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Classification of Sleep Apnea Syndrome From EEG Signals Using Spectrogram-Based Entropy and MLPNN Model

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ABSTRACT: In this study, we focus on the classification of sleep apnea syndrome from electroencephalogram (EEG) signals by using the spectrogram-based entropy and multilayer perceptron neural network (MLPNN) classifier model. For this aim, EEG signals with different apnea-hypopnea index (AHI) taken from Polysomnography (PSG) recordings are divided into 30 sec windows, the windowed EEG signals are decomposing into frequency sub-bands by using short time Fourier transform (STFT), and then these frequency sub-bands are normalized into the range of [0, 1]. Next, Shannon entropy values of spectrograms obtained from the normalized frequency sub-bands are used as input to the MLPNN model for the classification of sleep apnea syndrome Finally, although success ratios of 53.4% for quadruple classification, 62.6% for mild sleep apnea, 60.7% for moderate sleep apnea and 87.4% for severe sleep apnea are achieved in the implemented classification experiments, the highest success ratio is succeeded in the classification of severe sleep apnea syndrome.

Keywords – *EEG signals, sleep apnea, Spectrogram, entropy, MLPNN.*

Spektrogram-Tabanlı Entropi ve MLPNN Modeli Kullanılarak EEG İşaretlerinden Uyku Apne Sendromu Sınıflandırması

ÖZET: Bu çalışmada, spektrogram-tabanlı entropi ve çok katmanlı algılayıcı sinir ağı (MLPNN) sınıflandırıcı modelini kullanarak elektroansefalogram (EEG) işaretlerinden uyku apne sendromunun sınıflandırılmasına odaklanılmaktadır. Bu amaç için, Polisomnografi (PSG) kayıtlarından alınan farklı apne-hipoapne indeksine (AHI) sahip EEG işaretleri 30 saniyelik pencerelere bölünmekte, pencereli EEG işaretleri kısa zamanlı Fourier dönüşümü (STFT) kullanılarak frekans alt bantlarına ayrıştırılmakta ve bu altbantlar [0, 1] aralığına normalize edilmektedir. Daha sonra, normalize edilen frekans altbantlarından elde edilen spektrogramların Shannon entropi değerleri uyku apne sendromu sınıflandırılması için MLPNN modeline giriş olarak kullanılmaktadır. Sonuç olarak, gerçekleştirilen sınıflandırma deneylerinde dörtlü sınıflandırma için %53.4, hafif uyku apne için %62.6, orta uyku apne için %60.7 ve şiddetli uyku apne için %87.4 başarı oranlarına ulaşılmakla birlikte, en yüksek başarı oranı şiddetli uyku apne sendromunun sınıflandırılmasında elde edilmektedir.

Anahtar Kelimeler- *EEG işareti, Uyku apnesi, Spektrogram, Entropi, MLPNN.*

1. Introduction

Sleep apnea syndrome is a syndrome occurring because of reducing or completely cessation of air flow due to repeating upper respiratory tract obstructions during sleep. This health problem is an important condition affecting anyone, regardless of age or gender, and requires treatment (Karamustafaoglu, 2014). The standard method used for the diagnosis of sleep apnea syndrome is Polysomnography (PSG) examination during the night. This examination includes a detailed analysis of the nightly sleep recording by a specialist doctor. Therefore, the diagnosis of apnea and similar conditions is a time-consuming process and is an evaluation open to various interpretations (Ucar et al., 2014). The focus of engineering studies on sleep apnea is to obtain patients' records in a meaningful way without distortion. For this purpose, various cues of patients are obtained by using PSG devices known as multi-channel data acquisition systems, recording simultaneously during the patient's sleep. These records are then analyzed by using various methods and used for the diagnosis and classification of diseases (Dogan, 2016).

In recent years, the increase in signal processing-based studies has contributed greatly to the detection of the sleep apnea syndrome. Szilagyi et al. used multiple resolution wavelet separation to separate the electroencephalogram (EEG) signal into different spectral components and provided these components as input to an artificial neural network (ANN), achieving the success of identifying all test signals with an accuracy ratio of over 95% (Szilagy et al., 2002). Dr. Erdamar's study showed that the first apnea that occurred during sleep was successfully predicted in more than 60% of subjects with the method used to predict sleep apnea from PSG recordings (Erdamar, 2007). Álvarez et al. proposed a fuzzy logic-based solution for the detection of apneic events in apnea hypopnea syndrome and supported their proposed algorithm with 86% certainty and 87% validity ratios (Alvarez et al., 2009). Duman et al. used the decision tree algorithm to detect sleep spindles after the analysis of EEG signals, and successfully applied three different approaches which are the short time Fourier transform (STFT), the multiple signal classification (MUSIC) algorithm and the teager energy operator (TEO) approaches. (Duman et al., 2009). Balakrishnan and colleagues developed a sleep quality index to distinguish between people with normal sleep and obstructive sleep apnea. This index was calculated by comparing the time spent in sleep of healthy and sick people to the total time spent asleep (Balakrishnan et al., 2009). Acir et al. proposed a system with ANN to automatically recognize EEG signals. In experimental studies, they achieved a 94.6% specificity ratio and a 4% error ratio (Acir et al., 2004). In the study of Aksahin et al., they determined the strengths of the frequency bands in the EEG signal separately and calculated the ratios between these powers. It was found that the ratios of alpha and beta frequency bands were different in apnea and non-apnea periods (Aksahin et. Al., 2017). In another study, Yoruk conducted a spectral analysis of EEG signals recorded during sleep apnea and observed that entropy is an important attribute (Yoruk, 2019). In Umut's study, he investigated the usability of EEG frequency bands in the diagnosis of sleep apnea and concluded that the Beta frequency was the most decisive among four different frequency bands (Umut, 2011). In an application carried out by Civaner et al., deep learning methods were used to distinguish snoring sounds in children. Voice recordings of children with obstructive sleep apnea syndrome (OSAS) and snoring were studied, and the accuracy value of a network trained by using the Adadelta algorithm was obtained as 91% (Civaner et al., 2018). Hafezi et al. detected sleep apnea using tracheal respiratory signals recorded together with PSG recordings. They extracted 25 features from the signals and classified them by using a hybrid deep learning algorithm consisting of a combination of convolutional neural networks (CNN) and long-short-term memory (LSTM). As a result of the classification, they achieved the accuracy of 84%, the sensitivity of 81% and the specificity of 87% (Hafezi et al., 2020). Abdulla et al. proposed an intelligent model based on multi-channel tissue color analysis to classify sleep staging. STFT was applied to convert EEG signals into 30-sec image form. The obtained spectrograms were used as input to the multi-channel information local binary pattern (MILBP), and classification success was achieved with 95% and 96% accuracy (Abdulla et al., 2023). Han et al. proposed a machine learning-based model to detect radar-based sleep apnea syndrome. In their study, they achieved over 90% accuracy in the classification experiment after smoothing the ultra-weight band (UWB) envelope based on radar spectrograms through variational mode decomposition (Han et al., 2022).

In this study, since the diagnosis of sleep apnea from all-night PSG recordings is a time-consuming process, EEG signals that are frequently used in the literature and have a high success ratio were selected and this study was recommended to increase the success of the classification. Figure 1 shows the schematic illustration of the implementation steps of the model proposed in the study.

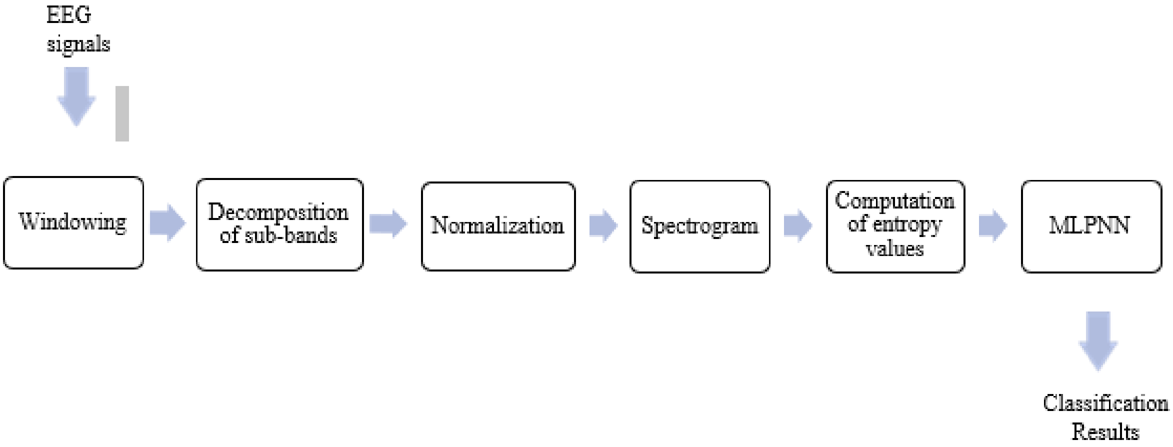


Fig.1. Schematic illustration of the porposed model

As seen in Figure 1, EEG signals are divided into 30-sec windows to facilitate processing and increase the number of samples since they are all-night recordings. Using this windowing process, 260 segments were obtained for each EEG signal. After each segment was decomposed into 4 frequency sub-bands by using STFT, each sub-band was normalized to the range of [0, 1]. In this way, the number of normalized sub-bands was 1040 for each signal. The spectrograms of the normalized sub-bands were obtained, and Shannon entropy values of the obtained spectrograms were applied as input to the Multilayer perceptual neural network (MLPNN) model for the classification of sleep apnea syndrome. In the evaluation of the proposed approach, the binary and quadruple classification experiments were implemented by using MLPNN classifier model. In other sections of the study, materials and methods, experimental results, discussion, and conclusion are presented in detail.

2. Materials and Methods

2.1. Dataset

In this study, EEG signals taken from the open-source database of *www.physionet.org* website and containing gender, age and weight information of the patients were used. The number of apneas per hour during sleep is called as apnea index (AI), and the total number of apneas and hypopneas seen at the beginning of hour is called apnea-hypopnea index (AHI). While an AHI > 5 is considered as sufficient for the diagnosis of sleep apnea syndrome, it was understood that apnea and hypopnea are seen in healthy individuals in recent years, and the limit value is accepted as 20 and above (Aydin et al., 2005). The AHI values of signals and the sleep durations per night used in the study are given in Table 1.

Table 1. AHI values and sleep durations of EEG signals

Class	AHI values	Sleep durations (hr.)
Healthy	2	6.8
Mild	5	6.4
Moderate	25	7.2
Severe	91	5.9

As seen in Table 1, EEG signals of healthy, mild, moderate and severe apnea classes with an average duration of 6-7 hours were used. These signals were recorded overnight with C3-A2 electrodes. Individuals with different AHI were preferred when selecting EEG signals. The windowing process was performed by dividing the EEG signals into 30-second segments. A schematic representation of the windowing process is given in Figure 2.

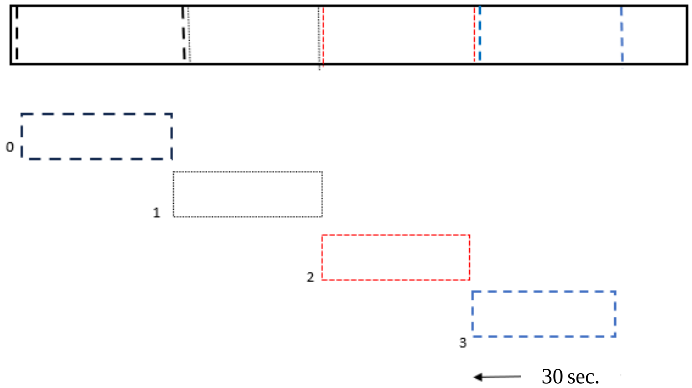


Fig. 2. Windowing 30 sec

As seen in Figure 2, EEG recordings were divided into 30-second segments after windowing and 260 segments were obtained for each signal. The windowed EEG signals are divided into 4 frequency sub-bands. Table 2 shows the frequency and amplitude values of the obtained frequency sub-bands.

Table 2. Frequency and amplitude values of sub-bands

	Frequency (Hz)	**Amplitude (µV)**
Delta	0.5-4	20-400
Theta	4-8	5-100
Alpha	8-13	2-10
Beta	13-30	1-5
Range	30<	1<

As seen in Table 2, the number of segments of each EEG signal after the divide into sub-bands of different amplitude and frequency range was 1040. Since EEG signals do not contain information at frequencies above 30 Hz, the Gamma band does not occur. The obtained frequency sub-bands were normalized by using the commonly used min-max normalization method. Figure 3 shows the examples of normalized sub-bands.

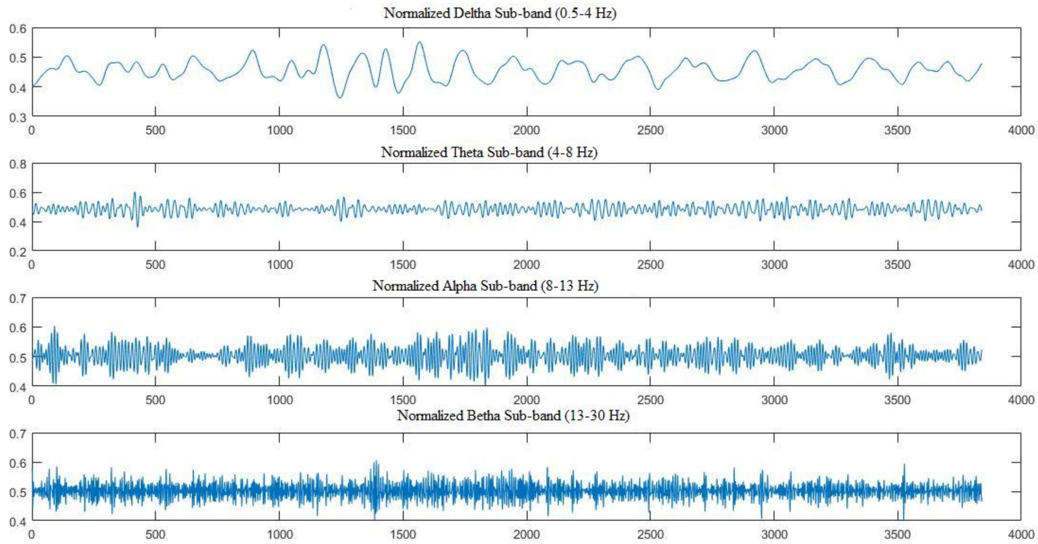


Fig. 3. The normalized sub-bands of windowed EEG signal

As seen in Figure 3, the raw data is normalized linearly to the range of [0, 1] using the min-max normalization approach.

2.2. Spectrogram-based entropy

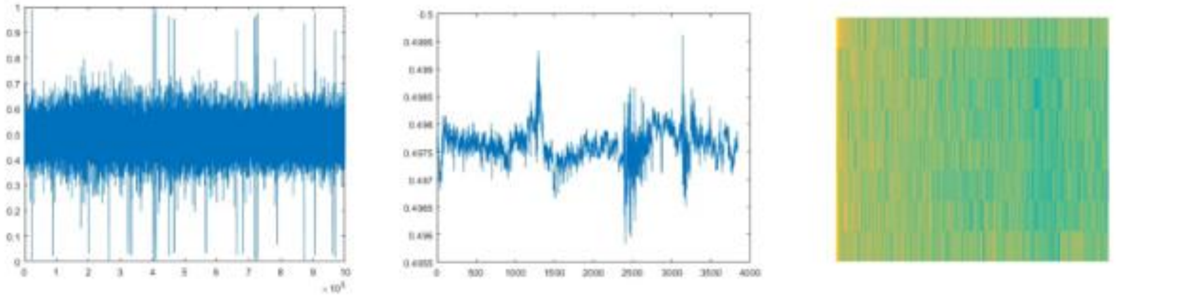
Spectrogram is a graph that shows the power of a signal over time for a frequency range. It shows the energy variation over time and points to the frequencies where the energy of the signal is maximum. The signal divides into a time-domain signal which has equal length for generate a spectrogram. Then, all segments transform from time domain to the frequency domain by using fast Fourier transform (FFT) (Koseoglu et al., 2023). FFT is an algorithm that obtains the frequency information of a signal by computing discrete Fourier transform (DFT) of discrete time signals. In this method, sequence of signals divided into the components of different frequencies. Although this method is useful in a lot of areas, computing it directly from the definition takes too many times. FFT performs the transformation quickly by factorizing the DFT. The spectrogram of a signal is mapped as the power distribution of STFT and given by

$$S\,(t, f) = X\,(t, f)^2 \tag{1}$$

where, $X\,(t, f)$ is STFT of the weighted signal by a time window $\omega[t]$ that is moved in time:

$$X(t, f) = \int_{-\propto}^{\propto} x(t)w(t-\tau)e^{-j\omega t}dt \tag{2}$$

An example of EEG signal, its windowed form and spectrogram is given in Figure 4.



(a) An EEG signal (b) A windowed signal (c) A spectrogram of windowed signal

Fig. 4. An example of EEG signals and its spectrogram

Shannon entropy is a measure of the uncertainty of a random signal. An EEG signal is a random signal, and the spectrogram obtained from this signal also contains uncertainty. Therefore, the entropy values of the spectrograms were calculated by using Eq. 3, and then applied as input to the MLPNN model for classification experiments.

$$H(i) = -\sum_i p_i log_2 p_i \quad (3)$$

where, $H(i)$ is Shannon entropy value, and p_i is the probability of value.

2.3. Multilayer perceptual neural network (MLPNN)

MLPNN model has three layers that are input, hidden and output layers. Input layer accepts incoming data from the outside world. The hidden layer produces the results by processing the inputs through neurons. The number of neurons in this layer is usually determined by trial and error. This number is important for avoiding over- or under-training. The last layer is the output layer generating the results and it performs the task of classification. MLPNN structure is designed to enable ANNs to perform complex functions and is often used in deep learning processes (Ubeyli, 2008).

MLPNN model can reduce errors and learn them by using the backpropagation algorithm. This algorithm involves an optimization process to reduce the error ratio of the model. Previous studies show that MLPNN models achieved high success ratio for classification sleep apnea syndrome by using EEG signal, so in this study a MLPNN model is proposed. The proposed MLPNN model has 1 input layer, 1 hidden layer containing 10 neurons, and 1 output layer. For training 70% of the input data, for validation %15 of the input data and for testing %15 of the input data is used. In the used MLPNN model, the hyperbolic tangent function was selected as the activation function, and the Levenberg-Marquardt backpropagation algorithm was selected as the training algorithm. The MLPNN classifier model used in the study is given in Figure 5.

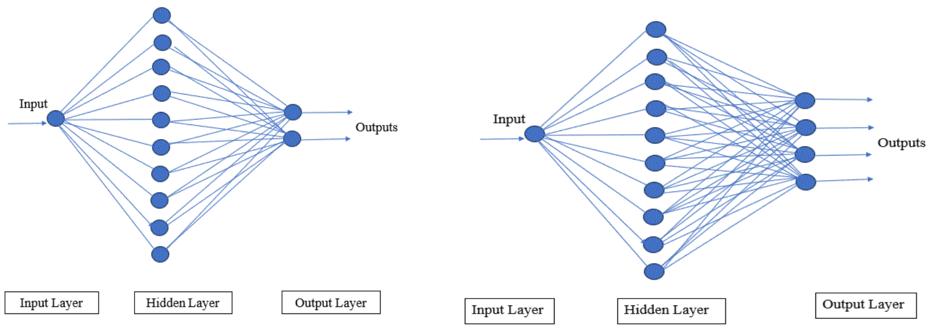


Fig. 5. MLPNN model used for binary and quadruple classification

In the study, two experiments were implemented for the evaluation of our approach. Experiment 1 is a binary classification (healthy-mild, healthy-moderate, healthy-severe), which includes the comparison of the data of each class with the healthy class, and Experiment 2 is a quadruple classification that is evaluated as a result of applying all classes to the input at the same time.

3. Results and discussion

In the study, EEG signals taken from PSG recordings of individuals with different AHI values were divided into 30-second segments. After these segments were decomposed into frequency sub-bands (alpha, beta, gamma and theta), the obtained sub-bands were normalized to the range of [0, 1]. Spectrograms were obtained for each sub-band segment, and the entropy values of these spectrograms were used as input to the MLPNN model. The classification experiments were performed in the MATLAB R2022a. Two experiments were implemented for the evaluation of the proposed approach. In binary classification experiment, the dataset of healthy individuals was compared with mild, moderate and severe sleep apnea syndrome dataset one by one. In quadruple classification experiment, the dataset of all classes was used as input to the MLPNN model collectively. In both cases, 70% of the dataset was used for training, 15% for validation, and 15% for testing. The used model has a structure that includes 1 input layer, 1 hidden layer with 10 neurons, and 1 output layer.

The classification success of the proposed model was evaluated by using sensitivity, specificity, and total correct classification (TCC) ratios defined as in Eq. 4,5 and 6.

$$Sensitivity\ (Sens) = \frac{TP}{TP+FN} \times 100\% \qquad (4)$$

$$Specificity\ (Spec) = \frac{TN}{TN+FP} \times 100\% \qquad (5)$$

$$Total\ Correct\ Classification\ Ratio\ (TCC) = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \qquad (6)$$

TP: true positive, number of actual positive and predicted as positive
TN: true negative, number of actual negative and predicted as negative
FP: false positive, number of actual negative and predicted as positive
FN: false negative, number of actual positive and predicted as negative

TCC: total correct classification ratio, ratio of correct decisions to all cases

Receiver processing characteristic (ROC) curve shows all possible breakpoints and provides information about each breakpoint. The larger the area under the curve, the higher the sensitivity of the test. The closer the area under the curve is to 1, the better the classification performance of the model. The confusion matrix and total correct classification ratios of the binary classification performed in the study are given in Table 3.

Table 3. Confusion matrices of the experiment, and Sens, Spec and TCC ratios

(a) Mild sleep apnea binary classification

	Healthy	Mild	Sens (%)	Spec (%)	TCC (%)
Healthy	619	357	59,5	63,4	62,6
Mild	421	683	65,7	61,9	

(b) Moderate sleep apnea binary classification

	Healthy	Moderate	Sens (%)	Spec (%)	TCC (%)
Healthy	731	509	70,3	59	60,7
Moderate	309	531	51,1	63,2	

(c) Severe sleep apnea binary classification

	Healthy	Severe	Sens (%)	Spec (%)	TCC (%)
Healthy	632	154	89,6	85,8	87,4
Severe	108	886	85,2	89,1	

As can be seen in Table 3, the success ratios of mild and moderate apnea classification were lower than severe apnea. If the AHI values are close to each other, it can reduce the ratio of correct estimation of the classes. TCC ratios were 62.6%, 60.7% and 87.4% for mild, moderate and severe sleep apneas, respectively. Sensitivity is lower than specificity in the classification of moderate and severe sleep apnea. The opposite is the case in the mild sleep apnea classification. High AHI value caused significant differences in EEG signal in apnea and hypopnea, and thus increased the success ratio. ROC curves of the classification experiments are given in Figure 6.

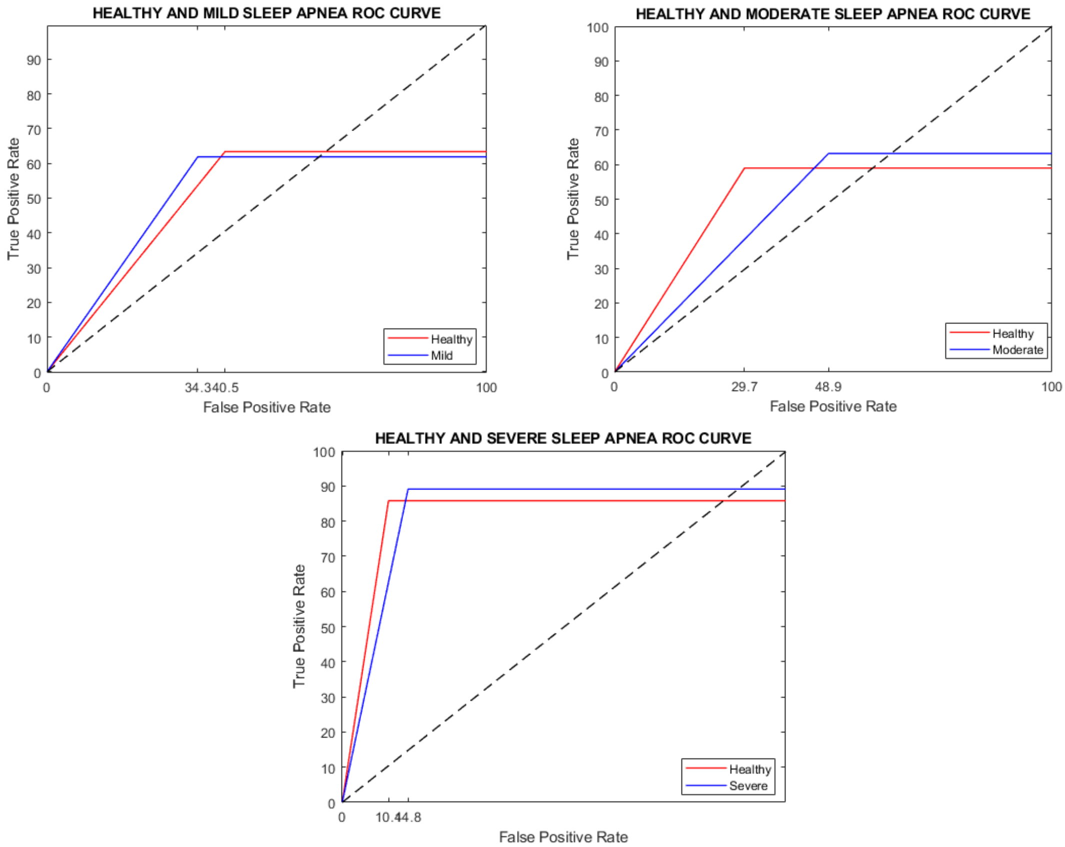


Fig. 6. Binary classification ROC curves

As seen in Figure 6, the classification experiments are nearly the same with mild and moderate sleep apnea classification. The area under the ROC curve is closer to 1 in the severe apnea classification. This means that the success ratio is higher than others and high sensitivity with low false positive ratio.

In the second experiment of the study, the entropy values of all classes were applied as input to a four-output MLPNN model, and their classification ratios were evaluated. The results of this classification experiment are given in Table 4.

Table 4. Quadruple classification accuracy ratios

	Mild	Moderate	Severe	Healthy	Sens. (%)	Spec. (%)	TCC (%)
Mild	566	260	0	349	54,4	48,2	
Moderate	81	376	0	189	36,2	58,2	53,4
Severe	76	76	884	106	85	77,4	
Healthy	317	328	156	396	38,1	33,1	

As seen in Table 4, the TCC ratio of quadruple classification was 53.4%. Since the dataset of the healthy class and the classes with mild and moderate apnea syndrome were close to each other, the success of the quadruple classification was lower than the binary classification. According to the confusion matrices, no data with mild and moderate apnea were assigned to the severe class, while 76 data from both classes were assigned to the severe class. TP and FP values of healthy data were close to each other compared to other classes. This situation also reduced its originality and selectivity. In severe apnea, it has a TP value of 884 with 85% selectivity. The ROC curve plotted according to the results in Table 4 is given in Figure 7.

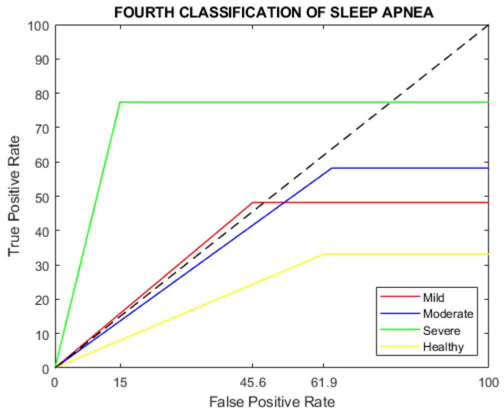


Fig. 7. Quadruple classification ROC curves

As seen in Figure 7, the ratio of classification of individuals with severe sleep apnea is higher than others. Lower false positive ratio optimizes the ROC curve. The areas under the ROC curve demonstrates that the severe sleep apnea classifier has higher specificity and sensitivity. This is important in terms of developing a method that can detect the disease while taking EEG recordings without the need for individuals with sleep apnea to stay in sleep laboratories overnight. In addition, it may be possible to further refine the model by collecting more data. This study provides a new way to classify sleep apnea syndrome and allows for further research in the future.

4. Conclusions

In this study, we proposed the spectrogram-based entropy approach for the classification of sleep apnea syndrome from EEG signals by using MLPNN classifier model. Two experiments were implemented for the evaluation of the proposed approach. In binary classification experiment, the dataset of healthy individuals was compared with mild, moderate and severe sleep apnea syndrome dataset one by one. In quadruple classification experiment, the dataset of all classes was used as input into the MLPNN model. High AHI value caused significant differences in EEG signal in apnea and hypopnea, and thus increased the success ratio. As a result, due to its high achievement, the proposed model can be used as an aid tool in the classification of sleep apnea syndrome. As another result of this study, the fact that the spectrogram-based entropy approach has not been used before in sleep apnea syndrome classification has led to the idea that it can be used as a new model in biomedical studies.

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