Turkish Journal of Science & Technology
19(1), 257-263, 2024

Research Paper
https://doi.org/10.55525/tjst.1419740

Performance Comparison of Standard Polysomnographic Parameters Used in the Diagnosis of Sleep Apnea

Seda Arslan TUNCER[1], Yakup ÇİÇEK[2], Taner TUNCER[3*]
[1,2] Software Engineering, Faculty of Engineering, Fırat University, Elazig, Turkey
[3] Computer Engineering, Faculty of Engineering, Fırat University, Elazig, Turkey
[1] satuncer@firat.edu.tr, [3] ttuncer@firat.edu.tr

(Geliş/Received: 15/01/2024; Kabul/Accepted: 21/03/2024)

Abstract: Obstructive sleep apnea (OSAS), which is one of the leading sleep disorders and can result in death if not diagnosed and treated early, is most often confused with snoring. OSAS disease, the prevalence of which varies between 0.9% and 1.9% in Turkey, is a serious health problem that occurs as a result of complete or partial obstruction of the respiratory tract during sleep, resulting in sleep disruption, poor quality sleep, paralysis and even death in sleep. Polysomnography signal recordings (PSG) obtained from sleep laboratories are used for the diagnosis of OSAS, which is related to factors such as the individual's age, gender, neck diameter, smoking-alcohol consumption, and the occurrence of other sleep disorders. Polysomnography is used in the diagnosis and treatment of sleep disorders such as snoring, sleep apnea, parasomnia (abnormal behaviors during sleep), narcolepsy (sleep attacks that develop during the day) and restless legs syndrome. It allows recording various parameters such as brain waves, eye movements, heart and chest activity measurement, respiratory activities, and the amount of oxygen in the blood with the help of electrodes placed in different parts of the patient's body during night sleep. In this article, the performance of PSG signal data for the diagnosis of sleep apnea was examined on the basis of both signal parameters and the method used. First, feature extraction was made from PSG signals, then the feature vector was classified with Artificial Neural Networks, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN) and Logistic Regression (LR).

Key words: Sleep, Sleep Apnea, PSG, Classification.

Uyku Apnesinin Teşhisinde Kullanılan Standart Polisomnografik Parametrelerin Performans Karşılaştırılması

Öz: Erken tanı konulmadığında ve tedavi edilmediği zaman ölümle sonuçlanabilen ve uyku hastalıklarının başından gelen Tıkayıcı uyku apnesi (OSAS) en çok horlama ile karıştırılmaktadır. Türkiye'de görülme yaygınlığı %0,9 ila %1,9 değişen OSAS hastalığı uyku süresi boyunca solunum yollarnın tamamen veya kısmen tıkanması sonucunda görülen uyku bölünmesi, kalitesiz uyku geçirme, felç olma ve hatta uykuda ölümün bile görülmesi gibi sonuçlar doğuran ciddi bir sağlık sorunudur. Bireyin yaşı, cinsiyeti boyun çapı, sigara-alkol tüketimi, diğer uyku rahatsızlıkların görülme durumu gibi etmenlerle ilişkili olan OSAS tanı için uyku laboratuvarlarından alınan Polisomnografi sinyal kayıtları (PSG) kullanılmaktadır. Polisomnografi horlama, uyku apnesi, parasomnia (uyku esnasında anormal davranışlar), narkolepsi (gün içinde gelişen uyku atakları), huzursuz bacak sendromu gibi uyku bozukluklarının tanı ve tedavisinde kullanılır. Gece uykusu boyunca hasta vücudunun farklı bölgelerine yerleştirilen elektrotlar yardımıyla beyin dalgaları, göz hareketleri, kalp ve göğüs aktivitesinin ölçülmesi, solunum etkinlikleri, kandaki oksijen miktarı gibi çeşitli parametrelerin kayıt altına alınmasını sağlar. Bu makalede, PSG sinyal verilerinin uyku apnesinin teşhisine yönelik başarımları hem sinyal parametreleri hem de kullanılan yöntem bazında incelendi. İlk olarak PSG sinyallerinden özellik çıkartımı yapıldı daha sonra özellik vektörü yapay sinir ağları, destek vektör makinesi (DVM), k-enyakın komşu (k-NN) ve lojistik regrasyon (LR) ile sınıflandırıldı.

Anahtar kelimeler: Uyku, Uyku Apnesi, PSG, Sınıflandırma.

1. Introduction

Sleep is an unconscious state in which the activity of a person's body organs decreases, brain and neural activities continue, but some stimuli from the outside world are not perceived. Sleep apnea is a breathing disorder and can be defined as a situation in which a person cannot breathe for at least 10 seconds or more during sleep. Although treatment is possible, people suffering from sleep apnea, which is often confused with snoring, may neglect treatment as a result of not being able to recognize the disease or noticing it too late. Diagnosis can be made by the physician by obtaining PSG signal data with the help of a polysomnography device in sleep laboratories [1]. Polysomnographic signal data includes data such as EEG (Electroencephalography), EOG (Electrooculography), EMG (Electromyography), ECG (Electrocardiography), Airflow, chest and abdominal movements, SpO2 (Oxygen saturation), PTT (Pulse transit time).

* Corresponding author: ttuncer@firat.edu.tr. ORCID Number of authors: [1] 0000-0001-6472-8306, [2] 0000-0003-1414-3187, [3] 0000-0003-0526-4526

Sleep apnea types are divided into three: Obstructive Sleep Apnea (OSAS), Central Sleep Apneoa (CSA) and Mixed Sleep Apnea (MSA). The incidence of these species is 85%, 14%, and 1%, respectively. It is important to examine OSAS disease due to its frequency, and the level of the disease is determined according to the AHI (Apnea Hypopnea Index) index.

AHI, which determines the severity of apnea, is the hourly average of apneas and hypopneas occurring throughout sleep. OSAS types are classified as mild OSAS patients between 5-15, moderate OSAS patients between 15-30, and severe OSAS patients 30 and above, depending on the AHI (Apnea-Hypopnea index/total number of apnea-hypopneas per hour of sleep) level [2].

In OSAS, the most common type of sleep apnea, shortness of breath occurs for more than 20 seconds and can last up to 1-2 minutes in severe cases. It is the most common of all known sleep apneas. In this type of sleep apnea, which first shows OSAS symptoms and then evolves into Compound Sleep Apnea, the disease progresses rapidly for 5-10 years, eventually confining the patient to bed. In Central Sleep Apnea, which is rarer than other types of sleep apnea, the person experiences more frequent awakenings. All known sleep apneas, CSA constitutes approximately 1%.

There are many studies in the literature on sleep apnea using clinical and computer-aided programming approaches. Xie et al. found that there was a relationship between heart rate variability (HRV) and OSAS [3]. Marcos et al. They diagnosed sleep apnea with bayesian neuron networks using oxygen saturation (SaO2) [4]. Liu et al. analyzed the EEG signals in the ANN method and classified them for the detection of OSAS, and they achieved a 91% success rate as a result of the classification [5]. Akhter et al. obtained the OSAS model with a Naive Bayes-based model with a sensitivity of 92%, specificity of 81%, and average accuracy of 82%. They used REM and NREM data in the voice recordings taken from OSAS patients [6]. Sharma et al. reported the accuracy, sensitivity, specificity, and F1score values as 90.11%, 90.87%, 88.88%, and 0.92%, respectively, using wavelet filter bank (BAWFB) in the ECG-based OSA-CAD system for OSAS detection [7]. Jane et al. proposed a 2-layer Feedforward multilayer neural network to detect the snoring of people with OSAS and healthy people. The model has 82% sensitivity and 90% positive predictive value [8]. Kunyang et al. developed a method based on hidden markov model (HMM) and deep neural network using ECG signal. The method has been reported to have approximately 85% classification accuracy and 88.9% sensitivity [9]. Banluesombatkul et al., who introduced a new approach for OSAS severity classification with the deep learning method. They used one-dimensional convolutional neural networks and deep recurrent neural networks with long short-term memory. The method used has an accuracy rate of 79.45% [10]. Akılotu et al. examined the effect of OSAS, the most common type of sleep apnea, on sleep stages and REM sleep using vector machines and artificial neural networks [11]. Khandoker et al. applied support vector machines to detect different types of OSAS by taking ECG recordings from 42 subjects, and as a result, they determined the accuracy to be 92.85% and Cohen's kappa value to be 0.85 [12]. To diagnose OSAS, Almazaydeh et al. developed a neural network using the SpO2 measurements [13]. Lin et al. examined the EEG signals they received from patients diagnosed with OSAS with classifiers such as kNN, SVM, LDA (Linear discriminant analysis) [14]. Karandikar et al. detected sleep apnea from electrocardiogram signals. In this study, sensitivity, specificity and misclassification parameters (91.93%), specificity (85.84%) and misclassification (11.94%) results were obtained [15]. Mostafa et al. developed a sleep apnea detection system using the deep learning method using SpO2 signal data obtained from 33 subjects [16]. Jezzini et al. achieved 98.7% accuracy using classification in ECG signals for sleep apnea detection [17]. Lee at. al. compared the clinical and polysomnography (PSG) features of patients with suspected OSAS in otolaryngology, neurology, and psychiatry clinics. Patients' medical records and PSG reports were analyzed retrospectively [18]. Chien et al. examined 10 years of electronic medical records of OSAS patients. Baseline PSG parameters were compared between patients with and without memory impairment. In this study, Subgroup analyzes based on OSAS severity and associations of PSG parameters with memory impairment were presented [19]. Gasa et al. applied cluster analysis to data obtained from routine polysomnography to optimize OSAS categorization. In this study, it has been emphasized that OSAS severity using the AHI approach is assessed with an inaccurate or incomplete analysis of the heterogeneity of the disorder [20]. Edis et. al. evaluated possible risk factors that may lead to sleep-disordered breathing. Apnea-Hypopnea Index (AHI) scores were calculated for all patients, taking into account thorax computed tomography, respiratory function tests, carbon monoxide diffusion tests, and echocardiography polysomnography records [21]. Zhou et al. evaluated the performance of a wearable multisensory system compared to polysomnography (PSG) in measuring sleep stages and investigating OSAS [22]. Apart from these studies, compilation studies in the literature on systems that will help classify or detect sleep apnea are also presented in [23, 24, 25].

The contributions of the study to the literature are as follows.

- Identifying effective signals in the diagnosis of OSAS by examining all PSG signals in the diagnosis of OSAS
- Extracting features from PSG signals and detecting OSAS with classical machine learning algorithms of the feature vector

2. Material and Method

2.1 Material

PSG signals were collected from 30 OSAS patients and 30 healthy individuals who applied to Fırat University neurology outpatient clinic, with the decision of the non-invasive ethics committee. Polysomnographic data of a total of 60 people were examined by a specialist doctor and created in two classes. The PSG signal of each patient consists of 16 channels. Table 1. Characteristics of the collected data. Figure 1 shows from which body positions the collected PSG signals were obtained.

Table 1. Dataset and features

Total Number of Data	60
Number of Patient Data	30
Number of stray data	30
Number of Sick/Healthy Men	15/15
Number of Sick/Healthy Women	15/15
Weight Range of Sick and Healthy People	50-87
Apnea-Hypopnea Index Level of Patients	Intermediate Level (AHI, Between 15-30)
Number of PSG Channels for Each Individual	16

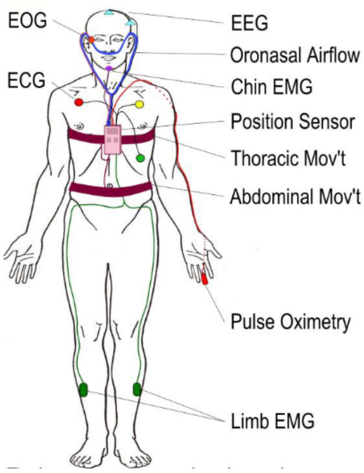

Figure 1. PSG signals

2.2. The Proposed Method

People diagnosed with sleep apnea face many serious problems both during night sleep and during the day. Daytime insomnia, headache upon awakening; Sudden death at night, paralysis, and respiratory failure in lung patients are examples of these negativities. Therefore, there is a need for information systems that will assist the physician in the decision-making process in detecting OSAS disease.

A 2-stage model is proposed for the detection of sleep apnea from PSG signal data. First, feature extraction was performed from the 16-channel PSG signals of each patient. Secondly, the resulting feature vector was classified. Figure 2. Shows the structure of the proposed model.

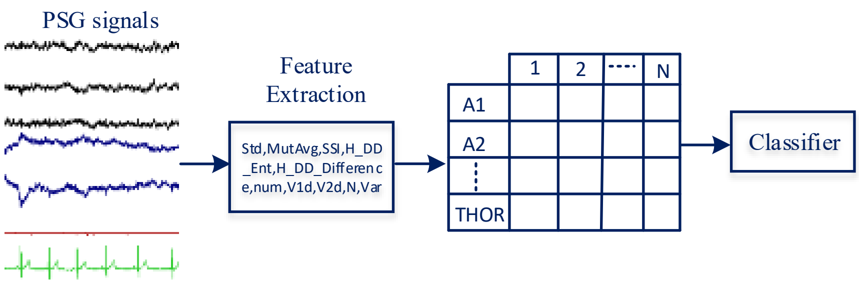

Figure 2. The proposed method

The PSG signal of each individual has 16 channels and each channel contains 960 values over time. In the feature extraction phase, features such as standard deviation, average value, total value, and entropy were extracted for each channel. The definitions of the extracted features are as in table 2.

Table 2. The extracted features

Feature	Defination
Std	Standard Deviation of the Signal
MutAvg	Absolute Average value of the signal
SSI	Sum of square of the signal
H_DD_Ent	Normalized Shannon wavelet entropy of the signal
H_DD_Difference	Difference between the maximum and minimum value of the signal
num	Sum of local maximum and local minimum values of the signal
V1d	variance of the first derivative of the signal
V2d	variance of the second derivative of the signal
N	average value of the average difference of the elements of the signal
Var	Variance of the signal

The feature vector obtained as a result of feature extraction was fed as input to the classification algorithms. Many classification algorithms were used to investigate the effect of PSG parameters on the diagnosis of OSAS disease. These are ANN, SVM, k-NN and logistic regression classifiers.

ANN is defined as a model network structure inspired by the functioning of neurons in the human brain. This network consists of nerve cells arranged in layers. The model basically has three types of layers: input, hidden, and output layers. In this study, the input and hidden layers consist of 10 nerve cells and the output layer consists of a single nerve cell.

SVM, which is used for both classification and regression problems, is especially effective in two-class problems. SVM attempts to classify data points with a specific hyperplane. It creates a decision boundary between two classes and tries to maximize the distance between these boundaries. The main goal of SVM is to determine the hyperplane that draws this decision boundary with a "maximum margin" between data points. This margin is the distance between the decision boundary and the closest data points, and this distance is tried to be maximized. Since this study had two classes, a linear kernel was used in the classification process.

In k-NN, neighboring data points are taken into account to determine the class of data. In the algorithm, the distances between all other training data points of the data are calculated. This distance is usually the Euclidean distance. A k value is selected for the Nearest Neighbor's Determination. This determines the number of neighbors of the predicted point. Euclidean distance and k value of 2 were selected in the classification process.

Logistic regression, which is widely used especially in binary classification problems, estimates the probability of an event based on input features. In the classification process, a sigmoid and a threshold value of 0.5 were selected as the logistic function.

3. Results

Confusion matrix is a matrix model that provides detailed details about the performance of the classification algorithm. The confusion matrix and the False Positive (FP), False Negative (FN), True Positive (TP) and True Negative (TN) obtained from this matrix were used to determine the performance of the proposed model.

- False Positive (FP): a healthy person is diagnosed as sick
- False Negative (FN): diagnosing the sick person as healthy
- True Positive (TP): the sick person is diagnosed as sick
- True Negative (TN): diagnosing a healthy person as healthy

The performance of the classifiers was determined by the accuracy (A), sensitivity (S), specificity (Sp), precision (P) and F1 score values shown in equations (1) to (5) which can be obtained from the confusion matrix.

$$A=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$S=\frac{TP}{TP+FN} \tag{2}$$

$$Sp=\frac{TN}{TN+FP} \tag{3}$$

$$P=\frac{TP}{TP+FP} \tag{4}$$

$$F1\ Score = \frac{2TP}{2TP+FP+FN} \quad (5)$$

The results regarding the signals trained in the artificial neural network are given in table 3. According to the table, the signals showing the best results are LOC, O1, O2 with 100% accuracy, A2 with 98.3% accuracy, AIRFLOW, C4, ECG2, NASAL, PTT, A1 with 96.7% accuracy, SPO2 with 94.5% accuracy, the accuracy degree was obtained as C3 with 91.7%, the accuracy degree as SNORE with 80% and the accuracy degree as THOR with 76.7%.

Table 3. Results obtained with the ANN algorithm.

Signal	A	S	Sp	P	F1
A1	96.7	96.7	96.7	94.5	96.7
A2	98.3	96.8	100	100	98.3
ABDO	76.7	78.6	75.0	73.3	75.8
AIRFLOW	98.3	100	96.8	96.7	98.3
C3	91.7	87.9	96.3	90	92.0
C4	98.3	96.8	100	100	98.3
ECG1	95.4	97.2	91.1	89.8	89.7
ECG2	98.3	100	96.8	96.1	98.3
LOC	100	100	100	100	100
NASAL	98.3	96.8	100	100	91.7
O1	100	100	100	100	100
O2	100	100	100	100	100
PTT	98.3	96.8	100	100	98.3
SNORE	80	82.1	78.1	76.6	79.3
SPO2	94.5	92.6	95.7	88.2	89.6
THOR	76.7	68.2	94	91.5	81.0

Table 4. SVM, k-NN and Logistic Regression classification results

Signal	Classifier	A	S	SP	P	F1
A1	k-NN	93.3	100	86.6	88.2	93.7
A2	LR	93.3	93.3	93.3	93.3	93.3
ABDO	SVM	81.7	80	80	80.6	81.9
AIRFLOW	LR	80	76.6	83.3	82.1	79.3
C3	SVM	80	90	70	75	81.8
C4	k-NN	96.7	96.7	96.7	96.7	96.7
ECG1	SVM	98.3	100	96	100	98.3
ECG2	SVM	96.7	93.3	100	100	96.5
LOC	LR	100	100	100	100	100
NASAL	SVM	91.7	90	93.3	93.1	91.5
O1	LR	98.3	96	100	100	98.3
O2	k-NN	100	100	100	100	100
PTT	SVM	96.7	96	96	87.1	96.5
SNORE	SVM	73.3	72	74	72.4	71.1
SPO2	LR	100	100	100	100	100
THOR	SVM	78.4	75	71.9	73.5	77.2

The results for the signals trained with SVM, k-NN and Logistic Regression are given in table 4 above. According to the table, the signals showing the best results are LOC, O2, SPO2 with an accuracy level of 100%, ECG1 with an accuracy level of 98.3%, O1 with an accuracy level of 96.7%, C4 with an accuracy level of 96.7%, PTT, ECG2 with an accuracy level of 93.3%, A1 with an accuracy level of 81.7%. With ABDO, the accuracy rate was 80% for AIRFLOW, C3, 78.4% for THOR, and 73.3% for SNORE. Figure 3 shows the comparison of the results obtained with ANN and other classifiers in terms of accuracy.

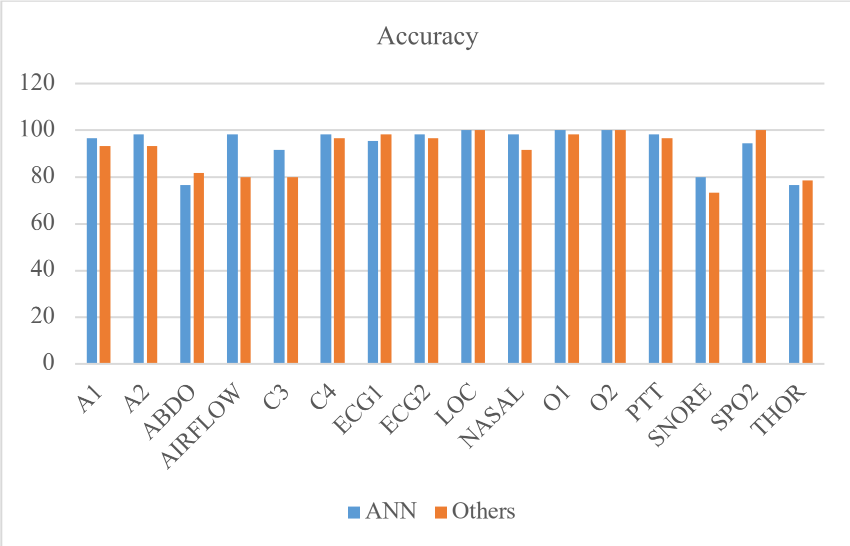

Figure 3. Comparison of ANN and other classifiers in terms of accuracy

4. Conclusion

Sleep apnea, which is often confused with snoring, is a chronic respiratory disorder that can result in stroke, suffocation, heart attack and death. Studies have been conducted on many support systems related to sleep apnea, especially to help diagnose and treat sleep apnea. Polysomnographic signal data were used in most of these studies. In our study, classification algorithms from machine learning methods were used. After the features of the PSG parameters were extracted, they were made suitable for studying with machine learning. PSG signal data subjected to machine learning methods were examined together in this study and the accuracy of the most effective parameters was determined comparatively. By comparing the accuracy, sensitivity, specificity, sensitivity and F1Score values of the PSG signal data examined in the classification algorithms, the effect on disease diagnosis was tried to be determined.

At the end of the study, the parameters that had the most impact on determining OSAS disease were determined to be LOC, O1 and O2 signals with 100% accuracy in ANN classifiers.

One of the most important gains and differences of this study is that all standard PSG signals (16) obtained from OSAS patients were examined together and the results were evaluated comparatively. It can be envisaged that PSG signals with high accuracy values will be further examined in future studies in order to produce auxiliary systems for both diagnosis and treatment of OSAS. Another important finding in the evaluation of classifiers is that signals such as LOC, O1, O2, SPO2, ECG1, which have a high level of accuracy, can be re-examined with different methods for diagnosis.

Acknowledgment

We express our gratitude to Prof. Dr. Caner Feyzi Demir from the Neurology Department at Fırat University for his invaluable contribution during the data collection and labeling process.

References

[1] Akılotu BN, Tuncer SA. OSAS Evaluation By Means Of Machine Learning And Artificial Neural Networks By Using Polisomnographic Report Data, International Conference on Engineering Technologies (ICENTE'17), 2017.
[2] Demir A, et al. Türk Toraks Derneği Obstrüktif Uyku Apne Sendromu Tanı Ve Tedavi Uzlaşı Raporu", Türk Toraks Dergisi, Cilt 13, Vol.13, 2012.
[3] Xıe J, Yu W, Wan Z, Han F, Wang Q, Chen R. Correlation Analysis between Obstructive Sleep Apnea Syndrome (OSAS) and Heart Rate Variability, Iran J Public Health., 46(11), p:1502–1511, 2017.

[4] Marcos C, Hornero JVR, Álvarez D, Nabney IT. Automated detection of obstructive sleep apnoea syndrome from oxygen saturation recordings using linear discriminant analysis, Med Biol Eng Comput ., 48(9):895-902, 2010.
[5] Liu D, Pang Z, Lloyd SR. A neural network method for detection of obstructive sleep apnea and narcolepsy based on pupil size and EEG, IEEE Transactions on Neural Networks, 19(2), 308-318, 2008.
[6] Akhter S, Abeyratne UR, Swarnkar V. Characterization of REM/NREM sleep using breath sounds in OSA, Biomedical Signal Processing and Control, 25, 130-142, 2016.
[7] Sharma M, Agarwal S, Acharya UR. Application of an optimal class of antisymmetric wavelet filter banks for obstructive sleep apnea diagnosis using ECG signals, Computers in Biology and Medicine, vol.100, 100-113, 2018.
[8] Jane R, Sola-Soler J, Fiz JA, Morera J. Automatic detection of snoring signals: validation with simple snorers and OSAS patients, Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 2000
[9] Kunyang L, Weifeng P, Yifan L, Qing J, Guanzheng L. A method to detect sleep apnea based on deep neural network and hidden Markov model using single-lead ECG signal, Neurocomputing, Vol.294, 94-101, 2018.
[10] Banluesombatkul N, Rakthanmanon T, Rapaport TW. Single Channel ECG for Obstructive Sleep Apnea Severity Detection Using a Deep Learning Approach, TENCON 2018 - pp. 2011-2016, 2018.
[11] Akılotu BN, Tuncer SA. Evaluation of the Effect of CPAP Device on REM Sleep in OSAS Patients Using YSA and SVM, International Conference on Engineering Technologies", (ICENTE'17), Dec 07-09, Konya, Turkey, 2017.
[12] Khandoker AH, Palaniswami M, Karmakar CK. Support Vector Machines for Automated Recognition of Obstructive Sleep Apnea Syndrome From ECG Recordings, IEEE transactions on information technology in biomedicine, 13(1),37-48, 2009.
[13] Almazaydeh L, Faezipour M, Elleithy K. A Neural Network System for Detection of Obstructive Sleep Apnea Through SpO2 Signal Features, International Journal of Advanced Computer Science and Applications, 3(5), 7-11, 2012.
[14] Lin SY, Wu Y, Mao W, Wang P. EEG signal analysis of patients with obstructive sleep apnea syndrome (OSAS) using power spectrum and fuzzy entropy, 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Guilin, China, pp. 740-744, 2017.
[15] Karandikar K, Le T, Sa-ngasoongsong A, Wongdhamma W, Bukkapatnam S. Detection of sleep apnea events via tracking nonlinear dynamic cardio-respiratory coupling from electrocardiogram signals, Annu Int Conf IEEE Eng Med Biol Soc., 7088-91, 2013.
[16] Mostafa SS, Mendonça F, Morgado-Dias F, Ravelo-García A. SpO2 based sleep apnea detection using deep learning, IEEE 21st International Conference on Intelligent Engineering Systems (INES), Larnaca, Cyprus, 2017.
[17] Jezzini A, Ayache M, Elkhansa L, Ibrahim Z. ECG classification for sleep apnea detection, 2015 International Conference on Advances in Biomedical Engineering (ICABME), Beirut, Lebanon, pp. 301-304, 2015.
[18] Lee, E., Lee, H. Clinical and Polysomnographic Characteristics of Adult Patients with Suspected OSAS from Different Sleep Clinics at a Single Tertiary Center. Neurol Ther, 2024.
[19] Chien, W.-C. Et.al. The Associations between Polysomnographic Parameters and Memory Impairment among Patients with Obstructive Sleep Apnea: A 10-Year Hospital-Based Longitudinal Study. Biomedicines, 11, 621, 2023.
[20] M. Gasa, et al., Polysomnographic Phenotypes of Obstructive Sleep Apnea in a Real-Life Cohort: A Pathophysiological Approach, Archivos de Bronconeumología Vol. 59. Issue 10., pages 638-644 , 2023.
[21] E.Ç. Edis, et.al. Polysomnography findings and risk factors for sleep-disordered breathing in patients with systemic sclerosis, Archives of Rheumatology, 36(3), 2021.
[22] Zhou SJ, et. al. Measuring Sleep Stages and Screening for Obstructive Sleep Apnea with a Wearable Multi-Sensor System in Comparison to Polysomnography", Nat Sci Sleep., 15:353-362, 2023.
[23] Garg VK, Bansal RK, Intelligent Computing Techniques for the Detection of Sleep Disorders: A Review, International Journal of Computer Applications, 110, 0975 – 8887,1, 2015.
[24] Alvarez-Estevez D, Moret-Bonillo V. Computer-Assisted Diagnosis of the Sleep Apnea-Hypopnea Syndrome: A Review, Sleep Disorders, 2015:237878, 2015.
[25] Motamedi-Fakhr S et. al. Signal processing techniques applied to human sleep EEG signals-A review, Biomedical Signal Processing and Control. 10, 21–33, 2014.