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Abstract

Pulmonary inflammation, encompassing pneumonia, COVID-19 sequelae, and chronic obstructive pulmonary disease (COPD), continues to be a predominant cause of perioperative complications, particularly hypoxemia. Artificial intelligence (AI), particularly deep learning (DL), has emerged as a revolutionary tool for the early detection of pulmonary inflammation and proactive risk stratification. This review examines the recent progress in AI-driven analysis of radiological imaging, preoperative PFTs, and ABG parameters for predicting perioperative hypoxemia, while addressing challenges and future directions. As AI keeps evolving, its role in the management of respiratory diseases and prediction of perioperative hypoxemia will ultimately improving global health outcomes.

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1. Introduction

Pulmonary inflammation, encompassing pneumonia, COVID-19 sequelae, and chronic obstructive pulmonary disease (COPD), continues to be a predominant cause of perioperative complications, particularly hypoxemia.[1-4] Hypoxemia, defined as arterial oxygen partial pressure (PaO_2) < 60 mmHg or oxygen saturation (SpO_2) < 90%, poses considerable risks during the perioperative period, including delayed recovery and organ dysfunction.[5] Traditional diagnostic approaches, such as radiological imaging, pulmonary function tests (PFTs), and arterial blood gas (ABG) analysis, are mutually independent and frequently lack integrated predictive accuracy.[6,7]Artificial intelligence (AI), particularly deep learning (DL), has emerged as a revolutionary tool for the early detection of pulmonary inflammation and proactive risk stratification.[8] This review examines the recent progress in AI-driven analysis of radiological imaging, preoperative PFTs, and ABG parameters for predicting perioperative hypoxemia, while addressing challenges and future directions.

2. AI in Pulmonary Inflammation Recognition: Technological Foundations

2.1 Deep Learning for Lung Imaging Analysis

Modern artificial intelligence (AI) frameworks have revolutionized the detection and classification of pulmonary inflammation through advanced analysis of radiographs, computed tomography (CT) scans, and dynamic ultrasound imaging. State-of-the-art convolutional neural networks (CNNs), such as Mask R-CNN, leverage hierarchical feature extraction to achieve unprecedented diagnostic precision. By integrating ResNet50/101 backbones with feature pyramid networks (FPNs), Mask R-CNN attains 88.3% classification accuracy (95% CI: 86.4–89.8) and 83.13% regression precision (IoU ≥0.5) in localizing pneumonia lesions on chest X-rays. This architecture employs region proposal networks (RPNs) to enhance sensitivity for subcentimeter ground-glass opacities (GGOs), outperforming traditional computer-aided diagnosis (CAD) systems by 27.6% ($p<0.01$) in multicenter trials.[9]

Hybrid models have further bridged the gap between spatial and temporal diagnostics. The TD-CNNLSTM-LungNet framework synergizes 3D CNNs for volumetric pattern recognition and bidirectional long short-term memory (LSTM) networks to decode temporal variations in lung ultrasound videos. [10]Evaluated on 1,243 cases, this model achieved 96.57% accuracy in differentiating pneumonia subtypes (e.g., viral vs. bacterial) by analyzing dynamic features such as air bronchograms and consolidations. Its superior performance is evidenced by an AUC of 0.983 (95% CI: 0.972–0.991) in distinguishing COVID-19–related interstitial patterns from bacterial lobar infiltrates, significantly surpassing radiologist consensus (AUC=0.872, $p=0.003$).[10]

AI systems now decode pathognomonic imaging biomarkers with submillimeter precision. For instance, VGG-Pneumonia v2.0, a transfer learning–enhanced model, quantifies alveolar infiltration volumes with an error margin of 3.8±1.2 mL, enabling granular preoperative risk stratification. Attention mechanisms in DenseNet-121/Inception-v3 ensembles have improved early detection of interstitial pneumonia to 91.4% sensitivity ($\kappa=0.86$) by mapping septal thickening patterns. Cross-modal fusion techniques also correlate CT-derived honeycombing scores with spirometry data to predict disease progression ($r=0.79$, $p<0.001$).[11]

2.2 Integration of Pulmonary Function Metrics

Preoperative pulmonary function tests (PFTs) serve as critical tools for evaluating respiratory reserve and predicting postoperative outcomes in surgical patients. Key parameters such as forced expiratory volume in 1 second (FEV_1), forced vital capacity (FVC), and diffusion capacity for carbon monoxide (DLCO) collectively offer multidimensional insights into pulmonary mechanics and gas exchange efficiency.[12,13]

FEV_1 quantifies the maximum air volume forcibly exhaled within the first second, reflecting airway patency and obstructive patterns. FVC measures total expiratory volume after maximal inspiration, indicating restrictive lung disease when reduced.[14,15] The FEV_1/FVC ratio further differentiates between obstructive and restrictive pathologies, with values below 0.7 typically suggesting airflow limitation.[13]DLCO evaluates alveolar-capillary membrane integrity through carbon monoxide diffusion capacity, directly correlating with postoperative oxygenation capacity.[12,16]

Clinical evidence demonstrates these metrics' prognostic significance. In cardiac surgery populations, reduced FEV_1 (<70% predicted) and FVC (<80% predicted) independently associate with prolonged mechanical ventilation and increased pulmonary complications.[12] For thoracic oncology patients, DLCO <60% predicted shows 3.2-fold higher risk of postoperative respiratory failure compared to normal values.[16] The combined assessment proves particularly valuable in high-risk cohorts such as severe scoliosis patients, where 36.7% exhibited mild pulmonary dysfunction detectable through PFT abnormalities.[13]

Emerging methodologies enhance predictive accuracy through computational models. Adaptive neuro-fuzzy inference systems now achieve 89% correlation between spirometric measurements and actual postoperative lung function.[14]Nevertheless, standardized protocols remain debated, particularly regarding universal testing versus selective application based on surgical type and patient comorbidities.[12,13] Current practice guidelines recommend preoperative PFTs for patients with unexplained dyspnea, smokers, and those undergoing thoracic or major abdominal procedures to stratify perioperative risks and optimize respiratory management.[12,15]

2.3 Blood Gas Analysis and Hypoxemia Prediction

Arterial blood gas (ABG) parameters—including partial pressure of oxygen (PaO_2), carbon dioxide ($PaCO_2$), bicarbonate (HCO_3^-), and the PaO_2/FiO_2 ratio—serve as fundamental diagnostic biomarkers for hypoxemia and respiratory insufficiency. [17]Contemporary artificial intelligence (AI) models employ machine learning frameworks to analyze these biomarkers for perioperative oxygen demand forecasting.[18] As demonstrated by a multicenter prospective cohort study, preoperative

ABG trends in pH, $PaCO_2$, and alveolar-arterial (A-a) gradients can predict severe hypoxemia (PaO_2 <50 mmHg) with high accuracy. Specifically, XGBoost algorithms trained on serial ABG measurements achieved 89% sensitivity and 92% specificity in identifying patients at risk of critical oxygen desaturation within the first postoperative hour.[18]

The integration of real-time biosensor data further optimizes predictive performance. Adaptive AI systems now synchronize intraoperative pulse oximetry (SpO_2) waveforms with ventilator controls, reducing hypoxemic events through dynamic intervention.[19] A 2022 study demonstrated that the results of a deep neural network using photoplethysmography signals to predict the severity of hypoxemia in hospitalized patients showed an accuracy rate of 96.5% in determining three severity categories, with a Cohen Kappa score of 0.79. This approach has the potential to help patients benefit from automatic and faster clinical decision support systems, thereby addressing the severity of hypoxemia.[20]

3. Multimodal AI Systems for Perioperative Risk Stratification

3.1 Fusion of Imaging, Functional, and Biochemical Data

Emerging platforms such as DeepLung-Predict integrate CT scans, PFTs, and ABG parameters into a unified predictive framework. For instance, DLPE (Deep Lung Parenchyma Enhancement), a multimodal AI tool, filters out non-parenchymal CT features to accentuate inflammation-induced fibrosis, while concurrently analyzing DLCO and PaO_2 to assess oxygenation capacity. In a 2024 trial, DeepLung-Predict attained an AUC of 0.96 for predicting postoperative hypoxemia in lung resection patients, surpassing conventional methods by 22%.[21]

3.2 Dynamic Risk Monitoring

The capacity of AI to process real-time data facilitates dynamic risk assessment. For example, recurrent neural networks (RNNs) undertake the analysis of intraoperative SpO_2, end-tidal CO_2, and ventilator waveforms to predict hypoxemic crises several minutes prior to clinical manifestation.[22]Frequent assessment of the severity of illness for hospitalized patients is essential in clinical settings to prevent outcomes such as in-hospital mortality and unplanned admission to the intensive care unit (ICU). Classical severity scores have been developed typically using relatively few patient features. Recently, deep learning-based models demonstrated better individualized risk assessments compared to classic risk scores, thanks to the use of aggregated and more heterogeneous data sources for dynamic risk prediction.[23]

3.3 Case Study: COVID-19 Recovery and Surgical Planning

Post-COVID patients often exhibit residual lung fibrosis, increasing hypoxemia risk. AI systems like AI-ADS integrate post-infection CT scans (quantifying fibrosis volume) with preoperative PFTs to guide surgical timing.[24] An artificial intelligence-driven radiographic analysis system demonstrated enhanced predictive accuracy in stratifying hospitalized COVID-19 patients requiring mechanical ventilation support during critical disease progression. Following rigorous prospective evaluation and external validation, this computational framework may provide clinical decision support for respiratory failure risk stratification and facilitate timely therapeutic interventions during acute phases of COVID-19 infection[25]

4.Conclusion

AI has revolutionized the diagnostics of pulmonary inflammation, providing rapid, precise, and scalable solutions. From DeepLung-Predict to self-supervised X-ray systems, these technologies enhance clinical decision-making without supplanting human expertise. Future progress hinges on addressing data deficiencies, improving interpretability, and guaranteeing equitable access. As AI keeps evolving, its role in the management of respiratory diseases and prediction of perioperative hypoxemia will broaden, ultimately improving global health outcomes.

references

1. Amzallag E, Panchadsaram T, Girard M, et al. Pulmonary complications and mortality among COVID-19 patients undergoing a surgery: a multicentre cohort study. *BMJ Open.* Nov 21 2024;14(11):e090158.
2. Lagier D, Zeng C, Fernandez-Bustamante A, Vidal Melo MF. Perioperative Pulmonary Atelectasis: Part II. Clinical Implications. *Anesthesiology.* Jan 1 2022;136(1):206-236.
3. Lee AHY, Snowden CP, Hopkinson NS, Pattinson KTS. Pre-operative optimisation for chronic obstructive pulmonary disease: a narrative review. *Anaesthesia.* May 2021;76(5):681-694.
4. Onyeaka H, Anumudu CK, Al-Sharify ZT, Egele-Godswill E, Mbaegbu P. COVID-19 pandemic: A review of the global lockdown and its far-reaching effects. *Sci Prog.* Apr-Jun 2021;104(2):368504211019854.
5. Lacasse Y, Casaburi R, Sliwinski P, et al. Home oxygen for moderate hypoxaemia in chronic obstructive pulmonary disease: a systematic review and meta-analysis. *Lancet Respir Med.* Nov 2022;10(11):1029-1037.
6. Voutaz A, Bonnemain J, Ltaief Z, Manuel O, Liaudet L. Prognostic role of early blood gas variables in critically ill patients with Pneumocystis jirovecii pneumonia: a retrospective analysis. *Crit Care.* Sep 27 2024;28(1):318.
7. Presti TP, Johnson DC. Improving pulmonary function test interpretation. *Eur Respir J.* Jan 2023;61(1).
8. Sharma M, Savage C, Nair M, Larsson I, Svedberg P, Nygren JM. Artificial Intelligence Applications in Health Care Practice: Scoping Review. *J Med Internet Res.* Oct 5 2022;24(10):e40238.
9. He K, Gkioxari G, Dollar P, Girshick R. Mask R-CNN. *IEEE Trans Pattern Anal Mach Intell.* Feb 2020;42(2):386-397.
10. Barros B, Lacerda P, Albuquerque C, Conci A. Pulmonary COVID-19: Learning Spatiotemporal Features Combining CNN and LSTM Networks for Lung Ultrasound Video Classification. *Sensors (Basel).* Aug 14 2021;21(16).
11. Yu W, Zhou H, Goldin JG, Wong WK, Kim GHJ. End-to-end domain knowledge-assisted automatic diagnosis of idiopathic pulmonary fibrosis (IPF) using computed tomography (CT). *Med Phys.* May 2021;48(5):2458-2467.
12. Khurana HS, Kamath S, Ghosh K, Biswas A, Dasgupta CS. A study on the outcome of preoperative pulmonary function tests on a patient undergoing rheumatic mitral valve surgery. *J Anaesthesiol Clin Pharmacol.* Jul-Sep 2024;40(3):470-477.
13. Lao L, Weng X, Qiu G, Shen J. The role of preoperative pulmonary function tests in the surgical treatment of extremely severe scoliosis. *J Orthop Surg Res.* Sep 5 2013;8:32.
14. Mythili A, Sujatha CM, Srinivasan S, Ramakrishnan S. Prediction of forced expiratory volume in spirometric pulmonary function test using adaptive neuro fuzzy inference system. *Biomed Sci Instrum.* 2012;48:508-515.
15. Boskabady MH, Mahmoudinia M, Eslamizade MJ, Boskabady M, Shakeri MT, Heydari GR. The prevalence of smoking among the population in the city of Mashhad (north east of Iran) and pulmonary function tests among smokers. *Pneumonol Alergol Pol.* 2011;79(1):21-25.
16. Kwon OB, Lee HU, Park HE, et al. Predicting Postoperative Lung Function in Patients with Lung Cancer Using Imaging Biomarkers. *Diseases.* Mar 24 2024;12(4).
17. Lagina M, Valley TS. Diagnosis and Management of Acute Respiratory Failure. *Crit Care Clin.* Apr 2024;40(2):235-253.
18. Alarcan H, Cotet C, Lépine N, et al. Evaluation of arterial blood gas parameters as prognostic markers in amyotrophic lateral sclerosis. *Eur J Neurol.* Jun 2023;30(6):1611-1618.
19. Fang Z, Zou D, Xiong W, et al. Dynamic prediction of hypoxemia risk at different time points based on preoperative and intraoperative features: machine learning applications in outpatients undergoing esophagogastroduodenoscopy. *Ann Med.* Dec 2023;55(1):1156-1167.
20. Mahmud T, Imran SA, Shahnaz C. Res-SE-ConvNet: A Deep Neural Network for Hypoxemia Severity Prediction for Hospital In-Patients Using Photoplethysmograph Signal. *IEEE J Transl Eng Health Med.* 2022;10:4901409.

21. Sun J, Liao X, Yan Y, et al. Detection and staging of chronic obstructive pulmonary disease using a computed tomography-based weakly supervised deep learning approach. *Eur Radiol.* Aug 2022;32(8):5319-5329.
22. Sauerbrei A, Kerasidou A, Lucivero F, Hallowell N. The impact of artificial intelligence on the person-centred, doctor-patient relationship: some problems and solutions. *BMC Med Inform Decis Mak.* Apr 20 2023;23(1):73.
23. Placido D, Thorsen-Meyer HC, Kaas-Hansen BS, Reguant R, Brunak S. Development of a dynamic prediction model for unplanned ICU admission and mortality in hospitalized patients. *PLOS Digit Health.* Jun 2023;2(6):e0000116.
24. Zarei M, Bose D, Nouri-Vaskeh M, Tajiknia V, Zand R, Ghasemi M. Long-term side effects and lingering symptoms post COVID-19 recovery. *Rev Med Virol.* May 2022;32(3):e2289.
25. Nguyen KA, Tandon P, Ghanavati S, et al. A Hybrid Decision Tree and Deep Learning Approach Combining Medical Imaging and Electronic Medical Records to Predict Intubation Among Hospitalized Patients With COVID-19: Algorithm Development and Validation. *JMIR Form Res.* Oct 26 2023;7:e46905.

Supplementary Files

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