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Evaluating Machine Learning Algorithms For The Detection Of Patient Ventilator Asynchrony In Hypoxemic Respiratory Failure Patients: A Systematic Review

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Moumita Chakraborty[1], Imsha Imitiaz Ali[2]

[1]Vice Principal and Associate Professor, Dept of Respiratory Technology, Narayana Hrudayalaya Institute of Allied Health Sciences, Bengaluru, India,

[2]Assistant Professor ,Department Of Anaesthesia And Operation Theatre Technology ,Yenepoya School Of Allied Health Sciences, India

Correspondence: Moumita Chakraborty, chakrabortymoumita27@gmail.com

Abstract

Background: Patient–ventilator asynchrony (PVA) remains a major challenge during invasive mechanical ventilation, resulting from inadequate coordination between ventilator-delivered breaths and the patient's intrinsic respiratory effort. PVA is clinically significant due to its high prevalence and its association with ventilator-induced lung injury (VILI), prolonged mechanical ventilation, and increased ICU stay, particularly in patients with hypoxemic respiratory failure. The most frequently reported PVA subtypes include reverse triggering, double triggering, and ineffective inspiratory effort. Artificial intelligence (AI), particularly neural network-based machine learning models, has emerged as a promising approach for automated waveform analysis and real-time detection of PVA.

Methods: A systematic review was conducted using structured database searches of Pub Med, Web of Science, and Embase. Ten original studies (7 prospective and 3 retrospective) published between 2018 and 2025 were included, focusing on neural network-based automated detection of PVA using ventilator waveform data. Model performance, detection of PVA sub-types, and diagnostic accuracy were evaluated.

Results: Among the included studies,convolutional neural networks (CNN) were utilized in 4studies, 3 studies utilized recurrent neural network architectures(RNN), Logistic regression and decision tree were applied in 1 and 2 studies respectively with some studies employing hybrid deep learning frameworks. Sample sizes ranged from 750 patient recordings and 40,807,279 breath counts. Neural network models demonstrated high diagnostic performance, with sensitivity >0.90 and specificity ranging from >0.90, F1 scores>0.90. Accuracy (AUC) values greater >0.90. Reverse triggering and double triggering demonstrated the highest detection accuracy (>92% in several studies), whereas ineffective inspiratory effort detection accuracy ranged between 54% and 90%.

Conclusion: Neural network-driven detection systems show strong potential for accurate real-time identification of PVA and may enhance ventilator management and patient outcomes.

Keywords: PVA, Machine Learning, Hypoxemic Respiratory Failure, ARDS

INTRODUCTION

Patient-ventilator Asynchrony (PVA) reflects a mismatch between the patient's intrinsic timing of inspiration and expiration and the ventilator's breath delivery[1,3].I The incidence rates of PVA in mechanically ventilated patients ranges from 10% to 85%.[4].It is recognized as a significant driver of ventilator-induced lung injury (VILI),and is associated with worst clinical outcomes. and may contribute to ongoing lung injury[2,5,6,7].VILI is described as a dynamic process , evolving over time and is easily not captured at a single point.Patients with acute hypoxemic respiratory failure (AHRF) are particularly vulnerable to asynchronous respiratory effort.[8]. Many studies have shown that acute respiratory distress syndrome(ARDS),a type of AHRF;is associated with multiple types of PVA, adding a layer of complexity to the optimizing of lung protective ventilatory strategy.[5,6,9]In determining the prevalence of patient-ventilator asynchrony it is important to distinguish between different types of asynchrony.

PVA is categorised into three distinct phases of the respiratory cycle : triggering,flow and cycling. triggering asynchronies such as, ineffective, reverse,double and auto triggering, occur at breath initiation;flow asynchronies involve a mismatch between ventilator delivery and patient demand during inspiration such as insufficient flow, excessive flow; and cycling asynchronies-comprising premature or delayed termination-manifest at transition to expiration.Collectively, these waveforms serve as critical diagnostic indicators for optimizing mechanical ventilation and improving patient-ventilator asynchrony.[10].Despite manual waveform review being the gold standard for identifying PVA, bedside clinicians often struggle with low diagnostic precision.To bridge this gap, artificial intelligence provides a sophisticated alternative capable of parsing vast streams of breath-by-breath data in real-time—a task that is otherwise too labor-intensive for human practitioners.[11].

Various machine learning models that have been including decision trees, Gaussian Naïve Bayes, and deep learning architectures like Long short term memory (LSTM)and convoluted neural networks (CNN), have proven effective for PVA identification and management. These computational approaches consistently achieve robust performance, often yielding significant F1 scores>0.90.[12]

Despite the clinical importance of identifying patient-ventilator asynchrony (PVA), there is a notable research gap concerning its detection specifically in hypoxemic respiratory failure. Because existing evidence is fragmented across general studies, this systematic review aims to synthesize the diverse AI tools utilized for these patients, establishing a technical framework for more responsive, automated monitoring systems.

MATERIALS AND METHODS

Reporting

This review is in concordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (figure 1) and is registered on the International Prospective Register of Systematic Reviews (PROSPERO identifier CRD420261326057).

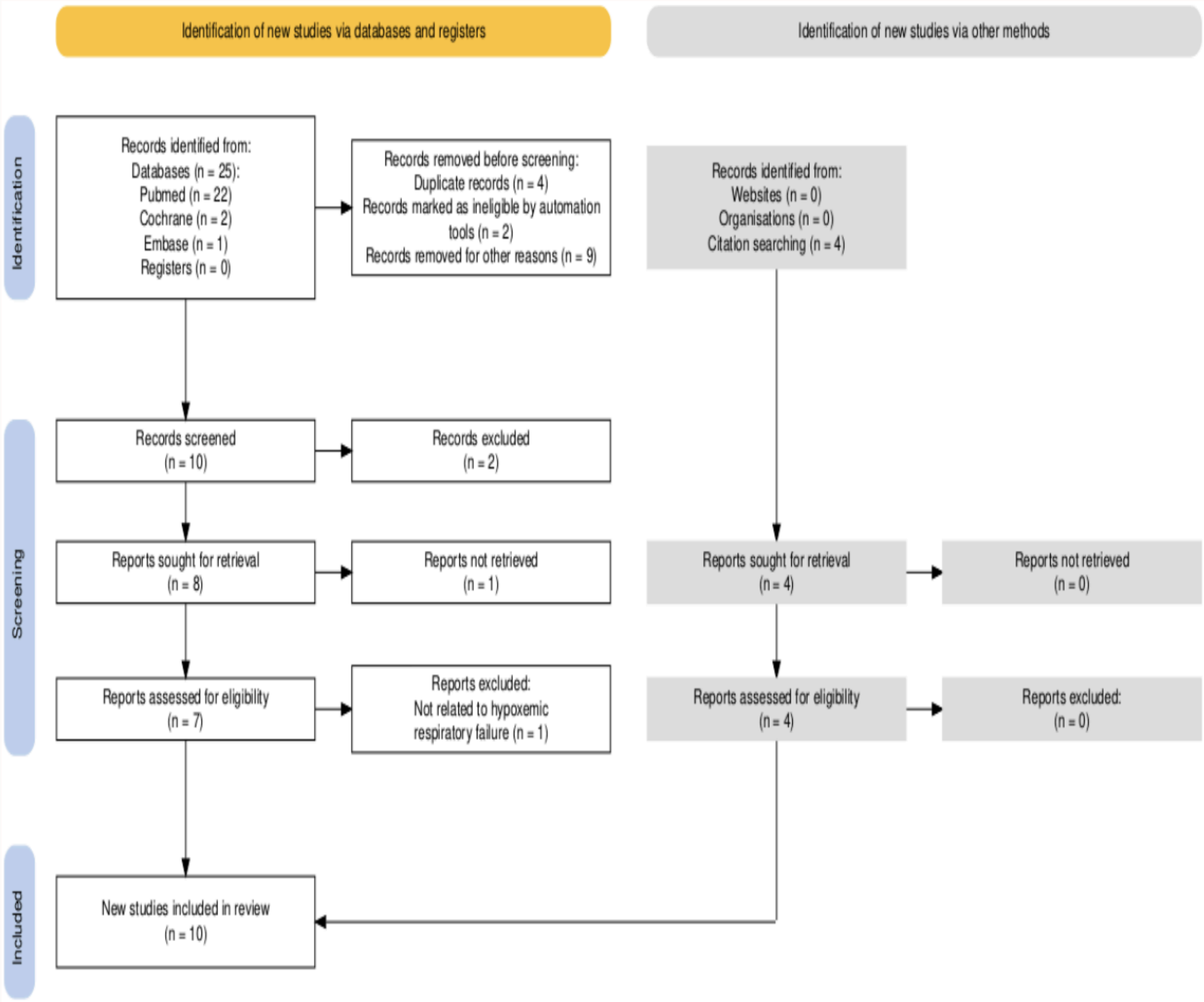

Figure 1:PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in the review

Literature Search

The following databases were searched systematically: (a) PubMed, (b) Embase, (c) Cochrane, for articles published from inception to November 2024 using terms associating ML techniques with PVA in hypoxemic respiratory failure. In addition, a manual search was also conducted on Google Scholar to find potential articles cited by the collected papers.

Eligibility Criteria

In this study, The Population (P) was defined as patients undergoing invasive mechanical ventilation, particularly those with hypoxemic respiratory failure who are at risk for PVA . The Intervention (I) focused Use of machine learning tools, , for automated ventilator waveform analysis and real-time detection of PVA in hypoxemic respiratory failure patients.No Comparator (C) was included, as the review aimed to describe and evaluate the performance and application characteristics of ML models themselves. The Outcomes (O) included high diagnostic performance (Sensitivity, Specificity, F1 scores, and AUC > 0.90). Specifically, high accuracy in detecting subtypes like reverse triggering and double triggering (> 92%).

Based on the defined PICOS framework and the study objectives,the eligibility criteria focused on studies published as original articles in English, involving adult patients suffering from hypoxemic respiratory failure who were managed with invasive mechanical ventilation. To be included, studies must have utilized machine learning (ML) —specifically neural network models—as the primary intervention to detect PVA. The inclusion required detailed breath analysis and waveform evaluation, with data samples ranging from 715 patient recordings to over 40,807,279 breath counts. Studies were included if they reported specific performance metrics such as sensitivity, specificity, F1 scores, and Area Under the Curve (AUC) for PVA subtypes like reverse triggering, double triggering, and ineffective inspiratory effort.Conversely, studies were excluded if they did not involve adult patients on MV, non hypoxemic failure patients, did not apply ML algorithms specifically to PVA,or were non-original research such as editorials, letters, conference abstracts, or review articles.

Data Extraction And Analysis

Two researchers independently screened titles and abstracts of the identified articles. Then, they obtained and read the full texts of potential articles;disagreements were solved via discussion between authors. Data that was extracted from the included articles encompassed study characteristics, such as year of publication, sample size, type of PVA,and breath counts. Information specific to the machine learning models was also collected, including the type of data which was used, the specific ML methods employed, and reported performance metrics (e.g., accuracy, sensitivity, specificity, F1 Score, and area under the curve [AUC].

Risk Of Bias Assessment

The term "risk of bias" describes the possibility of methodological errors, biases in data collection, or implementation deviations.We assessed independently the risk of bias systematic reviews using the ROBVIS web application using the ROBIN -1 tool (Figure 2). It examines the following domains :confounding, selection of participants, classification of intervention, deviation from intended intervention,missing data,measurement of outcome,selection of reported results[13,14]

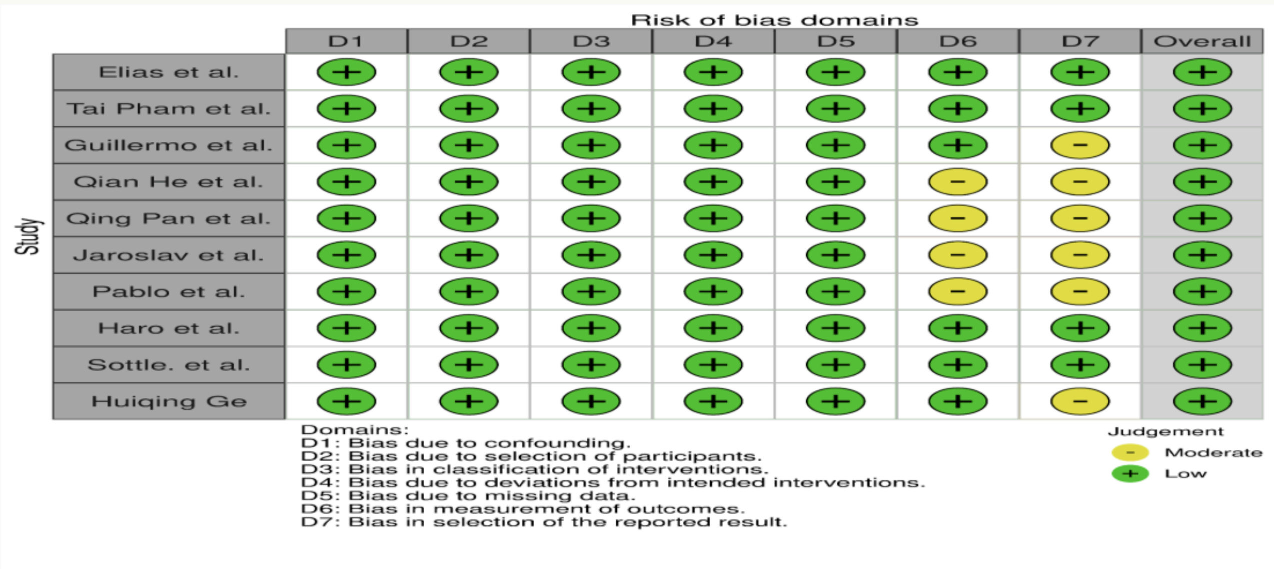

Figure 2: Risk of bias assessment:We assessed independently the risk of bias systematic reviews using the ROBVIS web application using the ROBIN -1 tool

Results

We included 10 studies (Figure 3) that enrolled 715 adult patients on mechanical ventilation. Seven studies were prospective and three retrospective.Five ML models were identified that were used to detect PVA in hypoxemic respiratory failure patients.

The research period spanned from 2018–2025.All three types of major asynchronies were identified- (I)Trigger asynchrony – reverse triggering (RT)with or without breath stacking,double triggering (DT)with or without breath stacking,auto triggering, Ineffective efforts (IEE); (II) Flow asynchrony – flow starvation ;(III) Cycle asynchrony – premature and double cycling.Among the identified PVA, the most common was RT, DT & IEE.40,807,279 breaths were analyzed cumulatively.

Nine studies included ARDS patients and one study included hypoxemic RF patients.

Two of the studies identified PVA in ARDS and other conditions (such as major trauma,COPD, etc). One study [18] identified major ventilatory events such as fluid accumulation , leakage like patterns and other circuit event that could further lead to PVA Among the employed ML models, the model that attained highest accuracy and sensitivity is CNN & logistic regression(accuracy: 99%with F1 score: 99.90,accuracy 95.5 , sensitivity PPV= 97.6, specificity 99.4 respectively).

Author	Year	Study type	Type of PVA	Type of ML	Sample size	Accuracy	Sensitivity	Specificity
Elias et al.[15]	2023	Prospective observational study	Reverse triggering with breath stacking and midcycle reverse triggering	CNN LSTM *ResNet	15- training set 13-validation ARDS Breaths-33,244 Reverse triggering-8718		F1 score>75%	
Tai pham et al.[16]	2021	Prospective Multicentre observational study	Reverse triggering	Logistic regression	Breaths -4,509 Reverse triggering- 1,073 Hypoxemic patient-20	95.5	83.1 PPV-97.6	99.4
Guillermo et al.[17]	2025	Prospective observational study	Double triggering, Ineffective inspiratory effort, auto triggering, cycling and complex	Random forest	ARDS-50,712 Sample size-44	91 81 87 93	Model 1-92 Model 2-90 F1=0.92 92%	>95 M1-92% M2-87%
Qian He et al.[18]	2021	Prospective observational study Cohort study	Fluid accumulation like patterns, leakage like patterns, respiratory circuit events	YOLO CNN	Sample size-48 Breaths -50,296 ARDS Pneumonia	>99	F1=99.90	
Qing Pan et al.[19]	2021	Retrospective technical study	Double triggering, Ineffective inspiratory effort	CNN LSTM	Covid 19	90%	DT F1= 0.98 IEE F1=0.97	>0.94

Jaroslav et al.[20]	2025	Cohort study	Ineffective trigger, double cycling, high inspiratory effort	Bi directional LSTM Deep neural network SMART alert system	Covid 19 Multiple major trauma and elective surgery	AUROC 0.951 (weighted)	IE- F1=0.60 DC=0.667 IE=0.8	98.5% For all the PVAs
Rodrigues et al.[21]	2019	Prospective Observational study	Double triggering, reverse triggering	CNN	ARDS-11 Patients Breaths-1,881	92%		
Haro et al.[22]	2025	Observational study in prospective cohort	Double triggering and reverse triggering with and withoutbreath stacking	BC link platform Better care	Sample size-82 Covid 19 ARDS Breaths – 3,64,06,637	99 % reverse Triggering and double riggering		
Sottile et al.[23]	2018	Prospective Observational study	Double triggering, flow starvation, premature cycling, ineffective effort	Binary classifier, ADABOOST, And random forest and gaussian naïve bayes	Sample size-62 Breaths- 4.2 million ARDS	0.54 ROC-0.61	>0.23	>0.47
Huiquing Ge et al.[24]	2020	Retrospective study	Double triggering, sc , premature cycling, ineffective effort	Binomial regression model (CNN) Alexnet	ARDS COPD Sample size-160 mixed	>95%	>0.95	>0.95

Figure 3:Characteristics and diagnostic performance of AI/ML-based detection of patient–ventilator asynchrony

DISCUSSION

Patient–ventilator asynchrony (PVA) is still a common and important problem in patients on mechanical ventilation. Detecting it usually requires careful and time-consuming assessment by experienced clinicians. Machine learning (ML) may help by providing automated and more objective detection and prediction of PVA, which could reduce the limitations of traditional manual methods.Although some systematic reviews have discussed PVA and related technologies, only a few original studies have used ML specifically to identify PVA in patients with hypoxemic respiratory failure (RF). This shows that there is still a gap in the research. In this review, we examine the methods and technical aspects of ML models developed for PVA detection, with special focus on their use in hypoxemic RF patients.

Among the original studies identified in this review, several have explored different machine learning approaches for automated detection of specific types of asynchrony.

A study by Elias et al[15].focused on developing and comparing a rule-based program and a deep neural network.His study demonstrated that both rule-based algorithms and deep neural networks can accurately detect RT, achieving high specificity (>95%) and good overall performance (F1 >75%).RT is clinically important due to its association with breath stacking, increased tidal volumes, and potential ventilator-induced lung injury. Their findings highlight the feasibility of automated waveform analysis in identifying clinically relevant dys synchrony patterns.

Similarly,Tai Pham et al.[16]developed an automated algorithm using airway pressure and flow signals to detect reverse triggering in mechanically ventilated patients, achieving 95.5% accuracy with 83.1% sensitivity and 99.4% specificity versus expert manual detection. In 20 hypoxemic ICU patients, reverse triggering occurred in 24% of breaths with wide variability (0-93% per patient), and inspiratory effort ranged from 1.3 to 36.8 cmH_2O (median ~9 cmH_2O), with breath-stacking phenotypes producing the highest pressures. This automated approach enables continuous monitoring without requiring invasive esophageal pressure measurements.The Gutierrez et al.[17] study developed Random Forest algorithms to detect asynchronous breathing and to classify asynchrony types, reporting 91% accuracy for detection and 82% for classification.Pan et al.[19]developed an image-based transfer learning method for detecting patient-ventilator asynchrony by converting ventilator waveforms into 2D images and using pretrained convolutional neural networks. The approach achieved ~90% accuracy using only 1% of the original training data, significantly outperforming traditional training-from-scratch models (~80%) on small datasets, demonstrating that transfer learning effectively addresses the challenge of limited labeled data in clinical ventilator monitoring.

Pažout et al.[20] developed SmartAlert, a real-time machine learning system that extracts waveforms from ventilator screen video to detect patient-ventilator asynchronies. Trained on 381,280 breath units, it achieved 89.3% accuracy for classifying ineffective triggering, double cycling, and high inspiratory effort (AUC 0.951), with >94% specificity and alarm stratification by urgency, though prospective clinical validation is still needed.

CONCLUSION

However, the available studies show considerable differences in study design, patient populations, types of ventilators, definitions of asynchrony, and ML algorithms used. Many studies also have small sample sizes and limited external validation, which affects the reliability and generalizability of their findings. In addition, real-world clinical applicability remains uncertain, as few models have been tested in routine bedside settings. Therefore, larger, well-designed studies with standardized definitions and proper external validation are needed before ML-based PVA detection can be widely implemented in clinical practice.

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