Detection of Sleep Stages Using EEG Signal Based On Convolutional Neural Network

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Abstract

Diagnosing sleep and wakefulness is an important method in diagnosing sleep problems. This work is done by specialists based on the physical examination of biological signals such as EEG, EOG, ECG, EMG, etc. The deep learning method based on convolutional neural network is one of the newest and most important methods of analysis, separation, and diagnosis, which is expanding day by day. In this article, the deep learning-based convolutional neural network is used to extract features from the time-frequency domain of the EEG signal to classify sleep stages. Here, from the EEG signal, the time-frequency image of the signal is calculated based on the spectrogram. Then deep features are extracted using a convolutional neural network with Alexnet architecture with 8th-order fully connected layers. Finally, without changing the nature of the signal, sleep stages are detected with acceptable accuracy. Finally, by using the SVM classifier, sleep stages were classified with acceptable accuracy. An accuracy of 99.6% was obtained for the classification of sleep stages, which indicates the ability of the method to distinguish sleep stages.

Keywords: EEG signal, deep learning, sleep stages, convolutional neural network.

1. Introduction

According to the standard of the World Health Organization, sleep has 6 stages, including rapid eye movement (REM), slow eye movement (NREM), first stage NREM, second stage NREM, and third stage NREM. This process of sleep stages occurs every 30 seconds, which is called a cycle [1]. EEG, EOG, EMG, ECG, PPG, and other signals are used to classify the sleep stage. Sleep is one of the basic needs of human's daily life and its study is very important to investigate its problems and solve them.

In recent years, sleep stage classification has been used using machine learning and deep learning methods. Deep learning is one of the new methods in signal and image processing. The convolutional neural network automatically extracts deep features. Today, it is very popular in the fields of engineering and medical engineering and has always had better results than other methods. Spectrogram-based power spectral features have been used to classify sleep stages from EEG signals [2]. In another research, Fast Fourier Transform (FFT) features were used to classify sleep stages, which reached 95.3% accuracy [3]. In the research [4], the energy of the relative frequency bands of the EEG signal was used for the NN classifier, and the new method was ahead of its time, but it was able to obtain 94.7% accuracy. The features of the time-frequency domain are very useful for classifying sleep stages and have been used in many studies. The use of time-frequency domain histograms (TFI) of EEG signals has been used for the automatic classification of sleep stages [5], [6]. Old classical methods and deep learning approaches have been proposed for the processing and classification of EEG signals [7].

Various feature extraction methods, including linear and non-linear, time and frequency, etc., are used by researchers to extract features from the EEG signal. [8, 9]. In [10] researchers proposed a method that used time-frequency images (TFIs) for EEG processing. This method performs the classification of sleep stages using the SVM classifier and features of TFIs. Deep models have many applications in the field of biomedicine (biomedical signals are EEG, ECG, EMG, and EOG [11]. In [12], deep learning models have been used for sleep stage classification. Based on convolutional neural network (CNN) AlexNet has been used to classify sleep stages.

In [13], a convolutional neural network (CNN), VGGNet, has been used to classify five sleep stages.

2. Materials and Methods

2.1. Database

This study uses the data set available on the Phiziont website. A dataset that is freely available online to researchers. The Sleep Heart Health Study (SHHS) is designed to examine sleep stages. It contains many recorded channels of patients included. EOG, EEG, EMG, ECG, Nasal Airflow, and EEG are in European Standard Data Format (EDF). These numerical values correspond to the stage of sleep described by the expert according to the criteria of Rechtschaffen and Kales. Table 1 shows the stages of sleep and their labels.

Table 1. Stages of sleep

Number class	Sleep stages
-1	Wake stage
0	REM stage
1	S1 stage
2	S2 Stage
3	S3 Stage
4	S4 Stage

2.2. Preprocessing

The signals with a sampling frequency of 125 Hz are available on the site, and in this article, the C3/A2 EEG signal is used with a 30-second window.

2.3. Signal processing

To use the convolutional neural network, the input of the network must be images, for this purpose, the two-dimensional image of the signal based on the spectrogram is used in this article.

2.4. Time-frequency image of the signal based on spectrogram

Vital signals are non-static, and uniformity and stability in themean non-existence, and for this reason, analyzing and analyzing them with other common methods cannot extract important features from the signal and achieve good results. Investigating and studying such signals in the time domain or in the frequency domain alone is useless and does not give good results and is not enough. In the simultaneous analysis and investigation of time-frequency, useful information can be obtained from the behavior of the signal, which is very useful and important.

To construct the time-frequency image of the proposed signal, the ECG signals in the time domain are first converted into a two-dimensional time-frequency spectrum using the short-time Fourier transform (STFT).

STFT is an advanced mathematical equation derived from the Discrete Fourier Transform (DFT), to discover the frequency and instantaneous amplitude of waves, whose similarity equation is shown in formula 1.

Its energy is assumed to be the spectrogram of the signal mentioned in equation number 2.

$$STFT(n,k) = \sum_{m=-\infty}^{\infty} \omega(m) X(n+m) e^{-j\frac{\pi}{\mathrm{mk}}} \tag{1}$$

The STFT energy form is called a spectrogram. Define as below:

$$SPEC(t,\omega) = |STFT(t,\omega)|^2 \tag{2}$$

The results obtained using STFT can obtain information about the temporal evolution of the signal frequency change, because the complete time interval is divided into a number of small time intervals and then they are analyzed alone using the Fourier transform[16].

Then windowing was done according to the R&K standard and each signal window was transferred to the time-frequency domain according to [16], [17]. To achieve the time-frequency domain, relations [18] have been used. Reassignment is specified as a comma-separated pair consisting of a logical value and "reassignment". If this is true in the program, then the spectrum sharpens the localization of the spectral estimates by performing time and frequency reassignment. The reassignment method produces periodograms and spectrograms that are easier to read and interpret. This method estimates each spectrum to the energy center of its bin instead of the geometric center of the bin. This technique provides accurate localization [19].

2.5. Convolutional Neural Network(AlexNet architecture)

This model has been trained and tested on more than one million images and can classify images with 1000 classes, which has many applications in image analysis and classification and has acceptable accuracy. Grid Grid Alex creates a hierarchical representation of the input images. This network consists of 25 layers, which have 8 layers with learnable weights: 5 convolutional layers and 3 fully connected layers [14]. The flowchart of the method is shown in Figure 1.

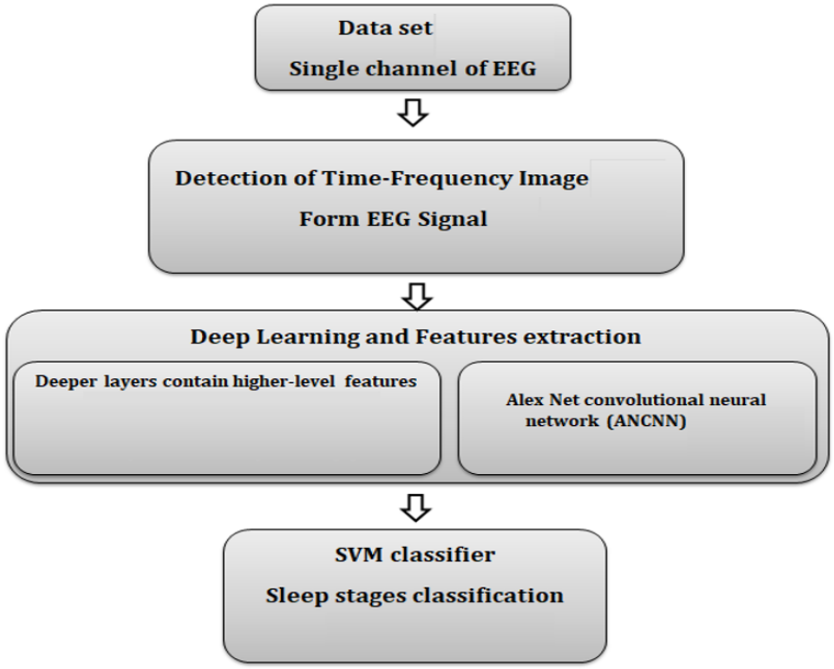

Fig.1. Flowchart of the general work method

3. Results

All processing steps have been performed using an HP laptop with a CORE I7 processor and 16 GB of RAM and using MATLAB 2020b software.

The signals with a sampling frequency of 125 Hz are available on the site, and in this article, the C3/A2 EEG signal is used with a 30-second window. Figure 2 shows samples of EEG signals in different states.

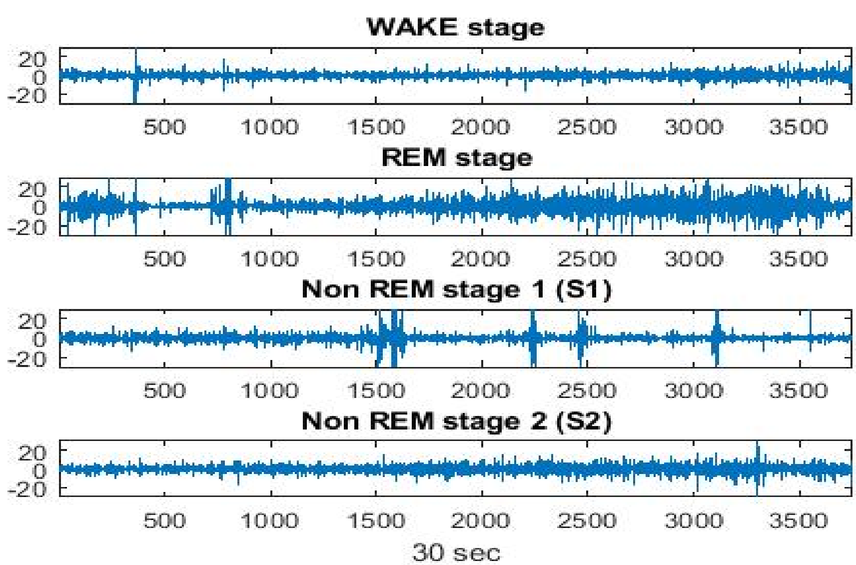

Fig.2. EEG signal in different sleep states

TFI is obtained using the method in [16,17]. Convolutional neural network is used here to analyze the results. Here ALEXNET network with fully connected layer fc8 (Softmax) is used and 1000 features are extracted. Finally, the features have been used to classify and diagnose sleep stages. Figure 3 shows the time-frequency domain (TFI) of the EEG data.

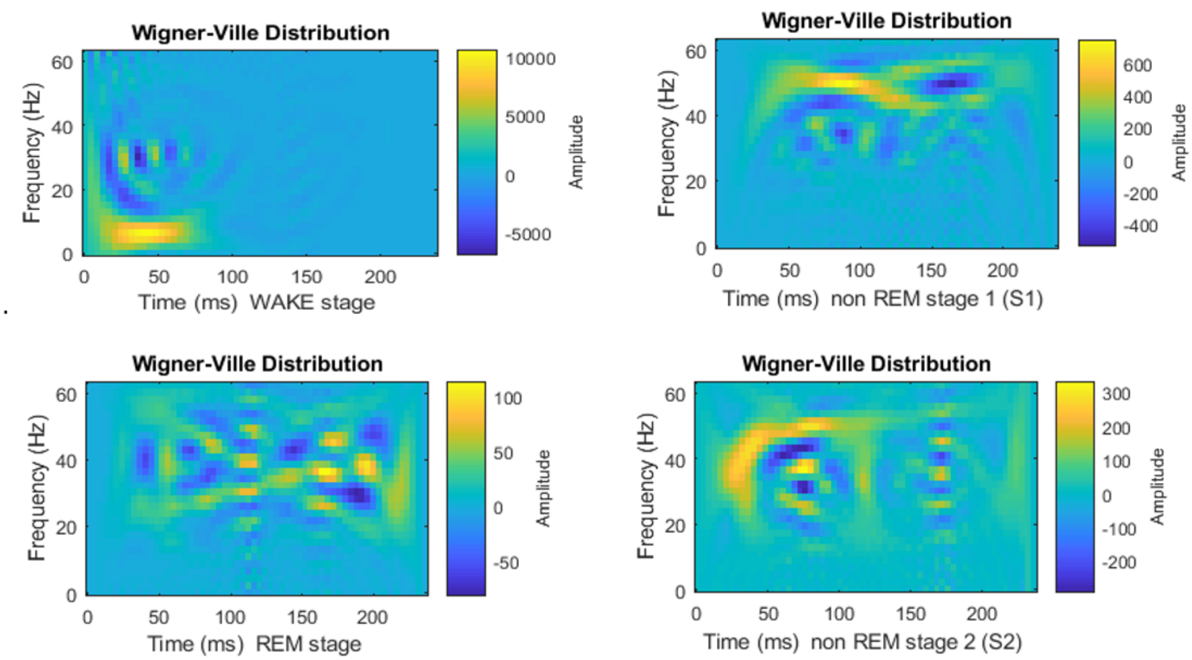

Fig.3. Time-frequency domain of EEG signal in different sleep states

Here using 'fc8' by alexnet deep learning to extract deep features.

3.1.Classifier

At this stage, due to the great attention paid to SVM, we have used this method. However, due to the use of invalid articles of different cores, we used all three cores for analysis. The purpose of presenting this work is to detect the depth of sleep with acceptable accuracy. Here, the results have been calculated using the confusion matrix according to Table 2 and the accuracy, precision, and sensitivity of the classifier using equations 2, 3, and 4, also with 10-fold validation.

Table 2.Confusion matrix

		predict	
		normal	Ab normal
taret	normal	TP	FP
	Ab normal	FN	FP

The method of calculating the accuracy, sensitivity, and precision of each class is calculated using the following equations.

$$Accuracy = \frac{(TN + TP)}{\mathrm{TN} + \mathrm{FP} + \mathrm{FN} + \mathrm{TP}} * 100 \tag{3}$$

$$\mathrm{Precision} = \frac{(TN)}{\mathrm{TN} + \mathrm{TP}} * 100 \tag{4}$$

$$\mathrm{Sensitivity} = \frac{(TP)}{\mathrm{TP} + \mathrm{FN}} * 100 \tag{5}$$

In Tables 3, 4, and 5, you can see the accuracy, precision, and average sensitivity results of the classifier

Table 3. Average accuracy results of the classifier

average accuracy	classifier
99.6	Alexnet convolutional neural network

Table 4. Average precision results of the classifier

avrage precision	classifier
99.3	Alexnet convolutional neural network

Table 5. Average sensitivity results of the classifier

average sensitivity	classifier
99.4	Alexnet convolutional neural network

4. Discussion

The data is obtained from the site with the validity and availability of Physionet. In this study, the time-frequency domain of the EEG signal is presented to classify the stages of sleep using the deep learning method. Most methods use EEG signal features to classify sleep stages.To reduce the calculation load, an optimized convolutional neural network based on Alexnet architecture was used, and the layers were reduced from 25 layers to 8 layers. Time-frequency domain features used to detect sleep stages by SVM classifier. Here, inspired by [7], we obtained the time-frequency image of the signal. Then, in the feature extraction phase, unlike all the deep learning methods used, which extracts features from the EEG signal. We extracted deeper features from the time-frequency image by fully connected ALEXNET without manual intervention and then used SVM method for classification to achieve high accuracy.

The accuracy of the proposed method was 99.6, which indicates that the proposed method is suitable for separating sleep stages. In the common methods of deep neural networks, the extracted features take a lot of time due to the large number of layers of the neural network architectures, and even in some cases, it does not cause a significant increase. In this research, we have reduced and optimized the layers of the widely used AlexNet architecture. In this work, we merged consecutive layers together and reduced from 5 convolution layers with 3 x 3 and 2 x 2 filters to one 8 x 8 convolution layer.

Also, the fully connected layers were reduced to one layer and finally the 8 main layers of our selection and optimal and proposed architecture reached 8 layers. This greatly reduced the processing time and reduced the computational load and complexity of the system to 0.3, and the results did not decrease significantly. According to the accuracy results obtained and the reduction of calculation load and processing time, it can be said that the proposed method is a suitable method for detecting sleep stages and other diagnostic methods.

References

[1] Stanislas Chambon1, 2, Mathieu N. Galtier2, Pierrick J. Arnal2, Gilles Wainrib3, and Alexandre Gramfort," A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series" IEEE Transactions on Neural Systems and Rehabilitation Engineering (Volume: 26, Issue: 4, April 2018 , Pages 758 - 769.

[2] OzalYildirim, UlasBaranBaloglu U Rajendra Acharya "A Deep Learning Model for Automated Sleep Stages Classification Using PSG Signals" International Journal of Environmental Research and Public Health2019, 16, 599 Pages 1 _ 21.

[3] Fathi, M., taghizadeh, M., moradi, M., shojaat, G. Diagnosis of Covid-19 using optimized convolutional neural network. journalof Artificial Intelligence in Electrical Engineering, 2023; 11(44): 25-32.

[4] Fatehi, M., khajooee, M., adlband, N., moradi, M. Detection of healthy and unhealthy ECG signal using optimized convolutional neural network. journal *of Artificial* Intelligence *in Electrical Engineering*, 2022; 11(43): 61-69.

[5] Zhihong Cui,1,2 Xiangwei Zheng ,1,2 Xuexiao Shao,1,2 and Lizhen Cui "employed a novel three-band time-frequency " HindawiComplexityVolume 2018, Article ID 9248410, 13 pages.

[6] EminaAlickovic and AbdulhamitSubasi " Ensemble SVM method for automatic sleep stage classification ".IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, 0018-9456, 2018 IEEE, pages 1_8.

[7] Varun BajajRam Bilas Pachori 'Automatic classification of sleep stages based on the time-frequency image of EEG signals Computer Methods and Programs in BiomedicineVolume 112, Issue 3, December 2013, Pages 320-328.

[8] Manish Sharma , Deepanshu Goyal , P V Achuth , U Rajendra Acharya"An accurate sleep stages classification system using a new class of optimally time-frequency localized three-band wavelet filter bank" Computers in Biology and Medicine · May 2018, pages 1-40.

[9] Béla WeissZsófia ClemensRóbertBódizsPéterHalász "Comparison of fractal and power spectral EEG features: Effects of topography and sleep stages " Brain Research BulletinVolume 84, Issue 6, 5 April 2011, Pages 359-375.

[10] L. G. Doroshenkov, V. A. Konyshev&S. V. Selishchev ." Classification of human sleep stages based on EEG processing using hidden Markov models "Biomedical Engineeringvolume 41, pages 25–28 (2007).

[11] Yu-Liang HsuYa-Ting YangJeenShing WangChung-Yao Hsu "Automatic sleep stage recurrent neural classifier using energy features of EEG signals" NeurocomputingVolume 104, 15 March 2013, Pages 105-114.

[12] B.Koley, D.Dey"An ensemble system for automatic sleep stage classification using single-channel EEG signal Computers in Biology and Medicine"Volume 42, 12December 2012, Pages 1186-1195.

[13] LuayFraiwanKhaldonLweesyNatheerKhasawnehHeinrich WenzHartmutDickhaus "Automated sleep stage identification system based on time-frequency analysis of a single EEG channel and random forest classifier " Computer Methods and Programs in Biomedicine, Volume 108, Issue 1, October 2012, Pages 10-19.

[14] B Bashash, L.Boubchir And G.Azemi" Methodologhy For Time_Freguency Image Processing Applied To The Classification Of Non-Stationary Multichannel Signals Using Instantaneous Frequency Discriptors With Applications To Newborn Eeg Signals", Journal On Advances In Signal Processing volume 2012, (2012), Pages 1-21.

[15] RonzhinaJanoušek, Koláˇrová, Nováková, Honzík, Provazník "Sleep scoring using artificial neural networks" Sleep Medicine Reviews 16 (3): pages 251 263 · October 2011

[16] Individuals Reza Boostani, ForoozanKarimzadeh, Mohammad TorabiNami" A Comparative Review on Sleep Stage Classification Methods in Patients and healthy MED SYS 2014 pages 77 - 91.

[17] Alborz Rezazadeh, SereshkehRobert, TrottAurélienBricoutTom Chau " Online EEG Classification of Covert Speech for Brain-Computer Interfacing " International Journal of Neural SystemsVol. 27, No. 08, 1750033 (2017) pages 1 - 16.

[18] Oliver FaustYuki HagiwaraTan Jen HongOh ShuLihU Rajendra Acharya " Deep learning for healthcare applications based on physiological signals: A review " Computer Methods and Programs in BiomedicineVolume 161, July 2018, Pages 1-13.

[19] Shu.Lih, Oh.Eddie, Y.K.Ng, Ru.San, Tan.U. Rajendra.Acharya"Automated diagnosis of arrhythmia using combination of Cnn and Lstm techniques with variable length heartbeats Author links open overlay panel" Computers in Biology and MedicineVolume 102, 1 November 2018, Pages 278-287.

[20] Shu Lih Oh, Yuki Hagiwara, U. RaghavendraRajamanickamYuvaraj, N. Arunkumar, U. Rajendra Acharya " A deep learning approach for Parkinson's disease diagnosis from EEG signals " Neural Computing and Applicationsvolume 32, pages10927–10933(2020).

[21] Moradi, M., Fatehi, M., Masoumi, H., Taghizadeh, M. Deep neural network method for classification of sleep stages using spectrogram of signal based on transfer learning with different domain data. *Scientia Iranica*, 2022; 29(4): 1898-1903.

[22] Moradi, M., Fatehi, M., Masoumi, H., Taghizadeh, M. Deep Learning Method for Sleep Stages Classification by Time-Frequency Image. *Signal Processing and Renewable Energy*, 2021; 5(3): 67-83.

[23] Moradi MM, Fatehi MH, Masoumi H, Taghizadeh M. Adaptive neuro-fuzzy method for sleep stages detection by PPG signal. Journal of Advanced Pharmacy Education & Research| Jan-Mar. 2020; 10(S1).