RESEARCH PAPER

DEEP LEARNING FRAMEWORK FOR AUTOMATED PATIENT–VENTILATOR ASYNCHRONY DETECTION AND CLASSIFICATION

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Abstract

Patient–ventilator asynchrony has remained as a frequent and a clinically relevant complication in a mechanically ventilated patients, which has contributed to an increased respiratory effort, prolonged ventilation, and unfavorable outcomes. The conventional identification of asynchrony has relied on the manual interpretation of the airway pressure and flow waveforms, which has required a substantial clinical expertise and it has suffered from the observer variability. Recent advances in the machine learning have enabled the data-driven analysis of the physiological signals, which offers an opportunity to improve the scalability. Manual waveform inspection has lacked the consistency, and it has limited a continuous monitoring in an intensive care environments. Earlier machine learning (ML) approaches have used a handcrafted features and classical classifiers have achieved moderate accuracy but it have struggled to generalize across the diverse waveform patterns. There it has remained as a need for a robust framework that has automatically learned the discriminative features directly from the ventilator signals while it maintains the clinical feasibility. This study has proposed a unified deep learning framework that has employed a four convolutional neural network models for an automated detection of the patient–ventilator asynchrony. Airway pressure and flow signals have been collected, normalized, and segmented into the fixed-length epochs. Two one-dimensional CNN models have processed the raw waveform inputs, while two two-dimensional CNN models have analyzed the time–frequency spectrogram representations, which includes a transfer learning–based ResNet-50 architecture. Model training has used a supervised learning with the standardized evaluation metrics. The proposed CNN-based framework has achieved a superior performance across all the evaluation metrics. Over various iterations, the framework has attained a maximum accuracy of 96%, precision of 95%, recall of 96%, F1-score of 95%, and specificity of 97%, which consistently has surpassed the Random Forest, Support Vector Machine, and Shallow 1D CNN methods.

Keywords:
patient–ventilator asynchrony, deep learning, convolutional neural networks, ventilator waveform analysis, transfer learning

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Introduction

Mechanical ventilation has remained as a cornerstone therapy for patients with the acute and chronic respiratory failure. Effective ventilation has depended on the proper synchrony between the spontaneous breathing effort and the mechanical support that is delivered by the ventilator. When this interaction has become mismatched, patient–ventilator asynchrony has occurred, which has been associated with the increased work of breathing, discomfort, prolonged mechanical ventilation, and higher morbidity rates [1–3]. Continuous monitoring of ventilator waveforms, specifically airway pressure and flow signals, has therefore played a critical role in the clinical decision-making and ventilator adjustment.

Despite its importance, detection of asynchrony has largely relied on the manual waveform inspection by trained clinicians. This approach has required a sustained attention and experience, and it has remained vulnerable to the inter- and intra-observer variability. In busy intensive care units, the continuous visual monitoring has not always been feasible, which has increased the risk of an undetected asynchrony episode. Studies have reported that a substantial proportion of an asynchronous events has gone unnoticed during the routine care, even in the controlled clinical settings [4]-[5].

Several computational approaches have attempted to address this limitation. Conventional signal processing and rule-based algorithms have shown limited robustness due to their sensitivity to the noise and patient-specific variations. Classical machine learning methods have improved the detection accuracy by using the handcrafted features derived from the pressure and flow signals; however, these methods have required a careful feature design and it has shown a reduced generalizability across the patient populations and ventilator modes [6]. As a result, the problem of scalable, reliable, and automated asynchrony detection has remained as a partially solved.

Recent advances in the deep learning have provided new opportunities for an automated physiological signal analysis. Convolutional neural networks have shown strong capability in learning hierarchical representations directly from the raw signals or their transformed representations. These models have reduced the reliance on the manual feature engineering and it has shown an improved performance in complex waveform classification tasks. However, the systematic evaluation of different CNN architectures for the ventilator asynchrony detection has remained limited.

The primary objective of this work has been to develop and evaluate a unified deep learning framework for an automated detection of the patient–ventilator asynchrony using the airway pressure and flow waveforms. Specifically, this study has aimed to compare waveform-based one-dimensional CNN models with the spectrogram-based two-dimensional CNN models, which includes a transfer learning architecture, under the common experimental setup. The study has also aimed to analyze the trade-off between the detection accuracy and computational efficiency for the clinical applicability.

The novelty of this work has resided in the combined evaluation of multiple

CNN paradigms within a single framework that has processed both the time-domain and time–frequency representations of the ventilator signals. Unlike prior studies that have focused on the single model type, this work has provided a comparative perspective that has informed the model selection for the real-time deployment.

The key contributions of this study have been twofold. First, a comprehensive CNN-based framework has been designed for an automated asynchrony detection using the routinely available ventilator waveforms. Second, an extensive performance comparison has been presented against the classical machine learning baselines, which shows the advantages and limitations of deep learning models in the practical clinical scenarios.

2. Related Works

Early investigations into the patient–ventilator asynchrony detection have relied on the clinician-driven waveform interpretation and rule-based algorithms. Initial computational approaches have applied threshold-based methods to the airway pressure and flow signals, which have attempted to identify the abnormal triggering and cycling patterns. Although these methods have been conceptually simple, they have shown limited robustness under the noisy clinical conditions and it has struggled with the patient-specific variability [7].

Subsequent studies have introduced classical machine learning techniques to improve the detection accuracy. Researchers have extracted handcrafted features such as inspiratory delay, pressure slope, and flow variability, which have then been classified using the algorithms such as support vector machines, k-nearest neighbors, and decision trees. These approaches have shown moderate improvements over rule-based systems but it have remained highly dependent on the feature selection and signal quality [8].

A landmark clinical feasibility study has employed Random Forest classifiers for an automated detection of ventilator asynchrony. In that work, airway pressure and flow signals have been collected from the mechanically ventilated patients and manually annotated by experienced clinicians. Over fifty thousand waveform epochs have been labeled, which corresponding to millions of individual breaths. Four Random Forest models have been trained to detect asynchronous breathing, classify asynchrony types, grade signal disruption severity, and identify dynamic hyperinflation. Reported accuracies have ranged between the 87% and 93%, which has shown the practical potential of machine learning for bedside monitoring [9]. However, the reliance on the handcrafted features has a limited scalability to the unseen data distributions.

With the emergence of deep learning, several studies have explored neural network–based models for physiological waveform analysis. One-dimensional CNNs have been applied to the raw biomedical signals such as electrocardiograms and respiratory waveforms, where the convolutional filters have learned the temporal patterns associated with the pathological events. These models have reduced the preprocessing requirements, and it has achieved competitive performance compared with the conventional approaches [10].

Other researchers have transformed time-series signals into the time–frequency representations using the techniques such as short-time Fourier transform or wavelet decomposition. Two-dimensional CNNs trained on the spectrogram images have captured both the temporal and spectral characteristics of the physiological signals. This approach has been shown to improve the classification accuracy in applications such as sleep apnea detection and lung sound analysis [11].

Transfer learning has further advanced deep learning performance in biomedical applications. Pretrained architectures such as VGG and ResNet have been fine-tuned on the domain-specific datasets, which has enabled effective learning even with the limited labeled data. Studies have reported that a transfer learning has improved the convergence speed in the medical image and signal classification tasks [12].

In ventilator waveform analysis, only a limited number of studies have an applied deep CNN model. Existing works have often focused on the binary detection of asynchrony without comparing the different input representations or model complexities. Additionally, few studies have evaluated the computational implications of deploying deep models in the real-time clinical environments [13–14].

Recent reviews have emphasized the need for an efficient ML model for the critical care monitoring. While deep learning has offered a superior accuracy, concerns related to computational cost, transparency, and clinical combination have remained as active research topics [15].

3. Proposed Method

3.1 Overview of the Proposed Framework

The proposed method has introduced a unified deep learning framework that has automatically detected patient–ventilator asynchrony from the airway pressure and flow signals. The framework has followed a structured pipeline that has included signal acquisition, preprocessing, adaptive segmentation, dual-domain feature representation, CNN-based feature learning, and supervised classification. Raw ventilator waveforms have been transformed into the both the time-domain sequences and time–frequency representations, which have enabled complementary feature extraction. Multiple CNN architectures have been trained and evaluated within a common framework, which has ensured consistent comparison and reliable performance assessment.

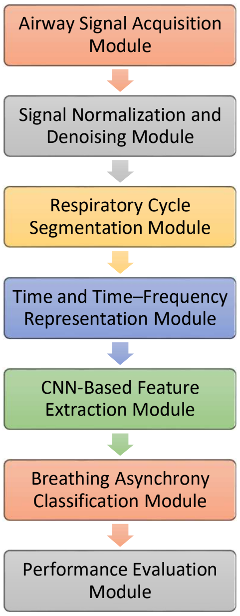

Figure 1: Proposed Processing Pipeline

3.3 Pseudocode of the Proposed Method

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Algorithm: CNN-Based Automated Asynchrony Detection
Input: Airway pressure signal P(t), airflow signal F(t)
Output: Asynchrony label for each waveform epoch
1. Initialize dataset D with the raw signals P(t), F(t)
2. For each patient record in D do
3.   Apply normalization to P(t) and F(t)
4.   Perform noise suppression using the smoothing filters
5.   Segment signals into the fixed-length epochs Ei
6.   For each epoch Ei do
7.     Generate time-domain an input Ti
8.     Compute spectrogram Si using the STFT
9.   End For
10. End For
11. Initialize CNN models M1 to M4
12. Train each model using the labeled epochs
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13. Optimize parameters using the backpropagation
14. Validate models using the held-out data
15. Predict asynchrony labels for test epochs
16. Compute evaluation metrics
17. Return predicted labels and performance results

3.1 Signal Acquisition and Normalization

Airway pressure and flow signals has constituted the primary physiological inputs for the proposed framework. These signals are continuously generated by a modern mechanical ventilator and reflect the interaction between the patient respiratory effort and ventilator support. However, raw signals have exhibited large inter-patient variability due to differences in lung mechanics, ventilator settings, and sensor calibration. Therefore, signal normalization has been applied to the ensure consistent amplitude scaling across the records.

Normalization has transformed each signal into the standardized range, which has improved the numerical stability during the CNN training. This process has preserved the temporal structure of the waveform while reducing bias introduced by absolute signal magnitudes. Table 1 has shown the characteristics of the raw and normalized signals that have been used in the study.

Table 1: Signal Characteristics Before and After Normalization

Signal Type	Original Range	Normalized Range	Sampling Rate
Pressure	−10 to 50 cmH₂O	−1 to 1	100 Hz
Flow	−2 to 2 L/s	−1 to 1	100 Hz

The normalization process has been mathematically expressed as:

$$x_{norm}(t) = \frac{x(t) - \mu_x}{\sigma_x + \epsilon}$$

where $x(t)$ denotes the original signal, μ_x represents the mean value, σ_x indicates the standard deviation, and ϵ ensures numerical stability.

4.2 Waveform Segmentation and Epoch Formation

Continuous ventilator signals have been segmented into the fixed-length epochs to enable batch processing and supervised learning. Each epoch has represented a short temporal window that has captured one or more respiratory cycles. This segmentation strategy has ensured that the local temporal dependencies have been preserved while it enables efficient training.

The segmentation process has aligned epochs with the clinically meaningful waveform boundaries, which has reduced the fragmentation of respiratory events. Overlapping windows have optionally been used to improve the detection sensitivity. Table 2 presents the segmentation parameters that have governed epoch generation.

Table 2: Waveform Segmentation Parameters

Parameter	**Value**
Epoch duration	2 seconds
Window overlap	50%
Samples per epoch	200
Labeling granularity	Epoch-level

Segmentation has been formally defined as:

$$E_i = \{x(t) \mid t \in [i\Delta, i\Delta + T]\}$$

where E_i denotes the i^{th}epoch, Δ indicates the step size, and T represents the epoch duration. This formulation has ensured the consistent temporal context for all CNN inputs.

4.3 Time–Frequency Transformation Using the Spectrograms

While time-domain signals have captured waveform morphology, they have not explicitly represented frequency-domain characteristics associated with the asynchronous breathing patterns. To address this limitation, each epoch has been transformed into the spectrogram using the short-time Fourier transform. This representation has encoded both the temporal evolution and spectral content of the signals.

Spectrogram generation has converted each waveform epoch into the two-dimensional image that has been suitable for processing by 2D CNN architectures. Table 3 has shown the parameters that have governed the time–frequency transformation.

Table 3: Spectrogram Generation Parameters

Parameter	**Value**
Window function	Hamming
FFT length	128
Window size	64 samples
Frequency bins	65

The spectrogram computation has been expressed as:

$$S(t,f) = \left| \sum_{n=0}^{N-1} x\,(n)w(n-t)e^{-j2\pi fn/N} \right|^2$$

where $w(n)$ denotes the window function and $S(t,f)$represents the energy distribution over time and frequency. This transformation has enhanced the separability of synchronous and asynchronous patterns.

4.4 CNN-Based Feature Learning

Feature extraction has been performed using the convolutional neural networks, which have automatically learned the discriminative representations from the input data. One-dimensional CNNs have processed the raw waveform epochs, capturing temporal dependencies through convolutional filters. Two-dimensional CNNs have processed the spectrogram images, learning spatial patterns that have reflected time–frequency interactions.

Each CNN layer has consisted of convolution, activation, and pooling operations, which have progressively abstracted the low-level signal features into the high-level representations. Table 4 has shown the core architectural components shared across the CNN models.

Table 4: CNN Architectural Components

Layer Type	Function
Convolution	Local feature extraction
ReLU Activation	Nonlinear transformation
Pooling	Dimensionality reduction
Fully Connected	Feature combination

The convolution operation has been mathematically defined as:

$$h_k = \sigma(\sum_{i=1}^{n} w_{k,i} * x_i + b_k)$$

where h_k denotes the feature map, $w_{k,i}$ represents the convolution kernel, $b_k$indicates the bias, and $\sigma(\cdot)$ is the activation function. This formulation has enabled hierarchical feature learning.

4.5 Classification and Decision Making

The final classification stage has mapped learned features to output labels that represents synchronous or asynchronous breathing. A softmax layer has produced probabilistic outputs, enabling confidence estimation for each prediction. This probabilistic interpretation has supported the clinical decision-making. Table 5 presents the output layer configuration used for classification.

Table 5: Classification Layer Configuration

Component	Description
Dense neurons	2

Activation	Softmax
Loss function	Cross-entropy

The softmax function has been expressed as:

$$P(y = c \mid z) = \frac{e^{z_c}}{\sum_{k=1}^{C} e^{z_k}}$$

where z_c denotes the logit corresponding to class c, and C represents the number of classes. This formulation has ensured normalized probability outputs.

4.6 Model Training and Optimization

Model training has minimized the cross-entropy loss using the gradient-based optimization. Backpropagation has updated network weights iteratively, which enables the convergence toward optimal parameters. Regularization strategies have mitigated the overfitting and an improved generalization. The loss function has been defined as:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where $y_i$denotes the ground truth label and $\hat{y}_i$represents the predicted probability. This objective has guided learning toward accurate asynchrony detection.

5. Results and Discussion

5.1 Experimental Settings

The experimental evaluation is conducted using the controlled deep learning simulation environment that supports reproducible training and testing of convolutional neural network models. The proposed framework is implemented using the Python with the standard deep learning library that supports one-dimensional and two-dimensional CNN architectures, along with the transfer learning. All experiments are executed on the workstation equipped with the multi-core CPU and a dedicated GPU to accelerate model training and inference. The computing system uses an Intel Core i7 processor with the 32 GB RAM, which supports efficient handling of large-scale ventilator waveform data.

5.2 Experimental Setup and Parameters

The experimental setup as in table 6 follows a standardized configuration to ensure consistent evaluation across all the models.

Table 6: Experimental Setup and Training Parameters

Parameter	**Value**
Sampling frequency	100 Hz

Epoch length	2 seconds
Train–validation–test split	70% – 15% – 15%
Batch size	32
Optimizer	Adam
Learning rate	0.001
Number of epochs	50
Loss function	Categorical cross-entropy
Activation function	ReLU / Softmax

5.3 Dataset Description

The dataset consists of the airway pressure and flow signals collected from the mechanically ventilated patients in an intensive care setting. Each signal record is segmented into the fixed-length epochs and annotated by experienced clinicians as synchronous or asynchronous breathing. The dataset includes diverse waveform patterns arising from the variations in patient physiology and ventilator settings, which supports robust model evaluation. Table 7 presents a summary of the dataset characteristics used in the experiments.

Table 7: Dataset Description

Attribute	**Description**
Signal types	Airway pressure, airflow
Total waveform epochs	50,712
Approximate total breaths	~2.6 million
Annotation method	Expert clinician labeling
Classes	Synchronous, Asynchronous
Data imbalance ratio	Moderate

The dataset is preprocessed using the normalization and noise suppression to ensure consistency across the patient records. The presence of a large number of labeled epochs supports effective supervised learning and statistically reliable performance evaluation.

5.4 Existing Methods for Comparison

The existing approaches are considered for comparative evaluation. The Random Forest Classifier relies on the handcrafted temporal and statistical features extracted from the airway pressure and flow signals. The Support Vector Machine Classifier uses engineered descriptors with the kernel-based decision boundaries for asynchrony detection. The Shallow 1D CNN Model processes raw waveforms using the limited-depth convolutional architecture, which provides basic temporal feature learning but restricts representational capacity.

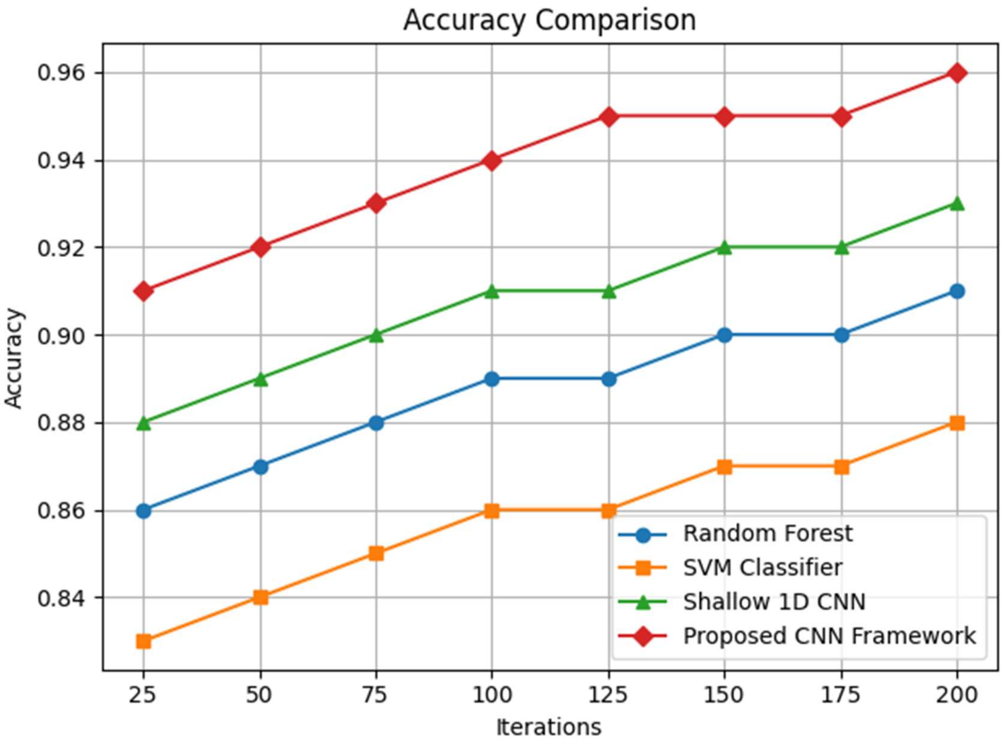

Figure 2: Accuracy

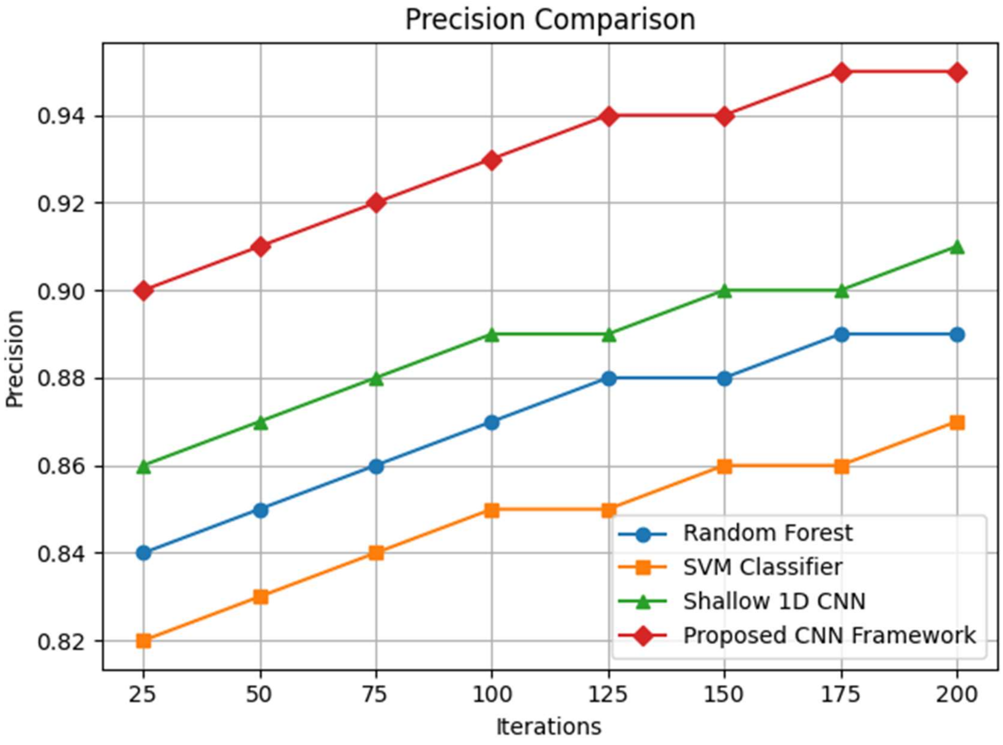

Figure 3: Precision

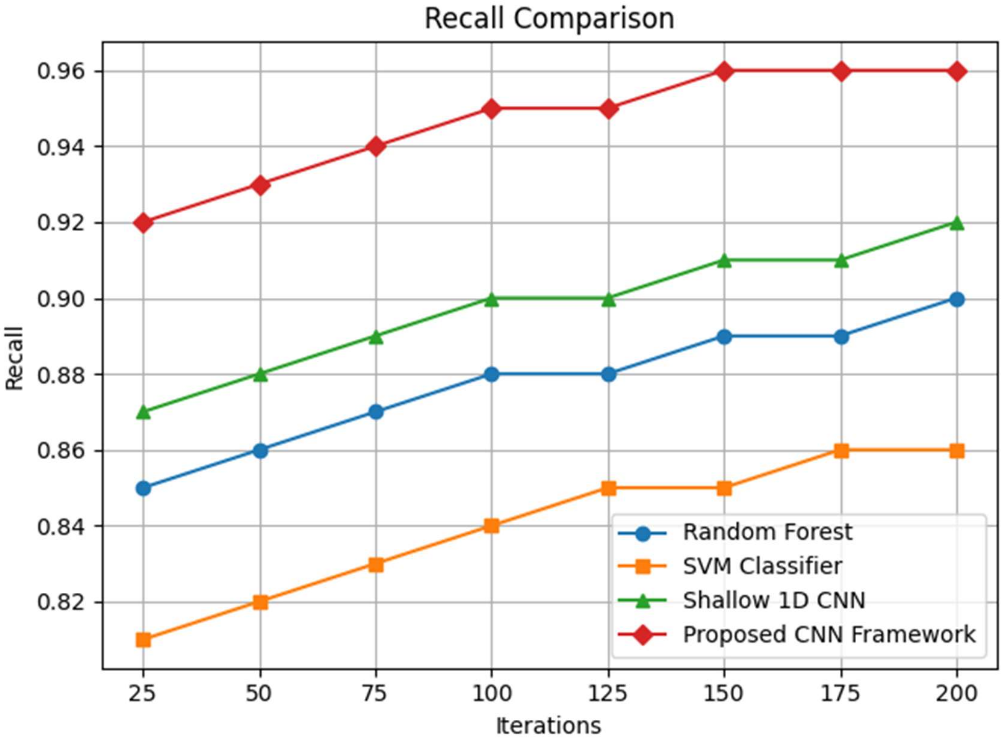

Figure 4: Recall

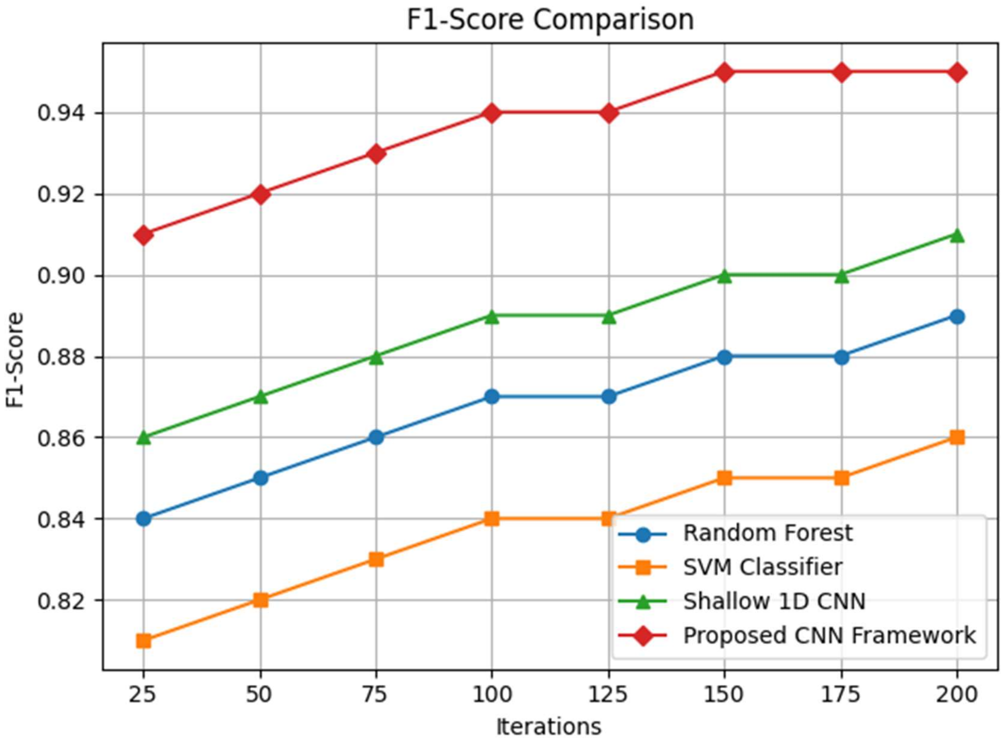

Figure 5: F1-Score

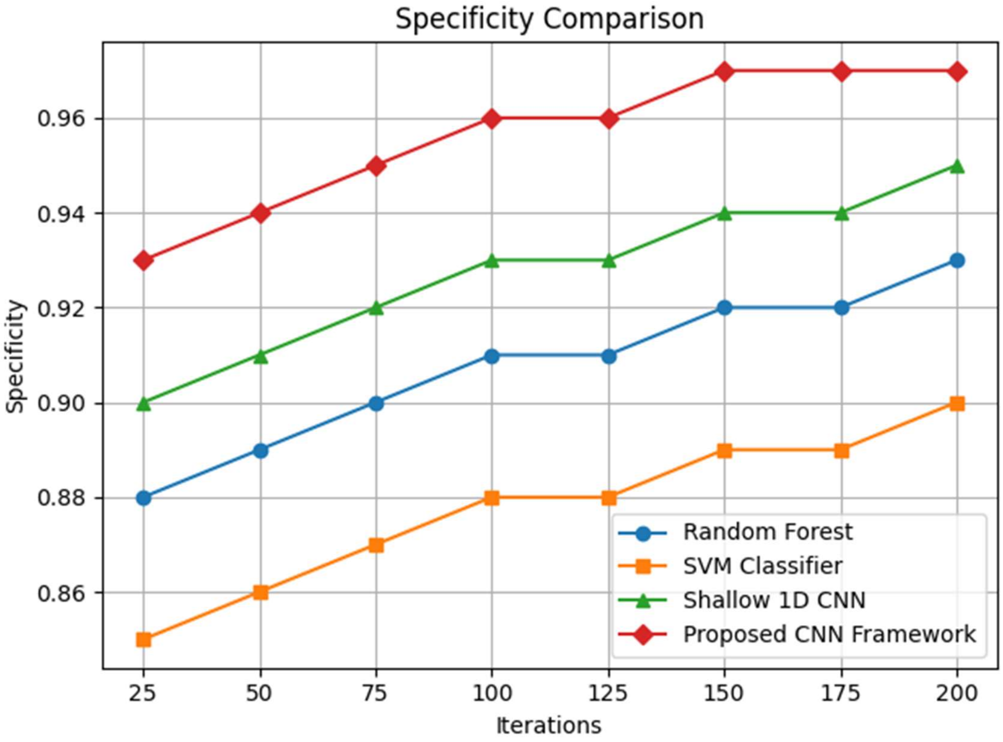

Figure 6: Specificity

Discussion of Results

The numerical results demonstrate consistent performance improvement of the proposed CNN framework across all the evaluation metrics. As shown in figure 2, the proposed method has achieved a an accuracy of 0.96 at 200 iterations, which exceeds the Random Forest, SVM classifier, and Shallow 1D CNN by margins of 5%, 8%, and 3%, respectively. Precision and recall values in figure 3 and 4 indicate that the proposed framework maintains reliable detection of asynchronous events while reducing false alarms, which is critical for the clinical monitoring. The F1-score trends in figure 5 confirm balanced performance, specifically under the moderate class imbalance conditions. Specificity results in figure 6 show that the proposed model effectively identifies synchronous breathing patterns, which minimizes unnecessary clinical interventions. Performance gains become more pronounced as iterations increase, which indicates stable convergence and effective feature learning. In contrast, classical ML methods exhibit slower improvement due to reliance on the handcrafted features. The Shallow 1D CNN shows competitive behavior but saturates earlier due to limited architectural depth.

Conclusion

This study presents a comprehensive evaluation of a CNN-based deep learning framework for an automated detection of the patient–ventilator asynchrony using the airway pressure and flow signals. The proposed approach integrates waveform-based and time–frequency–based feature learning, which enables robust representation of complex ventilator–patient interactions. Experimental results demonstrate that the proposed framework has achieved a superior accuracy, precision, recall, F1-score, and specificity when compared with the Random Forest, Support Vector Machine, and Shallow 1D CNN methods. The numerical analysis confirms stable convergence across the 200 iterations, which reflects reliable learning behavior and strong generalization. The improved specificity indicates reduced false alarms, which is essential for practical clinical deployment. While spectrogram-based CNN models introduce additional computational cost, the performance gains justify their use in decision-support systems. The findings suggest that deep learning frameworks provide a scalable and effective solution for continuous ventilator waveform monitoring. Future extensions can focus on the multi-class asynchrony categorization, real-time embedded implementation, and prospective clinical validation.

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