

Automatic Sleep Stage Classification Using 1D Convolutional Neural Network

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Received: 11 August 2020 / Accepted: 22 August 2020

Abstract

Purpose: Sleep is one of the necessities of the body, such as eating, drinking, etc., that affects different aspects of human life. Sleep monitoring and sleep stage classification play an important role in the diagnosis of sleep-related diseases and neurological disorders. Empirically, classification of sleep stages is a time-consuming, tedious, and complex task, which heavily depends on the experience of the experts. As a result, there is a crucial need for an automatic efficient sleep staging system.

Materials and Methods: This study develops a 13-layer 1D Convolutional Neural Network (CNN) using single-channel Electroencephalogram (EEG) signal for extracting features automatically and classifying the sleep stages. To overcome the negative effect of an imbalance dataset, we have used the Synthetic Minority Oversampling Technique (SMOTE). In our study, the single-channel EEG signal is given to a 1D CNN, without any feature extraction/selection processes. This deep network can self-learn the discriminative features from the EEG signal.

Results: Applying the proposed method to sleep-EDF dataset resulted in overall accuracy, sensitivity, specificity, and Precision of 94.09%, 74.73%, 96.43%, and 71.02%, respectively, for classifying five sleep stages. Using single-channel EEG and providing a network with fewer trainable parameters than most of the available deep learning-based methods are the main advantages of the proposed method.

Conclusion: In this study, a 13-layer 1D CNN model was proposed for sleep stage classification. This model has an end-to-end complete architecture and does not require any separate feature extraction/selection and classification stages. Having a low number of network parameters and layers while still having high classification accuracy, is the main advantage of the proposed method over most of the previous deep learning-based approaches.

Keywords: Sleep Staging; 1D Convolutional Neural Network; Classification, Electroencephalogram.

1. Introduction

Sleep plays an important role in human health, and the lack of healthy sleep can lead to neurological and physical illnesses. Classification of sleep stages is a costly and difficult task that needs considerable work by experts. Also, the quality of the scoring depends on the experience and fatigue of the expert. In fact, the inter-expert agreement is often less than 90% [1, 2]. In fact, the detection of discriminative patterns in EEG signal variation is so difficult, because it has a complex nature [3]. Hence, the existence of an automatic system for scoring sleep stages is essential.

The Polysomnography (PSG) is the data acquired for sleep staging and includes Electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG), etc. To record PSG data, the subject is required to wear many sensors to record various biological signals. These signals are very useful for monitoring an individual's sleep. Polysomnographic recordings are segmented into 20- or 30-s epochs according to the Rechtschaffen and Kales (R & K) rules [4]. Rechtschaffen and Kales assigned labels: Wake (W), stages 1-4 (S1, S2, S3, and S4) and rapid eye movement (REM) to each epoch of the PSG data. Later, according to the American Academy of Sleep Medicine (AASM), S3 and S4 stages were combined as Slow-Wave Sleep (SWS) stage [5].

A complete sleep cycle is between 90 to 110 minutes [6, 7]. Wake time before sleep is known as Wake stage (W). S1 is the first and the lightest stage of sleep. At this stage, the frequency of brain activity observed in EEG is significantly lower than wake time. Also, in S1 stage the breathing has a regular rate and the muscle tone and core body temperature decrease. S2 often follows S1 and is characterized by sawtooth waves and sleep spindles. In this stage, the eye movements stop. S3 and S4 sleep stages are called Slow Wave Sleep (SWS) and are the deepest stages of Non-REM (NREM) sleep since the brain activity is considerably reduced. The fifth stage, i.e. REM, is associated with dreaming. In REM stage, breathing is more irregular and the heart rate often increases [8].

The recording of PSG data is an expensive procedure and unpleasant for the subjects, hence, recording just EEG signals for sleep monitoring and staging is an easier economical process for at-home sleep monitoring.

Several studies have used multi-channel EEG signals to classify sleep stages accurately using rule-based methods [9], EEMD [10], and Convolutional Neural Network (CNN) [11]. The automatic sleep scoring by multi-channel EEG data has some physical and practical constraints [12]. Employing minimum and the most effective number of EEG channels is required to have an appropriate sleep signal localization and staging [13].

During the process of sleep stage classification, some steps like feature extraction, feature selection/reduction, and classification are performed. For the feature extraction step, time, frequency, time-frequency, and non-linear feature extraction methods have been used in different studies [14-16]. For the classification step, the existing literature provides several methods like fuzzy K-means clustering [17, 18], hidden Markov models [19-22], random forest [23, 24], support vector machine [25-29], and artificial neural networks [14], [26], [30-32]. However, almost all these methods are based on handcrafted features, which require designers to have an extensive knowledge of the field. Sometimes designers are not assured which features are useful to be employed among these handcrafted features.

Today, there are several machine learning based algorithms for automatic sleep stage classification using handcrafted features [33, 34], which consist of preprocessing step to remove noise and artifacts from EEG signals, feature extraction and selection step to select discriminative features, and finally, machine learning step to classify sleep stages based on the selected features. The success of these approaches completely depends on the quality of extracted features. On the other hand, deep learning-based approaches can automatically find the relation between the raw input and output, extract the discriminative complex features, and integrate feature extraction and classification procedures. Several deep learning algorithms have been proposed for sleep scoring, including autoencoders [35], Convolutional Neural Networks (CNN) [36], and recurrent neural networks [37], however, the ideal results in terms of both high classification accuracy and low model complexity have not been obtained yet. Consequently, proposing more effective deep learning-based approaches are still required.

In this study, we propose a one-Dimensional Convolutional Neural Network (1D CNN) which has an end-to-end structure for sleep stage classification. The main advantages of our study are as follows: using raw and single-channel EEG signals as the input of CNN, and providing a network with fewer trainable parameters and consequently less model complexity, while still having high classification accuracy.

This paper is organized as follows. In Section 2, a detailed description of the materials and methods is introduced. The results that can reflect the performance of our proposed method are presented in Section 3. Finally, in Section 4, the discussion about experimental results and the model analysis are put forward.

2. Materials and Methods

2.1. Sleep Dataset

In this study, we use the sleep-EDF [38] dataset to evaluate the proposed deep CNN model, which is available on the Physionet website [39]. This dataset contains Polysomnogram (PSG) recordings acquired from eight healthy male and female individuals. Each PSG recording composes of EEG (from Fpz-Cz and Pz-Cz channels), horizontal EOG, submental chin EMG, and oronasal respiration. EEG and EMG signals were recorded with a sampling frequency of 100 Hz. Each 30-s epoch was labeled for sleep stages as wake (W), Rapid Eye Movement (REM), S1, S2, S3, S4, M (movement time), and ? (not scored). Table 1 shows the number of samples of each sleep stage. The wake stage and S1 stage have the highest and lowest number of samples, respectively.

Table 1. Detailed information about the sleep-EDF Database [11]

Database	Sleep Stages						Total Samples
	Wake (W)	S1	S2	S3	S4	REM (R)	
sleep-edf	8055 (53.03%)	604 (3.97%)	3621 (23.84%)	672 (4.42%)	627 (4.12%)	1609 (10.59%)	15,188

As a result, it reduces computational complexity. The dropout layer avoids the overfitting problem by inactivating the neurons in the network. The last layer of a 1D CNN is called a fully connected layer, which is responsible for classification task.

2.2. Preprocessing

The continuous raw single-channel EEG data are segmented to 30-s epochs and a label is assigned to each epoch based on the annotation file. The stages include Wake (W), Rapid Eye Movement (REM), S1, S2, S3, S4, M (movement time), and ? (not scored). According to the American Academy of Sleep Medicine (AASM) standard, we integrated the stages of N3 and N4 in one class named N3 and excluded M (movement time), and ? (not scored) stages to have five sleep stages [46]. In our study, no filtering was applied to data, which is an important difference in comparison with other studies.

2.3. Convolutional Neural Network (CNN)

Convolutional neural networks are usually used to recognize the two-dimensional images [40], but there is no limitation about the dimension of input data [11]. The one-Dimensional Convolutional Neural Network (1D CNN) is suitable for one-dimensional input data, like biomedical signals [41]. The first element in 1D CNN is convolution operation shown in Equation 1 [11]:

$$(S * W)_n = \sum_{i=1}^{|W|} W(i)S(i + n + 1) \quad (1)$$

This equation is the discrete convolution operation between S (1D input data) and W (kernel or filter). In fact, kernels slide over the input data. The output of this convolution operation is called a feature map because this operation extracts features from the input data [11]. The pooling layer, which is the second element in the 1D CNN, reduces the dimension of the output of the convolution layer, as a down-sampling [42].

After convolution and fully connected layers, an activation function is applied. The activation function makes the network structure nonlinear. The Relu activation function, defined in Equation 2, is placed

after convolution and dense layers and creates nonlinearity in the network structure:

$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (2)$$

According to Equation 3, the Softmax activation function is used in the last layer of the 1D CNN and it predicts which input signal is related to the Wake, S1, S2, S3, and REM stages [11]:

$$p_i = \frac{e^{x_j}}{\sum_1^k e^{x_k}} \text{ for } j = 1, \dots, k \quad (3)$$

Where x is the input of the network and p_i is the output value the network.

2.4. Our Proposed Deep Model Architecture

The inputs of 1D CNN were segmented into segments of 3000 samples length. The first layer has 4×6 filters and 1 stride to extract 4×2995 features. The second layer is max-pooling with a pooling size of 2 and 2 strides, which produces an output signal of size 4×1497 .

The third layer of the network is a convolutional layer, which has 4×5 filters and 1 stride to generate feature maps of size 4×1493 . The fourth layer is max-pooling with a pooling size of 2 and 2 strides, which produces an output signal of size 4×746 . In the successive layers, these patterns are repeated similarly, but filters and strides are of different sizes. To prevent overfitting, the dropout layer is used with a rate of 0.5. The Flatten layer creates suitable dimensions for the dense layer, and the last layer is

softmax to obtain the probabilities of each network input belonging to different class labels. The softmax layer has five units, equal to the number of classes. The details of all layers and the parameters of our proposed 1D CNN are shown in Table 2.

2.5. System Performance Evaluation

There are four measures usually provided by the different works as performance indicators of our proposed sleep stage classification method: accuracy, sensitivity, specificity, and confusion matrix.

The classification accuracy, sensitivity, and specificity are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. To evaluate the system performance, we use a k-fold cross-validation algorithm. As explained by [43], the dataset is divided randomly into k equal-sized subsets. At each fold, the $(k - 1)$ subsets are used as the training and validating data and 1 subset is used for testing. This process is repeated k times equal to the number of folds. The results of the k folds are averaged and reported as the system performance. [43].

Table 2. The details of layers and parameters of our proposed 1D CNN for sleep staging

Layer No.	Layer Name	No. of Filter × Kernel Size	Region/Unit Size	Layer Parameters	No. of Trainable Parameters	Feature Map Size
1	1D Conv	4×6	-	ReLU, Stride=1	28	4×2995
2	MaxPool	-	2	Stride = 2	0	4×1497
3	1D Conv	4×5	-	ReLU, Stride=1	84	4×1493
4	MaxPool	-	2	Stride = 2	0	4×746
5	1D Conv	10×4	-	ReLU, Stride=1	170	10×743
6	MaxPool	-	2	Stride = 2	0	10×371
7	1D Conv	10×4	-	ReLU, Stride=1	410	10×368
8	MaxPool	-	2	Stride = 2	0	10×184
9	1D Conv	15×4	-	ReLU, Stride=1	615	15×181
10	MaxPool	-	2	Stride=2	0	15×90
11	Flatten	-	-	-	0	1350
12	Dropout	-	-	Dropout rate=0.5	0	1350
13	Dense	-	5	Softmax	6755	5

2.6. Experimental Design

The distribution of sleep stages in the sleep-EDF dataset is not uniform. The number of EEG epochs with wake stage and S2 stage are so greater than the number of those with other sleep stages. Moreover, stage 1 has the lowest number of EEG epochs in the sleep-EDF dataset. Most machine learning algorithms do not learn well the class imbalance issue. To solve this problem, we oversampled the dataset to have a balanced number of sleep stages in each class. For this purpose, we have used the Synthetic Minority Over-sampling Technique (SMOTE) to generate the synthetic data points [44].

For evaluating our proposed systems, we have used k-fold cross-validation. We set k to 20 for the sleep-EDF dataset. Our network was trained with 100 epochs. The Adam optimizer was used with mini-batches of size 30, a learning rate of $\alpha=0.01$, and a decay of $d=0.003$. The python programming language and Keras library were used to implement our proposed model.

3. Results

Table 3 shows the multi-class specificity, sensitivity, and accuracy. The most misclassified stage is S1 with 45.47 % of correct classification. The most correctly classified stage is Wake with 95.84 % of correct classification. The overall accuracy, sensitivity, and specificity are 94.09%, 74.73%, and 96.43% for classifying five sleep stages. According to Table 4, stage 1 is most often confused with REM, Wake, and S2 and almost never with S3. Sometimes S2 is confused with S3 and seldom with other stages. Also, S3 is confused with S2 and rarely with other stages. REM is most confused with S1 and S2 and

Table 3. The performance criteria of sleep stage classification obtained by using the proposed method

Sleep Stages	Specificity%	Sensitivity%	Accuracy%
Wake	97.66	94.23	95.84
S1	95.18	45.47	93.20
S2	95.70	78.94	91.67
S3	96.58	86.42	95.70
REM	97.05	68.59	94.04

rarely with other stages. Wake is usually confused with S1 and rarely confused with other stages.

Table 4. The confusion matrix of our proposed method

Predicted Labels	Wake	S1	S2	S3	REM
Wake	379	19	1	1	3
S1	5	14	5	0	7
S2	1	4	143	23	10
S3	0	0	8	56	0
REM	2	12	11	0	55

4. Discussion

4.1. Main Findings

Since multi-channel EEG recording is an expensive and unpleasant process compared with single-channel EEG recording, using less channels are a significant tendency. In this study, we have illustrated that it is feasible to use a single-channel EEG signal to classify sleep stages. Furthermore, our model does not require any special signal preprocessing step. Besides, we have performed a 1D CNN working on raw EEG signals without any separate feature extraction or feature selection step. Thus, there is no need to feature domain knowledge. This is an important advantage compared with other machine learning approaches because the network automatically learns the most important features for classification tasks. Training a large and deep convolutional neural network requires intensive computations, much training time, and much memory allocation. Therefore, performing a convolutional neural network with a fewer training parameter that can be carried out on a personal computer is efficient. Hence, we provide a 1D-convolutional neural network, much simpler than previous studies for scoring the sleep stages of EEG data.

4.2. Comparison with Other Methods

Table 5 illustrates some characteristics and performance metrics from recent studies on 1D convolutional neural networks for automatic sleep stage scoring. In comparison with the study [45], our total accuracy is higher while the number of training parameters is lower.

Table 5. Comparison of the results with the other published approaches

Reference	Dataset	Channel	Network	K-Fold or Train/Validation/Test	Input Size	Accuracy	S1-Sensitivity	No. of Trainable Parameters
[45]	EDFX	Fpz-Cz	1D CNN	20-fold	3000	0.75	-	1,114,000
[46]	EDFX	Fpz-Cz	1D CNN-LSTM	20-fold	3000	0.82	0.591	546,525,189
	EDFX	Pz-Cz		20-fold	3000	0.798	-	
	MASS	F4-EOG		31-fold	3840	0.862	0.593	
[47]	SHHS-1	C4-A1	1D CNN	0.5/0.2/0.3	15000	0.87	0.35	199,068,478
[48]	EDFX	Fpz-Cz	1D CNN	20-fold	3000	0.9197	-	13,485
	EDFX	Pz-Cz		20-fold	3000	0.9110	-	13,485
	EDFX	Ensemble		20-fold	6000	0.9265	-	40,595
[11]	EDFX	Fpz-Cz	1D CNN	0.7/0.15/0.15	3000	0.9048	-	1,091,893
	EDF	Fpz-Cz		0.7/0.15/0.15	3000	0.9083	0.19	
This study	EDF	Fpz-Cz	1D CNN	20-fold	3000	0.9409	0.4547	8,062

The study [46] has a higher S1-sensitivity than our method, but it has a more complex network with a higher number of training parameters. Our study has higher accuracy and S1-sensitivity rate in comparison with the study [47]. Besides, our network is simpler than the mentioned network.

Despite having fewer training parameters, Besides, our network is simpler than the mentioned network [48]. The last study [11] has a different train-test-split approach but having the same dataset as our study is an important point.

Our study has a considerably higher total accuracy and S1-sensitivity rate than [11]. Furthermore, our network has a small number of training parameters according to Table 5.

5. Conclusion

In this study, a 13-layer 1D-CNN model is proposed for the classification of sleep stages. This paper has proposed a novel sleep stage classification approach based on single-channel EEG signal. We have used the Synthetic Minority Over-sampling Technique (SMOTE) to handle the class-imbalance problem in sleep stage

classification. Moreover, in our proposed model, there is no need for any separate feature extraction, feature selection, and classification steps. Experiments verified that our proposed model has lower trainable parameters, higher overall accuracy, and higher S1-sensitivity compared with previous 1D CNN based studies. Our model requires labeled data, and obtaining labeled data is expensive. Therefore, Autoencoder as unsupervised training algorithm will also be our future work.

Acknowledgments

We would like to appreciate Cognitive Sciences and Technologies Council of IRAN (CSTC) for supporting this research.

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