Original Research

Chin Electromyogram, an Effectual and Useful Biosignal for the Diagnosis of Obstructive Sleep Apnea

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Abstract

Background and Objective: Obstructive sleep apnea (OSA) is among the critical sleep disorders, and researchers have been investigating its novel diagnostic methods. Polysomnography signals' complexity, difficult visual interpretation, and the need for an efficient algorithm based on simpler signals have made the study of sleep apnea a compelling issue. In this study, the accuracy of chin electromyogram in the diagnosis of OSA was evaluated.

Materials and Methods: The amplitude variation and power spectral density (PSD) of chin electromyograms of 100 patients during apnea and before-after apnea occurrences (non-apnea) periods were compared after complete processing of the raw signal. Two-dimensional (2D) spectrograms related to the specified periods were extracted and fed into the residual neural network (ResNet). The network performance was reported by model evaluation parameters.

Results: The results showed that OSA event influences the patient's chin muscle and increases the amplitude variances and power spectrum of the chin electromyogram. The ResNet-50 deep model classified the dataset of this sleep disorder with about 97% accuracy, which was higher than previous studies in this field.

Conclusion: Chin electromyogram can be introduced as a practical and useful biosignal for accurate OSA diagnosis with a deep classifier without the need for current specialized equipment and multiple vital signals.

Keywords: Obstructive sleep apnea; Deep learning; Polysomnography; Sleep-disordered breathing; Neural network models; Chin; Electromyogram

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Introduction

Sleep is a biological phenomenon characterized by the inactivation of voluntary muscles and an increase in the threshold of reaction to external stimuli (1). Sleep is a dynamic and active anabolic process involving physiological changes in the body that enables the growth and restoration of the immune, nervous, and muscular systems. The effect of sleep on the human physical and mental status is crucial and its changes have significant consequences (2).

Sleep disorders refer to conditions such as insomnia, frequent awakenings, and increased daytime drowsiness. Inadequate sleep impairs the body's natural functioning and the brain's operation (3). Given the impact of sleep disorders on personal and social life, the identification and evaluation of affected individuals are of great importance. Obstructive sleep apnea (OSA) is one of the most common sleep-related diseases, which occurs due to complete or partial airway obstruction. OSA is the cessation of respiratory airflow for at least 10 seconds despite respiratory effort (4). An imbalance in the tonic and phasic muscle activity of the pharyngeal dilatation muscles leads to obstruction of the upper airways. Fat accumu-

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lating in the peripheral tissue of the throat in obese persons can also reduce lung capacity. In healthy individuals, the periodic activity of the pharyngeal dilatation muscle decreases during the rapid eye movement (REM) phase of sleep, and the cross-sectional area of the pharynx becomes narrower (5). The severity of symptoms is exacerbated over the years and with increase in weight or age, and menopause (6).

The majority of sleep disorders are clinically detectable; however, some must be studied through advanced techniques (7). The need to diagnose these problems has necessitated the access of specialists to sleep information analysis systems called polysomnography (8). Polysomnography allows a comprehensive study of the body's biophysiological changes that occur during sleep by recording a variety of signals, including electroencephalogram, electrocardiogram, respiratory flow, and electromyogram. Evaluation and scoring of sleep stages and related disorders are done by sleep specialists after recording the signals (9). Visual evaluation of polysomnography signals is a difficult, time-consuming, and tedious process, and is prone to mental and visual error (10). In addition, it is visually difficult to detect changes due to the complex and turbulent nature of the signal (11).

Furthermore, polysomnography requires specialized equipment and overnight stay at the sleep clinic that is costly and overwhelming. Therefore, finding an easier, more accurate, and less expensive method to monitor OSA can be very helpful and will enable doctors to diagnose and treat more effectively. Hitherto, many studies have been performed to accurately diagnose sleep disorders using various vital signals and classifiers, and researchers are still trying to design automatic detection systems based on the latest biological signal processing methods (12). The main question that this study sought to answer was whether the electromyogram signal of the patient's chin muscle alone can be an effective and reliable diagnostic tool for OSA. Studies have shown that some respiratory diseases, especially OSA, are associated with the electrical activity of muscles and muscle tone of the body (13).

In a clinical study, electromyography (EMG) analysis was performed to assess sleep in individuals with narcolepsy and cataplexy, and chin EMG was found to be useful in terms of phasic polygraph and the diagnosis of neuromuscular paralysis during sleep as considered in the latest international classification of disorders (14). In the study by Senny et al., chin EMG was found to have a relationship with waking, sleeping, and disturbed sleep due to respiratory disorders (15).

In another study, chin EMG analysis for sleep disorders in REM showed that EMG could be used to evaluate the inhibitory effect of motor activity and muscle tone. The results showed that chin EMG in healthy individuals gradually decreases with the onset of sleep, and reaches its lowest level in the REM phase or completely eliminated in some cases. Chin EMG amplitude increases when stimulated and it increases in individuals with respiratory disorders (16). Gouveris et al. studied the statistical relationship between chin EMG and electroencephalography (EEG) and found that with increasing respiratory distress, cortical-muscular relationship decreases, but increases during REM (17).

Another study combined EMG and EEG to detect respiratory disease and concluded that changes in the spectral power of the encephalogram are associated with changes in the power of the electromyogram (18). The results of a study based on the combined analysis of EEG, EMG, and electrocardiography (ECG) indicated that there is a significant relationship between EMG and obstructive sleep disorders (19).

Another study found that the activity of the muscles that support the upper airway is higher when awake and decreases and in some cases disappears with sleep onset. Chin EMG reaches its lowest level during REM due to its inhibitory effect on motor activity and reduction of muscle tone. Chin EMG signal power is significantly higher in people with apnea than in healthy individuals at the end of sleep, and patients with OSA have higher upper respiratory tract muscle activity during sleep than when awake (20). The results of previous studies have indicated the superiority of chin EMG over other types of vital signals in sleep apnea diagnosis such as recording with fewer electrodes with minimal disturbance to the patient’s sleep; thus, the present study is based on the hypothesis that chin EMG, which is commonly used to monitor REM and muscle tone of the body, can be considered a clinical and efficient indicator for the diagnosis of obstructive sleep disorders. The selection and application of a classification algorithm for this disorder with more acceptable efficiency and accuracy than previous models was another aim of this study. Researchers have proposed and implemented a variety of classifications for the diagnosis of OSA, but in the meantime, deep learning neural networks have become more efficient due to newly developed techniques (21).

In this study, the relationship of OSA with chin electromyogram of patients was proven, and for the first time, this effectual and useful biosignal was introduced as the main and independent signal for the diagnosis of OSA. After signal analysis, information was converted into two-dimensional (2D) spectrograms and fed to one of the most popular deep neural networks. The results of our past research had shown that this novel technique based on chin EMG analysis can predict disorder more rapidly and accurately in comparison to other similar techniques and reduce equipment, cost, and the time of diagnosis.

Materials and Methods

Signal recording and processing: Chin EMG of 100 patients of Danesh Sleep Clinic of Tehran, Iran, formed the data of this study, and the sleep specialist’s scoring and patients’ airflow signals were the main indicators of apnea labeling. The age range of patients was 28-70 years and 61 participants were men. The initial clinical diagnosis for all selected patients was OSA with apnea-hypopnea index (AHI) $\geq$ 15. Nocturnal polysomnography was carried out after environmental patient adaptation. Lights-out time was based on the patient’s habits and sleep duration was between 5.30 and 8.30 hours. The respiratory pattern was monitored using nasal pressure cannula. Chin EMG was recorded using silver-silver chloride surface electrodes by placing a reference electrode under the lower lip on the chin and 2 other electrodes on either side of the submental muscles near the pharyngeal dilator muscles (14).

The impedance of the electrodes was less than 10 kOhm and the signal sampling rate was 200 Hz. Disruptive factors such as jaw muscle activity, bruxism, sleep speech, and lower throat muscle activity were removed after the clinical examination using device settings and filtration of motor artifacts in the preprocessing stage. A number of chin electromyograms including apnea and non-apnea episodes per patient were selected based on the clinical observations and sleep scoring of the sleep specialist, patient respiratory signal quality, and AHI.

The output of the polysomnography system was in the European Data Format (EDF) and was entered into MATLAB software (MathWorks, Portola Valley, CA, USA) by a reader program. A 1-minute chin electromyogram signal containing apnea events was selected for inclusion in the study (14, 20). The notch filter was used to eliminate line frequency (50 Hz) noise and the Butterworth band pass filter was used to extract any signal in the frequency range of 10-100 Hz (22). The galvanic response of the skin, respiratory artifacts, and frequency components of adjacent muscles were eliminated at this stage (23). Due to differences in the patients' signal amplitudes, data were normalized using the Z-scoring method (22).

Selected 1-minute signals were divided into 3 periods of before, during, and after apnea, and 60 one-second epochs were generated. The segmented signals were examined in terms of both time and frequency. In this way, amplitude variances and power spectral density (PSD) estimate of the chin EMG signals were calculated using Levene's test and Welch’s Method with Hamming windowing at 50% overlap (18) and the results associated with apnea/non-apnea periods were compared. Examples of the amplitude changes of the patient's chin electromyogram signal in the periods before, during, and after apnea are presented in figure 1. The vertical axis displays the signal amplitude in microvolts and the horizontal axis displays the sampling rate of the 1-second signal. Amplitude values were used to analyze amplitude variance in apnea and non-apnea periods.

The PSD of the chin EMG signals corresponding to before, during, and after the occurrence of apnea in different frequency ranges is depicted in figure 2. The vertical axis displays the power spectrum in decibels and the horizontal axis displays the frequency rate in hertz.

The 2D spectrograms of 6000 patients' chin electromyograms in apnea and non-apnea stages were generated using a short-time Fourier transform (STFT). The frequency spectrum of the spectrogram varies with time and different colors of the image show different amounts of energy (24). The horizontal axis of the spectrogram represents the time in seconds and the vertical axis shows the frequency components of the signal in Hz. An example of a patient’s chin electromyogram spectrogram is shown in figure 3. The generated spectrograms were stored in 2 folders named apnea and non-apnea, and were used as input to the deep learning model. Steps in this section were performed using the MATLAB 2020 signal processing toolbox.

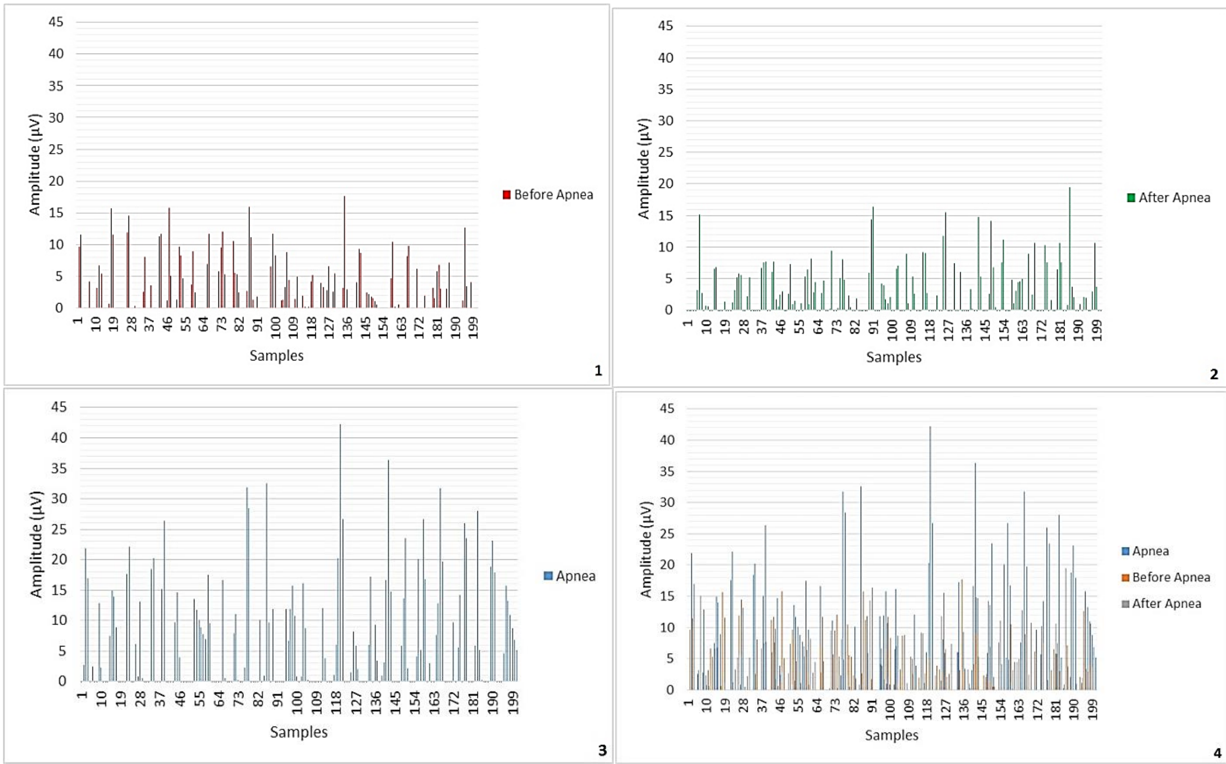

Figure 1. Amplitude diagram of the patient chin electromyogram based on the samples before, during, and after the occurrence of apnea (1-3) and (4) simultaneous display of events

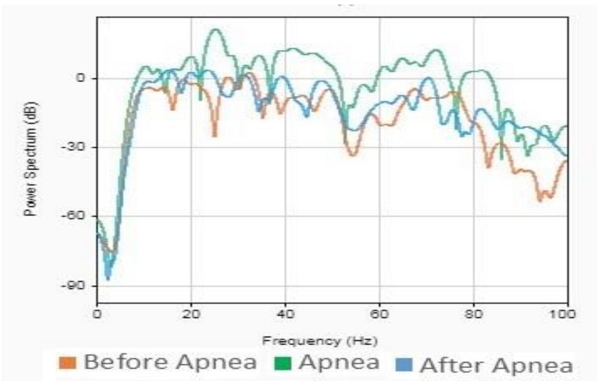

Figure 2. Comparison of the signal power spectrum based on frequency in the before, during, and after apnea segments

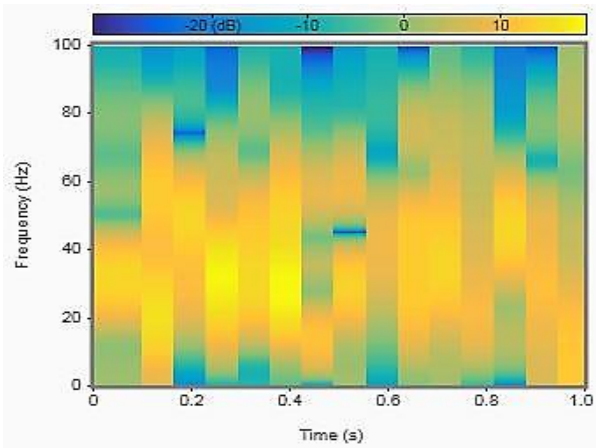

Figure 3. Two-dimensional spectrogram of a patient's chin electromyogram

Deep learning and Model evaluation: A systematic review by Mostafa et al. (21) has shown that deep models have shown better performance in diagnosing OSA compared to shallow networks. Deep learning provides the ability to solve complex, nonlinear problems without the need for human intelligence. In this method, complex concepts are broken down into simpler ones and the data is rendered into machine-understandable concepts. This network is made up of a combination of input, convolution layer, activity function, pooling, and fully connected layers.

Convolution reduces parameters, creates connections between pixels, and provides spatial stability. The pooling layer is used to combine similar features, reduce feature map size, and select the appropriate feature. Moreover, the fully connected layer converts the 2D feature map into a one-dimensional feature vector for classification (25). A variety of deep learning network architectures have been proposed by researchers. The increasing of layers in deep networks leads to the problem of gradient explosion, which is why residual networks have solved this problem. Residual network (ResNet) is a fast and robust pre-trained deep convolutional neural network (CNN). This type of network is easier to optimize and can achieve significant accuracy in image classification. In ResNet-50 architecture, first, the input is converted into different pieces, and then, it is entered into the network. Shortcut connection is the most significant feature of this model; it passes through 1 or more layers and does not consider them. In fact, it takes a shortcut and connects 1 layer to more distant layers. This model has less complexity than other common deep networks and has been used the most in the field of image classification in the last 2 years. (26).

In the present study, 6000 spectrograms of the patients' chin electromyograms were fed as input into the ResNet-50 after resizing to 224 * 224 *3. Modeling was performed in the Google Colab environment using the Python programming language and Keras and Tensorflow libraries. Furthermore, 80% of the data was allocated to training and 20% to testing. The number of epochs and mini-epochs was 100 and 50, respectively. A drop-out layer was used to prevent over-fitting. Shuffling was performed before each epoch and the learning rate was considered to be 0.0001. The results were reported by plotting the confusion matrix and the receiver operating characteristic curve (ROC) and calculating the accuracy, precision, specificity, recall, area under the curve (AUC), and F1-score using computational equations related to each of the performance indicators of the deep learning model.

Results

The selected one-minute chin EMG signals from every patient, which included the apnea events, were divided into 3 main windows. The first, second, third windows contain the Chin EMG before the onset of apnea, during apnea, and after the ending of apnea. Windows were divided into 1-second epochs, and amplitude and PSD changes of all the segments were evaluated. The amplitude fluctuation of signal in apnea and non-apnea periods was compared using Levene's test and the significance level was 0.05. According to the results, the variances of these events were statistically significant because all significance levels of periods which were compared were less than 0.05. The test report is presented in table 1.

Table 1. The comparison of amplitude variance of the patient's chin electromyogram in apnea and non-apnea periods

		Apnea
Before apnea	F	184.424
	P-value	< 0.001
After apnea	F	163.061
	P-value	< 0.001

The obtained results showed that the amplitude variance in the apnea period was higher than the non-apnea periods, which means that the chin muscles were stimulated during the obstructive apnea of the patient. Thus, signal amplitude intensification during apnea and the possibility of analyzing changes in the chin electromyogram signal to diagnose obstructive apnea was proven. The analysis was continued, the signal PSD estimate was calculated using Welch's method, and power spectrums were normalized by calculating the logarithm of the PSD.

The comparison of normalized power also showed significant differences in the apnea segment compared to the non-apnea periods. The results in this section indicate an increase in the power of chin EMG during the occurrences of apnea and a significant decrease after the termination of apnea.

The EMG power increase was due to the increased activity of the respiratory muscles during the temporary cessation of breathing due to obstructive apnea, and the partial fluctuation corresponding to the termination of apnea compared to the segment of before apnea events indicated the temporary effect of apnea. These results also confirmed the extensive effect of apnea on the frequency content of the patient's chin EMG signal. According to the results of the signal analysis in different periods, the variation in the amplitude and signal PSD of the chin electromyogram during the apnea period and the time of stimulation of the patient's submental muscles can be interpreted as the result of respiratory arrest, patient effort, and activity of the pharyngeal control muscles. These results verify the effect of OSA on the patient's chin electromyogram which is the research hypothesis.

Then, 2D spectrograms produced from the patient's chin electromyogram signal were fed into the pre-trained ResNet-50 to classify apnea disorder from non-apnea events. The results of the network performance are shown in a ROC diagram and confusion matrix in terms of true and predicted labels in figure 4.

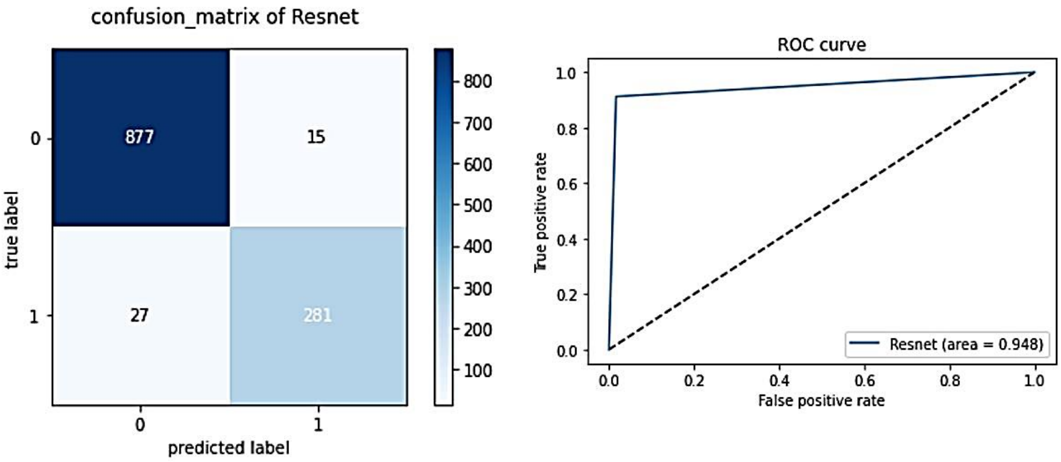

Figure 4. ROC diagram and confusion matrix of ResNet-50 with the patient's chin electromyogram spectrograms as input

As reported in the ROC diagram, the AUC, which is 0.948, is close to 1 which indicates the optimal performance of the model in classifying the data of this research.

The report of the performance of the model used in this paper in terms of network evaluation parameters is illustrated in figure 5. As can be seen, this model has classified the 2D chin spectrograms in the diagnosis of OSA with 98% and 96.5% accuracy in the training and validation stages, respectively.

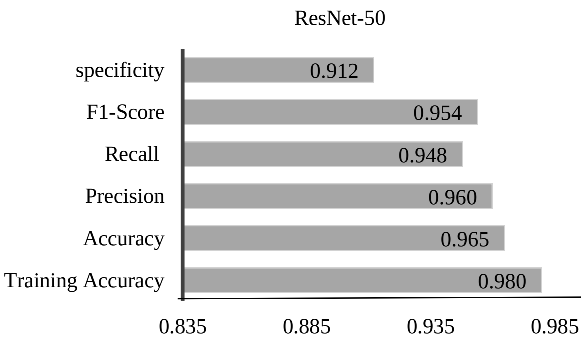

Figure 5. ResNet-50 performance report in obstructive sleep apnea classification based on chin EMG spectrograms

According to the above diagram, the values of all the effective parameters in the performance of the deep model are higher than 91%, which indicates the unique performance of this model in the diagnosis and classification of OSA based on chin electromyogram signal. According to the results, the ResNet-50 has obtained an acceptable AUC of 0.948. Other network evaluation parameters, which are recall, precision, specificity, and F1-score, were 0.948, 0.960, 0.912, and 0.954, respectively.

Discussion

As mentioned before, the recording and interpretation of various clinical signals in polysomnography is a difficult and time-consuming process, prone to mental error, and requires a variety of complex equipment. A visual interpretation of clinical signals is complicated and makes correct and real diagnoses dependent on experienced and knowledgeable medical personnel more than usual. Another concern is the high cost of the polysomnography test, and sometimes a delay in sleep disorder diagnosis due to the lack of access to facilities or financial resources. The need to find available, less costly, and more accurate ways of diagnosing the disease using fewer and more accessible signals to facilitate the process of diagnosis is another important reason for the implementation of this research. In this article, researchers have proposed an innovative method for the rapid and accurate diagnosis and classification of OSA using patients' chin electromyogram based on one of the top deep learning models. The results of the study by Al-Angari shows that chin electromyogram amplitude in people with respiratory disorders could increase when stimulated (16).

Azim et al. concluded that changes in the chin electromyogram power spectral can be associated with sleep disorders (18) and Moridani et al. indicated that obstructive sleep disorders and chin EMG may have a significant relationship (19). Another study indicated higher chin EMG power in patients with apnea, and more activity of upper respiratory tract muscles in those with OSA (20).

The results of our study through amplitude variance and PSD computation using Levene's test and Welch's method showed that the occurrence of obstructive sleep apnea causes a significant change in the amplitude and signal power of the patient's chin electromyogram. As soon as the apnea period is over, the changes decrease and the amplitude returns to the interval before the onset of apnea. It was found that respiratory paused due to sleep apnea, followed by the patient's respiratory effort, the body's muscle tone variation, and changes in the activity of the muscles that regulate the upper airway affect its adjacent muscles, the most prominent of which is the submandibular chin muscle. This important outcome proved the main hypothesis presented in this study. This hypothesis has proposed the effect of apnea on the electromyogram of the patient's chin and the possibility of diagnosing this disorder using this signal as a new biomarker in the field of polysomnography.

After preprocessing, segmentation, and conversion to 2D spectrograms, the research dataset were fed to the deep ResNet-50 model and the efficiency of this model in apnea classification was examined. The results of deep model implementation showed that these models in the field of 2D image classification have good accuracy and efficiency, and 2D convolution architecture can be used as an efficient tool to classify OSA using chin electromyogram spectrograms. The results of this study were compared with a number of domestic and foreign studies in the field of OSA diagnosis, which were performed using different deep neural models and routine biological signals. In previous studies using multiple hidden layers neural network (MHLNN), CNN, deep belief network (DBN), and long short-term memory (LSTM) models based on ECG, EEG, airflow, plethysmography, heart rate (HR), and blood oxygen saturation (SPO_2) input signals, the accuracy of apnea diagnosis was reported to be 68.3-89.0 percent (21).

In other researches, the accuracy of apnea classification using one-dimensional and 2D CNN on the basis of airflow, SPO2, EEG, and snoring signals was 79.6-91.3 percent (27-31). In a number of studies, use of CNN based on nasal airflow and pulse transit time signals provided diagnosis with an accuracy of 86.2-92.7 percent (29, 30). As can be seen, the efficiency and performance of the new technique presented in this study based on the patient's chin electromyogram signal are superior to that reported in similar studies performed using routine polysomnography signals. The results of this study indicate that the method proposed for chin electromyogram analysis and application of ResNet-50 for data classification has an acceptable and unique accuracy of 0.98% in training and more than 96% in the model test step.

Based on the obtained results of the OSA effect on the amplitude and power spectrum of chin electromyogram signal, this signal can be considered as a functional and usable biosignal in diagnosing this sleep disorder. OSA diagnosis and classification with a method based on chin EMG and achievement of remarkable accuracy based on deep learning are the points that make this research special and prominent in comparison with similar researches. The results of this study in comparison with other studies showed that processing, analyzing, and classifying the chin EMG signal based on deep models is an intelligent, simple, effective, helpful, and fast method for screening obstructive sleep disorders.

Conclusion

In this study, we proposed a novel approach for improving apnea diagnosis by focusing on chin EMG spectrogram features. The comparison of the results of this study with previous studies proved that the technique of intelligent diagnosis and classification of OSA with the patient’s chin electromyogram based on deep learning networks can be introduced as a novel and practical method to clinical specialists and researchers who are interested in sleep disorders to be utilized as an effectual and useful biosignal for accurate and rapid diagnosis of OSA. This technique makes it easy and possible to study and diagnose this disorder outside the sleep clinic without dependence on a polysomnography device. This novel technique decreases the time and cost of routine processes and increases the accuracy of OSA diagnosis. The results of this study indicate that our way for the prediction and diagnosis of OSA with the chin electromyogram of the patient by using ResNet-50, which was recently introduced as a popular model to the research community, has achieved about 97% accuracy and has led to the improvement of apnea diagnosis compared to recent studies. Our proposed system is able to help sleep experts and is helpful and beneficial in most healthcare related to the sleep disorders. The following recommendations were made based on the results of this study:

1. Designing of a light and portable device for the detection of OSA based on the technique presented in this study
2. Addition of the ability to calculate AHI to this suggested technique to complete the device

In this study, there were no serious limitations to make the planning and the research process difficult.

Conflict of Interests

Authors have no conflict of interests.

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