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RESEARCH ARTICLE

Multi-Modal Feature Fusion-Based Machine Learning to Detect Abnormal Mechanical Ventilation

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ABSTRACT Mechanical ventilation (MV) is a critical life-supportive technique for saving patients with acute respiratory failure. Abnormal ventilation happens frequently due to patient-ventilator dyssynchrony (PVD), condensation in the circuit, increased airway resistance, and so on. The previous studies that only rely on time-domain features fail to provide high identification accuracy. In this study, we develop a machine learning method to detect abnormal ventilation from ventilator waveforms. This method includes not only multi-modal features, but also time-domain, time-frequency, and entropic features in machine learning. We apply three classical machine learning models (random forest, support vector machine, and k-nearest neighboring) to detect five types of abnormal ventilation, including three types of PVD (missed triggering, double triggering, and prolonged cycling), circuitry condensation, and the flow expiration limit caused by high airway resistance. The results show that the optimal F1 scores for detecting prolonged cycling, double triggering, missed triggering, circuitry condensation, and expiratory flow limit are 97.56%, 92.26%, 96.46%, 89.18%, and 96.05%, respectively, which are superior to the results using purely time-domain features. In conclusion, the fusion of multi-modal features is beneficial to the identification of abnormal ventilation. It is promising to promote the application of machine learning models to detect abnormal ventilation in real clinical settings.

INDEX TERMS Patient-ventilator dyssynchrony, condensation, expiratory flow limit, multi-modal features, random forest.

I. INTRODUCTION

Mechanical ventilation (MV) is a critical life-supportive technique for saving patients with acute respiratory failure. The MV should be closely monitored to ensure the optimal match between the ventilator and the patients [1]. In real clinical settings, however, several types of abnormal MV occur frequently. First, the mismatch between the patients and the ventilator leads to patient-ventilator dyssynchrony (PVD), which is associated with poor clinical outcomes, such as prolongation of weaning, and increased incidence of ventilator-induced lung injury (VILI) [2]. Second, condensation in the circuit of MV will increase the circuitry resistance and thus limit the gas delivery to the patients [3]. It will also trigger the ventilator to deliver an inspiration without spontaneous effort, namely

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auto-triggering [4]. Third, expiratory flow limit, which is often observed in chronic obstructive pulmonary disease (COPD), indicates increased airway resistance and thus requires appropriate ventilation settings. Timely detection of these types of abnormal ventilation and adjust the ventilation settings properly could make the patients more comfortable, and probably benefit the treatment.

The abnormal ventilation can be observed at the bedside by inspecting the waveforms displayed on the ventilator. For example, the ineffective inspiratory effort during expiration (IEE), a type of PVD, is characterized by an increase in the flow-time waveform accompanied by a drop in the pressure-time waveform. Double triggering (DT), another typical PVD, is characterized by a very short interval between the first and the second inspirations. When condensation is present in the circuit, the waveform will manifest significant fluctuations. The expiratory flow limit is characterized by low peak expiratory flow and long expiration. However, the recognition ability of the clinicians is diverse [5]. Most junior clinicians are not able to recognize these abnormal ventilation waveforms. As a result, computerized algorithms for the automatic detection of abnormal ventilation are highly necessary.

Previous studies on automatic analysis of mechanical ventilation waveform mainly focus on the identification of PVD cycles. The early rule-based approaches are mostly based on finding characteristic notch and setting thresholds to identify specific types of PVD [6], [7], [8], [9], [10], [11]. The accuracy is susceptible to the quality of the signals and the selection of thresholds. In recent years, machine learning and deep learning emerge as promising approaches in this field. Although deep learning can obtain superior classification performance over conventional machine learning and rule-based approaches [12], [13], [14], it requires a large number of annotated samples. In contrast, conventional machine learning models, such as random forest (RF) and support vector machine (SVM), can achieve satisfactory performance in the detection of PVD using a small number of training samples [15], [16], [17].

Feature extraction is the key step for a well-performed conventional machine learning model. The step extracts hand-crafted features to characterize the distinct properties among the different categorical samples. The reported studies on MV waveform analysis examined features mainly in the time-domain, such as cycle duration, level of airway pressure, and flow velocity [15], [16]. Little attention was put to the time-frequency or entropic features, which are recognized as important features for other biomedical signals [18], [19]. In this study, we examine the effectiveness of fusing multi-modal features in detecting abnormal ventilator waveforms, including PVD events, circuitry condensation, and expiratory flow limit. First, we establish a dataset of ventilator waveforms annotated by clinical professionals. Five types of abnormal ventilator waveforms (three types of PVD events, circuitry condensation, and expiratory flow limit) are labeled. Then, multi-modal features, including time-domain, time-frequency, and entropic features, are extracted from each breath cycle. Third, we use a minimum redundancy maximum relevance (MRMR) algorithm [20] to select important features. Finally, the selected features were fed to machine learning models for identifying the abnormal ventilator waveforms. The experimental results illustrates that the optimal F1 scores for detecting prolonged cycling, double triggering, missed triggering, circuitry condensation, and expiratory flow limit are 97.56%, 92.26%, 96.46%, 89.18%, and 96.05%, respectively, which are superior to the results using purely time-domain features.

II. MATERIALS AND METHODS

A. OVERVIEW

The schematic diagram of the method is illustrated in Figure 1. The ventilator flow waveform was obtained and three categories of features, i.e., time-domain, time-frequency, and entropic features were extracted from the waveform. In total, 37 potential features were used for each machine learning model. These features were ranked by an MRMR feature selection approach. The selected 12 features were fed to a classifier for identifying the type of breath. Random forest (RF), k-nearest neighbors (KNN), and support vector machine (SVM) were adopted as the classifiers. Five types of abnormal ventilation were examined, including prolonged inspiration, DT, missed triggering, expiratory flow limitation, and condensation.

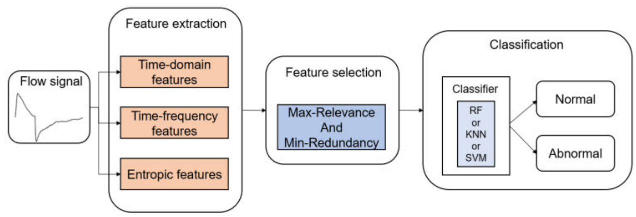

FIGURE 1. Schematic diagram of the proposed algorithm for identification of abnormal ventilation.

B. DATA COLLECTION AND ANNOTATION

The clinical data were collected from an ICU in the Second Affiliated Hospital, Zhejiang University School of Medicine between June and July 2020. The study is approved by the ethics committee of the Second Affiliated Hospital, Zhejiang University School of Medicine (No. 20220570). The patients were ventilated with Servo-i (Maquet, Sweden), PB840 (Covidien, U.S.), or Evita 4 (Draeger, Germany) ventilators. The ventilator waveform data was recorded using a ventilator information system (RespCare^{TM}, ZhiRuiSi, Hangzhou, China). The system output ventilator waveforms (including airway pressure and flow velocity) and parameters through the RS-232 serial port on the ventilator, and transmitted the signals to a central station via a local area network. The central station stored all the raw data for further analysis. The sampling frequencies were 50 Hz for both the Servo-i and PB840 ventilators, and 62.5 Hz for the Evita 4 ventilator.

The patient demographics were obtained from the electronic medical recording system of the hospital.

Three clinicians with professional knowledge of mechanical ventilation annotated the data. Five types of abnormal ventilator waveforms were considered in the study, including prolonged inspiration, DT, missed triggering, expiratory flow limitation, and condensation. Examples of abnormal ventilator waveforms are shown in Figure 2. The prolonged inspiration indicates that the preset inspiratory time is too long that the patients start to exhale before the inspiratory time is up. DT occurs because the inspiration continues after the delivery of the ventilator stops, and triggers a second delivery of gas before the inspired gas of the first breath is exhaled. Missed triggering is characterized by weak inspiratory efforts (mostly during expiration) which fail to trigger the ventilator. Expiratory flow limitation is mainly due to the high resistance of the expiratory airway. It is characterized by prolonged and sometimes incomplete expiration. The clinicians were educated to annotate the waveform according to the waveform characteristics of each PVD type. A specialized software was developed to show the ventilation waveform as well as the ventilator settings to assist the annotation.

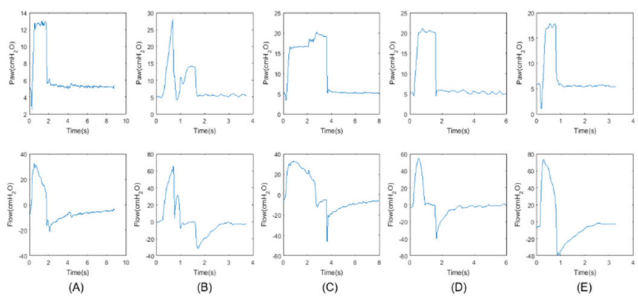

FIGURE 2. Examples of abnormal ventilator waveforms. The upper panels plot the airway pressure and the lower panels plot the flow rate. (A) missed triggering. (B) double triggering. (C) prolonged cycling. (D) condensation. (E) expiratory flow limitation.

C. FEATURE EXTRACTION

Three categories of features were extracted from the flow velocity waveforms, i.e., time-domain, time-frequency, and entropic features. All the features are listed in Table 1. Detailed descriptions of these features are described below.

D. TIME-DOMAIN FEATURES

Five time-domain features including maximum value (Max), minimum value (Min), standard deviation (SD), Kurtosis (K), skewness (S) were calculated. Suppose the signal sequence to be x_n, N is the number of sampling points of the data, and AM is the average value of the signal. Max, Min, SD, AM, and MN represent the maximum and minimum, the standard deviation, the average value, and the median value of the signal, respectively. Kurtosis is a statistic that describes the steepness of the distribution of all values in a population,

TABLE 1. The multi-modal features.

Category	Feature
Time-domain	Max
	Min
	SD
	K
	S
Time-frequency	MAVDn
	APDn
	SDDn
	SD1Dn
	SD2Dn
Entropic	FE
	AE

Abbreviations: SD: standard deviation. K: Kurtosis. S: Skewness.

which is defined as

$$K = \sum\nolimits_{n-1}^{N} (x_n - AM)\frac{4}{(N-1)SD^4} \tag{1}$$

Skewness is a measure of the direction and degree of skewness of statistical data distribution, which is calculated as

$$S = \sum\nolimits_{n-1}^{N} (x_n - AM)\frac{3}{(N-1)SD^3} \tag{2}$$

E. TIME-FREQUENCY FEATURES

The time-frequency features in this study are mainly based on wavelet decomposition. A six-order wavelet decomposition was performed using Daubechies-5 as the wavelet basis function. Mean of the absolute value (MAV), average power (AP), SD, and short-term/long-term standard deviation from the Poincare plot (SD1/SD2) were calculated for each wavelet sub-band. They are named as MAVDn, APDn, SDDn, SD1Dn, and SD2Dn in this study, where n indicates the order of the wavelet sub-band.

MAV and AP are calculated as

$$MAP = \frac{1}{N}\sum\nolimits_{n=1}^{N} |x_n| \tag{3}$$

and

$$AP = \frac{1}{N}\sum\nolimits_{n=1}^{N} x_n^2 \tag{4}$$

SD1 and SD2 are calculated from the Poincare plot, in which each sampling point in a time series is plotted against the next sampling point. It is widely used in analyzing heart rate variability, as it is capable of extracting the nonlinear features from the RR interval time series [21]. Calculation of SD1 and SD2 follows

$$d = \frac{1}{\sqrt{2}} \left| x_n - x_{n+1} \right|_{1,n} \tag{5}$$

$$M_{SD1} = \frac{1}{N-1} \sum_{n=1}^{N} d_{1,n} \tag{6}$$

$$SD1 = \sqrt{\frac{\left(d_{1,1} - M_{SD1}\right)^2 + \left(d_{1,2} - M_{SD1}\right)^2 + \ldots + \left(d_{1,n} - M_{SD1}\right)^2}{N-1}} \tag{7}$$

$$d \frac{1}{\sqrt{2}} \left| x_n + x_{n+1} - 2AM \right|_{2,n} \tag{8}$$

$$M_{SD2} = \frac{1}{N-1} \sum_{n=1}^{N} d_{2,n} \tag{9}$$

$$SD2 = \sqrt{\frac{\left(d_{2,1} - M_{SD2}\right)^2 + \left(d_{2,2} - M_{SD2}\right)^2 + \ldots + \left(d_{2,n} - M_{SD2}\right)^2}{N-1}} \tag{10}$$

where SD1 and SD2 are the mean of $d_{1,n}$ and $d_{2,n}$ respectively.

F. ENTROPIC FEATURES

Two commonly used entropic features, namely Fuzzy Entropy (FE) and Approximate Entropy (AE) were adopted in this study. Approximate entropy (AE) is a statistical parameter that can quantify the irregularity of a time series and can calculate the regularity of the time series. AE uses non-negative numbers to quantify the complexity of data and the formation of information in time series. AE is often used to classify emotions in ECG signals [22]. The AE is calculated as follows

$$AE(n, l, N) = \frac{1}{N-n+1} \sum_{i=1}^{N-n+1} logC_i^n(l) - \frac{1}{N-n} \sum_{i=1}^{N-n} logC_i^n(l) \tag{11}$$

where $C_i^n(l) = \frac{1}{N-n+1} \sum_{j=1}^{N-n+1} \theta(l - x_i - x_j)$ is the correlation integral, and l is 0.15 times the standard deviation of the original data series.

Fuzzy entropy (FE) is a new measurement criterion for measuring signal irregularity, and a complexity measurement based on comparing adjacent values of time series. It can be calculated as

$$FE = \lim_{N \to \infty} \left[ln\Phi^m(r) - ln\Phi^{m-1}(r) \right] \tag{12}$$

In the formula, N is the sequence length, M is the phase space dimension, and r is the similarity tolerance.

G. FEATURE SELECTION

Feature selection is an important step for conventional machine learning. It reduces the amount of calculation required to train the classifier and thus improves the classification performance. The Minimum Redundancy Maximum Relevance (MRMR) algorithm [20], which is based on the correlation and redundancy standards between features, was adopted to select features. The relationship and redundancy between the two features and the two categories are evaluated by calculating the symmetrical uncertainty (SU) value. The SU calculation method is based on entropy, which is a non-linear correlation measurement method. The calculation of SU is given as

$$SU(A, B) = 2[IG(A \,|B)/(H(A) + H(B))] \tag{13}$$

$$IG(A \,|B) = H(A) - H(A \,|B) \tag{14}$$

$$H(A) = -\sum_i P(a_i) log_2(P(a_i)) \tag{15}$$

where A and B represent a characteristic or a pair of class labels or any two characteristics. $IG(A \,|B)$ indicates the information gain of A to B. $P(a_i)$ indicates the probability of the variable a_i.

Max-Relevance is used to calculate the average of all mutual information values between individual feature x_i and class c. It is calculated as

$$max\, D(F, c), \quad D = \frac{1}{|F|} \sum_{x_i \in F} I(x_i; c) \tag{16}$$

where F is a feature set with m features $\{x_i\}$.

The features selected by Max-Relevance may be redundant and strongly dependent on each other. When two features are redundant, the output result of the classifier will not change greatly by removing one of the features. Therefore, Min-Redundancy is used to determine whether two features are redundant.

$$min\, R(F), \quad R = \frac{1}{|F|^2} \sum_{x_i, x_j \in F} SU(x_i, x_j) \tag{17}$$

The operator $\Phi(D, R)$ combining the Max-Relevance and Min-Redundancy is considered to optimize the feature set.

$$max\, \Phi(D, R), \quad \Phi = D - R \tag{18}$$

The effect of the features on the classification problem was evaluated by increasing the number of features from one to maximum. If we already have a feature set F_{m-1} of $m-1$ features, then the next step is to select the mth feature from the feature set $\{X - F_{m-1}\}$.

$$\max_{x_j \in X - F_{m-1}} \left[I\left(x_j; c\right) - \frac{1}{m-1} \sum_{x_i \in F_{m-1}} SU\left(x_j, x_i\right) \right] \tag{19}$$

H. CLASSIFICATION AND EVALUATION

Binary classifiers were developed for each type of abnormal ventilator waveform. Three types of classical machine learning models: support vector machines (SVM), random forest (RF), and k-nearest neighboring (KNN) were adopted in this study. In each classifier, the positive class represented the specific type of PVD targeted for detection, while the negative class encompassed all other normal and abnormal samples. To ensure a balanced dataset for training and evaluation, we randomly selected samples from the negative class to match the number of samples in the positive class. A ten-fold cross-validation was carried out to evaluate the performance of the classifier. In this process, we divided the balanced dataset into ten equal parts. Nine of these parts were used as the training dataset, while the remaining part was reserved for testing. This process was repeated ten times, with each part serving as the test set once, until all samples in the dataset were used for both training and testing.

Sensitivity (Se), Specificity (Sp), F1 score (F1), and Accuracy (Acc) were calculated to evaluate their performance. They were calculated as follows:

$$Se = \frac{TP}{TP + FN} \times 100\% \tag{20}$$

$$Sp = \frac{TN}{TN + FP} \times 100\% \tag{21}$$

$$F1 = \frac{2 \times TP}{2{\times}TP + FP + FN} \times 100\% \tag{22}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{23}$$

where TP is the number of true-positive samples, TN is the number of true-negative samples, FN is the number of false-negative samples, and FP is the number of false-positive samples. All the algorithms were developed using Python with the scikit-learn package and run on a desktop computer (Windows 10, Intel(R) Core i5-2670QM 2.20 GHz microprocessor and 16 GB RAM).

The classifiers were compared with that using the time-domain features reported by Sottile et al. [16]. The features adopted for recognizing the three PVD types (missed triggering, DT, and prolonged cycling) can be referred in the supplementary materials of the literature [16].

III. RESULTS

In total, 158 hours of ventilation waveforms were obtained from twenty-five subjects in the study. The ventilation modes include volume-control ventilation (VCV) and pressure-support ventilation (PSV). The number of annotated cycles is given in Table 2. We observe that the number of annotated PVD cycles and expiratory flow limit cycles are from ∼800 to ∼3100. The number of annotated cycles with condensation is ∼20000. All the cycles without a label of abnormal ventilation are categorized as others.

We rank the features using the MRMR method. The top-10 features selected by the MRMR method are listed in Table 3. It is observed that the time-frequency domain features occupy 6 to 7 in 10 for the detection of each type of abnormal ventilation. In particular, the SD1 feature plays a more vital role in comparison with others.

The dependence of the classification performance on the number of features is shown from Figure 3 to Figure 7. The features are involved according to their rank by the MRMR method. Taking the F1-score as the index for comparison between different classifiers, RF shows superior and relatively stable performance over the other two classifiers. With the elevation in the number of features, the performance of RF increases significantly in the beginning and then reaches a plateau despite the further elevation. The performance of KNN is inferior to the RF, though its relationship with the number of features is similar to that of RF. The SVM shows poor and unstable performance. When the number of involved features was below 10, the performance of SVM is only slightly lower than RF and comparable with KNN. However, when the number of features further increases, its performance drops significantly for most of the classification tasks.

TABLE 2. Number of samples for each type of abnormal ventilation cycle.

Type	Number of cycles
Prolonged cycling	853
Missed triggering	2723
Double triggering	1100
Expiratory flow limit	3095
Condensation	20340
Others	84309

TABLE 3. The top-10 features selected by the MRMR method for each classifier.

FEATURE RANKING	PROLONGED CYCLING	MISSED TRIGGERING	DOUBLE TRIGGERING	EXPIRATORY FLOW LIMIT	CONDENSATION
1	S	APD4	Max	APD6	APD6
2	SD1D6	FE	SD1D6	FE	FE
3	SD2D5	MAVD2	FE	SD1D5	SD1D4
4	FE	SD1D6	SD1D4	AE	SD1D5
5	SD2D6	SD1D5	S	Min	SD1D3
6	SD1D4	SD1D4	MAVD1	SD1D2	SD1D6
7	SD1D5	MAVD4	SD1D5	SD1D6	MAVD1
8	MAVD1	SD2D1	SD1D2	SD	S
9	Min	K	AE	SD2D6	SD1D2
10	MAVD2	AE	SD2D1	MAVD1	AE

Table 4 gives the comparison of our results with that obtained using only the time-domain features. The results are based on using the optimal number of features. It is observed that the proposed feature extraction method was superior to those purely time-domain features proposed by Sottile et al., except for the detection of prolonged cycling using RF. For the detection of all types of abnormal ventilation, the RF gave the best performance, with an F1 score of 97.56%, 96.46%, 92.26%, 96.05%, and 89.18% for prolonged cycling, missed triggering, double triggering, expiratory flow limit, and condensation, respectively.

IV. DISSCUSSION

Mechanical ventilation attracts more and more attention in the outbreak of the COVID-19 pandemic [23]. The ventilator waveforms convey important information about the matching between the ventilator and the patients. Correction of the PVD could make the ventilation to the patients more comfortable, and probably benefits the treatment. Timely detection and processing of circuitry condensation in MV are important for reducing airway resistance and the probability of infection. Detection of expiratory flow limit may uncover the condition of airway resistance, thus assist the clinicians to

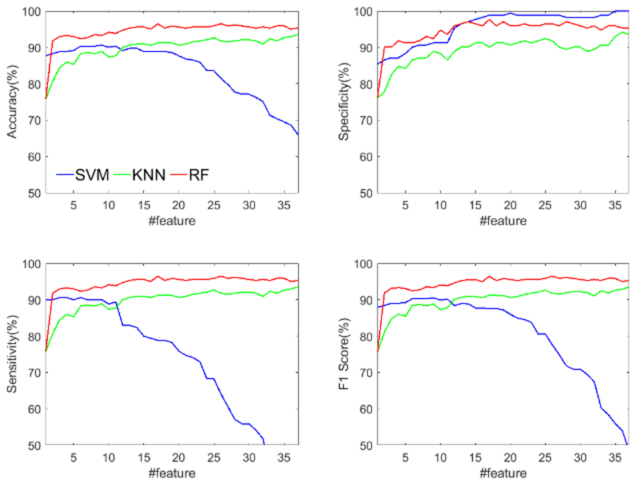

FIGURE 3. The accuracy, specificity, sensitivity, and F1 score of different features using the SVM, KNN, and RF algorithm for missed triggering. #features: number of features selected.

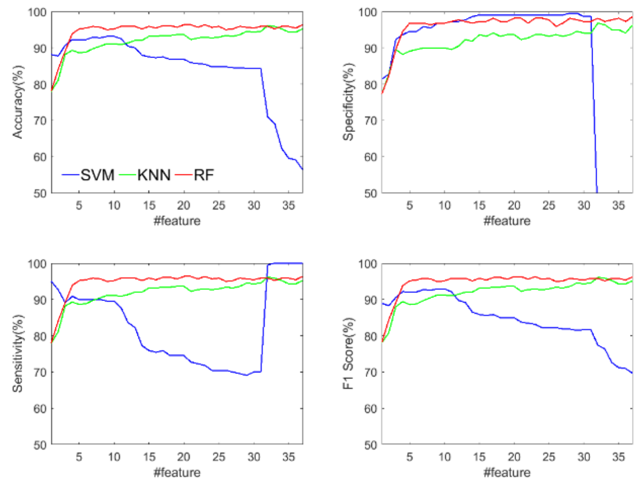

FIGURE 5. The accuracy, specificity, sensitivity, and f1 score of different features using the SVM, KNN, and RF algorithm for prolonged cycling. #features: number of features selected.

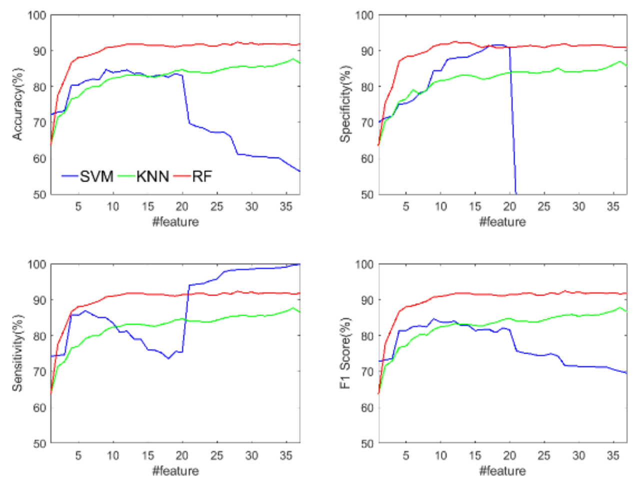

FIGURE 4. The accuracy, specificity, sensitivity, and f1 score of different features using the SVM, KNN, and RF algorithm for DT. #features: number of features selected.

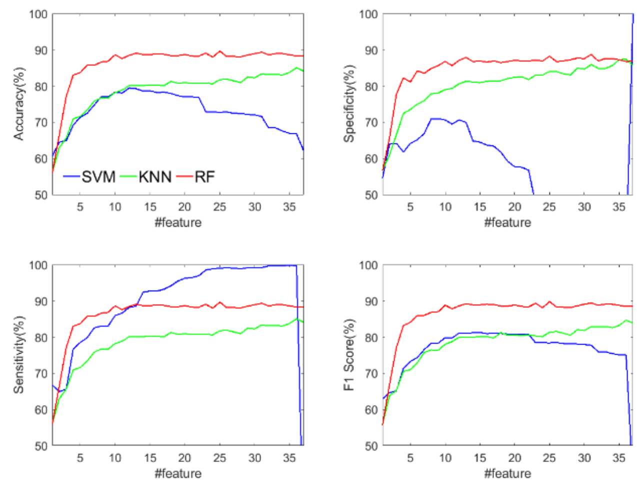

FIGURE 6. The accuracy, specificity, sensitivity, and f1 score of different features using the SVM, KNN, and RF algorithm for condensation detection. #features: number of features selected.

improve the management of the airway. Our study provides a solution for detecting these types of abnormal ventilation with high accuracy.

Machine learning models have been adopted for detecting PVD previously. Several studies adopted RF, AdaBoost, Gaussian Bayesian classifier, and logistic regression to identify different types of PVD [15], [16], [17]. Sottile et al. adopted 6, 5, and 31 time-domain features for identifying DT, prolonged cycling, and IEE, respectively. However, most of them only considered time-domain features, rather than the time-frequency features and the entropic features that have been widely applied in the analysis of biomedical signals, such as the electrocardiogram (ECG) [24], [25] and electroencephalogram (EEG) [26]. Therefore, we propose to apply the time-frequency features and entropic features in the machine learning models to enhance their performance. The experimental results show that the involvement of the time-frequency and entropic features was helpful to improve the F1 score of the classifiers. In particular, the time-frequency features play a vital role in the classification, as they occupy a high percentage in the top-10 features selected by the MRMR method (Table 3). It is because the wavelet decomposition allows for separating the signals with different degrees of oscillation. Therefore, it is capable of capturing the characteristics of the abnormal ventilation from each level of sub-band of the signal.

The SD1 and SD2 features extracted from the Poincare plot in combination with the wavelet analysis mainly reflect the dynamic features of the ventilator waveforms. SD1 reflects the point-by-point fluctuations whereas SD2 reflects the overall fluctuations of the sampling points. They mainly represent the non-linear features conveyed in each sub-band of the signal. The successful application of the multi-modal features allows for the detection of not only PVD, but also circuitry

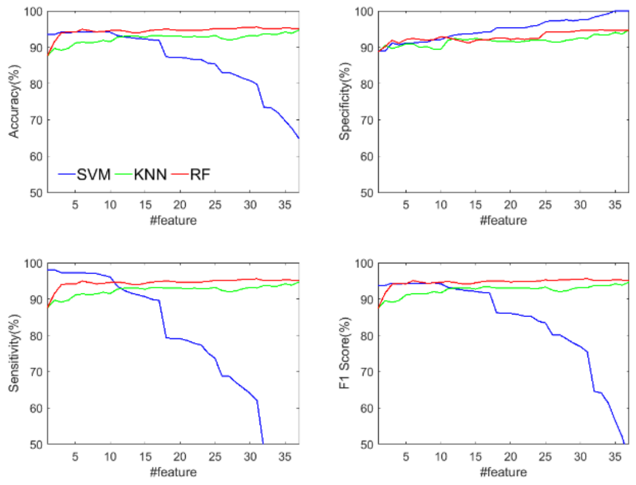

FIGURE 7. The accuracy, specificity, sensitivity, and F1 score of different features using the SVM, KNN, and RF algorithm for expiratory flow limit. #features: number of features selected.

condensation as well as expiratory flow limit, which are rarely reported in previous literatures.

Previous studies reported superior performance on PVD detection using deep learning in comparison with conventional machine learning and rule-based approach [13], [14]. However, their deep learning model has to be trained with a large amount of data, which is difficult to obtain in the clinic. In addition, the deep learning models are difficult to explain, despite the efforts to highlight the parts that contribute to the classification [14]. By contrast, our proposed algorithm was capable of achieving satisfactory results based on a small dataset. Also, it is feasible to analyze the features that contribute most to the classification, which helps the clinicians to trust the developed machine learning algorithms for clinical application.

The comparison among the three typical classifiers shows that RF exhibits the best performance concerning accuracy and stability. The finding agrees with previous studies [15], [16], suggesting that RF is a robust classifier for such kind of problem. The SVM model, which is good at binary classification, shows highly unstable results when the number of features varies. The SVM converts the nonlinear classification problem from a low-dimensional workspace to a high-dimensional workspace using the kernel function. The increase in the number of features requires a substantial increase in training samples. Insufficient samples lead to a significant reduction in classification accuracy. The KNN exhibits moderate results. As it is a distance-based method, its performance is highly dependent on the distance among different classes. For the task of abnormal ventilation detection, the breaths of different categories may share similar features, and thus be mixed in the Euclidean space. Therefore, the distance-based method shows inferior performance in comparison with the tree-based method.

The pressure waveform was not considered in the study, because the abnormal characteristics manifest more

TABLE 4. Performance of the machine learning models on detecting the five types of abnormal mechanical ventilation.

		Features	Accuracy(%)	Sensitivity(%)	Specificity(%)	F1 score (%)
Prolonged cycling	RF	Sottile et al.	97.52±0.40	97.34±0.74	97.71±0.32	97.56±0.41
		Proposed	96.32±0.37	96.45±1.60	96.13±0.93	96.19±0.29
	KNN	Sottile et al.	96.00±0.46	95.72±0.44	96.27±0.74	96.01±0.52
		Proposed	96.14±1.05	95.98±2.01	96.30±1.14	96.17±0.99
	SVM	Sottile et al.	61.07±2.25	22.64±2.63	100.00±0.00	71.85±1.69
		Proposed	92.95±0.82	94.80±2.18	91.04±2.99	92.86±0.99
Missed triggering	RF	Sottile et al.	95.51±0.90	95.28±0.70	95.75±1.92	95.48±1.00
		Proposed	96.54±0.79	95.88±1.83	97.20±1.86	96.46±0.88
	KNN	Sottile et al.	92.90±1.01	93.42±0.73	92.43±2.29	92.88±0.99
		Proposed	93.49±1.16	92.29±2.31	94.73±1.32	93.56±1.22
	SVM	Sottile et al.	60.09±4.50	55.14±40.69	66.39±45.53	54.84±24.54
		Proposed	90.32±1.96	92.69±3.62	87.56±1.39	89.67±1.49
Double triggering	RF	Sottile et al.	91.96±0.50	90.66±0.85	93.31±0.26	91.91±0.48
		Proposed	92.12±0.47	91.39±1.14	92.85±1.14	92.26±0.55
	KNN	Sottile et al.	84.77±1.07	84.31±1.52	85.23±1.23	84.83±1.09
		Proposed	87.86±1.05	87.26±1.24	88.46±1.66	87.82±1.08
	SVM	Sottile et al.	64.14±0.22	29.72±0.68	99.40±0.30	73.25±0.28
		Proposed	90.32±1.96	92.69±3.62	87.56±1.39	89.67±1.49
Expiratory flow limit	RF	Sottile et al.	95.75±0.53	95.00±0.85	96.52±0.88	95.75±0.49
		Proposed	96.09±0.59	95.30±0.53	96.88±0.86	96.05±0.69
	KNN	Sottile et al.	92.19±0.75	91.37±0.57	93.00±1.07	92.27±0.85
		Proposed	94.64±0.49	93.51±0.73	95.75±0.61	94.73±0.48
	SVM	Sottile et al.	72.24±1.25	99.46±0.23	45.13±1.28	61.96±1.17
		Proposed	94.02±0.38	90.82±0.63	97.27±0.56	94.16±0.37
Conden-sation	RF	Sottile et al.	89.21±0.70	88.38±1.04	90.07±0.85	89.28±0.72
		Proposed	88.79±0.69	85.77±1.04	91.76±0.57	89.18±0.61
	KNN	Sottile et al.	80.31±0.65	80.36±0.60	80.27±1.48	80.13±0.79
		Proposed	82.57±1.25	83.10±1.63	82.01±1.50	82.28±1.41
	SVM	Sottile et al.	65.07±0.60	30.47±0.82	99.66±0.07	74.05±0.47
		Proposed	78.74±1.07	63.57±3.29	93.85±2.75	81.56±1.12

significantly in some types of abnormal ventilation, such as for missed triggering and expiratory flow limit. For the other types, the pressure and velocity waveforms convey similar information about the abnormal characteristics. Inclusion of the pressure waveform indicates that the number of the candidate features will be doubled, which requires more samples to guarantee the performance of the machine learning models. In the future study, the effect of including pressure waveform should be examined when there are more samples available.

The performance for detecting condensation is below that of the other four types of abnormal ventilation. While the PVD and expiratory flow limit all exhibit distinct characteristics in the waveform, the morphology of the waveforms manifesting circuitry condensation is heterogeneous, as it may include the features of other types of abnormal ventilation. The results suggest that a robust circuitry condensation detector should be trained by involving training samples with more diverse ventilation modes, settings, and types of abnormal ventilation.

For the detection of asynchrony between the patients and the ventilators, a limitation is that the present study lacks validation against the golden standards, such as the electrical activity of the diaphragm (EAdi), or esophageal pressure (Pes) monitoring. Utilization of these techniques allows for more accurate recognition of PVD [27], [28], [29], particularly for some specific types of PVD, such as reverse triggering [30], [31]. Also, the annotations for the condensation and the expiratory flow limit are based on the experience of the annotators. In the future, these monitoring techniques should be employed for better labeling of the samples for machine learning. However, as EAdi or Pes are too complex to be routinely applied in the clinic, the technique without monitoring of EAdi or Pes for detecting PVD is still meaningful for clinical routine.

The proposed algorithm is difficult to be applied at bedside to assist the clinicians at present. However, recent advances in ventilator monitoring systems [32] may shed a light to make the developed algorithms applicable to the clinicians in the near future. The systems are capable of collecting ventilator waveforms in real time and allows for complex computation at bedside. Alerts of the occurrence of PVD can be delivered to the clinicians through user interface to improve mechanical ventilation.

V. CONCLUSION

We explore the value of fusing multi-modal features in identifying PVD breaths and breaths with circuitry condensation and expiratory flow limit in mechanical ventilation. The results indicate that fusion of multiple categories of features could enhance the recognizing ability of abnormal ventilator waveforms. Such techniques are promising to remind the clinicians to correct PVD, to clear the accumulated water, or to provide proper treatment for the patients with high airway resistance, to improve the management of ventilatory support. The trained model can be embedded into a ventilator information system [32], to remind the clinicians about the occurrence of PVA or provide the statistics of PVA occurrence over time.

Future studies could focus on the outliers in the PVD dataset, as the PVD shows high heterogeneity due to its patient-ventilator interaction nature. Outlier detection methods are promising to further improve the performance of PVD detection.

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