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Comparison of EEG and EOG signals in classification of sleep stages

Uyku evrelerinin sınıflandırılmasında EEG ve EOG sinyallerinin karşılaştırılması

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Abstract

The value of sleep, which is the most significant part of life, increases with the emergence of health problems caused by insomnia. To solve this problem, it is extremely important to interpret the different signal patterns that occur during sleep stages. In order to achieve this goal, systems are created that provide automatic scoring of sleep stages. In sleep scoring, valuable information about sleep is obtained by considering the electrophysiological signals of the sleeper. The ISRUC-Sleep dataset, which was presented as open access to researchers working in the field of sleep, was used in the study. The main goal of the study is to investigate the effect of electroencephalography (EEG) and electrooculography (EOG) biosignals in the classification of sleep stages. The analysis was carried out by considering the third group of the data set, which defines three different groups belonging to the ISRUC platform. The 10 participants of subgrup_3 in the dataset were considered. By extracting effective features and applying different classification methods, it was investigated which one of the EEG or EOG signals was better in the classification of stages. In terms of performance evaluation of the classification methods used, the new Roza metric presented in our previous study was applied. It has been proven that EEG signals are more successful than EOG in the classification of sleep stages, thanks to the Welch feature extraction method and the ensemble of bagged tree classification technique. These sleep stages were classified by using EEG signals with a success rate of 77.7%.

Keywords: Sleep, EEG, EOG, Feature extraction, Classification, Roza.

Öz

Yaşamın en önemli parçası olan uykunun değeri, uykusuzluğun neden olduğu sağlık sorunlarının ortaya çıkmasıyla birlikte artmaktadır. Bu sorunu çözmek için uyku evrelerinde ortaya çıkan farklı sinyal kalıplarını yorumlamak son derece önemlidir. Bu amaca ulaşmak için uyku evrelerinin otomatik olarak puanlanmasını sağlayan sistemler oluşturulur. Uyku puanlamasında uyuyan kişinin elektrofizyolojik sinyalleri dikkate alınarak uyku hakkında değerli bilgiler elde edilir. Çalışmada uyku alanında çalışan araştırmacılara açık erişim olarak sunulan ISRUC-Sleep veri seti kullanılmıştır. Çalışmanın temel amacı, uyku evrelerinin sınıflandırılmasında elektroensefalografi (EEG) ve elektrookülografi (EOG) biyosinyallerinin etkisini araştırmaktır. Analiz, ISRUC platformuna ait üç farklı grubu tanımlayan veri setinin üçüncü grubu dikkate alınarak gerçekleştirilmiştir. Veri setindeki alt grup_3'ün 10 katılımcısı dikkate alınmıştır. Etkili öznitelikler çıkarılarak ve farklı sınıflandırma yöntemleri uygulanarak aşamaların sınıflandırılmasında EEG veya EOG sinyallerinden hangisinin daha iyi olduğu araştırılmıştır. Kullanılan sınıflandırma yöntemlerinin performans değerlendirmesi açısından önceki çalışmamızda sunulan yeni Roza metriği uygulanmıştır. Welch öznitelik çıkarma yöntemi ve toplu ağaç sınıflandırma tekniği sayesinde uyku evrelerinin sınıflandırılmasında EEG sinyallerinin EOG'dan daha başarılı olduğu kanıtlanmıştır. Bu uyku evreleri EEG sinyallerini kullanarak %77.7 başarı oranıyla sınıflandırılmıştır.

Anahtar kelimeler: Uyku, EEG, EOG, Öznitelik çıkarma, Sınıflandırma, Roza.

1 Introduction

The display and measurement of electrical activities in the brains of living things are known as EEG (Electroencephalography). EEG is measured with electrodes that are carefully placed on the subject's scalp. A standard EEG signal has a frequency range of 0.1 to 100 Hz and an amplitude of 10 to 100 µV. In addition to disease diagnosis, another important application area of EEG signals is to seek solutions for insomnia and sleep problems caused by stress [1]. Another important biosignal in sleep is EOG [2]. Thanks to the electrooculography technique, the stopping potential between the front and back of the eye is measured. The signal obtained as a result of this measurement is called an electrooculogram (EOG). Sleep, which is defined by physiological measures such as EEG and EOG, is a mental and physical resting process that has an important place in all vital stages of human life. The sleep factor, which controls and affects one's personal performance [3], learning life, and balanced physical movements, can turn many people's lives into nightmares and serious problems when not completed [4],[5]. The factors that impact people's sleep stages and cause insomnia, such as depressive disorders [6], sleepwalking, stress, respiratory disorders, and rapid eye movement (REM) sleep behavior disorder should be examined and treated.

The first step in the treatment process is to observe the sleep signals of the sleeper. The polysomnography (PSG) test, which is frequently used in sleep studies, is the uninterrupted follow-up of the physiological behaviors of the sleeper who has problems with sleep by experts throughout the night [7]. This objective test evaluation revealed abnormal features of irregular sleep and sleep stages, and many bio signals that affect sleep [8]. The advantage of the PSG test performed in the sleep laboratory is the measurement of different body bio signals. Additional measurements provide doctors with valuable information and shed light on accurate diagnoses. Another

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advantage is that there is no need to start recording by directly intervening as a result of any sensor loosening due to uninterrupted monitoring. In addition to these advantages, PSG's dependence on the sleep laboratory [9], the possibility that the sleep signals received during the test are of poor quality compared to the sleep state, and the high cost are the disadvantages of this method [10]. Considering these situations, it has been aimed to design an automatic, self-applicable, and inexpensive sleep scoring model for a long time with the development of technology in the scientific world [11].

Sleep scoring studies started in the 1960s to simplify the difficulties of the PSG sleep analysis method and speed up the process [12]. The idea and basic principles of developing an automatic sleep scoring model were presented by Penzel and Conradt [13]. The standard for the analysis of human sleep stages was based on the classification guideline previously presented by Rechtschaffen and Kales (R&K). In this standard, which divides sleep into 7 stages, the stages are represented as wakefulness, S1, S2, S3, and S4, REM stage, and movement time (MT) [14]. This standard, which divides the sleep stages into many redundant stages, has a low temporal resolution. On the other hand, it has been criticized by many studies because of the weak relationship between electrophysiological activity and sleep stages, loss of spatial information, and neglect of movement-related resources that affect sleep [15]. In order to partially solve these problems, the revised version of R&K was made by the American Academy of Sleep Medicine (AASM) and presented in 2007 [16]. In AASM, which is based on the R&K standard, the first change is the terminology change. S1, S2, S3, and S4 phases were changed to N1, N2, and N3. In short, the descending stages from seven to five are wakefulness (W), N1, N2, and N3, and REM (R). In some studies, sleep stages have been broadly divided into awake, non-rapid eye movement (NREM) sleep, and rapid eye movement (REM) sleep categories. In these sources, the NREM stage is subdivided into three stages sleepy, light sleep, and deep sleep [17].

The wakefulness stage represents the time when the eyes are closed, as a state of body relaxation and transition to sleep. At this stage, beta and alpha waves are seen in the EEG frequency bands [18]. Electrical activity of muscle nerves or EMG signals can take a high or medium value according to muscle tension.

Since the sleep process has started, the N1 stage takes a shorter time. At this stage, EEG signals show themselves with suppressed alpha values. As expected, EMG signals weaken and decrease, REMs begin to disappear while slow rotating eye movements appear. In the N2 stage, the low amplitude EEG seen in the previous stages is manifested by high voltage. EMG signals become very weak and REMs are lost [19]. In N3 stage, High-amplitude EEG signals, low-frequency delta band waves, and further reduced EMG signals appear, while REMs are rare [20]. During the REM sleep stage, a low-amplitude EEG signal resembling wakefulness is displayed. The EMG signal contains short tones originating from heart rate or blood pressure. At this stage, the EOG sign appears predominantly as rapid eye movement.

Following the introduction of sleep stages, more than ten simultaneous physiological signals obtained as a result of the PSG test are scored by sleep experts according to R&K and AASM standards to get an idea about sleep stages. This expert interpretation process, based on a personal point of view, is very time-consuming and laborious [21]. In this laborious observation, the sleep recording is split into 30-second epochs [9]. In observation by sleep experts, a stage is assigned to each dividing epoch. If more stages appear during an epoch, the dominant stage is selected by looking at the majority for 30 seconds duration. Taking into account different physiological signals and observing many parameters at the same time, the process of scoring sleep is a very complex and error-prone process. Inspired by the working principle of human intelligence, artificial intelligence (AI) is developed by machines and sheds light on the research field. Machine algorithms based on artificial intelligence take an important place in the field of sleep scoring by providing systems with the opportunity to learn and improve automatically. The sleep scoring procedure, which is done manually by experts, is simplified and accelerated by machine learning [9].

In the research area, the classification of sleep stages has been the favorite subject of many studies [22],[23]. Many pattern recognition tools and model designs have been realized in automatic sleep stages recognition studies. In these studies conducted on different data sets, a definite comparison of the developed models and methods cannot be made due to the differences in the physiological and recording conditions of the subjects [7]. Although automatic sleep scoring has not achieved the desired success worldwide, model development studies in this area continue unabated [24], [25]. The high diversity in these systems and the low agreement among this diversity made the definitive acceptance of the scoring systems difficult [26]. Patterns of EEG recordings are frequently used in sleep scoring systems due to the different features they contain [27]. Different signal processing methods are used to obtain useful information about sleep from EEG signals. These methods are divided into linear and nonlinear groups and are defined as analysis in time [28], frequency [29], and time-frequency space [30].

1.1 Related researches

Holzmann et al., who prepared a different platform for infants, achieved 96.4% success by developing an expert system to classify sleep and wake states [31]. In addition, in this system, which was developed on the data free from artifacts, it was determined that the purified signals were effective in the successful performance. In a study conducted in 1999 in the field of sleep scoring classification, 76.6% success was achieved by concentrating on artificial neural networks and calculating the power of the obtained EEG signals for seven different frequency bands [32]. A computer-assisted sleep stage classification study was presented in [33]. In this study, based on the R&K standard, 20-second epochs in the presented model showed an 80.6% agreement compared to manual scoring. Three different algorithms were used for the analysis of sleep signals by making use of EEG signals [34]. Success evaluation of five different classifications in a model and which one was successful in sleep stage classification was investigated. In this study, the neural network algorithm was chosen as the best classifier with a success rate of 72% [35]. In 2008, discrimination of REM sleep, wakefulness, and sleep spindles was done. In this study, phase classification was performed using wavelet transform and artificial neural networks algorithm, and 95.55% success was achieved [36]. Polysomnography signals obtained in the sleep scoring area sometimes deviate from the correct path as a result of erroneous observation. In order to ensure strong standardization in this area, an automatic system has been established to classify sleep and wakefulness. By extracting effective features, the stages are separated with 78% success by an artificial neural network classifier [37]. By applying the genetic fuzzy classifier method, it has been shown that the proposed artificial intelligence-based model and the visual staging process are compatible with a success rate of 84.6% in the classification of the four sleep stages [38]. By using the artificial neural networks algorithm, which has a common role in sleep stages, in a feed-forward manner, 74.7% success was achieved in classifying the five sleep stages [17]. In the sleep stage classification analysis, 90.93% success was achieved in the 5-stage discrimination study by making use of time-frequency features, sequential class-based feature selection method, and artificial intelligence algorithm [39]. The study mainly focuses on the idea of feature extraction from EEG signals in the classification of sleep stages, emphasizing the acquisition of informative measures. A review of feature-based automatic sleep scoring classification studies was conducted in 2012 [40]. Effective identification of sleep stages has been achieved using the artificial neural network model. The features extracted depending on the energy of the sleep signals were analyzed and the active features were applied to a feedback artificial neural network algorithm. In this model, 5 sleep stages were classified with 87.2% success [41]. The performance of these proposed models has a different accuracy range. In a different sleep stage classification study [42], a comprehensive comparison study was conducted by considering effective feature extraction and classification algorithms in the model focusing on machine learning steps. When the effect of feature selection is examined in terms of performance evaluation, it has been proven that the success rate increases compared to the situation with all the features. In the method proposed by this team, an overall success rate of 98% was achieved. Considering this study, one of the biggest problems in scoring sleep stages, namely the selection of data that carries valuable information, is solved automatically. A comprehensive compilation study was conducted by gathering the studies using various feature extraction and classification algorithms. In this study, it has been proven that the success rates are between 70% and 94%, considering the different approaches of the studies focusing on the sleep stages classification target. In addition, in this study, they suggested a new model that achieved 93% success by concentrating on 10-second epochs thanks to the use of new features [2].

When focusing on the classification studies of sleep stages in this area, it is not overlooked that there are different approaches in the range of about 17 years (i.e., from 1999 to 2016). In these approaches, consideration of the selected stages, feature extraction techniques, classification algorithms [43], [44], EEG channels included in the analysis, data sets, and classification performance evaluation methods are crucial to obtain an accurate comparison and a strong benchmark.

A study conducted in 2017 focused on a single channel in sleep staging classification on non-stationary EEG signals. In the study, after obtaining useful information about the amplitude and frequency changes of the EEG signals using the discrete energy separation algorithm, feature extraction was focused on. Finally, a successful machine learning model is developed by applying the random forest classifier [45]. In order to establish a reliable and portable sleep stage classification system on large data sets, a model working on a single EEG channel has been developed. In this model, a three-band filter bank was taken into account by obtaining wavelet-based features. Acceptable results were obtained in the phase classification using the SVM classifier [27]. In another study, a state-space-based model was designed and classification was performed for different sleep stages. In this study, which was carried out on the Sleep-EDF database, the success rates ranged from 78% to 98.6% [46].

Looking at the recent studies with the same goal, an automatic sleep stages classification model has been realized with a success rate of 97.8% by separating the EEG signals into sub band frequencies, obtaining statistical features after filtering and using the decision tree, support vector machine, and random forest algorithms [47]. Another system was proposed in a study conducted in 2021 for sleep disorders, which is one of the biggest challenges in the world. In this study, linear and nonlinear features were taken into account, concentrating on the ISRUC-Sleep subgroup_1 data set. In this study on test data, 98.6% success was achieved [47].

The accuracy rate seems to have an important role in the classification of sleep stages using software-assisted methods. Since there is no equal number of observations, this metric is considered to be insufficient in terms of evaluation. To close this gap a comprehensive metric is needed in terms of system performance. In a study, a new and updated the Roza metric was presented in a sleep staging systems comparison study. Considering all the features of this metric, it has been proven to provide smooth, reliable, and powerful performance [48].

When an overview of the sleep datasets is taken, the sleep heart health study (SHHS) dataset [49] is determined to be suitable for examining the relationship between sleep disorders and heart diseases. On the other hand, this data set can only be made available to the researcher upon special request. The Montreal archive of the sleep study (MASS) dataset [50] is an open-access dataset proposed by O'Reilly et al. Although this dataset includes signals from 200 subjects, it was collected from 8 types of research protocols in 3 different laboratories. The subgroups of the dataset differ in the number of channels, epoching, filtering, scoring conditions, and other aspects [51]. In this context, the PhysioBank data set [52] was used in sleep stage analyses by taking into account several studies. In addition, MIT-BIH [53], Sleep-EDF [54], and Extended Sleep-EDF [55] were defined as general-purpose sleep analysis datasets.

This article focuses on the analysis of the efficiency of EEG and EOG signals in the sleep stages classification study using the ISRUC-Sleep dataset. The contributions and limitations of the proposed model are summarized below:

- The most important goal of the study is to show whether EOG signals are as important as EEG signals in sleep stages classification,
- Another focus of the study is to ensure patient comfort. Therefore, single-channel use is targeted to achieve low cost and ease of recording at the same time,
- In sleep stages classification studies, the accuracy rate was generally used for performance analysis. Considering only one metric to evaluate model performance is not sufficient to interpret model success. In the proposed study, the newly recognized Roza metric was used a combination of different metrics to provide a fairer and more comprehensive result,
- EEG and EOG signals obtained from 10 individuals were analyzed in order to establish the basic structure in the model design. It is aimed to increase the number of people in order to present a wider and more detailed real-time model,

- Based on the mathematical formula of the Roza metric used, the Roza metric cannot be calculated when any of the combined metrics used in this metric are not defined (NaN),
- Because the Roza metric is polygonal, at least three metrics are required to use this metric.

1.2 ISRUC-Sleep dataset

In the related works section of this article, it seems that the sleep stage classification field has a very wide range. It is extremely important to have attained open-access datasets in order to provide an easy comparison of these studies conducted with different methods. An open-access dataset based on the ISRUP-Sleep polysomnography sleep study consisting of three groups was used in the study [7]. Sleep data includes three different types of candidates who are healthy, sleep-disturbed, and using medication to correct this disorder. From the PSG recordings made in the sleep analysis laboratory of the Combira University hospital, each recording was randomly selected. This three-group dataset was categorized as follows: one recording session per subject with 100 subjects (Subgroup_1), two recording sessions per subject with 8 subjects (Subgroup_2), and recording from 10 healthy subjects (Subgroup_3). Obtained PSG recordings were visually examined and scored by two experts [7]. In subgroup_2, the recording process took place on different days. Thus, the analysis of the time effect was also taken into account.

The signal recording was carried out with the SomnoStar Pro sleep system, and several sensors which are in accordance with the international 10-20 standard [56]. The recording process, which took place from 19 channels, was made according to the guideline determined by AASM. The layout of these channels is shown in Figure 1 [57]. The Letters C, P, F, and O Represent the Central, Parietal, Frontal, and Occipital Regions, Respectively.

The recording environment was prepared by arranging the rooms of the individual whose sleep signal was recorded and the expert/technician rooms separately. Approved by the hospital ethics committee of the University of Coimbra, this research provides a supervised machine learning model that is independent of the subject, greatly aiding sleep studies in terms of comparison [7].

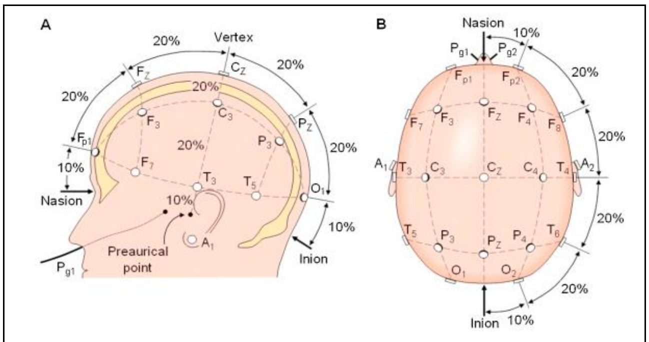


Figure 1(A): Shows the left and (B): Shows the upper part of the head.

Signals from a total of 19 channels were sampled at a frequency of 200 Hz. Detailed information on these channels was presented in [7]. EEG signals recorded from six channels (F_3, C_3, O_1, F_4, C_4, O_2) represent the frontal, central, and occipital lobes, respectively. Two EOG channels (LOC and ROC) were taken into account to examine the right and left eye movements in detail. The electrical activity of the chin muscle was recorded by the electrode placed between the lower lip and the chin. In the ISRUC dataset, in addition to the chin muscle, two different electrodes that record right and left leg movements were also included in the electromyogram (EMG) signal recording category.

Notch and Butterworth filters were applied as preprocessing on the recorded raw signals in order to remove artifacts. Recordings obtained in accordance with the AASM sleep guidelines were divided into 30-second epochs [58] and scored by two experts. In this scoring process, wakefulness, three-step NREM, and REM stages were taken into account.

In this study, focusing on the ISRUC-Sleep data set, the effectiveness of PSG recordings including EEG and EOG signals of sleep scoring was evaluated. Based on the second expert's manual observation and successful channel selection of sleep stage classification studies, C_3, C_4, LOC, and ROC channels were chosen for analysis in this study. By examining the obtained signal processing steps, the performance comparison evaluation of these signals in sleep signals analysis was presented. Characteristics of subgroup_3 of the ISRUC-Sleep dataset were briefly presented in Table 1. This dataset has been the focus of several studies [59],[3].

Table 1. Characteristics of subgroup_3 of ISRUC-sleep dataset

Dataset	Subgrup_3
Subjects number/ ages	10/ 30-58 (Average=40)
Characteristics	Healthy
Number of recording	One session per subject

2 Material and methods

Signal processing steps on PSG signals obtained from the ISRUC-Sleep dataset can be divided into three basic parts preprocessing, feature extraction, and classification. Matlab 2019b software was utilized for all computations of the proposed method. A brief introduction of the methods used in these stages was presented below.

2.1 Preprocessing

Preprocessing was performed for 30-second segmented EEG and EOG recordings obtained based on the 10-20 electrode placement system. A third-order Butterworth filter was used to pass frequencies between 0.1-45 Hz [58], [42]. Normalization was performed to minimize the effect of size change among the analyzed epochs [60]. By applying the Z-score normalized method [61], signals whose amplitude is normalized and frequency components were formed in the desired band range were prepared for feature extraction.

2.2 Welch feature extraction method

In the Welch method, the signal is split into overlapping segments to perform the windowing process. In the study, the Hanning window was applied with a 75% overlap rate for each segment in order to spectral leakage prevention [62]. Window selection and its five-second length were chosen by the trial and error method. The spectral density estimation or periodogram was performed by calculating the Fast Fourier Transform (FFT) on the windowed segments [48]. By taking the average of these periodograms, the Welch method was realized.

In the study, frequency bands were divided into 8 subbands between 0-45 Hz in EEG and EOG signal analysis (i.e. 0-4, 4-8, 8-12, 12-16, 16-20, 20-30, 30-40, and 40-45). Using the Welch method, eight features were extracted for eight frequency bands. The feature representing each band was calculated by applying the mean operation of FFT coefficients across the band.

2.3 Classification algorithms and performance analysis, ensemble of bagged Tree classifier, decision tree classifier, and k-Nearest Neighbors (k-NN) classifier

Ensemble of bagged tree which is used in large-scale machine learning areas, is considered in the proposed study. This algorithm, which spruces up the irregularity of classes, is used in the fields of artificial intelligence with the aim of increasing stability and accuracy [63], [64]. The maximum number of splitting ("MaxNumSplits") was chosen as 8588 according to the sleep dataset.

Another high-performance algorithm that solves regression and classification problems is the decision tree [65]. In this study, the decision tree was chosen for sleep stage classification in terms of high speed and easy understanding [66]. This method, which divides the sleep dataset into the root and internal nodes [67], determines the class of the unknown sample based on the training data. The first node is known as the root node. In root analysis, the observation process is classified. Features are represented by internal nodes and located below the root node [68]. The optimum number of nodes prevents model complexity. In this algorithm, which is expressed as a flowchart, the results are known as the bottom nodes called leaves. In this study, the maximum number of splitting ("MaxNumSplits") was chosen as 100 according to node splitting rules [69].

The k-NN classifier [70], [71] is a simple non-parametric supervised classification method [72]. This method, which has a wide range of applications, is also included in sleep stage classification studies [73]. In this powerful method, it is important to determine the parameter k or the number of nearest neighbors. Euclidean distance calculation function was used to apply the distance logic in the study. Thus, thanks to this function, similarity analysis was made between the test and training samples [74]. In the study, k=1 was determined.

K-fold cross-validation strategy was used to evaluate and validate the results of the classification algorithms in this study. K value was taken as 10. After performing this strategy, the parameters of each classification algorithm were obtained [60].

2.4 Roza metric

Accuracy rate, sensitivity, and Roza metric were used for model evaluation in the study. The Roza metric not only determines the superiority of the designed model but also organizes a logical and fair comparison in classes with unbalanced sample numbers. In the analysis of performance criteria of different classification algorithms used in systems, the superiority of one system over the other cannot be determined. But the Roza metric provides a comprehensive analysis of performance using a combination of predetermined metrics.

In the proposed study, the Roza metric was created by calculating the accuracy and sensitivity of the five sleep stage classifications [48]. Considering this situation, the Roza performance analysis consisting of a total of 6 factors will be looked at as hexagonal. The mathematical formula of the Roza metric is given in Equation (1).

$$ROZA = \frac{1}{N}\sum_{1}^{N}\frac{NAoGP_i}{CG_i} \quad (1)$$

In the formula shown, NAoGP is the normalized area of the general polygon, CG is the distance between the two centers of gravity, and N is the number of permutations.

In the proposed classification model, the diagram of the Roza graph representing 6 metrics in five permutations is shown in Figure 2. as regular hexagons and irregular hexagons. Centers of gravity are represented by the star symbol.

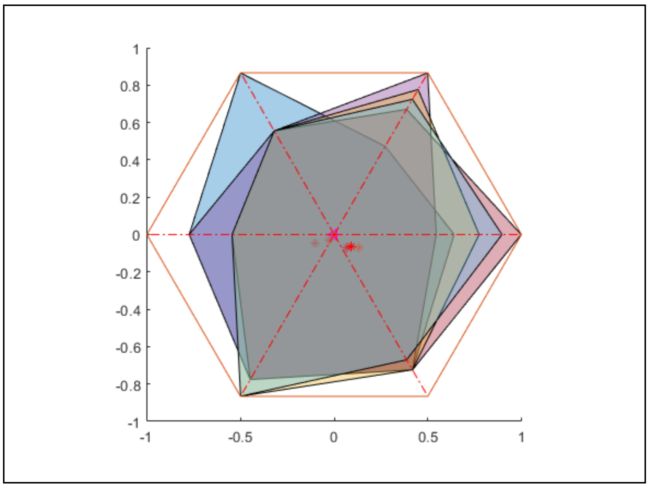


Figure 2. The diagram of the Roza graph for proposed model.

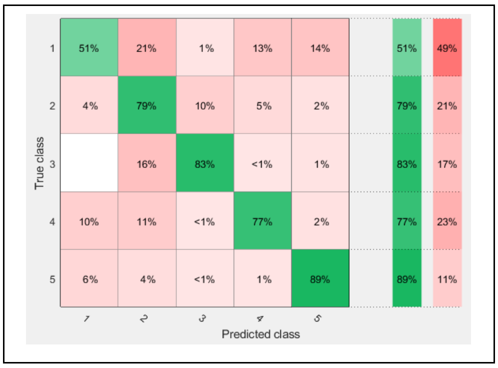
3 Results

Sleep scoring analysis is the first intervention to reach the early diagnosis information of diseases from PSG records. In the study, a machine learning model was developed using this technique. Each observed score represents one of the sleep stages. Using this model, the effectiveness of EEG and EOG signals in stage classification was investigated. The results of the feature extraction and classification algorithms mentioned above were presented in Table 2.

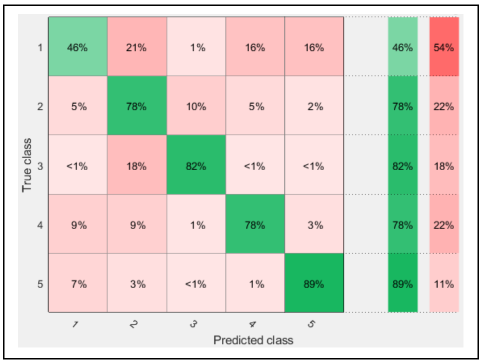
Table 2. Classification results of sleep-staging in the subgroup_3 of the ISRUC Sleep dataset.

	Fine tree	Medium k-NN	Bagged-tree	Roza metric
EEG_C3	71.8	73.1	77.7	7.0497
EEG_C4	72.5	73.1	76.8	5.9406
EOG_ROC	67.3	70.4	74.1	6.1687
EOG_LOC	67.5	69.7	73.5	5.5312

The Roza metric used in the performance analysis of the model is in the last column of Table 2 in three classification techniques for each channel. It is observed that the bagged tree algorithm is more successful than the other two algorithms. In the sleep stage classification study in the ISRUC-Sleep dataset, the C3 channel stood out as the most successful channel with 77.7% accuracy and a Roza metric of 7.0497. If value is high in a model that is taken into performance analysis with the Roza metric, the success of the system is higher. Based on Table 2, the confusion matrix for C_3, C_4, ROC, and LOC channels were presented in Figure 3 (A), (B), (C), and (D), respectively. With a general overview, it was observed that EEG signals gave a similar result compared to EOG, but EEG signals were more successful in the study aimed at determining the efficiency of EEG or EOG channels [75]. In the evaluation of EOG, ROC among the right and left eye channels seems to be more successful in the bagged tree algorithm with 74.1% compared to LOC in terms of stage classification. After the ensemble of the bagged tree classification algorithm, the second successful classifier among decision tree and *k*-NN was determined as the *k*-NN. In this classifier, the C_3 channel performed five sleep stage classifications with 73.1% success.



(A)



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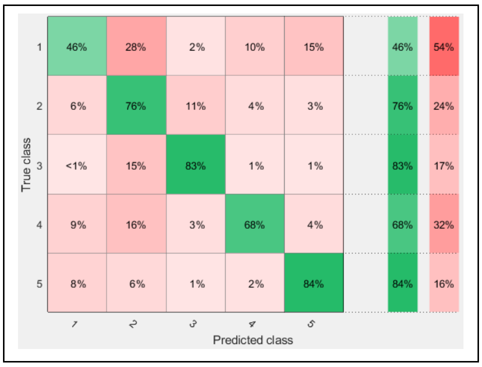

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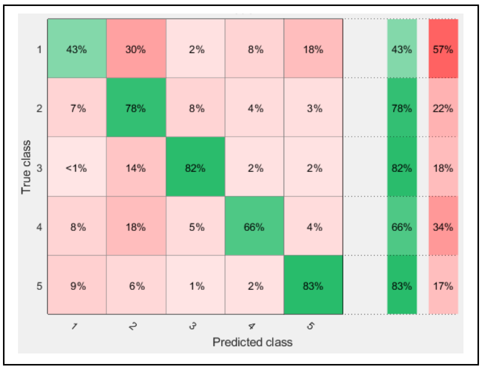

(D)

Figure 3. Confusion matrix for C3 (A), C4 (B), ROC (C), and LOC (D) channels.

4 Discussion

Different datasets are available for detailed analysis of sleep patterns using PSG recordings. Since some of these data sets are largely far from statistical approaches, they may not have the correct evaluation in terms of comparison with new methods [76]. Open-access datasets have an important place in the scientific world in order to ensure that researchers in the field of sleep scoring speak a common language. A detailed evaluation of some open-access datasets was presented in [7]. Some open-access datasets such as ''PhysioBank'' have been the focus of different researches [52]. Due to the limited number of subjects in the datasets named ''MIT-BIH [77], Sleep-EDF [40], and extended Sleep-EDF [78]'', it does not seem appropriate to conduct extensive research on these datasets. There are 108 records in the dataset named "CAP-Sleep dataset", which draws attention from the PhysioBank archive. This data set was deemed suitable for studies aiming at circular variable model design [79].

The "sleep health study (SHHS)" data set, which focuses only on the (C3-A2 and C4-A1) channels, is not known as a complementary dataset for general-purpose studies due to channel limitations. This data set has been the focus of research on solving sleep problems caused by heart and respiratory diseases in general [49]. The comprehensive sleep analysis dataset named ''Montreal archive of the sleep study (MASS)'', which includes recordings from 200 healthy subjects, was used [51]. Some restrictions on access to the information presented in this dataset are not overlooked. Among the sleep analysis datasets briefly introduced, MIT-BIH, Sleep-EDF, and MASS seem suitable for sleep researchers doing general-purpose studies.

The use of a single physiological signal in the analysis of sleep scoring studies may sometimes be insufficient in terms of stage classification. The use of multiple physiology signals sometimes increases the margin of error because it makes room for unnecessary information [80]. Therefore, it is important to balance the use of multiple physiological signals and automatic sleep stage scoring. EEG patterns have been used in many sleep stage classification studies because they contain different features of sleep signals [81].

EOG signals, which are of great importance in the classification of the REM stage [80], are obtained from the continuous measurement of the eye potential. EOG electrode placement has a patient-friendly feature to obtain these signals and can be easily done by the subjects. In sleep stage classification studies using EOG, it is of great importance that the signal recording process can be directed by the subject when long and continuous recordings are required. In a 2007 study, an automatic model of sleep stages classification was realized using two EOG channels [75]. In another study, stage classification was made using a single EOG channel. In this study, a higher success was achieved than EEG and EOG-based sleep stage classification methods [82].

In this study of the classification of sleep stages based on EEG and EOG signals [3], [83] the ISRUC-sleep dataset was concentrated. During the literature review, no sleep stage classification studies were found in this data set using EEG and EOG channels. The aim is to investigate which of these signals is more successful in stage classification. Brain signals carrying valuable information also reflect the changes in sleep stages thanks to the modifications in the frequency bands they contain [16]. In the data set consisting of three different parts, the third subgroup of 10 people was used. C_3 and C_4 EEG channels and LOC, ROC EOG channels, which are frequently used in sleep stage classification studies, were taken into account. The classification results obtained by applying the signal processing procedure separately for EEG and EOG signals were compared. Feature extraction was performed on preprocessed EEG and EOG signals using the Welch method [84]. After the effective features were obtained, ensemble, *k*-NN, and decision tree [84] algorithms were applied for powerful performance classification [85]. When focusing on the results, it is observed that EEG signals play an important role in the separation of sleep stages. Eye movements in the analyzed EOG signals are common in wakefulness and REM, but rare in NREM [85].

When we look at the classification results in general, it seems that EEG signals are more successful than EOG in sleep stage classification. In the five-stage sleep classification study, 77.7% success was achieved for the C_3 channel of the EEG signal as a result of the application of Welch feature extraction and ensemble of bagged tree classification algorithm. If this result is applied with the decision tree and k-NN algorithm, the success of stage classification was calculated as 71.8% and 73.1%, respectively. A brief summary of some similar studies on different datasets is shown in Table 3.

Table 3. A brief summary of some similar studies on different datasets.

Study	Channels	Aim	Metric, successful result
[75]	Two EOG channels	Automatic sleep stage classification	epoch-by-epoch agreement, Cohen's Kappa, 73%, 0.63
[82]	Single EOG channel	Sleep stage classification using single-channel EOG	low accuracy of the S1 sleep stage classification, A superior accuracy result using RUSBoost classifier
[3]	Multiple channel combinations	Automatic sleep staging	sleep-wake detection and multiclass sleep staging
[86]	EEG-Single channel	An automatic single-channel EEG-based	Accuracy, 80.4%
[87]	EEG	An Automatic Sleep Stage Classification Algorithm	Accuracy, 81.65%
Proposed study	EEG, EOG	Comparison of EEG and EOG Signals	Accuracy, Roza, 77.7%, 7.0497

5 Conclusions

In this study, the effectiveness of EEG and EOG signals in stage classification was taken into account by focusing on the standard signal processing steps of automatic sleep stage classifications. Based on the results obtained, it was observed that the brain signals were more successful in sleep stage classification compared to the signals formed as a result of eye movement. The aim of the proposed study is to design an automatic machine learning model for the classification of sleep stages without the need for experts. On the other hand, the main goal is to examine which of the EEG and EOG signals shows better success in stage classification in this pre-trained artificial classifier design. For this purpose, preprocessing was carried out on the recorded PSG signals. Preparations were made for the classification process by selecting the effective feature for the sleep signals that are cleared from noise and artifacts as much as possible. The Welch method represents sleep stages features. The ensemble of bagged tree classifier is the best performing algorithm among the tested classifiers.

When the study is developed, it is hoped that it will be very useful for real-time applications in the diagnosis pattern recognition of conditions such as fatigue, different sleep disorders, and drowsiness. In future studies, the effectiveness of EEG and EOG signals in the classification of sleep stages can be analyzed by focusing on different data sets. In the signal processing stage, an effective comparison study can be made by using other preprocessing, feature extraction methods, and classification algorithms.

6 Author contribution statements

Negin MELEK took part in the study's experimental study process and writing phase and provided control and supervision and also in the literature research, construction, and writing of the experiments.

7 Ethics committee approval and conflict of interest statement

“There is no need to obtain permission from the ethics committee for the article prepared”. “There is no conflict of interest with any person/institution in the article prepared”.

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