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A deep learning-based decision support system for diagnosis of OSAS using PTT signals

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ABSTRACT

Sleep disorders, which negatively affect an individual's daily quality of life, are a common problem for most of society. The most dangerous sleep disorder is obstructive sleep apnea syndrome (OSAS), which manifests itself during sleep and can cause the sudden death of patients. Many important parameters related to the diagnosis and treatments of such sleep disorders are simultaneously examined. This process is exhausting and time-consuming for experts and also requires experience; thus, it can cause difference of opinion among experts. Because of this, automatic sleep staging systems have been designed. In this study, a decision support system was developed to determine OSAS patients. In the developed decision support system, unlike in the available published literature, patient and healthy individual classification was performed using only the Pulse Transition Time (PTT) parameter rather than other parameters obtained from polysomnographic data like ECG (Electrocardiogram), EEG (Electroencephalography), carbon dioxide measurement and EMG (Electromyography). The suggested method can perform feature extraction from PTT signals by means of a deep-learning method. AlexNet and VGG-16, which are two Convolutional Neural Network (CNN) models, have been used for feature extraction. With the features obtained, patients and healthy individuals were classified by the Support Vector Machine (SVM) and the k-nearest neighbors (k-NN) algorithms. When the performance of the study was compared with other studies in published literature, it was seen that satisfactory results were obtained.

Introduction

Sleep apnea is a significant disease defined as respiratory standstill during sleep, which is caused by snoring. It can occur many times during the night. During apnea, the muscles that allow the upper respiratory tract to open, relax. As a result of that, the base of the tongue, the palate or excessively enlarged tonsils block the airway; patients cannot breathe for at least 10 s. Fig. 1 shows the comparison of respiration between healthy individuals and patients with apnea [1].

There are three sleep apneas: Obstructive Sleep Apnea Syndrome (OSAS), Central Sleep Apnea (CSA) and Mixed Sleep Apnea (MSA). In terms of prevalence, the most common one is OSAS at approximately 84%. OSAS occurs when the muscles in the throat relax and the throat is blocked preventing air circulation [2–4]. The Polysomnography test (PSG) is used to identify OSAS. PSG records the brain activity and respiratory incidences of the patient throughout the night. It is based on the measurement of brain waves, eye movements, air flow from the mouth and nose, snoring, heart rate, leg movements and oxygen levels.

One of the most important symptoms of sleep apnea is respiratory standstill during sleep. The diagnosis of the disease is clinically examined using ECG, EEG and EMG signals and carbon dioxide measurements obtained from the patient [5]. OSAS can be determined as a result of examining the signals by identifying many parameters, such as how many times and how long respiration stops during sleep, how oxygen values and heart rate are affected and whether the patient falls into a deep sleep [6–17].

Motivation

Individuals who experience sleep apnea symptoms can be faced with many serious problems during the day. These include sudden death during sleep, strokes, heart attacks and coronary failure, insufficient respiration in lung patients and uncontrollable diabetes. Thus, for the determination of OSAS disease, the systems supported with machine learning algorithms are necessary to help doctors during the diagnostic process. This study developed a decision support system that classifies individuals using the pulse transition time (PTT) obtained from the PSG data of OSAS patients and healthy individuals. AlexNet

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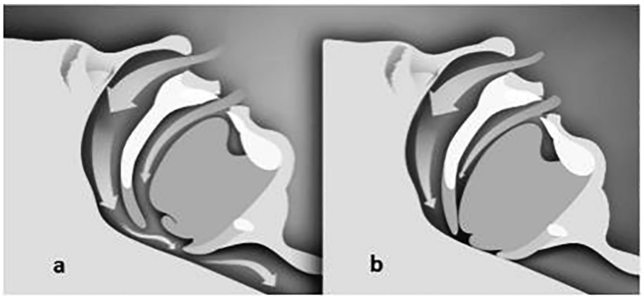

Fig. 1. (a) Respiration in a healthy individual, (b) Respiration in an individual with apnea.

and VGG-16, which are Convolutional Neural Network (CNN) models, were used to extract features from PTT signals. In the study, feature vectors were obtained from the fc6 and fc7 layers of both models. OSAS disease was identified using the Support Vector Machine and k-Nearest Neighbors algorithms, which both use these feature vectors as their input.

Contribution

When comparing the present study with other methods in published literature, the achievements obtained and originality of the study can be summarized as follows:

- As distinct from the signal data (EEG, EMG etc.) used in published literature, the identification of OSAS could be made with high specificity by using only PTT signals. Additional equipment is used to obtain signals such as EEG, ECG, and obtaining these signals are more difficult and costly than obtaining PTT signals. So PTT signals were preferred on detection of OSAS.
- AlexNet and VGG-16 were used for the diagnosis of the disease. Feature extraction was performed by using the fc6 and fc7 layers. With the help of the features obtained, OSAS patients were classified by the SVM and k-NN algorithms
- Unlike the dataset used in published literature, a new PSG dataset was constructed
- While OSAS was identified from PSG data, the OSAS diagnosis was performed to decrease the process cost by using only PTT signals
- An average of 92.78% success was achieved.

Study outline

This study has been organized as follows: In Section “Related works”, a literature review is made and the methods and success rates of the studies carried out in this field are presented. In Section “Material”, the dataset used are given with its features, while the decision support system method is detailed in Section “Proposed method”. The experimental results of the study are compared and discussed with those in published literature in Sections “Experimental results” and “Discussion”. Section 7 is the Conclusions.

Related works

In published literature, there are numerous studies on sleep apnea in the clinical and engineering fields. Alptekin et al. measured the oxidation occurring in the brain during OSAS with a functional infrared method and examined the effects of OSAS on oxidation in the bioengineering field [6]. Isik et al. classified sleep apneas through k-signals by means of an artificial intelligence method. Wavelet transforms were carried out on these signals and the signals were classified by using Artificial Neural Networks (ANNs) [7]. Oter et al. diagnosed and categorized sleep apnea by using parametric methods via smart systems. In the first stage, sleep stages were determined and separated by using ANNs, and then OSAS was identified by labeling methods. In the study using only ANNs, the success performance was low. When morphological filters were used, the classification performance increased considerably and an average of 90.7% accuracy was obtained [8]. Sleep apnea diagnosis was performed by Dogan et al. with the help of the sounds occurring during respiration. In another study, lung signals were used in the diagnosis of sleep apnea. In the developed method, the success was determined to be around the 84% level. The results of parametric methods and band spectral methods previously used in the database could not even reach 80%. The difference between the developed algorithmic method and the previously used methods in terms of performance parameters is outlined [9]. In the study by Tabak and Yildiz, the k-NN algorithm was used to diagnose sleep apnea by using both coronary and respiratory sounds. The apnea-free regions were diagnosed with 100% accuracy, while the regions with apnea were diagnosed with 48% accuracy [10]. Karamustafaoglu et al. used ECG signals for the diagnosis of sleep apnea by means of a signal processing interface [11]. In a study performed by Civaner et al., deep-learning methods were used to distinguish snoring sounds in children. For a network performance test, sounds of children with OSAS and snoring disease were processed, and the network was trained with the Adadelta algorithm. A 1200 sample dataset was used in the network structure and the accuracy was found to be 91% [12]. Memis et al. tried a new method based on the features of oxygen saturation and ECG signals obtained from OSAS data. They used the ReliefF feature selection algorithm to obtain valid features from both biological signals and Naive Bayes, k-NN and SVM classifiers were selected to test these features. They achieved a 4.67% improvement in results compared to the published literature by using the PhysioNet dataset [13]. Liu et al. classified EEG signals with ANNs and achieved OSAS identification, as a result of which the study could diagnose with 91% accuracy [14]. Selvaraj et al. presented a new algorithm internalizing the features based on filtering and the statistical distribution of nasal airflow respiration signals, and also identifying the number of occurrences of apnea. Data recordings were randomly selected from the Sleep Heart Health Study (SHHS-2) database in such a way that the apnea experiment with an Apnea-Hypopnea Index (AHI) less than 5 and also AHI varying between 30 and 75 was selected; the sensitivity and positive predictive values were found to be 83.6% and 72.3%, respectively [15]. Almazaydeh et al. suggested an automatic approach to define the existence of sleep apnea depending on respiratory acoustic signals. The classification algorithm was tested on real respiratory signals obtained with a Voice Activity Detection (VAD) algorithm and 97% accuracy was obtained [16]. Tagluk et al. developed a new technique using the bispectral features of an EEG signal and ANNs. An accuracy of 96.15% was obtained using the proposed technique [17]. Gunes et al. suggested a new feature selection – called multi-class f-score feature selection – to make a classification based on light, moderate and critical non-OSAS degrees. After the feature selection process, an MLPANN (Multi-Layer Perceptron Artificial Neural Network) was used to make an OSAS diagnosis for different degrees of the disease. The classification accuracy with MLPANN was 63.41%, while it was found to be 84.14% using f-score feature selection and MLPANN [18]. Yucelbas et al. used the Continuous Positive Airway Pressure (CPAP) method – the most efficient and specific treatment – to identify OSAS disease. ECG data obtained from 30 OSAS patients in two different databases were analyzed and the disease was classified as light, moderate or severe. Features were extracted from data with the Sequential Backward Feature Selection (SBFS) algorithm and two different dataset were constructed. The success rate was found to be 97.2% and 90.18% with the algorithm using ANNs, while it was 96.23% and 88.75% when SVM was used [19]. Akhter et al. could make a disease diagnosis by developing a model distinguishing REM from NREM snoring by using sound recordings obtained from 12 OSAS patients. The developed sleep model was Naive Bayes based, and as a result of classification, sensitivity, specificity and average accuracy values were found to be 92%, 81% and 82%, respectively. It was emphasized that the proposed method would be a foundation model to develop non-contact technologies for OSAS diagnosis [20]. Kim et al. developed an R-wave determination algorithm to analyze Heart Rate Variability (HRV) in OSAS patients. With the help of the developed algorithm, apnea was classified with an accuracy of 99.7% [21]. Sharma et al. designed a computer-aided CAD system for OSAS diagnosis. In the proposed ECG-based OSAS-CAD system, a new optimal biorthogonal antisymmetric wavelet filter bank (BAWFB) was used. A least squares SVM method was used as the classification algorithm, and accuracy, sensitivity, specificity and f-score values were found to be 90.11%, 90.87%, 88.88% and 0.92%, respectively [22]. Tripaty et al. diagnosed sleep apnea with the features extracted from HRV- and ECG-derived respiration (EDR) signals. The classification was made by using a kernel extreme learning machine. Sensitivity and specificity values were found to be 78.02% and 74.64%, respectively [23]. In the decision support system suggested for a sleep clinic, Daniel et al. evaluated the relationship between medical information, symptoms and diseases as fuzzy rules. The relationships were obtained with a fuzzy extraction mechanism. Tests were carried out on 21 patients and OSAS disease was identified with 95% accuracy [24]. Fang et al. proposed a new sleep Respiratory Rate (RR) determination method based on characteristic moment wavelets (CMW) with a high calculation rate on the basis that RR during sleep is a vital criterion in the identification of OSAS. RR was determined with a 98.4% success rate [25].

In the studies summarized above, OSAS diagnosis and classification is made with artificial intelligence algorithms by using one or more PSG parameters and the studies on OSAS disease diagnosis have continued.

Material

PSG signals are used in the diagnosis of sleep disorders such as insomnia, snoring and sleep apnea. In PSG, many parameters like ECG, EEG, EOG (Electroocurography), carbon dioxide measurement and EMG can be obtained. Basic signal parameters used in PSG are shown in Table 1 with their characteristics.

Another signal, PTT, obtained from PSG shows the elapsed time of the movement of the pulse pressure wave between the aortic valve and the periphery of heart. The R wave in ECG is considered to be the initial point. The moment when the pulse wave reaches the periphery is determined with finger photoplethysmography. As respiratory effort increases, the PTT signal gradually extends and it suddenly decreases with stimulation. The extension in the PTT signal is related to the increased negativity from esophageal pressure.

In this study, PTT data was obtained from Fırat University Research Hospital Sleep Room PSG recordings. The individuals, whose PTT data was obtained, were moderate OSAS patients. AHI was used to determine the degree of the disease and was between 15 and 30. This value was obtained by using Eq. (1).

$$\text{AHI} = (\text{the number of apnea} + \text{the number of hypopnea})/\text{total sleep time} \tag{1}$$

AHI is calculated by averaging the hourly number of apnea (the moment respiration stops) and the hourly number of hypopnea (the moment respiration continues at decreased rates) during sleep [26].

Table 2
Data characteristics.

Data Set Information	
Total Number of Data	100
Number of Patient Data	50
Number of Healthy Individuals	50
Number of Patients / Healthy Males	25/25
Number of Patients / Healthy Females	25/25
Age Ranges of Patients and Healthy Individuals	63/77
Weight Range of Patients and Healthy Individuals	68/86
Apnea Levels of Patients	Moderate apnea (AHİ, 15–30)

The characteristics of the PSG dataset collected in this study are shown in Table 2 in detail. Of the PSD data obtained from a total of 100 individuals, 50 of them belonged to patients and the remaining data belonged to healthy individuals; the degree of apnea was moderate. The PSG data were collected from individuals in an age range varying from 63 to 77, consisting of 50 female and 50 male individuals.

Proposed method

In this article, the decision support system shown in Fig. 4 was developed to diagnose OSAS patients. In this developed system, first the PSG data were obtained and then PTT signals were extracted from these data and converted to spectrogram images that were subsequently applied to the deep-learning method as inputs. The feature vectors obtained were classified by SVM and k-NN algorithms and OSAS disease was identified. The suggested decision support system is detailed in Fig. 2.

PSG data and PTT signals

A Profusion PSG 3.2 sleep system was used to obtain the data used in this study. It can record signal data, be manually operated, modify signal data, convert signal data to ASCII format and store data belonging to a CPAP device. Moreover, it has a camera and all necessary recording systems. Fig. 3 shows the variation of PSG signals obtained from a patient.

Formation of spectrogram images

To extract features from the PTT data obtained from 100 individuals, it must be converted to spectrogram images. For this, firstly, a Fourier transform of the PTT signals is calculated. While obtaining the spectrogram images used in the study, a Hamming window with a width of 48 ms was used, the overlap value was 8 ms and the Fourier transform number for the EEG signal was 256. Spectrogram images were recorded by using a viridis color map. Fig. 3 shows a spectrogram of PTT signals and Fig. 4 shows the signals belonging to OSAS patients and healthy individuals [27].

Convolutional Neural Networks (CNNs)

CNNs are a special type of layered sensors constructed by

Table 1
PSG signal parameters.

Characteristics	High-Frequency Filter (Hz)	Time Constant (sec)	Low-Frequency Filter (Hz)	Sensitivity
EEG	70 or 35	0.4	0.3	5–7 μV/mm
EOG	70 or 35	0.4	0.3	5–7 μV/mm
EMG	90	0.12	1.0	2–3 μV/mm
ECG	15	0.12	1.0	1 mV/cm to start; adjust
Airflow and Effort	15	1.0	0.1	5–7 mV/mm; adjust

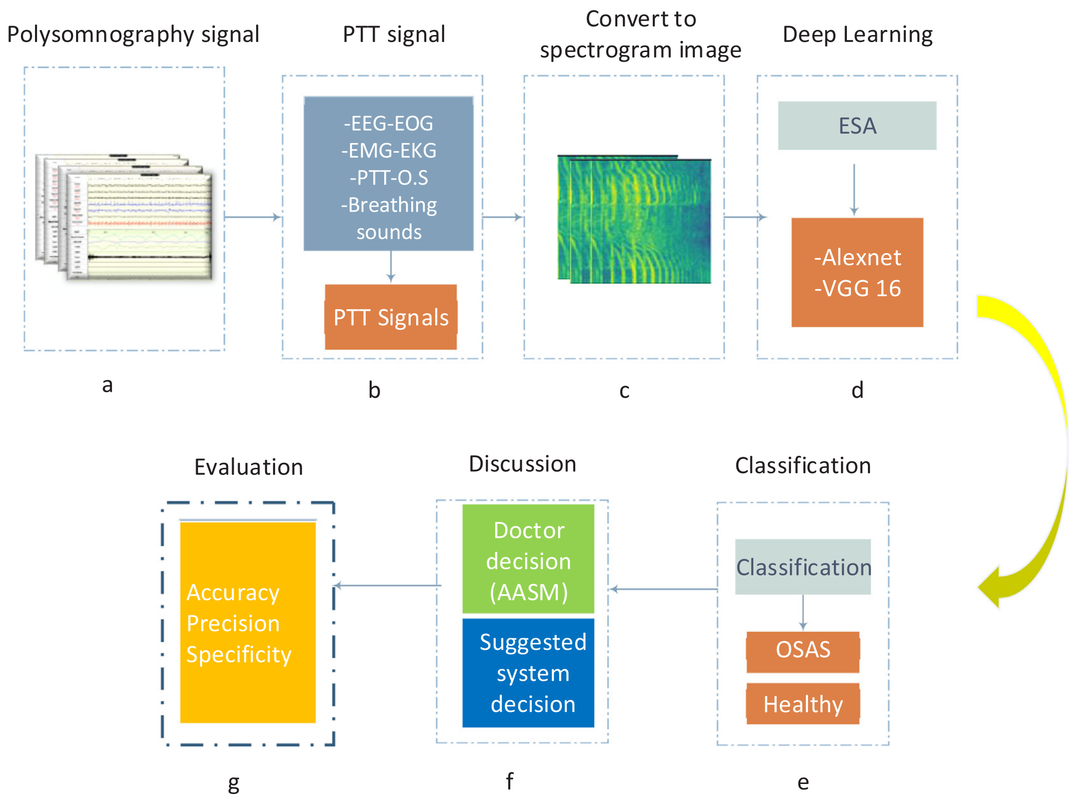

Fig. 2. The schematic for the suggested method.

considering the physiology of human vision. Today, they are one of the widely used deep-learning methods because of their successful results. They are used in object recognition, signal processing and classification [15]. In this study, AlexNet and VGG-16 CNNs models were used to extract features from the spectrogram images of the PTT signals.

AlexNet is the first model, and it has made CNNs widespread and popular. Basically, it resembles the LeNet model a lot because it has successive evolutionary and pooling layers. However, AlexNet has a deeper network structure. A Rectified Linear Unit (ReLU) is used as the activation function and max-pooling is used in the pooling layers [28].

VGG-16 model is a simple network model. Its difference from other models is that its binary and ternary convolutions follow the pooling layer. In other models, the pooling layer comes just after convolution [28]. The 1000-class softmax success is calculated at the output of the two fc layers. Approximately 138 million parameters are calculated. As in other models, the height and width values for the matrices decrease from the input to the output while their depth values (the number of channels) increase.

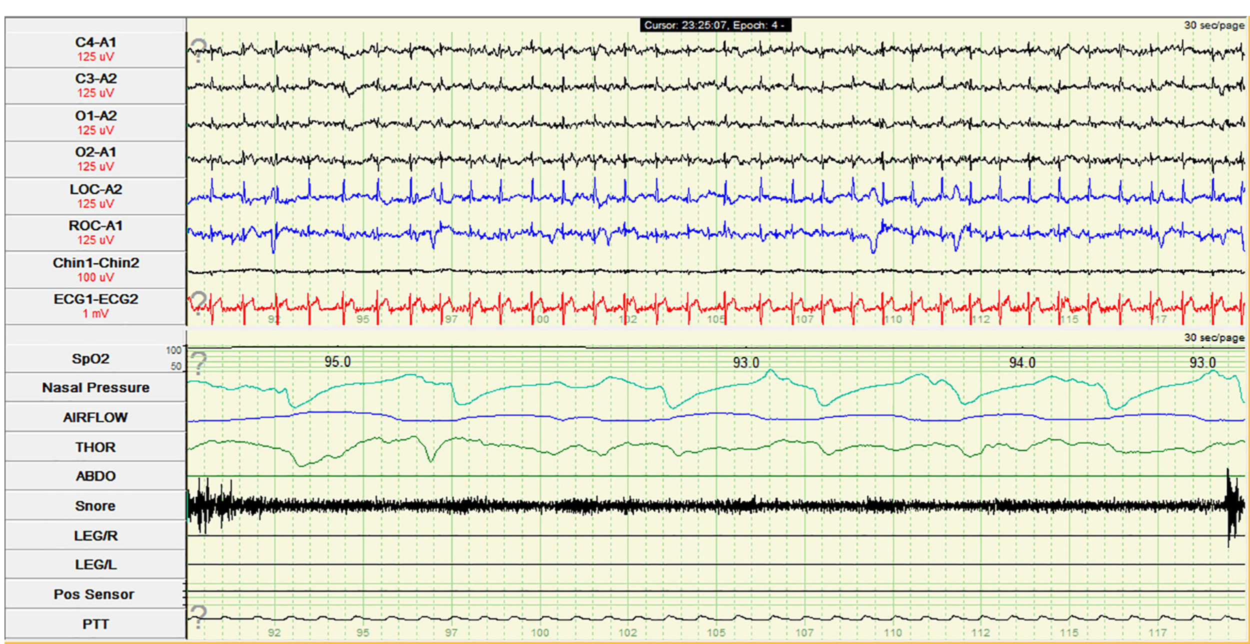

Fig. 3. The obtained PSG data.

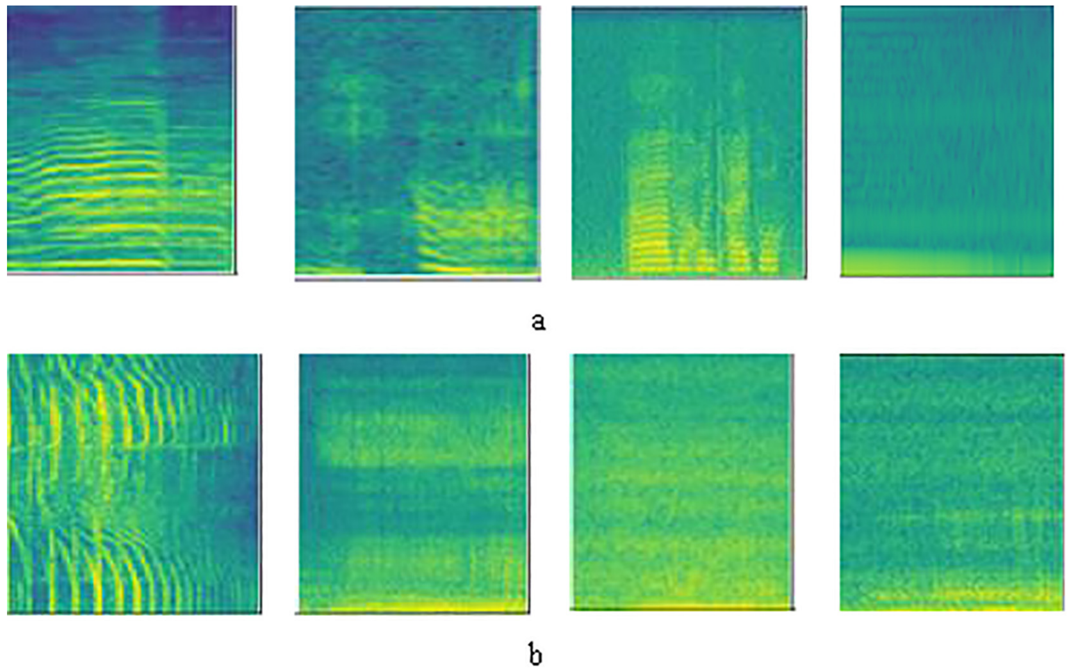

Fig. 4. Spectrogram images of: (a) a Healthy individual, (b) an OSAS patient.

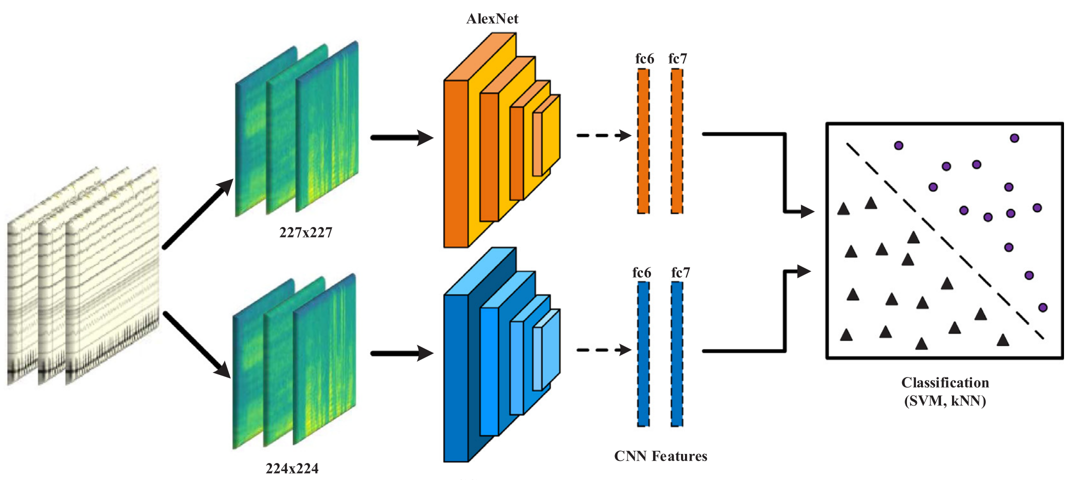

Fig. 5. The deep-learning method used.

There are large amounts of data required to train CNN models and powerful hardware is necessary to process that amount of data. Long times are involved in processing the data depending on the hardware characteristics. If there is no large amount of data for training, then pre-trained models are used. With the method called transfer learning, feature extraction is performed from a database in a different field by using pre-trained CNNs [29,36]. In this study, pre-trained CNN models were used for the feature extraction from PTT signals. Fig. 5 shows the feature extraction from spectrogram images.

Classification and performance evaluation

As shown in Fig. 5, the feature vectors obtained from spectrograms were supplied to classifiers as inputs. The classification algorithms used in this study were the SVM and k-NN algorithms. SVM – one of the trained learning methods – is one of the most efficient methods among the available classification methods. SVM is a machine learning algorithm based on structural risk minimization. The purpose of SVM is to find end points in the class called support vector where the distance between two classes is a maximum. SVM aims to determine the best hyperplane that can separate two classes. It may not be possible to distinguish classes with linear SVM in real-world problems. In this case, non-linear SVMs are used. Non-linear SVMs transfer the data to another space to distinguish the classes from each other. Core functions are used for that purpose. In this paper, Linear function, Radial Basis Function (RBF) and Polynomial are used as the core functions in SVM algorithm. Also, the parameter C was selected between 10^{-3} and 10^{+3}, which controls the trade off between errors of the SVM on training data and margin maximization.

Another algorithm widely used in published literature for classification is the k-NN algorithm. Based on this algorithm, using features extracted during classification, the aim is to examine the proximity of the new data to be classified to k number of previous data. The k parameter is set 5 for classification.

Accuracy, precision and specificity performance criteria were used to determine the classification success. The basic definitions used while determining the parameters are explained below [30]:

Patient: positive for the disease
Healthy: negative for the disease
True positive (TP) = the number of cases where the patient was correctly defined
False positive (FP) = the number of cases where the patient was incorrectly defined
True negative (TN) = the number of cases where a healthy individual was correctly defined
False negative (FN) = the number of cases where a healthy individual was incorrectly defined.

Accuracy (ACC): This is the ability to correctly distinguish between the patient and a healthy individual. For accurate prediction, true positive and true negative ratios should be calculated in all the cases evaluated. Eq. (2) shows the calculation of accuracy [30]:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Precision (P): The precision/sensitivity of a test is based on correctly determining patient cases. To find precision, the true positive ratio is calculated for patient cases. Eq. (3) shows the calculation for precision [30]:

$$P = \frac{TP}{TP + FN} \quad (3)$$

Specificity (S): The specificity value is the ability to determine healthy cases correctly. Thus, the true negative ratio must be found in healthy cases. Specificity is mathematically expressed in Eq. (4) [30]:

$$S = \frac{TN}{TN + FP} \quad (4)$$

f1-score: This parameter is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Eq. (5) shows the calculation for f1-score.

$$f1 - score = 2TP/(2TP + FP + FN) \quad (5)$$

Experimental results

The dimensions of the spectrogram images obtained from PTT signals was 875 × 656. AlexNet and VGG-16 models accept images of a specific dimension as input. Therefore, the spectrogram images were resized to be 227 × 227 for AlexNet and 224 × 224 for VGG-16. Then, the deep features of the spectrogram images were recorded. The features obtained were classified with SVM and k-NN algorithms. For experimental results, a computer with an Intel Core i5-4200 CPU processor and 8 GB of RAM was used. All data was processed in the MATLAB environment. 10-fold cross-validation was applied to the dataset. In addition, this operation was repeated 10 times and the average results are shown in Table 3. Fig. 6 shows classification results obtained from AlexNet and VGG-16.

Discussion

In this study, unlike previous studies, classification was made using PTT signals obtained from PSG data of OSAS patients and healthy individuals. To make use of PTT signals, AlexNet and VGG-16, which are CNNs with pre-trained network structures, were used. Both fc6 and fc7 layers were used and the SVM and k-NN algorithms were selected for classification. Similar to published literature, respiratory sounds, snoring sounds, EEG, EMG and ECG parameters were used for the diagnosis of sleep apnea. Although the relationship between pulse transition time and sleep apnea has been investigated in clinical studies, there have not been observed in any study using engineering-based approaches. The present study specifically employs this aspect.

The clinical datasets used to diagnose OSAS disease were PhysioNet [31], DRYAD [32] and MENDELEY [33]. In this study, PSG recordings were collected from 100 individuals and a new database was constructed. Table 4 shows the method and successes of the studies performed for OSAS identification.

As can be seen from Table 4, basic electrical PSG signals like ECG, EEG and ECG were used for OSAS identification. In addition, other parameters, including respiratory rate, heart rate variability, REM, NREM and snoring sounds were used. Throughout the study, machine learning algorithms like ANN, k-NN and Naive Bayes were used. Beside these algorithms, a deep-learning method was also used for OSAS diagnosis. According to Table 4, OSAS disease identification was found to be between 74% and 98%.

In this study, for the fc6 channel of the AlexNet model, the highest accuracy (92.64%) was obtained with the SVM algorithm, while the highest precision (92%) and specificity (96%) values were found with the k-NN algorithm. For the fc7 channel of the AlexNet model, the highest accuracy (92.6%) and precision (95.7%) values were found with the SVM algorithm, while the highest specificity (95.36%) values were obtained with the k-NN algorithm. For the fc6 channel of the VGG-16 model, the highest accuracy (92.78%), precision (94.25%) and specificity (98%) values were obtained with the SVM algorithm. For the fc7 channel of the VGG-16 model, the highest accuracy (92.18%) and specificity (95%) values were found with the k-NN algorithm, while the highest precision (90.06%) value was found with the SVM algorithm. According to these results, the accuracy, precision and specificity values obtained were 92.78%, 95.70% and 98.30%, respectively. In addition to these parameters, f1-score is used to determine the overall performance of the classification algorithms. Given Table.3, both the accuracy and f1 score values are highest in the fc6 layered structure of the VGG-16 model.

When evaluating the proposed system in terms of classification algorithms and CNNs, the highest performance was achieved with the

Table 3
Classification results of the features obtained from the fc6 and fc7 layers.

AlexNet					
Layer	Classifier	Accuracy (%)	Precision (%)	Specificity (%)	f1-score (%)
fc6	SVM	92.64 ± 1.44	86.26 ± 3.44	86.02 ± 2.01	92.17 ± 1.89
	k-NN	90.72 ± 3.24	92.00 ± 3.01	96.00 ± 1.26	90.86 ± 0.74
fc7	SVM	92.6 ± 1.77	95.70 ± 1.49	85.24 ± 3.98	91.28 ± 1.14
	k-NN	90.81 ± 2.89	93.26 ± 2.25	95.36 ± 1.55	90.92 ± 2.84
VGG16					
fc6	SVM	92.78 ± 1.04	94.25 ± 1.56	98.00 ± 0.80	92.89 ± 2.15
	k-NN	91.72 ± 2.46	94.00 ± 2.40	89.26 ± 3.78	92.03 ± 1.77
fc7	SVM	92.00 ± 1.78	90.06 ± 2.34	82.58 ± 4.06	90.45 ± 0.66
	k-NN	92.18 ± 1.86	84.36 ± 2.65	95.00 ± 1.20	92.25 ± 2.05

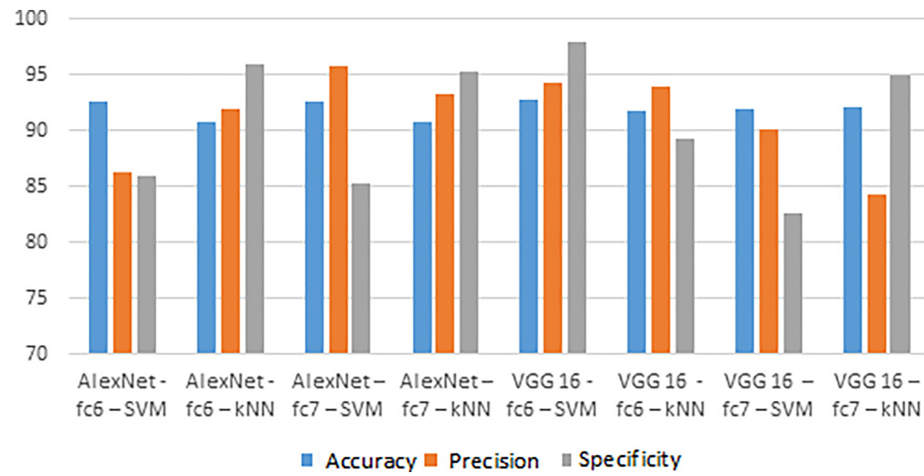

Fig. 6. Classification results obtained from AlexNet and VGG-16.

Table 4
Literature summary and comparison results.

Reference	Signal used	Method	Result
[8]	Respiratory signals	Parametric methods	ACC = 90.7%
[9]	Respiratory sounds	Parametric methods	ACC = 84%
[10]	Heart and respiratory sounds	k-nearest neighbors	ACC = 100%–48%
[12]	Snoring sounds	Deep Learning	ACC = 91%
[14]	EEG	ANN	ACC = 91%
[15]	ECG	A new apnea detection algorithm	Sensitivity = 83.6%
[16]	Respiratory sound signals	Voice Activity Detection	ACC = 97%
[17]	EEG	ANN	ACC = 96.15%
[18]	Oxygen saturation		ACC = 84.14%
[19]	ECG	ANN	Success rate = 97.2%
		SVM	Success rate = 96.23%–88.75%
[20]	Sound recordings, REM and NREM	Naive Bayes	ACC = 82%
[21]	Heart rate variability	R Algorithm	ACC = 99.7%
[22]	ECG	CAD Based System	ACC = 90.11%
[24]	Sleep respiratory rate	characteristic moment waveform (CMW) method	ACC = 98.4%
[34]	REM and NREM	ANN, SVM	ACC = 81.25%
[35]	REM and NREM	ANN, SVM	ACC = 74.41%
[36]	PTT	ANN, Naive Bayes	ACC = 90%
Proposed System	PTT	Alex-Net, VGG-16, SVM, k-NN	ACC = 92.78%
			P = 94.25%
			S = 98%
			f1-Score = 92.89%

SVM algorithm in the fc6 layered structure of the VGG-16 model. The AlexNet and VGG16 model architectures are different. AlexNet has different sizes and larger filters. Alexnet performs a convection process using a 11 × 11, 5 × 5 and 3 × 3 filter, respectively. In VGG, the filter size is fixed and a 3 × 3 filter is used. While 4 and 2 stride is used in AlexNet, 1 stride in convection layers and 2 stride in max polling is used in VGG16. These parameters are effective in providing better results of VGG. Also VGG is a deeper network than AlexNet. The experimental results show that VGG16 is more distinctive in used data. These results have revealed that PTT data can be used in OSAS diagnosis and an auxiliary system can be developed.

Conclusions

This study presented a sleep apnea identification method based on deep learning. This method aims to present a simple diagnosis method using only PTT signals obtained from PSG data rather than more complex systems in which doctors examine more parameters to arrive at the correct diagnosis. The results obtained in accordance with this purpose indicated that the proposed method is solid and effective in identifying OSAS and can be used as decision support system. Because the proposed method has been developed for OSAS diagnosis by using only the PTT parameter, it can also decrease the unit load in processing big data. Although deep-learning methods used in the study have been very successful, the complex internal mechanisms are a disadvantage of the system. The accuracy of the system can be improved with different parameters and machine learning algorithms. It is predicted from the performance tests that the proposed sleep apnea identification method can help doctors.

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Compliance with ethical standards

Conflict of interest: All authors read and approved the final manuscript. None of the authors had a conflict of interest.

Ethical approval: Ethics approval for the study protocol was obtained from the local area heath ethics committee.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.mehy.2019.03.026.

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