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Comparative analysis of artificial intelligence applications in acute respiratory distress syndrome

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ABSTRACT: In patients in the intensive care unit (ICU), acute respiratory distress syndrome (ARDS) is a frequent pulmonary condition that can be fatal. It is often linked to direct lung damage, which is followed by sepsis and multi-organ system failure. According to estimates, 10% of all ICU patients, 23% of ventilated patients, and 5.5 cases per ICU bed experience ARDS each year in critical care. ARDS patients have an overall death rate of 35–50%, which accounts for 4% of all hospital admissions and hasn't altered in ten years despite improvements in the healthcare system. In this paper we have done a comparative analysis of AI-driven approaches have gained significant traction in the diagnosis, prediction, and management of ARDS. This analysis compares various methodologies and AI applications across key studies in this field. Our main focus is on different machine learning (ML) models used for prediction purposes.

Keywords: Artificial Intelligent, Diagnosis, Medical informatics, respiratory distress syndrome

1 INTRODUCTION

ARDS is a critical condition where fluid accumulates in the lungs and prevents oxygen from reaching the body's organs. It often develops within 24-48 hours after trauma, infection, or injury to the lungs or brain [1]. The primary symptom is severe difficulty breathing, accompanied by rapid, shallow breathing, confusion, low blood pressure, and organ failure in severe cases. ARDS results from damage to the alveoli. The tiny air sacs in the lungs. which leads to oxygen deprivation throughout the body. Leads to the condition life-threatening if not treated promptly. Risk factors for ARDS include older age, a history of smoking, alcohol use, lung disease, and sepsis or trauma. It is commonly associated with other severe illnesses or injuries. In order to maintain breathing and treat the underlying cause, such as an infection or damage, treatment usually entails mechanical ventilation [2].

Figure 1: illustrates how (ARDS) affects the lungs by causing fluid buildup in the alveoli (air sacs) and makes difficult for the lungs to expand. The left side compares normal bronchioles and alveoli .an ARDS-affected lung shows fluid accumulation in the alveoli.

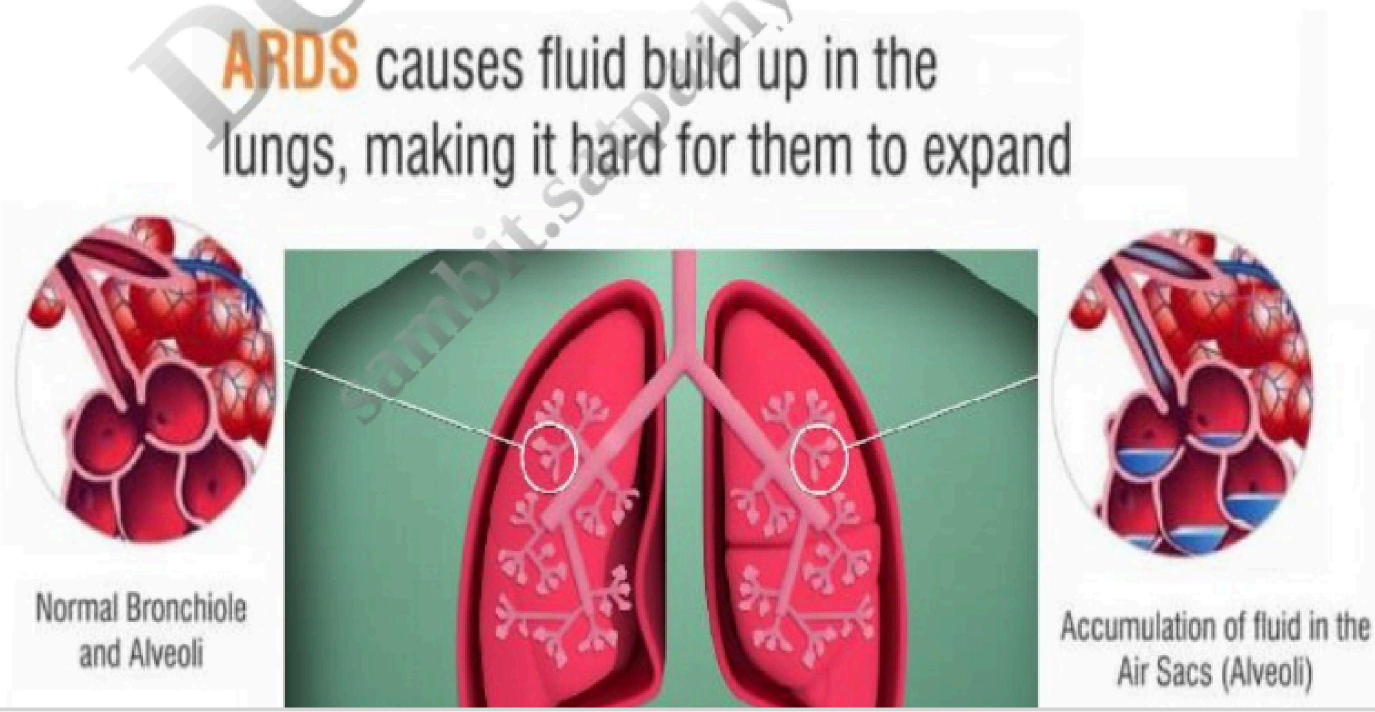

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Figure 1. Overview of acute respiratory distress syndrome (ARDS).

1.1 *The signs and symptoms of ARDS*

The major frequent symptom of ARDS is a sudden and severe struggle to breathe. Other indicators consist of [3]:

- Lips or nails that are blue due to low blood oxygen levels
- General weakness and fatigue
- Confusion and dizziness
- Fast and labored breathing
- Low blood pressure.
- Extreme sweating

1.2 *Recovery and improve quality of life*

- The rehabilitation team: which typically consists of doctors, nurses, and other specialists who will collaborate with you to create a personalized program. will assist you in regaining lung function so that you can resume regular daily activities.
- Give up smoking: If an individual smokes, he or she has to stop smoking. It's also crucial to stay away from chemicals that might irritate your lungs, such as hazardous fumes, and secondhand smoke.
- Support: It's crucial to have a strong support system of friends and family to help with daily tasks. This will not only help individuals deal with whatever physical limits they may be facing, but it will also help them feel less stressed, depressed, and anxious.

1.3 *Role of Artificial Intelligent (AI)*

AI plays an increasingly significant role in the identification, diagnosis, and management of ARDS [4].

- Early Diagnosis Using Medical Imaging
- Predictive Models for Risk Assessment
- Natural Language Processing (NLP) in EHRs
- Real-Time Monitoring in Critical Care
- AI-Powered Ventilator Management
- Predicting ARDS Outcomes
- AI-Driven Biomarker Discovery
- Clinical Decision Support Systems (CDSS)
- Accelerating Research and Drug Development

2 RELATED WORK

Recent work on the role of artificial intelligence (AI) in the identification and management of ARDS encompasses a variety of approaches, each with unique advantages and limitations.

Together, these studies showcase the diverse methodologies and the growing impact of AI on improving ARDS outcomes, while also highlighting the challenges in data integration, computational demand, and clinical validation.

3 COMPARATIVE ANALYSIS

In recent years, AI-driven approaches have gained significant traction in the diagnosis, prediction, and management of ARDS. This analysis compares various methodologies and AI applications across key studies in this field. Our main focus is on different machine learning (ML) models used for prediction purposes that shown in Table 1 (review) and Table 2 (comparision).

Table 1 Previous research work done in domain of XAI.

Reference	Objective	Methodology	Advantages	Limitations
[6] Rashid et al. 2022	Provide an overview of AI applications in ARDS by doing a methodical review.	Systematic review of PubMed and additional searches to identify studies employing AI in ARDS. 19 studies from 2002–2020 were included.	Provides a broad overview of AI applications in ARDS, including diagnosis, prediction, and management.	The review is limited to published studies in English and up to February 2021, which may miss recent developments.
[7] Rubulotta et al. 2024	Review of machine learning tools for ARDS detection and	Review of existing ML models, analyzing clinical data (vitals, lab results, imaging) for ARDS detection	Highlights the potential of ML in enhancing early ARDS detection and improving	General overview; lacks detailed experimental validation of the proposed tools.

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	detection and prediction.	results, imaging) for ARDS detection and risk prediction in ICU patients.	detection and improving patient outcomes in ICUs.	of the proposed tools.
[8] Le et al. 2020	Develop gradient-boosted tree models to predict ARDS early.	Analysis of 9,919 MIMIC-III patient contacts in the past. XGBoost models trained with clinical data and radiology reports using 10-fold cross-validation.	High AUROC values (up to 0.905) for early ARDS detection; provides up to 48-hour prediction windows.	Retrospective design; performance may differ in real-time clinical settings.
[9] Wong et al. 2020	Develop AI models combining clinical data and chest X-rays to detect ARDS.	Transfer learning for CNNs trained on external image datasets. Ensemble models with XGB, RF, LR used on clinical data.	Improved performance with combined models (AUC = 0.925); Grad-CAM provides explainability.	Requires extensive computational resources and large datasets for transfer learning.
[10] Pai et al. 2022	Develop ML models using ventilator waveform data for ARDS diagnosis.	Data from mechanical ventilation during the first 24 hours used to extract physiological features. RF models developed for ARDS discrimination.	High sensitivity and specificity for ARDS diagnosis using only ventilator waveform data.	Limited to intubated patients; does not incorporate other clinical or imaging data.
[11] Rehm et al. 2021	Screen for ARDS using raw ventilator waveform data.	ML models trained on waveform data to classify ARDS presence; AUROC used for performance assessment.	Facilitates early ARDS recognition without conventional diagnostic tools.	Reliant on ventilator data; limited to specific clinical settings.
[12] Wu et al. 2022	Predict moderate-to-severe inhalation-induced ARDS using ML.	Random forest models applied to vital signs (heart rate, respiratory rate, temperature) from ICU data.	Strong predictive ability (AUC = 0.9127); interpretable rules aid in clinical decision-making.	Focuses on a specific type of ARDS; may not generalize to other ARDS causes.
[13] Arrivé et al. 2021	Early identification of ARDS in non-intubated patients.	Review of ARDS definitions, especially for patients using non-invasive oxygenation strategies.	Proposes structured diagnostic work-up for early ARDS detection in non-intubated patients.	Lacks AI/ML-driven methodologies; focus is on early identification, not prediction.
[14] Luo et al. 2017	Identify ARDS risk in patients with severe pneumonia.	Retrospective cohort study using logistic regression and ROC curve analysis for risk factor identification.	Identifies clinical predictors of ARDS (e.g., PEEP > 6.5 cm H_2O, serum FiB > 5.15 g/L).	Traditional statistical methods; no use of advanced AI/ML approaches.

Table 2 Comparative analysis of different machine learning models.

Reference	Objective	Methodology	Dataset	Result
[15] Sinha *et al.* 2020	Develop machine learning classifiers to use clinical data to identify ARDS phenotypes.	Gradient-boosted machine algorithm using 24 variables (demographics, vitals, labs, respiratory). Three RCT cohorts for training (n = 2022), one RCT cohort for validation (n = 745).	ARMA, ALVEOLI, FACTT, SAILS trials.	GBML AUC: 0.95
[16] Lazzarini *et al.* 2022	Predict ARDS progression in COVID-19 patients using ML models.	Gradient Boosting Decision Tree with 817 diagnostic features from patient history. Panel of clinicians compared with the model. Split into training, testing, and validation sets.	289,351 COVID-19 patients, April 2020).	GBDT AUC: 0.695
[17] Afshar *et al.* 2018	Develop a computable ARDS phenotype using NLP and ML for radiology reports.	NLP feature extraction from radiology reports, used to train ML classifiers. Cross-validation 10 times on 80% of the data, with testing on the remaining 20%.	9,255 radiology reports from 533 patients.	AUC: 0.83
[18] Zhang and Pang 2023	Using machine learning algorithms, ARDS in patients with acute pancreatitis (AP) can be predicted early.	SVM, EDT, Bayesian Classifier, Nomogram models developed and optimized with feature selection. Trained with 5-fold cross-validation and evaluated using a test set.	460 patients with AP from January 2017 to August 2022.	BC AUC: 0.891
[19] Zhang *et al.* 2023	Develop binary and quaternary classification models for ARDS severity in severe acute pancreatitis.	Multiple ML models (LR, RF, SVM, DT, XGB, ANN) trained with retrospective data. SHAP values used for interpretability and model optimization.	SAP patients hospitalized from August 2017 to August 2022.	XGB AUC: 0.84

4 CONCLUSION AND FUTURE SCOPE

Applying machine learning (ML) models to ARDS diagnosis and prediction has shown promising results across different clinical contexts and datasets. Sinha *et al.* (2020) developed a gradient-boosted machine learning model that achieved a high AUC of 0.95, proving that clinical data from randomized controlled trials may be used to categorize ARDS phenotypes. Lazzarini *et al.* (2022) applied a gradient boosting decision tree to predict ARDS progression in COVID-19 patients, yielding a moderate AUC of 0.695, while Afshar *et al.* (2018) used natural language processing (NLP) combined with machine learning for ARDS identification from radiology reports, achieving an accuracy of 83%. In the context of acute pancreatitis (AP), Zhang and Pang (2023) and Zhang *et al.* (2023) applied various ML models such as ensemble decision trees (EDT), Bayesian classifiers, and support vector machines (SVM) for early ARDS prediction, achieving AUCs of 0.891 and 0.84, respectively as shown in Figure 2

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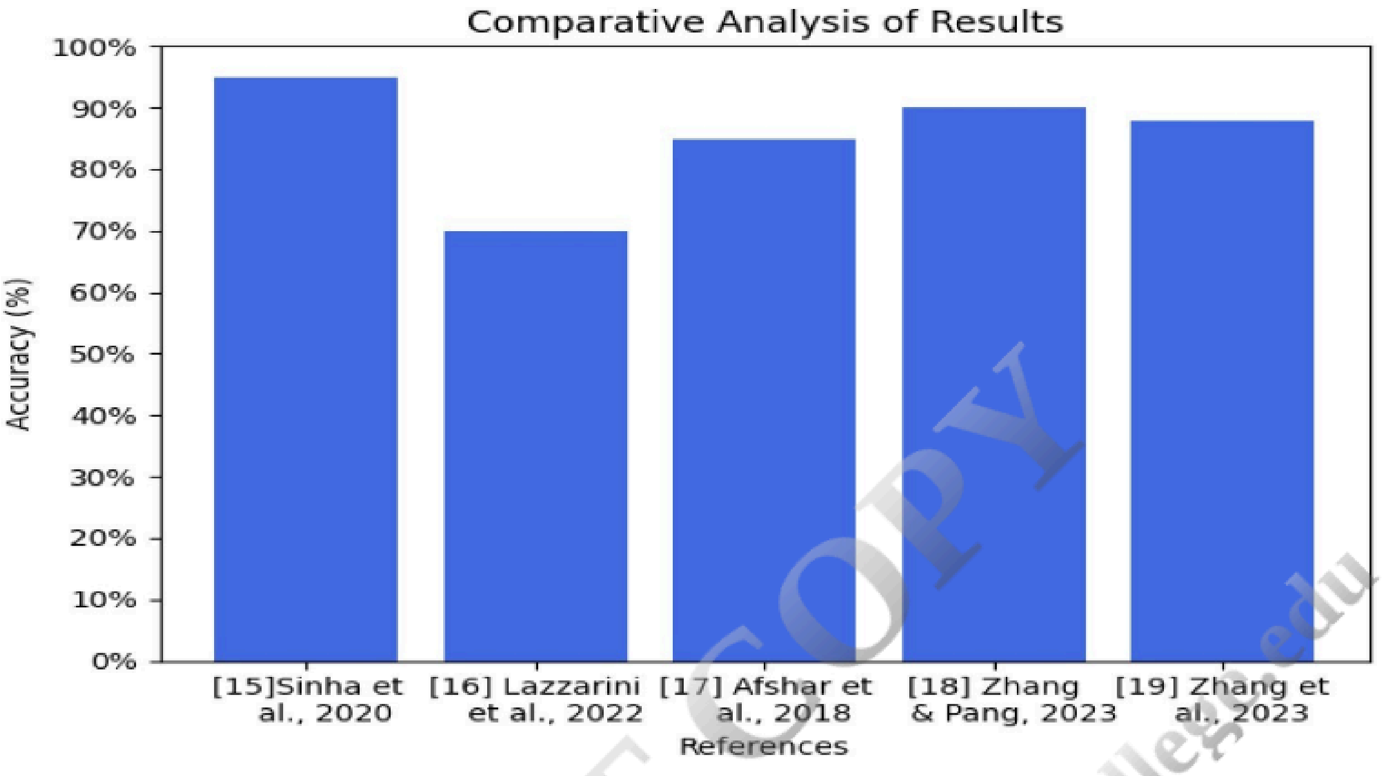

Figure 2. Comparative result analysis.

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