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Automatic Recognition and Classification of Patient–Ventilator Asynchrony Using Deep Learning with Generative Adversarial Networks

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Abstract

Purpose: Patient–ventilator asynchrony (PVA) is frequent in mechanically ventilated patients and is associated with poor outcomes. Automated recognition has

the potential to improve clinical care, but existing methods are limited by data scarcity and class imbalance. We aimed to develop and validate a deep learning model enhanced by synthetic data generation to improve the accuracy of PVA detection and classification.
Methods: We developed a two-step framework: (1) a self-attention CNN–LSTM generative adversarial network (SACL-GAN) to generate realistic respiratory cycles, and (2) a hybrid multi-head attention CNN–BiLSTM classifier (MHA-CBL) model trained on both real and synthetic data. 4,907 respiratory cycles from 32 ICU patients were annotated into normal breathing (NB) and four asynchrony categories: ineffective effort (IE), early cycling (EC), double triggering (DT), and airway oscillation (AO). Model performance was assessed using accuracy, precision, recall, and F1-score and other metrics.
Results: SACL-GAN successfully generated high-quality synthetic data with low mean squared error (MSE: 0.58-2.84 for pressure, 1.68-8.07 for flow) and dynamic time warping (DTW: 3.03-6.47 for pressure, 9.61-12.24 for flow). Without augmentation, the MHA-CBL classifier achieved high accuracy for NB and IE, but lower recall for minority classes (EC and AO). GAN augmentation improved overall accuracy (from 94.6% to 97.8%) and recall for minority classes (EC: 76.9% $\rightarrow$ 93.2%; AO: 74.6% $\rightarrow$ 91.8%). In binary classification (asynchrony vs NB), sensitivity improved from 94.4% to 98.0%, reducing missed detections.
Conclusion: Combining GAN-based augmentation with hybrid deep learning improved recognition of PVA, particularly for underrepresented categories. This strategy addresses dataset imbalance and enhances the clinical applicability of automated monitoring in ICU settings.

Keywords: Patient-ventilator asynchrony, Mechanical ventilation, Generative adversarial networks, Deep learning

1 Introduction

Mechanical ventilation (MV) is crucial in the management of acute respiratory failure and critical illness, supporting millions of patients worldwide annually. Its primary aim is to maintain adequate oxygenation and ventilation, either by assisting or replacing spontaneous breathing [1].

Patient–ventilator asynchrony (PVA) occurs when the ventilator support is not well aligned with the patient's effort. Asynchrony is frequent in the ICU and is linked to patient discomfort, prolonged MV, respiratory muscle injury, and higher mortality[2–4]. Accurate detection is therefore crucial for optimizing ventilatory support and improving outcomes.

Conventional recognition relies on clinicians' visual inspection of ventilator waveforms, which is labor-intensive, subjective, and often inadequate for real-time detection[5–7]. Automated recognition methods based on machine learning and deep learning have shown promise, yet remain limited by small datasets, reliance on invasive monitoring, and poor performance for rare asynchrony types[8–12].

Generative adversarial networks (GANs) have emerged as powerful tools for creating realistic synthetic data, with successful applications in medical imaging and

time-series analysis[13–16]. However, their application to PVA recognition remains limited. Addressing the imbalance of annotated data and improving detection of underrepresented PVA events are key unmet needs.

We therefore developed and validated a two-step approach: (1) a self-attention convolutional neural network (CNN)–long short-term memory (LSTM) network GAN (SACL-GAN) to generate realistic respiratory cycles, and (2) a hybrid multi-head attention CNN–Bidirectional LSTM (BiLSTM) classifier (MHA-CBL) trained on both real and generated data. We hypothesized that this strategy would improve classification accuracy, particularly for minority PVA types, and provide a clinically relevant tool for real-time ICU monitoring.

2 Materials and Methods

2.1 Study design and setting

This prospective observational study was conducted in the intensive care units of Beijing Chaoyang Hospital. The study protocol was approved by the institutional ethics committee (approval number 2019-KE-223) and conducted in accordance with the principles outlined in the Declaration of Helsinki. Informed consent was obtained where applicable.

2.2 Patients and data collection

Respiratory waveform data were collected from 32 mechanically ventilated patients (18 males, 14 females) in the ICU using a custom acquisition system presented in our previous study[17]. The age distribution was as follows: 65-70 years (n=19), 55-60 years (n=10), and 45-50 years (n=3). Continuous respiratory signals, including airway pressure, flow, temperature, humidity, and end-tidal carbon dioxide ($ETCO_2$), were collected at a sampling frequency of 30 Hz. Only airway pressure and flow were used in this study. The data collection workflow is illustrated in Fig. 1.

2.3 Data annotation and preprocessing

Experienced intensivists independently annotated all respiratory cycles, identifying five categories: normal breathing (NB), ineffective effort (IE), early cycling (EC), double triggering (DT), and airway oscillation (AO). Disagreements were resolved by consensus. The final real dataset comprised 4,907 respiratory cycles: NB (n=2,248), IE (n=1,177), EC (n=1,224), DT (n=160), and AO (n=98).

Raw waveform data underwent a multi-step preprocessing procedure. Outliers were removed, and a sliding average filter was applied to smooth the signal. Individual respiratory cycles were then segmented based on zero-crossing points in the flow signal. To ensure consistent input length for the model, the pressure and flow data from each cycle were resampled to a fixed length of 150 data points using linear interpolation. The detailed data preprocessing procedure was supplied in supplementary materials.

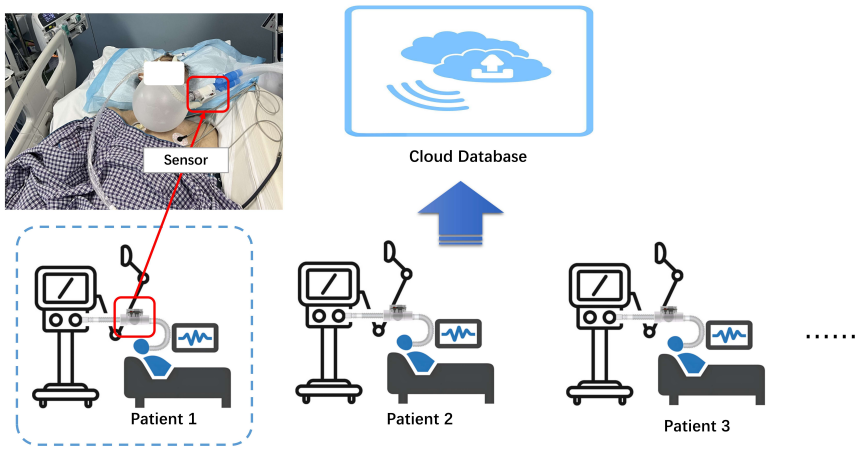


Fig. 1 Clinical data Collection flowchart.

2.4 SACL-GAN Model for PVA Data Generation

We developed a Self-Attention CNN-LSTM GAN (SACL-GAN) for generating synthetic PVA data. The generator combines fully connected layers, LSTM networks, and residual blocks with self-attention mechanisms. The architecture progressively transforms random noise into realistic flow and pressure waveforms with appropriate cycle durations. The discriminator employs CNN layers with spectral normalization to distinguish between real and synthetic data. GAN training was stabilized using the Wasserstein loss with gradient penalty[18], and optimization was performed using Adam[19]. The performance of the generated signals was assessed using the mean squared error (MSE) and dynamic time warping (DTW), established methods for evaluating similarity in time-series data.

A filtering and proportion control mechanism for generated data is developed to provide high-reliability and high-consistency training samples for subsequent classification models, ensuring that the PVA classification has good performance and generalization capabilities in clinical applications. The detailed information about the SACL-GAN structure and evaluation methods was supplied in the supplementary materials.

2.5 MHA-CBL Model for PVA Classification

We designed a hybrid deep learning classifier model, MHA-CBL, which combines CNN feature extraction, bidirectional LSTM temporal modeling, and multi-head attention mechanisms[20, 21]. This model's architecture was explicitly chosen to process waveform data effectively: 1) CNN layers extract local, salient features from the pressure and flow signals; 2) a BiLSTM network captures the temporal dependencies within the

respiratory cycle; and 3) a multi-head attention mechanism enables the model to focus on the most informative time-steps for accurate classification dynamically. Regularization techniques including dropout[22] and batch normalization[23] were applied to prevent overfitting. A final softmax layer classified each cycle into one of five categories (NB, IE, EC, DT, AO).

Data were randomly split into training (70%) and testing (30%) sets. For imbalanced classes, GAN-generated samples were included in the training set, while the testing set used only real patient data to ensure unbiased evaluation. Model performance was evaluated using standard classification metrics, including overall accuracy, macro-F1, micro-F1, precision, recall, and F1-score for each PVA event. Additionally, the model's performance for each PVA event is further analyzed using confusion matrices, receiver operating characteristic (ROC) curves, and area under the curve (AUC) values, which reveal how well the model performs across different PVA event types, aiding in adjusting model parameters to improve classification ability. To assess the model's ability to distinguish any asynchrony from normal breathing, we also calculated the binary classification performance. A detailed description of the model structure and evaluation is available in the supplementary materials.

3 Results

Thirty-two mechanically ventilated patients(18 males, 14 females) in the ICU were studied (Table 1). The age distribution was as follows: 65-70 years (n = 19), 55-60 years (n = 10), and 45-50 years (n = 3). The majority (56.25%) had pneumonia (18 patients) as the primary diagnosis. Six patients had respiratory failure (4 type II, 2 type I). All patients underwent either invasive or a combination of invasive and non-invasive mechanical ventilation.

3.1 SACL-GAN Performance

SACL-GAN successfully generated synthetic respiratory waveforms for all PVA types. A Comparison of selected generated respiratory cycles and real data waveforms is shown in Fig. 2. Visual inspection revealed high similarity between synthetic and real waveforms in terms of morphology, amplitude, and temporal characteristics. The MSE and DTW values are presented in Table 2. Quantitative evaluation showed acceptable MSE values for pressure (0.58-2.84) and flow (1.68-8.07) signals across all PVA types. DTW distances were similarly low for pressure (3.03-6.47) and flow (9.61-12.24), indicating good temporal alignment between synthetic and real data.

After rigorous screening and proportion control, the final augmented dataset comprised 9,888 respiratory cycles: NB (n = 2,248), IE (n = 2,154), EC (n = 2,348), DT (n = 1,760), and AO (n = 1,378). By introducing high-quality generated data, the asynchronous category, which initially had a small sample size, was effectively expanded, thereby effectively alleviating the imbalance in PVA category data.

Table 1 Patients' characteristics

Patient no.	**Age(years)**	**Sex**	**Primary diagnosis**	Patient no.	**Age(years)**	**Sex**	**Primary diagnosis**
1	68	M	Pneumonia	17	69	M	RF(II)
2	68	M	Pneumonia	18	60	F	Pneumonia
3	68	M	Pneumonia	19	45	M	Pneumonia
4	56	F	Pneumonia	20	60	M	Septic shock
5	70	M	RF(II)	21	59	F	IPA
6	67	F	Pneumonia	22	56	F	Pneumonia
7	70	F	Mucormycosis	23	66	F	Pneumonia
8	65	M	Pneumonia	24	67	M	RF(II)
9	68	M	RF(I)	25	60	F	Bronchiectasis
10	69	M	Pneumonia	26	59	M	AECOPD
11	69	M	RF(II)	27	59	F	IPA
12	69	M	Pneumonia	28	66	F	Bronchiectasis
13	50	M	Pneumonia	29	66	F	Pneumonia
14	65	F	RF(I)	30	66	F	Pneumonia
15	69	M	Pneumonia	31	59	F	Sepsis
16	47	M	Pneumonia	32	59	M	Pneumonia

RF: Respiratory failure. IPA: Invasive pulmonary aspergillosis. AECOPD: Acute exacerbation of chronic obstructive pulmonary disease.

Table 2 MSE and DTW Values for Flow and Pressure waveforms in Four PVA types

Type	**MSE (Pressure)**	**DTW (Pressure)**	**MSE (Flow)**	**DTW (Flow)**
IE	0.58	6.41	1.68	9.61
EC	1.48	6.47	8.07	12.14
DT	2.84	4.50	4.72	11.86
AO	1.42	3.03	5.73	12.24

PVA: Patient–ventilator asynchrony. MSE: Mean squared error. DTW: Dynamic time warping.

3.2 PVA Classification Performance based on MHA-CBL Model

The MHA-CBL model was evaluated using two strategies: training with real data only, and training with real plus GAN-generated data. The classification confusion matrices and metrics, as shown in Fig. 3 and Table 3, and 4. Without augmentation, the model achieved strong performance for NB, IE and DT, but lower recall for minority types such as EC and AO.

With GAN-augmented training, overall accuracy improved from 92.2% to 94.9%. Class-specific improvements were most pronounced for underrepresented categories. AO recall improved from 65.5% to 86.2% (+20.7%), while maintaining high precision (86.2%). EC recall increased from 91.3% to 92.9%, with improved F1-score from 89.7%

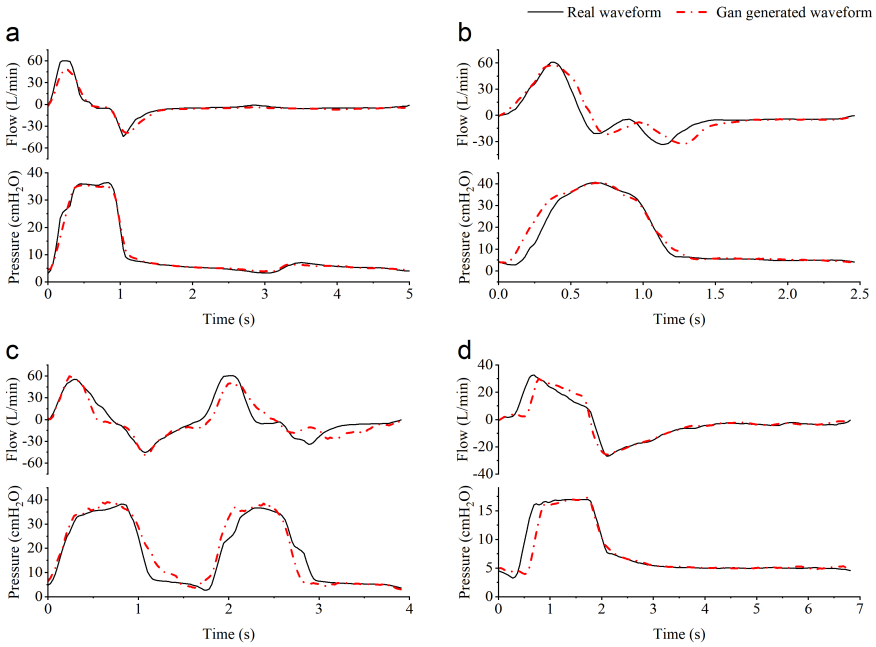


Fig. 2 Comparison of generated respiratory waveform and real respiratory waveform for four types of PVA. (a) Ineffective effort. (b) Early cycling. (c) Double triggering. (d) Airway oscillation.

to 93.2%. DT performance remained excellent, with recall improving from 95.8% to 97.9%.

Table 3 Classification Metrics for the MHA-CBL Model Using Real Data

Type	Precision	Recall	F1-Score	Accuracy	Macro-F1	Micro-F1
NB	93.4%	93.6%	0.935			
IE	93.4%	92.1%	0.927			
EC	88.2%	91.3%	0.897	92.2%	0.899	0.924
DT	100.0%	95.8%	0.979			
AO	90.5%	65.5 %	0.760			

NB: Normal Breathing. IE: Ineffective Effort. EC: Early Cycling. DT: Double Triggering. AO: Airway Oscillation.

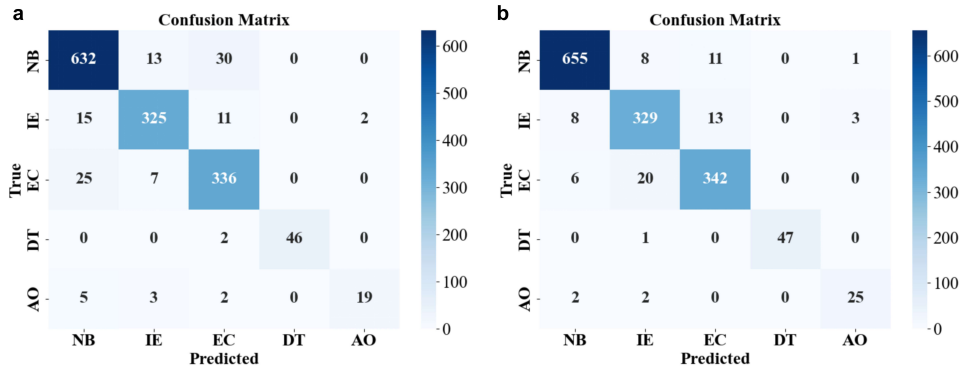


Fig. 3 Confusion Matrices for the MHA-CBL Model Performance. (a) Confusion Matrix with Real Data. (b) Confusion Matrix with Real and Generated Data.

Table 4 Classification Metrics for the MHA-CBL Model with Real and Generated Data

Type	Precision	Recall	F1-Score	Accuracy	Macro-F1	Micro-F1
NB	97.6%	97.0%	0.973			
IE	91.4 %	93.2%	0.923			
EC	93.4%	92.9%	0.932	94.9%	0.917	0.945
DT	100.0%	97.9%	0.989			
AO	86.2%	86.2%	0.862			

NB: Normal Breathing. IE: Ineffective Effort. EC: Early Cycling. DT: Double Triggering. AO: Airway Oscillation.

3.3 Binary PVA Classification

For the normal breathing or asynchrony classification, as shown in Fig. 4, after introducing generated data, the model's classification accuracy, sensitivity, and specificity for asynchronous events showed significant improvement. Specifically, sensitivity improved from 94.4% to 98.0%, and specificity improved from 93.6% to 97.0%.

4 Discussion

Missed detection of PVA is clinically more harmful than false alarms, as undiagnosed asynchrony may lead to inappropriate ventilator adjustments, prolonged mechanical ventilation, and increased risk of complications [3, 4, 24]. The classic method for PVA

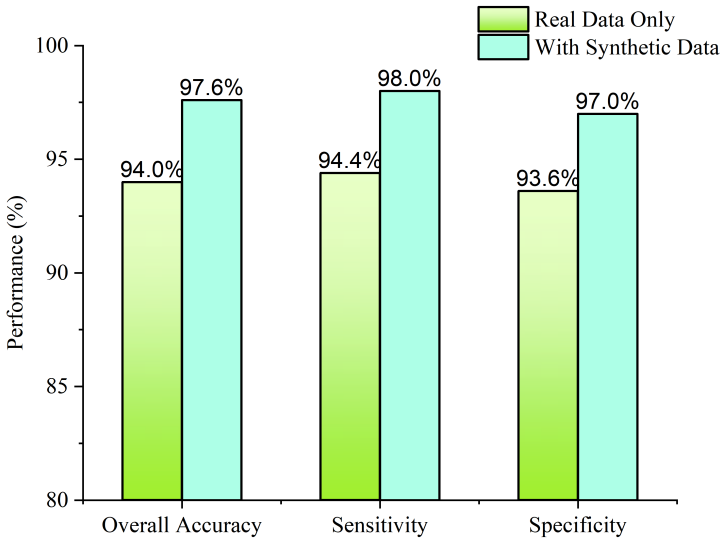


Fig. 4 Model Performance Before and After GAN Augmentation

recognition relies on ventilator waveform analysis, which is noninvasive and reliable[5]. However, this method depends on the clinicians' experience and skill, which requires professional training. Additionally, visual inspection of the ventilator is labor-intensive and may lead to missed detection of PVA.

To enhance the automation and convenience of PVA detection, transdiaphragmatic pressure (Pdi) and diaphragm electrical activity (EAdi) waveforms were utilized. The comparison results demonstrated that the manual and automated detection methods produced high reliability (Intraclass correlation coefficient = 0.95)[8]. Besides, a high overall sensitivity and specificity were achieved (sensitivity: 91 %, specificity: 97 %) in 3,343 analyzed breaths[6]. However, the Pdi and EAdi signals were obtained through a gastroesophageal cystic tube and a diaphragm electrical electrode, which are inconvenient and uncomfortable for long-term monitoring.

In recent years, with the rapid development of machine learning and deep learning technologies, the automatic detection of PVA-based waveforms has undergone significant improvements. The waveform signals contain significant and abundant information about PVA. Deep learning methods, utilizing a multi-layer structure, can extract hidden and abstract key information from waveform signals, which can be used for PVA detection and classification. Through training with a large amount of data, these methods demonstrate a remarkable ability, similar to that of professional doctors [25, 26]. Gholami et al.[9] developed a machine learning framework aiming to detect cycling asynchrony. Some landmarks, like a decrease or an increase in pressure, were extracted as features. After that, the random forests method was used for classification. However, as the authors note, only cycling asynchronies from 1,377 breath cycles (11 patients) were analyzed. The data and PVA types are not sufficient for clinic

using. Pan and Zhang et al.[10, 11] developed some deep learning frameworks which not need a separate feature extraction procedure to detect PVA. Both 1DCNN[11] and LSTM[10] models were used, and accuracy, sensitivity, specificity, and F1 scores were over 0.95 for pressure support ventilation (PSV) and pressure control ventilation (PCV) modes. The limitations, as the authors pointed that the insufficient data (20 patients) may influence the generalization ability of the proposed model, even though it has obtained good performance on the training and validation datasets. Besides, the proposed models were binary classification models, resulting in inconvenience and time spent in practical applications.

In this study, thirty-two mechanically ventilated patients were involved. Our principal findings are as follows: firstly, we developed the SACL-GAN model, which is used for data augmentation (from 4,907 (NB=2,248, IE=1,177, EC=1,224, DT=160, and AO=98)) to 9,888 (NB=2,248, IE=2,154, EC=2,348, DT=1,760, and AO=1,378)) respiratory cycles. The self-attention mechanism enables the model to focus on critical temporal features in respiratory waveforms, while the combination of CNN and LSTM components captures both spatial and temporal dependencies. Wasserstein loss with gradient penalty improves training stability compared to traditional GAN objectives. Supplementing the training dataset with high-fidelity synthetic data (MSE: 0.58-2.84 for pressure, 1.68-8.07 for flow; DTW: 3.03-6.47 for pressure, 9.61-12.24 for flow) addresses the critical challenge of data imbalance and scarcity, leading to a more robust and accurate classification model, especially for recognizing infrequent PVA types.

Secondly, we also developed the MHA-CBL model for multi-task PVA classification. The MHA-CBL classifier's multi-head attention mechanism enables the model to simultaneously attend to different aspects of the respiratory cycle, potentially capturing subtle patterns that distinguish various types of asynchrony. The CNN and bidirectional LSTM extract local, salient features and process information in both temporal directions, providing comprehensive context for classification decisions. Both multi-classification and binary classification were analyzed. The results in Fig. 3 and Table 3 and 4 highlight class-specific improvements. Specifically, the recall for NB, IE, EC, and DT is over 92%, AO is over 86%. Besides, in binary classification, the sensitivity and specificity reach 98.0% and 97.0%, which indicates a lower risk of overlooking critical events, directly supporting safer ventilatory management in ICU patients. The high sensitivity ensures that clinically significant asynchrony events are unlikely to be missed, enabling timely interventions such as ventilator parameter adjustments or sedation modifications.

A key advantage of our methodology is its reliance solely on standard, ventilator waveforms (pressure and flow), making it broadly applicable in any modern ICU. Furthermore, by creating a comprehensive classifier for multiple PVA types, our work moves beyond simple binary detection and provides the granular information clinicians need to make specific adjustments to ventilator settings.

4.1 Limitations and Future Directions

Several limitations merit consideration. First, data were collected from a single institution, which may limit generalizability across different ventilator brands, patient populations, and clinical practices. Multi-center validation is needed to confirm

broader applicability. Second, only flow and pressure signals were analyzed; incorporating multimodal physiological parameters such as $ETCO_2$, temperature, or humidity could further enhance performance. Third, while the SACL-GAN produced realistic waveforms, minor discrepancies between synthetic and real data remain. Continued advancements in generative models may further enhance the fidelity of data.

The computational requirements for real-time implementation in clinical settings need evaluation. Our model serves as a diagnostic tool; its output requires interpretation and action by a healthcare professional. While our models showed excellent offline performance, clinical deployment requires consideration of processing latency, computational resources, and integration with existing monitoring systems or ventilators.

Our findings suggest that generative augmentation is valuable for addressing data imbalance in critical care Artificial Intelligence [25, 27]. Future work should explore the integration of multimodal signals, larger multicenter datasets, and deployment in real-time ICU settings to evaluate clinical impact. Integration with closed-loop ventilation systems represents an exciting opportunity for automated ventilator adjustments based on real-time PVA detection. This could reduce workload for intensive care staff while potentially improving patient-ventilator synchronization.

5 Conclusion

This study presents a novel approach that combines generative adversarial networks with deep learning for the automated detection and classification of patient-ventilator asynchrony. The SACL-GAN generated realistic respiratory cycles that effectively mitigate the pervasive problem of data imbalance in medical datasets. The MHA-CBL model, combining convolutional, recurrent, and attention mechanisms, achieved robust classification performance.

The approach improved overall accuracy and significantly increased recall for minority events, reducing the likelihood of missed detections, which are known to affect outcomes negatively. These findings underscore the importance of generative augmentation in mitigating data imbalance, a prevalent issue in critical care research. Future studies should validate this approach across larger, multicenter cohorts, explore integration of additional physiological signals for broader applicability, and translate these technical advances into improved patient care and outcomes in intensive care medicine.

Declarations

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- Conflict of interest/Competing interests: The authors declare that they have no conflict of interest.
- Data availability: Data supporting this study are available from the corresponding author upon reasonable request and subject to ethical approval.

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