirometry, and clinical data within a single interpretable diagnostic architecture to overcome the gap in the literature. The proposed approach employs a multimodal architecture combining CNNs for Chest X-rays and feature extraction with transformer-based models like BERT and Clinical BERT for clinical notes. This makes HMX-COPD well-suited for scalable deployment in a primary care setting where complete multimodal data cannot always be guaranteed.

7. CONCLUSION

This PRISMA-based systematic review synthesised 84 AI-based COPD diagnostic studies published between 2007 and 2026 and characterised the field bibliometrically. The evidence shows a field that is CT-centric and single-modality dominated. Multimodal fusion is rising but remains image-plus-tabular and explainability is present in fewer than half of studies but applied inconsistently and rarely validated. No study and no public dataset

unite chest X-rays, spirometry and clinical text for one patient cohort within an interpretable architecture. The principal contribution of this review is to make that gap precise and to translate it into a concrete design: a hybrid multimodal explainable framework combining a CNN–Transformer backbone, attention-based fusion, and combined SHAP and Grad-CAM explanations. The clinical significance is scalable and trustworthy COPD case-finding where the diagnostic burden is greatest and its realisation depends less on novel network components than on the assembly of tri-modal cohorts, the rigorous validation of explanations and prospective clinical evaluation.

REFERENCES

- [1] M.J. Page, “PRISMA 2020 Explanation and Elaboration: Updated Guidance and Exemplars for Reporting Systematic Reviews”, *BMJ*, Vol. 4, pp. 1-9, 2021.
- [2] T.T. Ho, “A 3D-CNN Model with CT-based Parametric Response Mapping for Classifying COPD Subjects”, *Scientific Reports*, Vol. 11, No. 1, pp. 1-12, 2021.
- [3] J. Sun, “Detection and Staging of Chronic Obstructive Pulmonary Disease using a Computed Tomography-based Weakly Supervised Deep Learning Approach”, *European Radiology*, Vol. 32, No. 8, pp. 5319-5329, 2022.
- [4] S. Jabbour, D. Fouhey, E. Kazerooni, J. Wiens and M.W. Sjoding, “Combining Chest X-Rays and Electronic Health Record (EHR) Data using Machine Learning to Diagnose Acute Respiratory Failure”, *Journal of the American Medical Informatics Association*, Vol. 29, No. 6, pp. 1060-1068, 2022.
- [5] J. Yang, Z. Shi, J. Huang and X. Tang, “Prediction of Chronic Obstructive Pulmonary Disease based on a Novel Lightweight Multi-Feature Shuffling Convergence Network”, *Biomedical Signal Processing and Control*, Vol. 113, pp. 1-15, 2026.
- [6] W. Jeon, H. Jang, H. Lee and S. Choi, “COPD Multi-Task Diagnosis on Chest X-Ray using CNN-based Slot Attention”, *Applied Sciences*, Vol. 16, No. 1, pp. 1-14, 2025.
- [7] A.H. Curiale and R. San Jose Estepar, “Novel Lobe-based Transformer Model (LobTe) to Predict Emphysema Progression in Alpha-1 Antitrypsin Deficiency”, *Computers in Biology and Medicine*, Vol. 185, pp. 1-12, 2025.
- [8] Y. Yi, L. Shi, H. Liu, M. Wang, M. Feng and Y. Li, “COPD-MMDDxNet: A Multimodal Deep Learning Framework for Accurate COPD Diagnosis using Electronic Medical Records”, *Frontiers in Medicine*, Vol. 12, pp. 1-9, 2025.
- [9] Y. Wu, “Attention-Guided Multiple Instance Learning for COPD Identification: To Combine the Intensity and Morphology”, *Biocybernetics and Biomedical Engineering*, Vol. 43, No. 3, pp. 568-585, 2023.
- [10] A.N. Lee, A. Hsiao and K.A. Hasenstab, “Evaluating the Cumulative Benefit of Inspiratory CT, Expiratory CT and Clinical Data for COPD Diagnosis and Staging through Deep Learning”, *Radiology: Cardiothoracic Imaging*, Vol. 6, No. 6, pp. 1-11, 2024.
- [11] A.V. Ikechukwu and S. Murali, “xAI: An Explainable AI Model for the Diagnosis of COPD from CXR Images”, *Proceedings of International Conference on Data, Decision and Systems (ICDDS)*, Vol. 13, pp. 1-6, 2023.
- [12] X. Wang, “An Explainable Artificial Intelligence Framework for Risk Prediction of COPD in Smokers”, *BMC Public Health*, Vol. 23, No. 1, pp. 1-7, 2023.
- [13] C.T. Kor, Y.R. Li, P.R. Lin, S.H. Lin, B.Y. Wang and C.H. Lin, “Explainable Machine Learning Model for Predicting First-Time Acute Exacerbation in Patients with Chronic Obstructive Pulmonary Disease”, *JPM*, Vol. 12, No. 2, pp. 1-12, 2022.
- [14] S. Mei, “Deep Learning for Detecting and Early Predicting Chronic Obstructive Pulmonary Disease from Spirogram Time Series”, *NPJ Systems Biology and Applications*, Vol. 11, No. 1, pp. 1-18, 2025.
- [15] H. Deng, X. Ding, S. Zhu, X. Song and Y. Guo, “Prediction of Chronic Obstructive Pulmonary Disease based on Multimodal Data and Deep Learning”, *APL Bioengineering*, Vol. 9, No. 4, pp. 1-15, 2025.
- [16] T.A. Shaikat, S.H. Chowdhury, Md Shovon, M.M. Hossain, M.I. Hussain and M. Mamun, “Explainability Elevated Obstructive Pulmonary Disease Care: Severity Classification, Quality of Life Prediction and Treatment Impact Assessment”, *Proceedings of International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Vol. 12, pp. 1-6, 2025.
- [17] H. Sugimori, K. Shimizu, H. Makita, M. Suzuki and S. Konno, “A Comparative Evaluation of Computed Tomography Images for the Classification of Spirometric Severity of the Chronic Obstructive Pulmonary Disease with Deep Learning”, *Diagnostics*, Vol. 11, No. 6, pp. 1-9, 2021.
- [18] A.A. Khade, “A Hybrid Model for Predicting COPD using CNN”, *Proceedings of International Conference on Advancement in Computation and Computer Technologies (InCACCT)*, Vol. 8, pp. 52-57, 2023.
- [19] J. Chawla and N.K. Walia, “A Novel Artificial Intelligence based Approach for Diagnosis of Chronic Obstructive Pulmonary Disease”, *Proceedings of International Conference for Innovation in Technology (INOCON)*, Vol. 8, pp. 1-7, 2024.
- [20] E.T. Heyman, “A Novel Interpretable Deep Learning Model for Diagnosis in Emergency Department Dyspnoea Patients based on Complete Data from an Entire Health Care System”, *PLOS ONE*, Vol. 19, No. 12, pp. 1-11, 2024.
- [21] X. Zhang, “A Self-Supervised Framework for Emphysema Anomaly Detection and Staging in Computed Tomography Scans”, *Patterns*, Vol. 7, No. 2, pp. 1-13, 2025.
- [22] P. Jayadharshini, S. Santhiya, J. Rakshitaa, K. Nithika, N. Kannan and P. Tharun, “Advancing COPD Diagnosis through Deep Learning, GANs and Chest X-Ray Analysis for Precise Detection and Severity”, *Intelligent Computing and Control for Engineering and Business Systems (ICCEBS)*, Vol. 23, pp. 1-6, 2023.
- [23] R. Bigolin Lanfredi, J.D. Schroeder, C. Vachet and T. Tasdizen, “Adversarial Regression Training for Visualizing the Progression of Chronic Obstructive Pulmonary Disease with Chest X-Rays”, *Medical Image Computing and Computer Assisted Intervention*, Vol. 11769, pp. 685-693, 2024.
- [24] M.M. Saad, A.A. Bayoumy, M.M. EL-Nisr, N.M. Zaki, T.H. Khalil and A.F. EL-Serafi, “Assessment of Artificial Intelligence-Aided Chest Computed Tomography in Diagnosis of Chronic Obstructive Airway Disease: An

- Observational Study”, *Egyptian Journal of Radiology and Nuclear Medicine*, Vol. 54, No. 1, pp. 1-7, 2023.
- [25] Z. Zhang, “Detection of Chronic Obstructive Pulmonary Disease with Deep Learning using Inspiratory and Expiratory Chest Computed Tomography and Clinical Information”, *Journal of Thoracic Disease*, Vol. 16, No. 9, pp. 6101-6111, 2024.
- [26] F. Lin, “AutoCOPD-A Novel and Practical Machine Learning Model for COPD Detection using Whole-Lung Inspiratory Quantitative CT Measurements: A Retrospective, Multicenter Study”, *eClinicalMedicine*, Vol. 82, pp. 1-6, 2025.
- [27] A. Krishnaveni, G.V. Rajkumar, J.R.F. Raj, R.S. Krishnan, S. Murali and I.J. Settu, “MultimodNet: A Multimodal Deep Learning Model for COPD Staging based on Chest X-Ray and Pulmonary Function Tests”, *Proceedings of International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Vol. 21, pp. 1683-1690, 2024.
- [28] R. Wang, “Enabling Chronic Obstructive Pulmonary Disease Diagnosis through Chest X-Rays: A Multi-Site and Multi-Modality Study”, *International Journal of Medical Informatics*, Vol. 178, pp. 1-11, 2023.
- [29] K. Makimoto, J.C. Hogg, J. Bourbeau, W.C. Tan, M. Kirby and the CanCOLD Collaborative Research Group, “Enhancing COPD Classification using Combined Quantitative Computed Tomography and Texture-based Radiomics: A CanCOLD Cohort Study”, *ERJ Open Research*, Vol. 10, No. 4, pp. 968-2023, 2024.
- [30] N. Cai, Y. Xie, Z. Cai, Y. Liang, Y. Zhou and P. Wang, “Deep Learning Assisted Diagnosis of Chronic Obstructive Pulmonary Disease based on a Local-to-Global Framework”, *Electronics*, Vol. 13, No. 22, pp. 1-9, 2024.