Sputum deposition classification for mechanically ventilated patients using LSTM method based on airflow signals

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ABSTRACT

A novel sputum deposition classification method for mechanically ventilated patients based on the long-short-term memory network (LSTM) method was proposed in this study. A wireless ventilation airflow signals collection system was designed and used in this study. The ventilation airflow signals were collected wirelessly and used for sputum deposition classification. Two hundred sixty data groups from 15 patients in the intensive care unit were compiled and analyzed. A two-layer LSTM framework and 11 features extracted from the airflow signals were used for the model training. The cross-validations were adopted to test the classification performance. The sensitivity, specificity, precision, accuracy, F1 score, and G score were calculated. The proposed method has an accuracy of 84.7 ± 4.1% for sputum and non-sputum deposition classification. Moreover, compared with other classifiers (logistic regression, random forest, naive Bayes, support vector machine, and K-nearest neighbor), the proposed LSTM method is superior. In addition, the other advantages of using ventilation airflow signals for classification are its convenience and low complexity. Intelligent devices such as phones, laptops, or ventilators can be used for data processing and reminding medical staff to perform sputum suction. The proposed method could significantly reduce the workload of medical staff and increase the automation and efficiency of medical care, especially during the COVID-19 pandemic.

1. Introduction

Critically ill patients in the intensive care unit (ICU) often cannot breathe autonomously. Mechanical ventilation (MV) can replace or assist breathing to exchange oxygen and carbon dioxide for patients [1, 2, 3]. Especially during the COVID-19 pandemic, approximately 20% of people infected by COVID-19 become critically ill and need mechanical ventilation in the ICU [4].

However, compared with spontaneous breathing, MV may produce patient-ventilator asynchrony, which will stimulate the respiratory tract mucosa of patients and result in increased sputum secretion [5, 6]. Sputum deposition leads to insufficient ventilation and hypoxia, promotes bacterial reproduction and pulmonary infection, and seriously affects the safety of these patients.

Currently, sputum deposition is checked and judged through lung sound auscultation by experienced medical staff. After that, the sputum is aspirated by a suction catheter method, an invasive method [7, 8]. Using a suction catheter may injure the airway mucosa of patients. Otherwise, failure to engage in timely removal of sputum will lead to sputum deposition, which will result in insufficient ventilation or pulmonary infection. Therefore, it is essential to classify sputum deposition among mechanically ventilated patients.

The lung sound auscultation method relies heavily on the medical staff’s clinical experience, which has strong subjectivity and needs extensive training. In addition, this method is time-consuming and requires a manual operation, which significantly increases the work intensity of medical staff.

With the development of technology, some researchers have classified sputum deposition by integrating the knowledge of sensors,
digital signal processing, artificial intelligence, and computer technology [9, 10, 11, 12, 13, 14, 15, 16]. Almost all of the research has involved lung sound signal analysis for classifying sputum deposition. Artificial neural networks (ANNs) have been widely used in lung sound signal classification and medical image analysis. Yamashita et al. [9] proposed a sputum detection method by using lung sound signals. Lung sound data used for training were used in their study. The flow and pressure signals were used to segment the sound data. The sparse representation and support vector machine method was presented to classify sputum deposition for three patients. The accuracy of classification could reach 85%–97% [9]. Niu et al. [10] developed a sound data acquisition device to collect lung sound through a ventilation tube. Interestingly, they visualized the sound signals in time-frequency domains, the sound spectrum. Then, feature extraction and various classifiers were applied for image classification. Two hundred seventy-two samples from 12 patients were used in their study. An accuracy of 83.5% was achieved for classifying sputum deposition. In addition, Niu et al. [12] also used 13 image features of respiratory sounds to classify sputum deposition. According to the tenfold cross-validation results, the sensitivity and specificity exceeded 90% by using a logistic classifier. Shi et al. [11, 17] developed a wavelet denoised and decomposition method to extract lung sound data characteristic vectors. Linear discriminant analysis and a BP neural network were used to reduce the dimensions of the characteristic vectors and identify the lung sound types, respectively. The classification accuracy of sputum deposition was over 80%.

Additionally, some research is related to the identification and classification of crackle, wheeze, chronic obstructive pulmonary disease (COPD), and other respiratory diseases using lung sounds [18, 19, 20, 21, 22, 23, 24, 25]. Altan et al. [22] analyzed multichannel lung sounds through a deep learning method for classifying COPD and healthy subjects. Pham et al. [23] proposed a deep learning structure to classify respiratory anomalies and diseases by analyzing the lung sound spectrogram. Shuvo et al. [24] used a convolutional neural network (CNN) for chronic and pathological classification using lung sounds. The accuracy reached approximately 98% and exceeded the performance of VGG16, which is a well-known CNN architecture. Wu et al. [25] combined the random forest and empirical mode decomposition (EMD) methods to conduct six respiratory condition classifications. Akbal et al. [20] proposed a fused textural and statistical feature generation network method for sleep disease diagnosis through nocturnal sound.

Specifically, the recurrent neural network (RNN) that appeared in the 1980s has a strong processing ability for time sequence data and has been successfully used in language models, speech recognition, and machine translation. However, many researchers found that the gradient disappeared or exploded when using RNNs for modeling and training on long series data. As an improved RNN network, a long-short-term memory network (LSTM) could construct a long-term sequence relationship that has dominant memory units [26]. The memory cells in LSTM make the long-distance transmission of gradient information feasible during training. Otherwise, three kinds of gates (input gate, forget gate, and output gate) filter the information, blocking useless information and passing valuable information.

Recently, the LSTM method has been widely used in sleep detection, electrocardiogram classification, heart rate estimation, and so on [27, 28, 29, 30, 31, 32, 33, 34]. Chang et al. [27] proposed an LSTM model to classify the different sleep apnea syndromes. Different from the polysomnography method, abdominal and thoracic accelerometer signals, pulse oximetry saturation (SpO2) signals, and electrocardiogram signals were used in their study. The classification accuracy reached approximately 90%. Drzazga et al. [28] used the LSTM method to distinguish between apnea and hypopnea. ElMoqaet et al. [29] proposed a bidirectional LSTM model to classify obstructive, central, and mixed apnea. An autosleep apnea-hypopnea syndrome monitoring method using nasal airway pressure and temperature signals based on LSTM was developed by Yang et al. [31]. Saadatnejad et al. [32] proposed a lightweight and accurate electrocardiogram (ECG) classification algorithm based on LSTM. Sano et al. [33] used the LSTM method to classify sleep and wake, whose accuracy was 96.5%.

According to the related works above, lung sound signals processing was used for sputum deposition classification in all the researches. However, the disadvantage of using lung sound signals is that signal collection, and monitoring requires a specific device that inconveniences the patients and medical staff. Besides, the lung sound signals were processed on both time and frequency domains which are more complex than single time domain signals processing.

As a common fact, along with sputum gradually being deposited in respiratory airways, the airway resistance of mechanically ventilated patients will gradually increase, which changes the ventilation airflow. Therefore, the airflow for mechanically ventilated patients is a kind of sequence data with time series during the sputum deposition process. In addition, the detection of ventilation airflow is relatively easy and accurate and would not interfere with patients. To the best of our knowledge, there have been no related works involving ventilation airflow signals for sputum deposition classification.

Considering the limitations of current lung sound processing methods, the time sequence ventilation airflow signals were used for sputum deposition classification in this study. A novel sputum deposition classification method for mechanically ventilated patients based on the LSTM method was proposed. A wireless ventilation airflow collection system was developed and used in this study. Fifteen patients with more sputum in the ICU were recruited for this study. The ventilation airflows before and after the sputum suction operation were recorded. The main advantages of using ventilation airflow signals for classification are its convenience and its low complexity. Moreover, the algorithm proposed in this paper can be coded and downloaded to mobile phones, laptops, or ventilators to remind medical staff of sputum suction in clinical environments. The proposed method in this paper could significantly reduce the workload on medical staff and increase the automation and intelligence of medical care, especially during the COVID-19 pandemic.

More data are currently being collected based on our airflow collection system in several hospitals. The method for sputum deposition classification will be improved based on additional clinical data.

2. Materials and methods

2.1. Ventilation airflow data collection system

A novel airflow data collection system for mechanically ventilated patients is designed and manufactured in this study. The system consists of a collection device and receiving equipment. The collection device is presented in Figure 1. The flow-pressure sensor (FS6122, Siargo Ltd.) collected air pressure and flow signals. The sampling frequency is 200 Hz. The sensor was installed on the printed circuit board (PCB) and powered by a 5 V li-battery. Two different joints manufactured through the 3D print method were designed to connect the ventilation tube.

The data were transferred to a laptop or mobile phone through a wireless Wi-Fi network. A diagram of the airflow data collection system is shown in Figure 2. The pressure and flow signals were restored every 1 min in textual files on the laptop or mobile. In addition, the pressure and airflow curves can be presented on the screen of laptops or mobile phones for medical staff observation.

2.2. Data collection and preprocessing

Ventilation airflow data for 15 patients were collected in the ICU of Chao Yang Hospital, China. This study was approved by Beijing Chao Yang Hospital (Approval number: 20217234). The informed consent was obtained from all patients for the experiments. The detailed information for 15 patients has been supplied in Table 1.
According to the medical staff, the sputum deposition process is slow. Usually, sputum suction is conducted every 1–1.5 h. Therefore, we assumed no apparent changes in sputum deposition over 10 min. Ten minutes of data before and after the sputum suction operation were collected. The data collected before the suction operation were labeled sputum deposition, while the data collected after the suction operation were labeled non-sputum. In this study, only one-direction airflow data was used.

An example of 1-min ventilation airflow data is presented in Figure 3(a) and (b). The blue and red curves represent the airflow before and after the suction operation, respectively. To accurately analyze the ventilation airflow difference and extract the features before and after sputum suction, the airflow data were segmented with the interval of the patient ventilation cycle. After segmentation, the airflow data were divided by the black dashed line, as shown in Figure 3(a) and (b).

2.3. Feature extraction

The data of each ventilation cycle of patients were analyzed. Considering that the frequency of the airflow signal is low and the main features exist in the time domain, 11 features, which are the peak value, mean value, median, variance, kurtosis, skewness, root mean square, waveform factor, peak factor, pulse factor, and margin factor, were extracted and calculated. The formulas for calculating the features are presented in Eqs. (1), (2), (3), (4), (5), (6), (7), (8), (9), (10), and (11):

\[ F_{\text{peak}} = \max(x_1, x_2, \ldots, x_N) \]  
\[ F_{\text{mean}} = \frac{1}{N} \sum_{i=1}^{N} x_i \]  
\[ F_{\text{median}} = \text{median}(x_1, x_2, \ldots, x_N) \]  
\[ F_{\text{var}} = \frac{1}{N} \sum_{i=1}^{N} (x_i - F_{\text{mean}})^2 \]  
\[ F_{\text{kur}} = \frac{1}{N} \sum_{i=1}^{N} (x_i - F_{\text{mean}})^4 \left( \frac{\sum_{i=1}^{N} (x_i - F_{\text{mean}})^2}{N} \right)^{\frac{3}{2}} \]  

Table 1. The detailed information (age, gender and weight) about 15 patients.

| Subject | Age (years old) | Gender (M/F) | Weight (Kg) |
|---------|----------------|--------------|-------------|
| 1       | 67             | M            | 64          |
| 2       | 62             | M            | 56          |
| 3       | 32             | FM           | 60          |
| 4       | 69             | M            | 70          |
| 5       | 77             | M            | 55          |
| 6       | 40             | M            | 81          |
| 7       | 37             | M            | 78          |
| 8       | 53             | M            | 75          |
| 9       | 89             | M            | 69          |
| 10      | 77             | M            | 75          |
| 11      | 84             | FM           | 40          |
| 12      | 49             | FM           | 58          |
| 13      | 60             | M            | 68          |
| 14      | 45             | M            | 77          |
| 15      | 75             | FM           | 48          |

Figure 1. The ventilation airflow data collection device.

Figure 2. The diagram for clinical use of the ventilation airflow data collection system.
The subscripts peak, mean, median, var, kur, ske, rms, pea-f, wav-f, pul-f, and mar-f represent the peak value, mean value, median, variance, kurtosis, skewness, root mean square, waveform factor, peak factor, pulse factor, and margin factor, respectively. \( X_i \) represents the time sequence data. \( N \) is the number of the data sample.

All 11 features for each patient ventilation cycle were extracted. An example of the changes in features 1 min before and after the sputum suction operation is shown in Figure 4(a) and (b). The features before sputum suction are presented in the light blue background, and the features after sputum suction are presented in the light-yellow background.

### 2.4. Deep learning process

It is difficult to visually distinguish the features before and after sputum suction from Figure 4. Therefore, considering the accuracy and convenience in solving a nonlinear system model, a deep learning method was used in this study. RNN is very effective for data with time series characteristics. It can mine time-series information and semantic information in data. However, many researchers found that the gradient disappeared or exploded when using RNNs for modeling and training of long series data. As an improved RNN architecture, LSTM can construct a
long-term sequence relationship and has dominant memory units, which can solve the gradient disappearance or explosion problem of RNNs.

The memory cells from beginning to end in LSTM ensure that the long-distance transmission of gradient information in the training process is feasible. In addition, three gates (input gate, forget gate, and output gate) are established. The sigmoid activation function was used to filter the information. The detailed structure of LSTM is presented in Figure 5.

The function of the forget gate, presented in Eq. (12), is to decide the retention and discard of information. The previous hidden state and the current input are simultaneously transferred to the sigmoid function. The output value is between 0 and 1. If the output value is close to 1, it will be retained; otherwise, it will be discarded if the output value is close to 0.

\[
f_i(t) = \sigma(W_f \cdot [h^{(t-1)}, x^{(t)}] + b_f)
\]  

\(f_i(t)\) is the forget gate output. \(X(t)\) and \(h(t-1)\) are the previous hidden state and current input, respectively. \(W_f\) and \(b_f\) are the coefficient and offset values for the forget gate, respectively.

The input gate updates the cell state, determining how many network inputs are retained in the current cell state. The function of the input gate is shown in Eq. (13). The previous hidden state and the current input are the input data transferred to the sigmoid function for adjusting the values. The output value zero means unimportant, while one means essential. In addition, the tanh function is used for the previous hidden state and the current input to generate a candidate vector, as shown in Eq. (14). Finally, the cell state, presented in Eq. (15), is the output value from the sigmoid and candidate vectors.

\[
i_o(t) = \sigma(W_i \cdot [h^{(t-1)}, x^{(t)}] + b_i)
\]

\[
\hat{c}_i(t) = \tanh(W_c \cdot [h^{(t-1)}, x^{(t)}] + b_c)
\]

\[
c_i(t) = f_i(t) \cdot c^{(t-1)} + i_o(t) \cdot \hat{c}_i(t)
\]

\(i_o(t)\) is the input gate output. \(c_i(t)\) and \(c^{(t)}\) are candidate vector and cell state values, respectively. \(W_i\) and \(b_i\) are coefficient and offset values for the input gate. \(W_c\) and \(b_c\) are coefficient and offset values for the candidate vector.

As shown in Eq. (16), the output gate determines the next hidden state value. The previous hidden transmits to the sigmoid function together with the current input. Then, the new cell state passes to the tanh function. Finally, the current hidden state is the product of the output of the tanh function and output gate value, as shown in Eq. (17). Continuously, the new cell state and the current hidden state are transferred to the next step.

\[
o_o(t) = \sigma(W_o \cdot [h^{(t-1)}, x^{(t)}] + b_o)
\]

\[
h_i(t) = o_i(t) \cdot \tanh(c_i(t))
\]

2.5. Training procedure

In this study, a two-layer LSTM network was used for training. Figure 4 shows significant differences between the features of the airflow signals, which seriously affects the training classification ability of the network. Therefore, the 11 features of airflow are normalized in the (0,1) interval for each patient. In addition, the dropout layer and L2 regularization method were introduced to eliminate the overfitting of the network. Sputum and non-sputum classification was achieved through softmax and classification layers. As shown in Eq. (18), the softmax function is as follows:

\[
s_j = e^{z_j} \sum_{i=1}^{J} e^{z_i}, \quad \sum_{i=1}^{J} s_i = 1
\]

where \(z_j\) is the output of the fully connected layer. \(s_i\) is the output value through softmax for \(z_i\). \(J\) represents the number of neurons.

The cross-entropy loss function shown in Eq. (19), is used for classification.

![Figure 5. The detailed structure of LSTM.](Image)
$L = \frac{1}{N} \sum_{i=1}^{N} \left[ y_i \cdot \log(s_i) + (1 - y_i) \cdot \log(1 - s_i) \right]$  

(19)

$y_i$ is the label of sample $i$. 1 represents sputum, and 0 represents nonsputum.

The whole training process is presented in Figure 6. The number of neurons in the first and second LSTM layers was 200 and 100, respectively. The value of the dropout layer was set to 0.5. The piecewise learning rate schedule was adopted. The learning rate drop factor and drop period were set at 0.5 and 200, respectively. The L2 regularization method was used to prevent the over-fitting phenomenon. The value was set to 0.001. The adaptive moment estimation (ADAM) algorithm was used for optimization. The number of iterations was set at 16,000. The whole algorithm was implemented using MATLAB R2021 software. The code is available at reasonable request from the corresponding author.

3. Results

3.1. Cross-validation for sputum classification

According to the medical staff experience, the sputum volume of mechanically ventilated patients changes very little within 10 min before and after sputum suction. Therefore, we assumed that sputum would not increase 10 min before sputum suction and that new sputum would not be produced 10 min after sputum suction. The data collected before sputum suction were labeled nonsputum. We collected the ventilation airflow data of 15 mechanically ventilated patients before and after sputum suction every 10 min. The time-series data were divided at an interval of 1 min. Some data involving replacement of the tube, coughing, or other procedures that interface with normal ventilation have been removed. Finally, 260 groups of time series data were used for training and classification. There were 128 sputum deposition groups and 132 non-sputum groups. The cross-validation method was adopted to verify the model’s classification performance. Fifteen patients have been randomly divided into five groups. Each group contained three patients. One group was selected as a validation set, and the remaining four were used as training sets. The data from the same patient did not appear in the train and validation sets when performing cross-validation. The training sets were used to predict the validation set and obtain a corresponding classification result. The exact process has been applied in every five groups. Finally, five related classification results have been obtained. The confusion matrix of the classification results is shown in Figure 7(a)-(e).

The sensitivity, specificity, precision, accuracy, $F_1$ score, and $G$ score were calculated through Eqs. (20), (21), (22), (23), (24), and (25) and are presented in Table 2:

$$sensitivity = \frac{TP}{TP + FN}$$  

(20)

$$specificity = \frac{TN}{TN + FP}$$  

(21)

$$precision = \frac{TP}{TP + FP}$$  

(22)

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP}$$  

(23)

$$F_1 \ score = \frac{2}{1/sensitivity + 1/precision}$$  

(24)

$$G \ score = \sqrt{sensitivity \times precision}$$  

(25)

$TP$ and $TN$ represent the number of true positive and true negative samples, respectively. The $FP$ and $FN$ represent the number of false-positive and false-negative samples.

According to Table 2, we can see that the average and standard deviation values for sensitivity, specificity, precision, accuracy, $F_1$ score, and $G$ score for 5-fold validation were 83.0 ± 9.4%, 87.0 ± 6.5%, 87.3 ± 4.9%, 84.7 ± 4.1%, 84.7 ± 4.1%, and 85.0 ± 3.9%, respectively.

In addition, the receiver operating characteristic (ROC) curves and area under the ROC curve (AUC) values for cross-validations are presented in Figure 8(a)-(e). The horizontal coordinate is the false-positive rate (FPR) calculated with Eq. (26). All of the AUC values in the five validations were over 0.81, with an average of 0.85.

$$FPR = \frac{FP}{FP + TN}$$  

(26)

3.2. The performance of the LSTM method vs. other classifiers

Additionally, to compare the performance of the proposed method based on LSTM with other classification methods, the training process used logistic regression, random forest, naive Bayes, support vector machine (SVM), and K-nearest neighbor (KNN) algorithms. The same cross-validation method was used for validation. The comparison results for cross-validations are presented in Figure 9. The average accuracy and standard deviation values for cross-validations are shown in Table 3. The LSTM method used in this study had the highest accuracy of 84.7 ± 4.1% among the six classifiers.

In comparison, naive Bayes had the lowest accuracy of 74.6 ± 5.2%. The other four classifiers had an accuracy between 70% and 82%. Besides, the paired-samples t-test has been performed, and the results were
shown in Table 4. The $t$, $df$, and $p$ values have been calculated. It can be seen that all $p$ values are less than 0.05.

3.3. The performance of the LSTM method vs. others and our previous research

We also compared the classification accuracy with others and our previous research results [9, 10, 11, 12]. The comparison of classification accuracy is shown in Table 5. In the research of Yamashita et al. [9], the classification accuracy could reach as high as 97%. In Niu et al.’s research, sputum sound analysis was used, and the accuracy reached 83.5% and 93.36% with different time-frequency image features [10, 12]. Similarly, Shi et al.’s research used sputum sound signals and had an accuracy of 84.53%. The proposed method in this paper had a classification accuracy of 84.7%, which is higher than Shi et al. and Niu et al. [10, 11] and lower than Niu et al. [12].

4. Discussion

This study developed a novel sputum deposition classification method for mechanically ventilated patients based on the LSTM method using airflow time sequence signals. A wireless ventilation airflow collection system was designed and used for signal collection. According to the fivefold cross-validation results, the LSTM method proposed in this study had an accuracy of $84.7 \pm 4.1\%$ for sputum and non-sputum classification. Specifically, the sensitivity for cross-validation was $83.0 \pm 9.4\%$, which means that the proposed method performs well for sputum deposition classification. In addition, the average specificity reached $87.0 \pm 6.5\%$, which means that the method is less likely to make a false judgment for non-sputum situations. For accuracy, precision, $F_1$ score, and $G$ score, the average values were $84.7 \pm 4.1\%$, $87.3 \pm 4.9\%$, $84.7 \pm 4.1\%$, and $85.0 \pm 3.9\%$, respectively. This result indicated that the proposed method has good accuracy in classifying sputum and non-sputum situations. Meanwhile, the differences in the classification accuracy among the five cross-validation results were less than 10%, which shows that the method has good generalization ability.

The ROC curves and AUC values for cross-validations demonstrated the method proposed in this study in another way. The dashed line in Figure 8(a)–(e) represents a random classifier with an accuracy of 50%. The result in the zone above the dashed line means that the method has good classification performance. Conversely, the area below the dashed line results means the method has bad classification performance. The closer the result is to the upper left corner (point (0,1)), the better the classification performance is. The results in Figure 8(a)–(e) are all laid above the dashed line and closer to point (0,1), which validates the excellent performance of the proposed method in classifying sputum and non-sputum situations. The AUC value is another index used to evaluate the classification performance. The larger the AUC is, the better the classification performance of the classifier. The method has no predictive value if the AUC equals 0.5, the same as a random guess. All of the AUC values are above 0.8, which shows that the method has good classification performance.
values in Figure 8(a)–(e) were over 0.81 with an average of 0.85, demonstrating the proposed method’s classification performance.

Additionally, compared with logistic regression, random forest, naive Bayes, SVM, and KNN classifiers, the LSTM method proposed in this study achieved the highest accuracy of 84.7 ± 4.1%. The reason for this is that the LSTM method has a strong processing ability for time sequence data, which is consistent with the properties of ventilation airflow signals. In addition, the excellent performance of the LSTM method in classifying sputum deposition also validated the time variability of sputum deposition.

Unlike all previous research on sputum deposition classification, which uses lung sound signals, ventilation airflow signals were employed to classify sputum and non-sputum situations in this study. To the best of our knowledge, there have been no related works involving ventilation airflow signals. According to Table 5, although the classification accuracy can reach as high as 97% in Yamashita et al.’s research [9], only three subjects were involved in their study, which cannot validate the performance of their method. There were 272 and 220 samples from 12 patients in Niu et al.’s [10,12] researches. Sputum sound analysis was used, and the accuracy reached 83.5% and 93.36% with different time-frequency image features.

Similarly, Shi et al. used wavelet transform and the BP network method to analyze sputum sound signals. 84.53% was achieved in classifying sputum deposition also validated the time variability of sputum deposition. However, the sound signals were collected through a specially manufactured device inserted into the ventilation tube, which will interfere with normal mechanical ventilation. Besides, the sound signals were processed on both time and frequency domains which are more complex than single time domain signals processing.

Therefore, this study collected and analyzed 260 groups of time series data from 15 patients. A two-layer LSTM framework was adopted. Eleven time-domain features were extracted and used for LSTM model training. The classification accuracy of the method proposed in this study is higher than the results of Shi et al. [11] and Niu et al. [10] and lower than the result of Niu et al. [12].

Nonetheless, the disadvantage of using lung sound signals is that signal collection and monitoring require a specific device that inconveniences the patients and medical staff. However, the airflow signals are easily collected and measured through a flow sensor in series with tubes that would not interfere with patients. Furthermore, with the ventilator manufacturer’s cooperation, the ventilator’s flow sensor could be used for data collection, and the algorithm could be coded in the central system. Therefore, sputum deposition classification could be achieved through the ventilator. In addition, the algorithm could also be coded and downloaded to a mobile phone or laptop, which is handy for medical staff.

The proposed method in this paper could significantly reduce the workload on medical staff and increase the automation and intelligence of medical care, especially during the COVID-19 pandemic.

More data are currently being collected based on our airflow collection system in several hospitals. The method for sputum deposition classification will be improved based on additional clinical data.

5. Conclusions

A novel sputum deposition classification method for mechanically ventilated patients based on the LSTM method was proposed in this
study. Ventilation airflow signals were used for sputum deposition classification. A wireless ventilation airflow collection system was designed and used to collect airflow time sequence signals. Two hundred sixty groups of time series data from 15 patients in the ICU before and after sputum suction were collected and analyzed. Eleven time-domain features were extracted and used for LSTM model training. A two-layer LSTM network was adopted. The dropout layer and L2 regularization method were used to eliminate the network’s overfitting. Cross-validation was used for validation. The sensitivity, specificity, precision, accuracy, F1 score, and G score were calculated. All of these values were over 83%. The proposed method had an accuracy of 84.7 ± 4.1% for sputum and non-sputum deposition classification.

Moreover, we evaluated the proposed LSTM method by comparing it with other classifiers (logistic regression, random forest, naïve Bayes, SVM, and KNN). The results showed that the proposed LSTM method was superior. In addition, compared with other studies and our previous research results, the LSTM method has slightly improved performance. However, the most significant advantages of the method proposed in this paper are its convenience and low complexity. The airflow signals are easily collected through a flow sensor serially connected to tubes or embedded in the ventilator. Intelligent devices such as phones, laptops, or ventilators can be used for data processing and reminding medical staff about sputum suction.

The limitation of this study is that the training samples were insufficient for practical applications. Because of the inconvenience and strict protection procedure caused by the COVID-19, data collection has become more and more difficult. The method for sputum deposition classification will be improved based on additional clinical data. The CNN architecture is widely used for the two or higher dimension data. The study involving the one-dimension CNN architecture gradually increase. We plan to use the one-dimension CNN architecture with more clinical data to test if the new method could have higher classification accuracy in our following study.

The proposed method in this paper could significantly increase the automation and intelligence of medical care. With the cooperation of the ventilator manufacturer, this method can be improved and quickly applied in clinical use in the COVID-19 pandemic.

Declarations

Author contribution statement
Shuai Ren: Conceived and designed the experiments; Performed the experiments; Wrote the paper.
Jinglong Niu: Conceived and designed the experiments; Performed the experiments.
Maolin Cai, Tao Wang: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.
Yan Shi: Analyzed and interpreted the data.
Zujin Luo: Performed the experiments; Contributed reagents, materials, analysis tools or data.

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Data availability statement
Data will be made available on request.

Declaration of interest’s statement
The authors declare no conflict of interest.

Additional information
No additional information is available for this paper.

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