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Automated Sleep Stage Detection Based on Recurrence Quantification Analysis Using Machine Learning

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Abstract

In recent years, the use of intelligent methods for automatic detection of sleep stages in medical applications to increase diagnostic accuracy and reduce the workload of physicians in analyzing sleep data by visual inspection is one of the important issues. The most important step for the automatic classification of sleep stages is the extraction of useful features. In this paper, an EEG-based algorithm for automatic detection of sleep stages is presented using features extracted from the recurrence plot and artificial neural network. Due to the non-stationary of the EEG signal, the recurrence plot was used in this paper for nonlinear analysis and extraction of signal features. Various extracted features have different numerical ranges. Normalization was performed to prevent the undesirable effects of large values of data. As all normalized features could not correctly classify different stages of sleep, effective features were selected. The results of this paper show the selected features and the Multi-Layer Perceptron (MLP) neural network able to achieve the values of 98.54 ± 1.88%, 99.03 ± 1.43%, and 98.32 ± 2.11%, respectively, for specificity, sensitivity, and accuracy between the two types of sleep, i.e., Non-Rapid Eye Movement (Non-REM) and Rapid Eye Movement (REM). Also, the results show that the selection of Pz-Oz channel compared to Fpz-Cz channel leads us to a higher percentage for the separation of stages I-IV, awake, while the separation of REM stage using Fpz-Cz channel is better. The results show that the proposed method has a higher success rate in classifying sleep stages than previous studies. The proposed method could well identify and distinguish all stages of sleep at an acceptable level. In addition to saving time, automatic analysis of sleep stages can help better and more accurate diagnosis and reduce physicians' workload in analyzing sleep data through visual inspection.

Keywords: Sleep stages, EEG signal, Recurrence plot, Nonlinear features, Artificial neural networks.

1 | Introduction

Sleep is the brain's primary function and plays a fundamental role in individual performance, learning ability, and physical movement [1], [2]. One of the essential physiological processes of humans is sleep vital for physical and cognitive well-being and resurgence [3]. Sleep is a reversible state in which the eyes are closed, and several nerve centers are disabled [4]. Sleep creates partial or unique or full anesthesia for the individual, in which case the brain becomes a less complicated network [5], [6]. Today, PSG is done to identify various disorders based on the analysis of sleep stages, the main component of which is the measurement of brain activity with EEG signals [7]. *Fig. 1* shows the sleep cycle, which is divided into two parts of Rapid Eye Movement (REM) and NREM.

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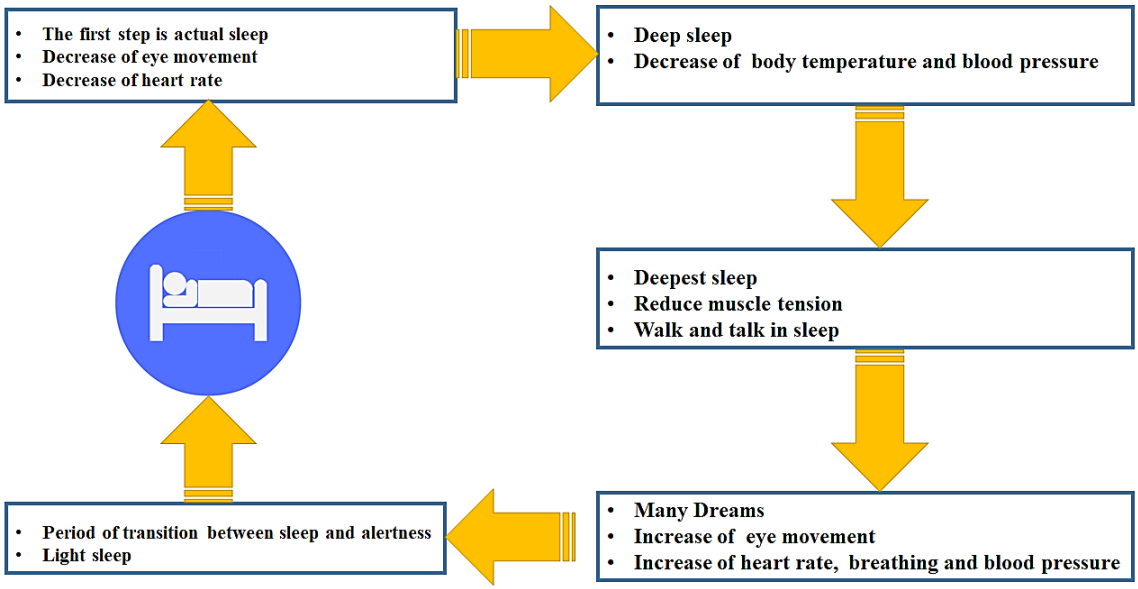

Fig. 1. Different stages of the sleep cycle.

Sleep disorders include several disorders associated with various symptoms such as insomnia, respiratory disorders, behavioral and motor-related sleep disorders that significantly affect EEG signals [8]. By classifying the different stages of sleep, the correct diagnosis of sleep-related disorders can be achieved. After recording the EEG signal, feature extraction, and analysis of the signal recorded in a specified range, a classification algorithm to identify the sleep stage is used [9], [10]. However, improving the classification accuracy and reducing complexity are two main challenges in the classification of sleep stages [11]. In the following, some of these methods are described.

Rechtschaffan & kales suggested a visual sleep scoring method for classifying sleep stages used for about 40 years [12]. According to the rules provided by R & K, human sleep consists of the WAKE, REM, and the four stages of the NREM (stages 1 to 4, which contain a light sleep to deep sleep). In a study carried out by Doroshenkov et al. [13], temporal features and Hidden Markov Model (HMM) were used in such a way that they measured signals with two channels of the EEG signal (Fpz-Cz and Pz-Oz). In 2012, Koley and Dey [14] used 39 features to differentiate sleep stages, including time-domain, frequency-domain, and nonlinear parametric analyses. A certain combination of the subset of optimal features from the single-channel EEG signal was selected to help the binary Support Vector Machine (SVM) classifier. A study on different models of classifying sleep stages was conducted by Şen et al. [15] in 2014. The data used in this method was recorded by a dataset provided by the Vincent University Hospital and the Dublin University College. Many extraction features were addressed, the selected features of which included time-domain, frequency-domain, time-frequency-domain. These features were applied as inputs to five classification algorithms, called a Random Forest (RF), a feed-forward neural network, an SVM, a radial basis function neural network, and a decision tree. According to other study, the two-stage classification was developed by Phan et al. [16] in 2013 with a single-channel EEG signal (Fpz-Cz). This method is called the KNN (k-nearest neighbors), which classifies the sleep stages to wake, Stage 1 + REM, Stage 2, and Slow Wave Sleep (SWS).

Deep Belief Network (DBN) is an algorithm that was welcomed in machine calculations because of its high accuracy. DBN works unsupervised where there is no calculation of output adjustment targets and is suitable for learning nonlinear features. Bi-LSTM is a combination of Long Short-Term Memory (LSTM) and Bi-Directional Recurrent Networks (Bi- RNN) [17].

In 2017, the proposed project of Tunable-Q factor Wavelet Transformed (TQWT) was raised by Hassan and Subasi [18] for the automatic classification of sleep stages. In this work, eight individuals of both genders, men and women with an age range between 21 and 35, were studied. The EEG signal with

Fpz-Cz and Pz-Oz channels has been used in this research to differentiate sleep stages. The method used in this work is different from EMD and Fourier transform [18]. TQWT is an advanced signal decomposition technique. It is ideal and flexible for processing oscillatory signals. The Q factor for the processing of signals with high oscillation should be low and, on the other hand, should be high for the processing of signals with low oscillation. TQWT eliminates this problem by setting the parameter Q for the analysis of signals and classification of EEG.

In recent years, research has been conducted to identify the stages of sleep with the help of brain and heart signals, some of the most important of which are listed below. Nico Surantha et al. [19] presented an accurate model for classifying sleep stages based on Heart Rate Variability (HRV) features extracted from an Electrocardiogram (ECG). The maximum classification accuracy obtained by the SVM method was 82.1%. Rahimi et al. [20] presented a sleep stage classification using HRV, and ECG-Derived Respiration (EDR) features with the SVM classification. The obtained results showed that this method's accuracy was 81.76% for two sleep stages and 76% for three sleep stages. In another paper, an automatic sleep stage classification was introduced based on a Polysomnographic (PSG) recording. The EEG, ECG, EMG (electromyographic), and respiratory signals were used as input. To sleep stage detection, the RF classifier was proposed. The maximum classification performance using RF classifier based on the combination of the EEG and respiratory signals achieved an accuracy of 93% [21]. Sharma et al. [22] proposed an automated sleep stage classification based on the unipolar (C4-A1) and bipolar (F4-C4) EEG. In this study, 1-D Wavelet Decomposition (WD) was used for feature extraction from each 30s epoch of EEG signal. The maximum accuracy obtained of this method was 85.1% with Cohen's Kappa coefficient of 0.8214 for balanced data based on the Ensemble of Bagged Tree (EBT) classifier with a 10-fold cross-validation strategy.

According to recent studies, most of the methods presented in the papers have not yet identified the types of sleep stages. In addition, most of the methods have the complexity of calculations, low execution speed, relatively acceptable results. But the method proposed in this article and the fast and automatic diagnosis of different stages of sleep can produce better results in terms of accuracy, sensitivity, and specificity in diagnosing sleep stages compared to similar studies.

The organization of this paper is as follows: Section 2 presented the data that we have used and the method proposed in this paper. Section 3 illustrated the neural network structure proposed in this paper. Section 4 has shown the results using the presented method, and Section 5 compares the results of studies conducted in this field so far. Finally, limitations and suggestions have been expressed in the conclusion part, presented in Section 6.

2 | Materials and Methods

A new method of nonlinear processing is based on a Recurrence Plot (RP). An important advantage of this approach is that it can also be used for non-stationary signals. Given the past efforts on the use of this method to diagnose brain-related diseases, it can be suggested that RPs and Recurrence Quantification Analysis (RQA), as a nonlinear method for analyzing the EEG signal of individuals in different sleep modes, can also be applied. In addition to the visualization of the transition situations in the signal due to the placement of people in different sleep positions, RQA sizes can also be used to quantify changes in the structure of brain dynamics. So, we introduce the nonlinear parameters obtained using a RP in this section. We will be looking for features that can effectively detect and differentiate the different stages of sleep.

Nonlinear methods in processing vital signals have been considered due to the nonlinear nature of the biological systems that produce these signals. Among these methods is the RP that provides a graphical and qualitative representation of the dynamics in the signal. After extracting the feature, because the features are of different types and have different sizes, the normalization method is used. Then the features were applied to the classifier, and by changing the classification structure and applying other training methods, the classifier's performance was evaluated. It should be noted that in each performance, the data for training and testing were selected by the cross-validation technique. *Fig.* 2 shows the different steps of the algorithm proposed in this paper to detect sleep stages automatically.

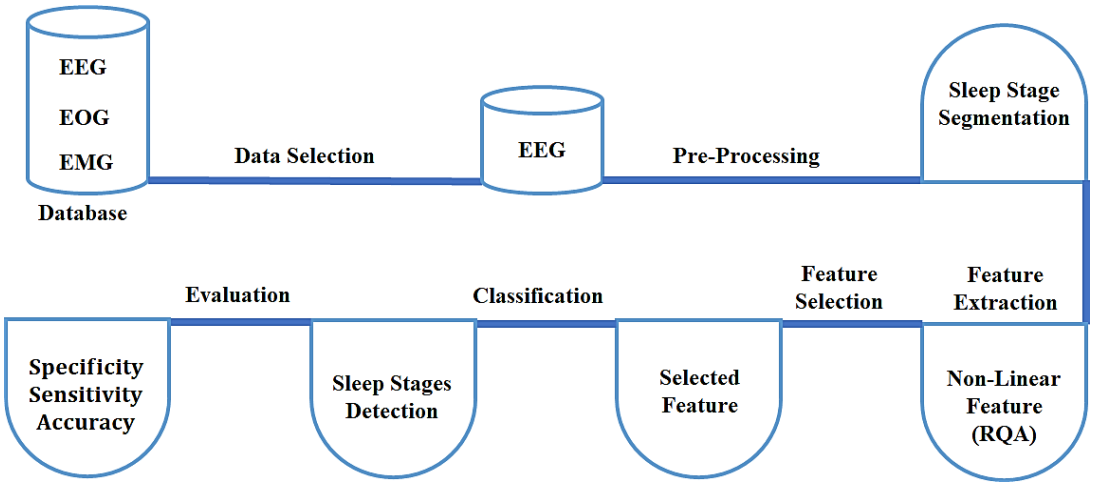

Fig. 2. Sleep stage classification system block diagram.

2.1 | Recurrence Quantification Analysis (RQA)

Two major small-scale structures can be seen in the RPs. The first is the structure of diagonal line with length L indicating that the two trajectory units have been in the neighborhood ε of each other for L the period, and the second is the structure of vertical line with length v indicating that the trajectory has not changed much for the v period.

2.2 | Complexity Sizes

To go beyond the visual expression resulting from the RPs, several sizes have been proposed for the complexity that quantifies the low-scale structures in RP and are known as RQA. These sizes are based on the density of recurrence points and the diagonal and vertical line structures in the RP.

2.3 | Recurrence Plot

Recurrence is an essential feature for many complex dynamic systems [23], and the human heart and brain are known as a dynamic systems with high complexity. Henry Poincaré first introduced the main concept of recurrences in 1890 [24], [25]; nevertheless, the issues raised by Poincaré has long remained dormant due to the lack of appropriate processing tools. Eventually, Eckmann et al. [26] in 1987 presented the RP method to visualize the recurrence of dynamic systems visually.

If we assume that the trajectory $\{\vec{x}_i\} \quad i = 1. \ldots . N$ exists for a system in phase space; the corresponding RP of this trajectory can be drawn using the recurrence matrix *R* with *Eq. (1)* in this case.

$$R_{i,j} = \Theta(\varepsilon - \| \varepsilon_i - x_j \|), i, j = 1,2,...N. \quad (1)$$

In the above relation, ε neighborhood radius, Θ Heaviside function, and N is the number of points measured $\vec{x}_i$. In the above relation, if the vectors of phase space *i* and *j* are close enough to each other,

then the value of $R_{i,j}$ is one and otherwise it will be zero. Because systems typically do not return exactly to the state they were previously in, considering this neighborhood is, therefore, essential [24], [25], [27]. In the defined matrix, if the system status at times *i* and *j* is similar (neighbors), the corresponding array of these two in the matrix is equal to one. Otherwise, the array is considered equal to zero. If only time series $x(i)$ is available, then the Taken's time delay theory can be used to reconstruct the phase space [28]. Accordingly, the trajectory$\vec{x}_i$ is reconstructed from the time series $x(i)$ and by *Eq. (2)*:

$$\vec{x}_i = [x(i), x(i+\tau), \ldots x(i+(m-1)\tau)]. \quad (2)$$

In which m is the reconstruction dimension of τ time delay. A common method for determining the reconstruction dimension is the False Nearest Neighbor (FNN) method and for the delay is the Mutual Information (MI) method [28] that these two approaches were used in this paper.

2.4 | Mutual Information Method

Swinney and Fraser presented the MI method as a tool for determining the delay time. Before applying this method, the autocorrelation function method was used to determine the delay time, but the problem with the autocorrelation function method was that the method only considered linear correlations [29]. Unlike the autocorrelation function, the MI method also considers the nonlinear correlations in the time series. MI for different values is calculated from *Eq. (3)*.

$$M(\tau) = -\sum_{i,j} p_{i,j}(\tau) \ln \frac{p_{i,j}(\tau)}{p_i p_j}. \quad (3)$$

In the above relation, p_i is the probability of finding a value of time series in i space and $p_{ij}(\tau)$ is the joint probability that observation happens at i-th space and the next observation happens with delay τ at j-th space. Finally, the first minimum of the function M regarding τ is considered as the optimal delay value.

2.5 | False Nearest Neighbor

To determine the minimum proper embedding dimension m, a method called the FNN was proposed by the kennel. Suppose that the minimum embedding dimension for time series {xi} is equal to m0. This means that the reconstructed absorption platform of a one-to-one image in an m0 dimensional delayed space is from the real absorption platform in the main phase space, especially since the topological properties are preserved in this dimension; so the neighbor of a point in the main space will be mapped to a neighbor in the delayed phase space. Due to supposing that the dynamics are smooth, the neighbors of points are also mapped to neighbors that shape and diameter of the neighborhood change based on Lyapunov exponents. But now suppose that absorption platform is imbedded in the dimension smaller than the real dimension (m < m0), the topological structure is not well maintained as a result of this imaging. Points are mapped to neighbors from other locations that were not neighbors in the higher dimension. These points are called false neighbors. Theoretically, it can be said that the nearest neighbor xi in the m-dimensional space can be found for every point xj in the time series. Then the distance between these two points in this space is calculated, and E(i) is calculated using *Eq. (4)* for all values i.

$$E(i) = \frac{\| x_{i+1} - x_{j+1} \|}{\| x_i - x_j \|}. \quad (4)$$

If E(i) exceeds a certain threshold, this point is labeled as the false neighbor. The criterion for determining the proper embedding dimension is that the fraction of the points in which > E(j) E(i) is zero or very small, or in other words, the $\frac{E(j)}{E(i)}$ the plot almost reaches saturation. *Fig. 3* shows the EEG signal and the RP generated with the above descriptions. Marwan toolbox has been used to plot the RP [30].

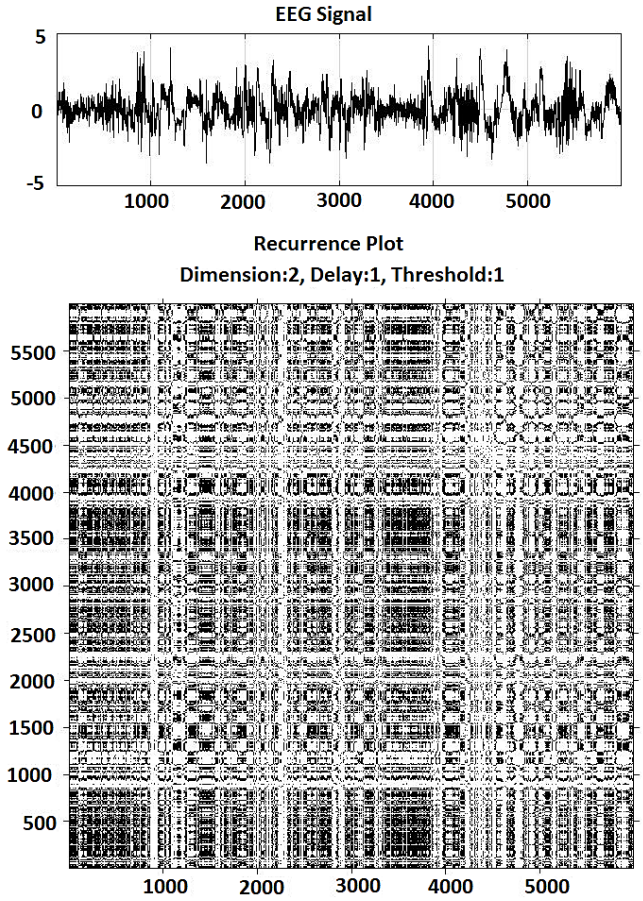

Fig. 3. Recurrence plot of EEG signals during sleep stages.

2.6 | Quantification of the Recurrence Plot

Three small-scale structures, including vertical lines, diagonal lines, and single points, are visible in the RPs.

Single points: it can occur when a rare condition happens; if this state only stands for a short time or strongly fluctuates.

Diagonal lines: a diagonal line of length L occurs when a part of the trajectory is traversed approximately parallel to the other part of the trajectory.

Vertical lines: a vertical line of length V represents the emergence of a stable state for V unit of time. In other words, the system is trapped for a few moments. To evaluate the structures quantitatively in the RPs, several features have been presented so far, which are further examined [24], [25].

Deterministic: the ratio of the recurrence points that follow the structure of the diagonal lines (with a minimum length l_{min}) to total recurrence points is defined as the deterministic feature, which is calculated from *Eq. (5)*.

$$DET = \frac{\sum_{l=l_{min}}^{N} lp(l)}{\sum_{l=1}^{N} pl(l)}. \quad (5)$$

In relation $P(l)$, the histogram of the diagonal lines is to the length of l. The emergence of diagonal lines in RPs is due to the parallel movement of two trajectory pieces. The duration of this movement is directly associated with the length of the diagonal lines. Deterministic is considered as the magnitude of predictability and determination in a system [31].

Recurrence Rate (REC): this index is a measure of the density of the recurrence points in the RP.

$$\mathrm{REC}(\varepsilon) = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{i,j=1} R_{i,j}(\varepsilon). \tag{6}$$

The average length of diagonal lines: this feature is considered the average prediction time in a system.

$$L_{mean} = \frac{\sum_{l=l_{min}}^{N} lp(l)}{\sum_{l=l_{mim}}^{N} p(l)}. \tag{7}$$

Eq. (7) shows how to calculate the diagonal lines.

If a system is stochastic, then the average prediction time is expected to be very small; in other words, the nature of a stochastic system makes it impossible to predict its behavior in the future.

The maximum length of diagonal lines: this feature is equal to the longest diagonal line available in the RP; contrary to this feature is considered as a divergence. *Eq. (8)* is the definition of this feature. N is the total number of diagonal lines.

$$L_{max} = \max(\{l_i; i = 1,2,\ldots,N_i\}). \tag{8}$$

The entropy of diagonal lines: this feature states the complexity of the RP compared to the diagonal lines [25]. The entropy related to the diagonal lines is obtained from *Eq. (9)*.

$$\mathrm{ENTR} = -\sum_{l=l_{min}}^{N} p(l)\ln p(l). \tag{9}$$

Laminarity: this feature is defined as the ratio between the recurrence points constituting the vertical structures to the total recurrence points and is achieved from *Eq. (10)*.

$$\mathrm{LAM} = \frac{\sum_{v=v_{min}}^{N} vp(v)}{\sum_{v=1}^{N} vp(l)}, p(v) = \sum_{i,j=1}^{N}(1-R_{i,j})(1-R_{i,j+v})\Pi_{k=0}^{v-1} R_{R_{i,j+k}}. \tag{10}$$

Calculation of *LAM* is realized for all v that is more than vmin so that the effect of tangential motion is reduced. *LAM* Shows the occurrence of laminar situations in the system, without describing the length of these laminar phases.

Trapping time: the average time a system stays in a certain situation or how much it will get stuck in the trap. In other words, this feature indicates the average length of the vertical lines. This feature can be calculated from *Eq. (11)*.

$$TT = \frac{\sum_{v=v_{min}}^{N} vp(v)}{\sum_{v=v_{mim}}^{N} p(v)}. \tag{11}$$

The maximum length of vertical lines: this feature can be considered somewhat in comparison with the standard size l_{max}. All of these features can be calculated over the whole RP or in windows that move along the main diagonal of the RP [32].

A detailed study of dynamic systems has shown that chaos is widely used in natural and engineering systems. Chaotic behavior was known as abnormal and unpredictable behavior and often attributed it to the random effects of the environment; while such systems are not stochastic and are deterministic systems, but their accurate prediction is very difficult. Thus, methods based on chaos theory and nonlinear theories have been considered in recent years to extract the EEG signal features.

3 | Neural Network Structure

One of the most important technologies in data mining is classification. Many of the different problems in the real world, whether commercial, industrial, or medical, can be solved by the classification method. As the correct diagnosis of individuals' condition is of great importance, it is necessary to use the methods for this diagnosis that have minimum error and maximum accuracy. Thus, an artificial neural network is used in this paper to classify different sleep stages on EEG signal data for enhancing the efficiency of the detailed classification process in the training and testing stages. This paper's intended neural network has a Multi-Layer Perceptron (MLP) structure that works better than other methods [33]. The structure of an MLP is a standard combination of inputs, linear and nonlinear neural units, and outputs. *Fig. 4* shows an MLP neural network structure with two layers (with a hidden layer). In this Figure, the network has three inputs, four neurons in the hidden layer, and two outputs.

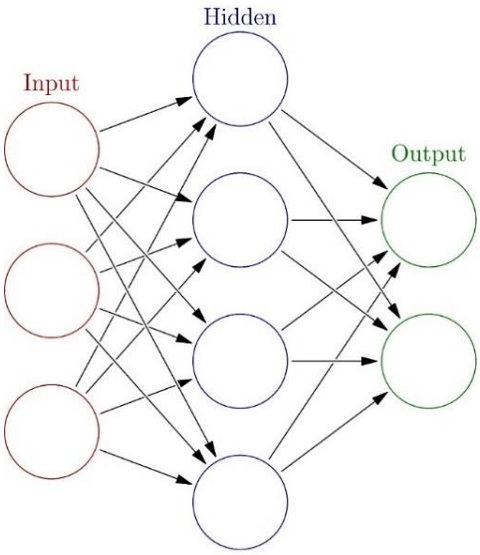

Fig. 4. Structure of the two-layer MLP neural network with a hidden layer.

3.1 | Evaluation of the Proposed Method

To evaluate the proposed method's performance in identifying the sleep stages, the specificity, sensitivity, and accuracy indexes were used by *Eqs. (12)-(14)*.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{12}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{13}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}. \tag{14}$$

4 | Simulation Results

The data used in this paper is extracted from a resource called Sleep-EDF in the Physionet database by Bob Kemp at the MCH-Westeinde Hospital located in the Netherlands [34]. This dataset was registered in 1989 and is still today available as a valid reference for researchers' studies. The samples were named based on steps 1, 2, 3, 4, REM and WAKE, and the polysomnography recorded from individuals within 48 hours includes EEG signals (Fpz-Cz and Pz-Oz channels), (horizontal) EOG and chin EMG. The EEG signals recorded from individuals and the private channel Fpz-Cz were used in this study to analyze various features and the classification of various sleep stages. The sampling frequency to record the EEG signal is considered to be 100 Hz. Ten samples to the separation of 5 men and five women were examined with different sleep stages and mean age of 39.7 ± 13.11; all subjects were healthy and did not use any medications. As shown in *Fig. 5*, a sample of an EEG signal is depicted for each part of the sleep stage, and *Table 1* also shows the number of each of the sleep stages in the studied samples.

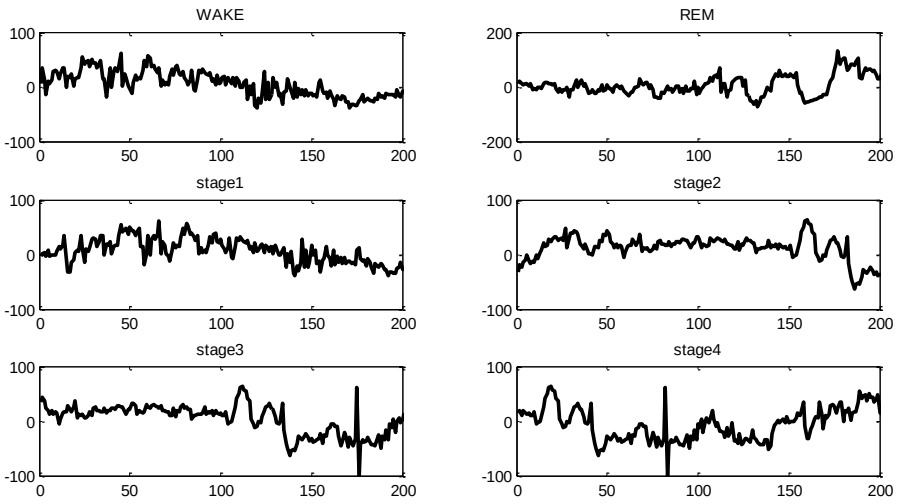

Fig. 5. Representing EEG signals at different stages of sleep.

Table 1. The number of sleep stages that occurred for the studied samples.

Number	Stage1	Stage2	Stage3	Stage4	REM	WAKE
sc4002	32	37	30	16	12	23
sc4012	42	55	29	9	18	17
sc4032	20	33	28	16	12	13
sc4062	25	26	17	9	6	14
sc4072	40	43	37	18	31	9
sc4082	23	55	46	11	8	12
sc4092	30	37	13	4	12	7
sc4102	41	50	10	0	3	12
sc4162	15	47	42	14	6	8
sc4171	15	53	64	17	10	22
Sum	283	436	316	114	118	137
Duration (min)	1-15	20	30-40		5-30	90

After identifying the target data, we dealt with the separation of various parts of the sleep stages in this paper using the existing labels of the EEG signals in the database. Then, to better identify these steps, we used seven nonlinear features that the calculation of them has been described in detail in the methods section. After that, the results of these features at different stages of sleep will be investigated and analyzed.

4.1 | Results of Nonlinear Features Extracted from Different Stages of Sleep

Because nonlinear features can reveal the dynamics of the EEG signal well, a comparison of the results obtained from the nonlinear features of the individual's EEG signal in the various sleep stages has been made in this section. *Table 2* indicates the mean and standard deviation of the nonlinear features extracted from each 10 seconds section of the EEG signal obtained for individuals at different sleep stages. In total, 100 sections of 30 seconds were selected from the database, and 300 sections of 10 seconds were obtained for feature extraction and classification of all available data. *Table 3* also shows the mean and standard deviation values of the first four stages, known as the Non-Rapid Eye Movement (Non-REM) stage. Considering that there were three different modes for the classification of sleep stages, 1125 feature vectors were obtained.

Table 2. The mean and standard deviation of nonlinear features at different stages of sleep.

Feature Type	Stage 1	Stage 2	Stage 3	Stage 4	REM	WAKE
Lmean	10.76±2.72	11.12±2.71	6.84±1.89	6.55±1.92	13.55±3.65	17.57±4.98
Lmax	56.70±18.55	91.50±26.78	36.05±10.43	41.41±12.14	105.73±42.87	154.85±48.21
REC	27.80±11.32	21.407±7.61	15.17±4.76	14.58±3.23	32.09±14.29	36.04±11.91
DET	95.88±24.56	94.64±24.54	92.04±23.98	92.18±24.00	96.77±2.10	97.31±1.66
ShanEn	2.80±0.58	2.72±0.51	2.33±0.34	2.36±0.42	3.047±0.48	3.29±0.52
LAM	34.23±8.6	33.71±8.3	31.09±7.38	31.62±6.97	43.76±9.32	52.12±12.53
TT	2.32±0.52	2.27±0.48	2.26±0.48	2.42±0.56	2.14±0.38	2.65±0.74

Table 3. The mean and standard deviation of nonlinear features at the first four stages of sleep.

Feature Type	Non-REM	REM	WAKE
Lmean	8.81±2.87	17.57±4.98	13.55±3.65
Lmax	56.42±17.10	154.85±48.21	105.73±42.87
REC	19.74±9.30	36.04±11.91	32.09±14.29
DET	93.68±2.92	97.31±1.66	96.77±2.10
ShanEn	2.55±0.43	3.29±0.52	3.047±0.48
LAM	32.67±7.67	52.12±12.53	43.76±9.32
TT	2.37±0.53	2.65±0.74	2.14±0.38

Changes in the values of the RP nonlinear features in the various stages of sleep are shown in *Figs. 6* to *9*. *Figs. 6-8* depict the features of Lmean, REC, DET, and ShanEn in the different stages of sleep as a boxplot, respectively. In *Fig. 5*, the Lmean feature values show a significant difference in the REM and non-REM stages. Due to this feature's property, it can be inferred that structures are more systematic when individuals are in the REM sleep stage, and the dynamics of the changes are reduced at this stage. This also represents an increase in the deterministic and predictability of the system in individuals' REM sleep stage. *Fig. 6* also shows that the REC feature, a measure of recurrence rate, has increased in REM mode compared to the non-REM mode, indicating a decrease in this sleep state's signal dynamics. Therefore, a recurrence to a point is more in REM conditions. The value of DET when people are in REM sleep mode has had a significant mutation compared to the non-REM mode. Increasing the value of DET represents the ability to predict the behavior of the signal after the non-REM mode. *Fig. 8* shows variations in the value of DET in different stages of sleep. The number of entropy of the diagonal lines in the RP is shown in *Fig. 9*. As shown in this Figure, when the individual is at the REM stage, the degree of entropy has a significant mutation, which can be argued that this feature creates a good

distinction between the REM and non-REM stages. Also, this feature shows that as the person reaches the REM sleep stage, the dynamics of the EEG signal are reduced.

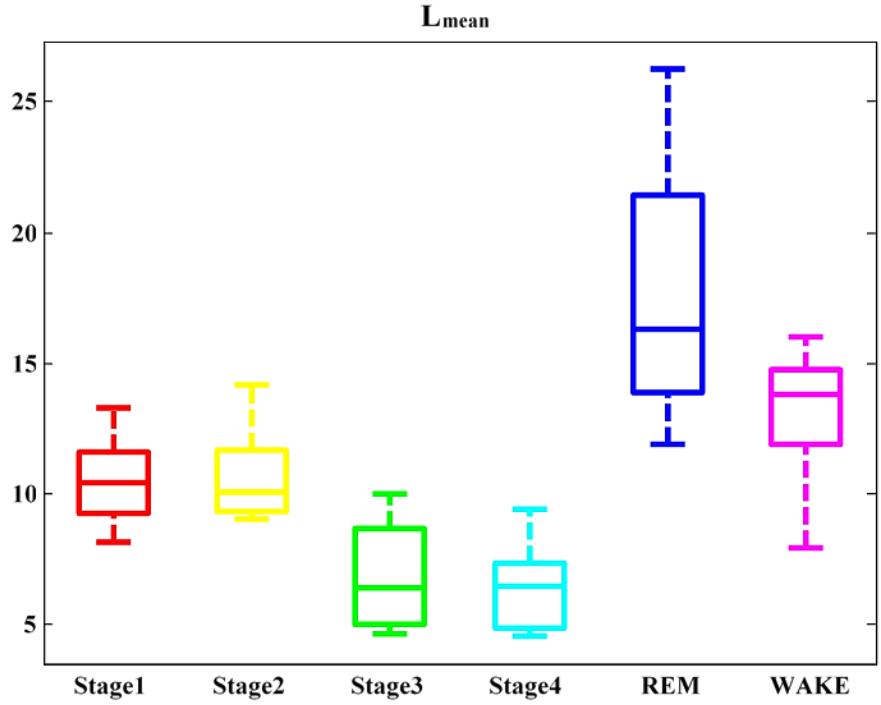

Fig. 6. Compare the sleep stages in L_{mean}.

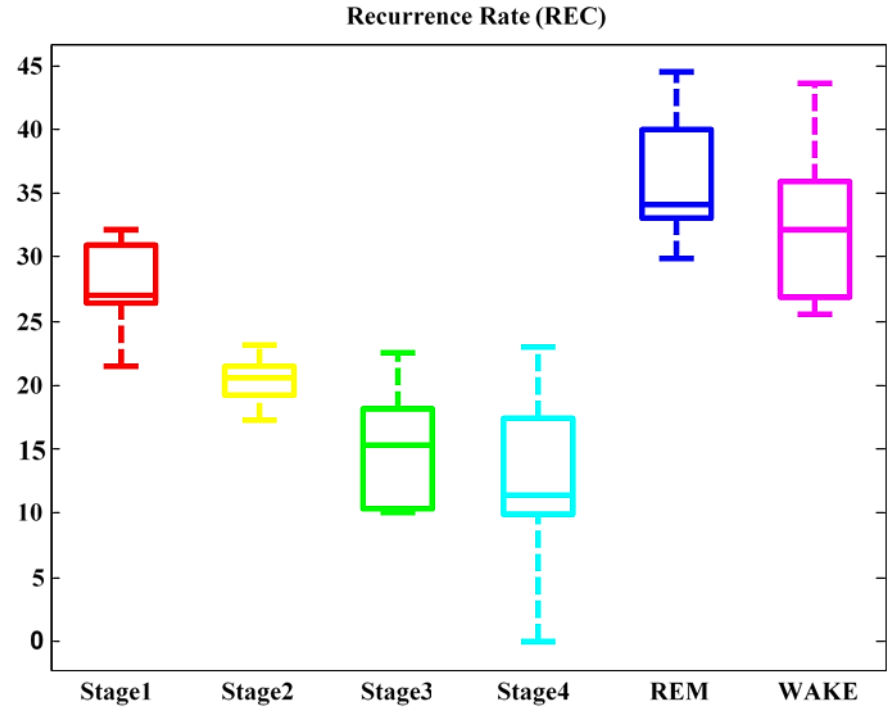

Fig. 7. Compare the sleep stages in Recurrence Rate (REC).

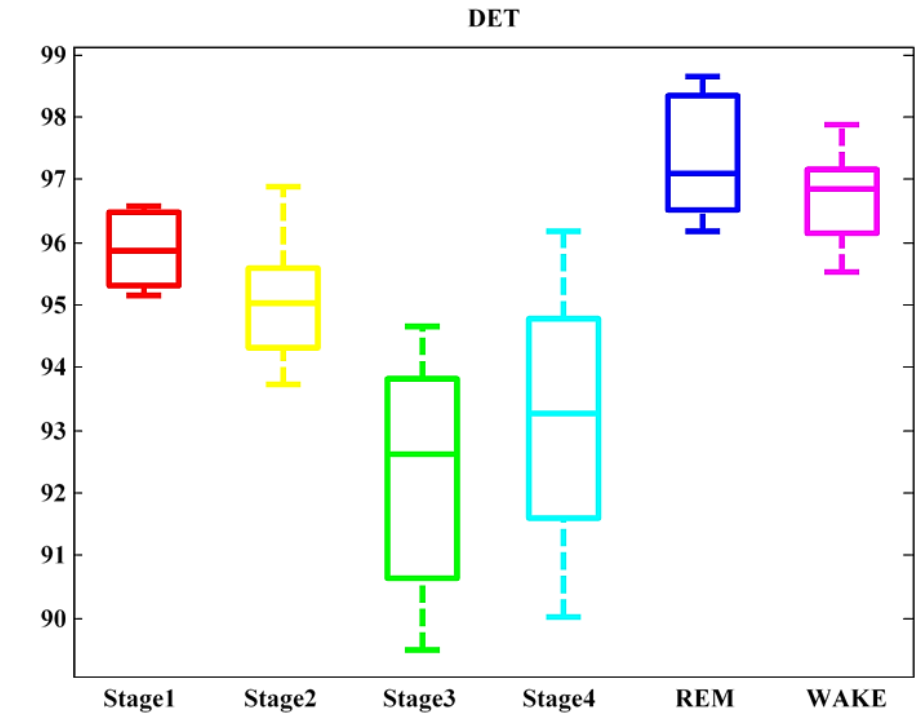

Fig. 8. Compare the sleep stages in DET.

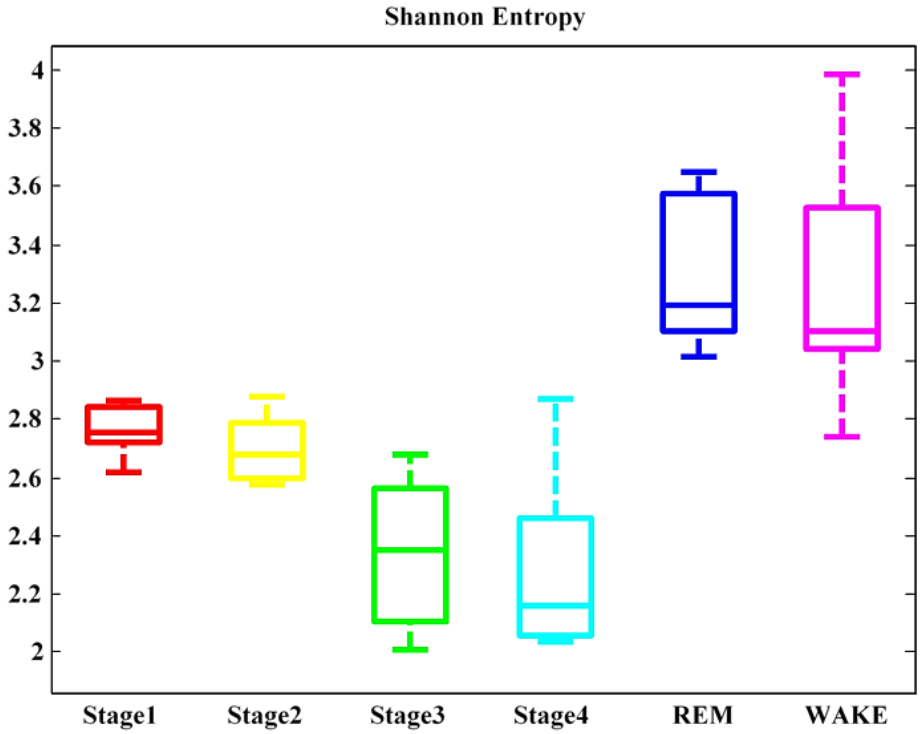

Fig. 9. Compare the sleep stages in ShanEn.

As shown in *Table 2* and *Figs. 6-9*, the separation of sleep stages cannot be easily addressed by these features. Still, the combination of these features together brings us to a correct diagnosis. Many features in the separation of the REM and AWAK stages have similar and close values together. To better distinguish these two states, we require to use intelligent systems for more accurate identification. Then, to determine the most proper number of hidden layers and neurons of each layer, the neural network performance accuracy was calculated for the layer change and the number of hidden layer neurons. The

structure of the neural and MLP layers optimized for the number of different features and the neural network's accuracy in the test mode has been shown in *Table 4*.

Table 4. Structure of optimal network for some different features.

N0. Features	N0. Input Layer 2	N0. Hidden Layer 1	N0. Hidden Layer 2	N0. Output Layer	Accuracy (%)
7	7	14	10	2	91.43±5.89
6	6	12	9	2	93.66±6.78
6	6	9	7	2	92.78±6.43
5	5	8	7	2	95.34±3.81
5	5	7	5	2	92.90±8.98
4	4	8	6	2	88.45±11.64
4	4	6	5	2	83.67±10.32

In MLP, the number of neurons in the input layer is equal to the number of features, and the number of neurons in the output layer is considered to be two. The number of hidden layers and neurons in each of them was determined by trial and error. Because the MLP training process begins with random weighting and the network converges to a different local minimum for each time, a fixed network's performance with a certain structure differs for different performances. To overcome this problem in optimization, the average accuracy rate of a network was used in 100 different performances for comparison. The sigmoid function was also selected as the activation function in neurons. As can be seen, the proposed system with 5 features, 8 neurons in the hidden layer 1, and 7 neurons in the hidden layer 2 is the best-achieved result, and the value of standard deviation is lower in this case. Finally, considering the network's desired structure based on the obtained accuracy, the neural network was trained 100 times, and the mean and standard deviation of specificity, sensitivity, and accuracy of the system were calculated according to the testing data. The results are presented in *Table 5*.

Table 5. Neural network performance using optimal structure.

Sleep Stages	Accuracy (%)	Sensitivity (%)	Specificity (%)
Non-REM-REM	98.32±2.11	99.03±1.43	98.54±1.88
Non-REM-Wake	97.76±2.34	98.71±1.95	98.02±1.23
REM-Wake	93.62±3.14	94.16±2.71	93.77±2.57

5 | Discussion

One of the methods considered by many investigators to determine the different stages of sleep is the use of brain signals. Despite extensive studies performed in the field of sleep stage detection using brain signals, recognizing sleep stages is still considered an interesting and serious issue for researchers. The first step to designing an automatic system for classifying sleep stages is quantifying recorded biological signals. Then, the quantified features achieved should be classified by a suitable system. The most important signal used in the classification of sleep stages is the EEG signal.

Recently, the use of nonlinear methods in processing physiological signals has gained much popularity due to the nonlinear nature of biological systems [42]. This paper aims to provide a new method based on the nonlinear analysis of the EEG signal to identify the various stages of sleep. RQA is a nonlinear algorithm that uses a RP of a dynamic system and quantifies the system's phase space features. Given the brain as a nonlinear system and an EEG signal as a manifestation of this system, some of the changes made in the EEG signal caused by mental state change can be realized through applying this algorithm.

As mentioned, the intuitive classification of sleep stages is time-consuming and tedious, and on the other hand, results depend on the level of experience of specialists. Thus, the automatic classification of sleep stages can facilitate this time-consuming and tedious work. This paper attempted to automatically separate the three Non-REM, REM, and Wake general modes using the EEG signal. To do this, the extraction of nonlinear features from different sleep stages was addressed using the EEG signal and reconstructing the

RP. Then, an Error Back Propagation Learning algorithm and an MLP neural network were used to classify the feature vectors. The results showed that the designed automatic system with a relatively good accuracy could separate these three modes. As stated in the definition of sleep stages, there is a similarity between the EEG signal in the REM sleep and stage 1 of NREM sleep. Therefore, the complete separation of sleep stages by the EEG signal alone is not possible, and EMG and EOG signals are required to recognize the sleep stages better. Researchers conducted in the field of automatic detection sleep stage, which are referred to in the introduction part to some of them, confirm this. In general, the research results in the field of sleep analysis are highly dependent on the way of data recording and the result of intuitive analysis by a specialist. *Table 6* shows the results of research carried out using different methods in recent years. A comparison of the results shown in *Table 6* clearly confirms the effectiveness of this paper's proposed method to separate the sleep stages with high accuracy. The use of fuzzy logic to quantify stress in each case is also a suggestion that researchers interested in this field may consider in the future [43]-[45].

Table 6. Compression techniques applied to EEG data for sleep stages detection.

N0.	Author(s)	Year	Method(s)	Channel Type	Accuracy
1	Ebrahimi et al. [35]	2008	ANN	Pz-Oz	93%
2	Li et al. [36]	2009	KNN	Fpz-Cz , Pz-Oz	81.7%
3	Güneş et al. [8]	2010	KNN and DT	-	82.21%
4	Vatankhah et al. [37]	2010	SVM	Fpz-Cz, Pz-Oz	98%
5	Jain et al. [48]	2012	ANN	-	93%
6	Huang et al. [4]	2013	SVM	-	70.92%
7	Hsu et al. [7]	2013	Elman Network	Fpz-cz	87.2%
8	Phan et al. [16]	2013	KNN	Fpz-Cz	94.49%
9	Şen et al. [15]	2014	DT	-	71.88%
10	Rodríguez-Sotelo et al. [39]	2014	ANN	Fpz-Cz, Pz-Oz	80%
12	Zhu et al. [46]	2014	SVM	Pz-Oz	87.5%
13	Obayya1 et al. [47]	2014	FCM	-	92.27%
14	Theodoridis et al. [40]	2015	Stacked sparse auto encoders NN	Fpz-Cz	78%
15	Hassan et al. [5]	2015	NB and LDA	Fz-Oz	88.62% , 90.11%
16	Aboalayon et al. [41]	2016	DT	Fpz-Cz	93.13%
17	Hassan and Subasi [18]	2017	TQWT	Fpz-Cz, Pz-Oz	95.35%
18	Rahimi et al. [20]	2019	SVM	ECG-HRV	81.76%
19	Tăutan et al. [21]	2020	RF	EEG-ECG-EMG	93%
20	Surantha et al. [19]	2021	SVM	HRV	82.1%
21	Sharma et al. [22]	2021	WD	EEG	85.1%
22	This Work	2021	RQA	Pz-Oz	98.32%

6 | Conclusion

The correct and accurate separation of each human sleep stage was performed in this paper using EEG data from the Physionet database. This separation was conducted by selected nonlinear features extracted from the Electroencephalography (EEG), whereas many of the proposed and raised methods by different researchers used time and frequency features. In the paper, after selecting the target data, we divided the signal to separate the sleep stages using the database tag. Then, to detect better identification of the algorithm, the extraction of features from different sections was performed using nonlinear features. To classify the data, features extracted from the various stages are separated into training and testing data. Using the MLP neural network and nonlinear features, results were obtained that made acceptable separation of sleep stages. Also, the separated stages for training include NREM, REM, and WAKE that the separation is also recognized for testing in this way.

Given that 6 to 8 hours of sleep at night is almost a standard rate, it can be said that the most common sleep disorders include disorders in the sleep cycle of people, which, due to living conditions and cultural changes, reduce or increase this standard rate. The incidence of sleep disorders is associated with a sleepless night, insomnia, apnea, etc., as well as neurological disorders such as stroke, Alzheimer's, or Parkinson's. The proposed algorithm of this paper can be very helpful in the field of timely clinical diagnosis and various diseases. The result of this paper could identify and distinguish all stages of sleep at an acceptable level. In addition to saving time, automatic analysis of sleep stages can help better and more accurate diagnosis and reduce physicians' workload in analyzing sleep data through visual inspection. As mentioned, the intuitive classification of sleep stages is time-consuming and tedious, and on the other hand, the results depend on expert experience. Thus, automatic classification of sleep stages can be time-consuming and tedious.

Separating sleep stages with the help of EEG signals alone cannot achieve 100% results. Therefore, using other signals such as EOG and EMG can help to diagnose sleep stages. Also, in general, the research results in the field of sleep analysis have been strongly correlated with the way it is recorded and the result of intuitive analysis by an expert. It is suggested that researchers pay attention to cardiac signals in future research to study the sleep stage. Using more data and deep learning techniques can also be an exciting topic for future research by researchers.

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Conflicts of Interest

All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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