A Deep-Learning Based Method to Detect Obstructive Sleep Apnea Using Abdomen Respiration Signals

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***Abstract*— The sleep disorder obstructive sleep apnea (OSA) is common, but often undiagnosed. OSA is characterized by pauses in breathing during sleep, which can disrupt your sleep schedule and have serious health consequences. In the past, polysomnography (PSG) signals have been most commonly used to diagnose OSA, which is accurate but very time consuming and inconvenient. Therefore, it is necessary to develop a lightweight and fast approach that can be used for easy monitoring at home. Numerous studies have been done on the classification of OSA from normal using deep learning. This paper proposed a method to classify OSA from normal by abdominal respiratory signal that can be collected with only an abdominal attached respiration sensor, which is more comfortable and cheaper than the PSG detection method. We propose a 1D convolutional neural network (CNN) approach to detect OSA by an abdominal respiratory signal only, which is a small network with three convolutional and five fully connected layers for fast classification. The experimental dataset uses the abdominal breathing signals from PhysioNet/Computing in Cardiology Challenge 2018. The accuracy of the experimental results reached 80.75%, specificity could reach 81.29%, and sensitivity could reach 80.64%, with a 0.813 F1 score. The above results illustrate that our proposed method can effectively perform the initial classification of OSA. The model is not only lightweight but also features low signal processing complexity and low computational effort, which can be achieved with simple home monitoring.**

Keywords—Deep learning, Medical diagnoses, Abdominal respiratory signal, Obstructive sleep apnea

I. Introduction

Obstructive sleep apnea (OSA) is a sleep disorder characterized by repeated episodes of complete or partial blockage of the upper airway during sleep [1]. These obstructions can cause a person to stop breathing momentarily, leading to disrupted sleep and a range of potential health issues like coronary artery disease, heart attack. In the past, polysomnography (PSG) signals have been most commonly used to diagnose OSA, which is accurate but requires the patient to have overnight monitoring in the lab by collecting 13 signals, including electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG), and abdominal respiration signals. The whole process is very uncomfortable and time consuming for the patient. These disadvantages necessitated the development of a lightweight and fast method for easy monitoring at home.

Machine learning techniques have solved problems more effectively in many fields, including medical diagnosis, and more and more researchers are using machine learning to detect OSA from normal [2]. Many methods for automatically detecting sleep apnea using different biosignals have been developed [3]. The state of patients' breathing when sleeping can be directly reflected by respiratory signals. Previous studies have generally been more complex in the signal preprocessing process and the model for classification [4]. To solve this problem, we use abdominal respiratory signal that can be collected with only an abdominal attached respiration sensor, which is more comfortable and cheaper than the PSG detection method, also more suitable for home monitoring. The recording that is collected by the sensor can be directly used as input data for OSA detecting models.

This paper proposed a method based on 1D convolutional neural networks (CNNs) to detect OSA by abdominal respiratory signals only and performed with an accuracy, specificity, sensitivity, and F1 score of 80.75%, 81.29%, 80.64%, and 0.813 respectively. Which is a small network with three convolutional and five fully connected layers for fast classification that suits home monitoring.

II. Database and Preprocessing

A. Database

For training, the PhysioNet/Computing in Cardiology Challenge 2018 (https://physionet.org/content/challenge-2018/1.0.0/) [5] was used, which provided PSG recordings following the American academy of sleep medicine (AASM) standards.

The dataset consists of PSG signals from 994 patients as they slept through the night, including: electroencephalogram (EEG), electromyogram (EMG), electrocardiogram (ECG), and abdominal respiration signals. During a normal night's sleep, the recording of each patient is continuous for approximately 8 hours. Seven clinical staffs annotated the signal as apnea region and normal region for every value in the signal. We used the abdominal respiration signals in this database for our study which were sampled at 200 Hz.

B. Preprocessing

During our study, the signal is split into samples with a window-width size. In order to avoid an apnea spanning two windows, we use a sliding window of size 30s to divide the signal, which means that the shape of each channel's data is 1×6000. To reduce noise in abdominal respiratory recordings, we transform the original signals by Fourier transform to the frequency domain because, in the frequency domain, it is possible to visualize the main frequency information of the signal, thus removing the secondary frequency information that can be considered noise. Then the signals from 0.5 Hz to 30 Hz are transformed further into the temporal domain by the inverse Fourier transform [6]. Other bands with minimal correlation and noise are filtered by this processing. Finally, feature normalization was implemented with z-score normalization to lessen patient individual differences. The following is a description of the z-score calculation formula:

$$y^j = \frac{x^j - \mu}{\sigma} \tag{1}$$

where x^j denotes the *jth* sampling point in the recording, μ represents the average value of the recording, and σ is the standard deviation of the recording.

III. Method

In this work, we proposed a network with three convolutional layers and five fully connected layers. The model is implemented with parameter configurations as follows:

- A stack of 1D CNNs with 128, 64, and 32 units, respectively.
- Each CNN layer is followed by batch normalization; the rectified linear unit (ReLU) activation function, and the max pooling process with a pool size equal to 2 in order to extract only important features from the output of its previous layer.
- A stack of fully-connected neural networks (DNNs) with layers of size 64, 16, 8, 4, and 2 hidden nodes to encode many features into a small number of close to 2 hidden nodes.
- All CNN layers and the first two DNN layers are followed by a dropout rate of 0.4 to prevent overfitting.

The overall architecture is shown in Figure 1.

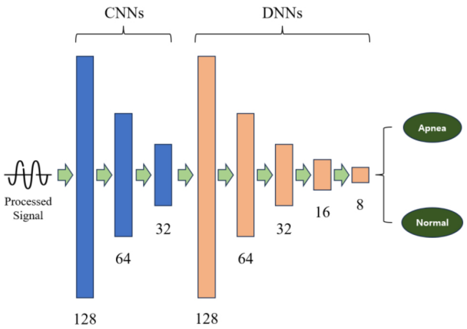

Fig. 1. The architecture of the proposed model.

IV. Result And Disscussion

After the experiment by our model using processed abdominal respiratory signals. As shown in Table 1, the proposed method achieved a performance of 80.75% accuracy, 81.29% specificity, 80.64% sensitivity, and 0.813 F1 score.

TABLE I. Model Performance

	Accuracy	Specificity	Sensitivity	F1 score
Proposed Model	80.75%	81.29%	80.64%	0.813

Based on the results, we can conclude that this method is effective in detecting apnea. The model based on only 3 convolution layers reduces a lot of computation with only 1,601,446 parameters. In addition, using an abdominal attached respiration sensor for collecting abdominal respiratory signals is much more comfortable and convenient for monitoring at home.

V. Conclusion

This study proposed a lightweight model with three convolutional layers and five fully connected layers in addition to using the abdominal respiration signal that can be easily collected by the attached respiration sensor for more convenient and quick home monitoring of patients with respiratory disorders. The achieved performance showed this method can effectively perform the initial classification of OSA, which is really helpful for simple home monitoring processes, instead of having overnight PSG monitoring in the lab.

In our future work, we hope to achieve a higher accuracy rate by enhancing the network of the model. Additionally, the model's small weight must be kept in place for easier home monitoring using the abdominal respiration signal. We also aim to develop lightweight and fast OSA detection model using other biosignals, such as ECG signals.

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