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Review of deep learning based methods for sleep apnea detection

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***Abstract*---**One of the most prevalent and serious causes of sleep disorders is sleep apnea syndrome. Manual identification of such disorders by investigating the EEG recordings is a time-consuming task. Hence, automatic detection of sleep apnea in EEG signals could be a preferred solution. In recent years, many deep learning algorithms are being reported for automatic sleep apnea detection. In this paper, a comprehensive review of various recently reported deep learning techniques like convolutional neural network (CNN), Bi-directional Long short-term memory (Bi-LSTM), recurrent neural network (RNN), etc., are presented and the performance of those techniques are compared.

***Keywords*---**convolutional neural network (CNN), deep learning (DL), electroencephalography (EEG), sleep apnea.

Introduction

Sleep apnea is a sleeping disorder that, if left untreated, can lead to major health issues such as high blood pressure and heart difficulties. Even with a full night's

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sleep, sleep apnea causes breathing to stop regularly throughout sleep, resulting in loud snoring and daytime exhaustion. Sleep apnea can affect anyone, although it is particularly common in overweight elderly men. Obstructive, central, and mixed sleep apneas are the three forms of sleep apnea.

In many countries, polysomnography (PSG) is used to diagnose this disease in sleep labs. This method takes more time to detect the disease and costs also more. Different biological signals such as EMG, ECG, and EEG are used to diagnose sleep apnea in many studies. EEG analysis has recently gained popularity as a method for detecting sleep apnea due to its ability to capture sleep respiratory disruption data, particularly repeated arousal. There are few approaches for detecting sleep apnea from an EEG signal that uses deep learning (DL) networks. For example, a convolutional network is used to detect apnea events using time-frequency pictures derived from EEG data.

In recent years many classification techniques for sleep apnea detection are reported [1-22]. An automatic recognition system based on the temporal dynamics of REM sleep EEG activity is suggested by S. Bayatfar, S. Seifpour, et al. in [1] to diagnose the sleep apnea syndrome. A two-stage neural network is proposed C. Sun, J. Fan, et al. in [2] to classify the sleep stages. M. A. Prucnal and A. G. Polak [13] are discussed one versus two Symmetrical EEG Channels are used to detect sleep apnea. A compact convolutional neural network (CNN) is proposed by A. M. Eldaraa, H. Baali, et al. [18] to classify the apnea and non-apnea sleep arousal categories. A sub-frame-based technique is proposed by I. A. Khan, T. I. Mahmud, et al. [19] to detect sleep apnea from EEG signals. T. Mahmud, I. A. Khan, et al. [21] proposed a unique method for automatically detecting apnea, which involves combining local fluctuations of temporal variables to discover global feature differences across a larger window. A deep fully convolutional-BiLSTM neural network is proposed by T. Mahmud, I. A. Khan, et al.in [22] for automatic detection of sleep apnea. A Variational mode decomposition (VMD) algorithm is used to increase the performance. This paper is organized as follows. In section II, Literature on Deep Learning based sleep apnea detection is presented. The performance comparison and analysis are presented in section III. Finally, the paper is concluded in Section IV.

Literature on Deep Learning Based Sleep Apnea Detection

Single-Channel EEG Signal based System for the Apnea classification

An automatic recognition system based on the temporal dynamics of REM sleep EEG activity is suggested by S. Bayatfar, S. Seifpour, et al. in [1] to diagnose the sleep apnea syndrome. The time-domain approach is used to extract the features from multiple EEG frequency bands of REM sleep. The minimal redundancy maximal relevance (mRMR) feature selection algorithm was used to reduce uninformative features. In the classification process, a random under-sampling boosting (RUSBoost) method is used. The sleep apnea detection method is proposed in the following steps: the EEG segments are divided into seven frequency bands in the first step. In the second step, 20 time-domain features were extracted from each frequency band separately. The most informative features were then chosen using the mRMR feature selection algorithm. Finally, the normal and apneic subjects are differentiated by using the RUSBoost classifier. To implement the experiments and assess the efficiency, DREAMS subject and DREAMS apnea databases [2] are used. In these databases, PSG recordings are taken for 20 healthy persons and 12 apnea patients in 32 whole nights with different types of SAS. EEG signals were recorded from Cz or C3, Fp1, and O1 electrode locations referenced to the left mastoid at a sampling frequency of 200 Hz (A1). By using the guidelines of Rechtschaffen and Kales (R&K) [3]the stages of sleep were explained. Also, the REM sleep data extracted from the Cz-A1 channel is used to design and testing of the proposed method.

In the feature extraction, the first step is using a bandpass filter with a hamming window, the EEG signal was divided into seven frequency bands. In the next step, the non-overlapped 5-second window [4] is used to extract the 20-time domain features. These features are used in clinical applications implementation due to their low computational complexity. To extract the information from EEG signals [5], [6], [7], the time-domain technique is motivated by signal processing researchers. The total number of 5-second EEG segments for healthy subjects and apneic patients was 18220 and 10364, respectively.

Given that irrelevant and noisy features have a significant impact on classification performance, the presence of a feature selection step in machine learning problems is critical for improving generalization and reducing classifier complexity [8]. To select an informative features subset, an mRMR supervised feature selection method was used. Using the concept of mutual information, the mRMR algorithm attempts to identify subsets of features with maximum statistical dependency by eliminating relevant but redundant features [9]. In multiple classifiers, an ensemble learning algorithm is used to make decisions based on their outputs.

Ensemble methods can effectively improve generalization power, accuracy, and classification speed, also reducing overfitting. The classification algorithms are divided into sequential and parallel methods [10]. To solve the imbalanced classification problem [11], a sequential ensemble algorithm RUSBoost is used. In [10], balanced and imbalanced problems are considered in the classification of the apneic patient and non-apneic subjects An accuracy, specificity, sensitivity, the Cohen's kappa coefficient was calculated to assess the efficiency of the proposed system by using 2, 5, and 10-fold cross-validations in both balanced and imbalanced classification problems.

A Feature & Sequence Learning, and Data Augmentation based Sleep stage Classification

A two-stage neural network is proposed C. Sun, J. Fan, et al. in [12] to classify the sleep stages. In this architecture, the stage-1 is the feature learning and stage-2 is the sequence learning. The fused feature matrix is provided by the feature learning stage and the temporal information between successive epochs are learned by the sequence learning stage. In the training model in [12], preprocessed the single single-channel EEG as raw data and the features are extracted from this preprocessed signals in two ways, one for extracting hand-crafted features, and the other for obtaining network trained features by the

WDBN in the first stage. To form a new feature matrix, these two distinct feature matrices are combined. The fused features from first stage are then given to second stage in time order to capture temporal information. After the proposed model has been trained through the sequence learning process, the predicted sleep stages can be obtained by sending the testing data into the trained model. The oversampling approach is used in pre training process to avoid class imbalance problem in sleep apnea classification. two publicly available databases, sleep-EDF and Sleep Apnea (SA) are used to calculate the performance of the method proposed in [12].

It is clear from the classification results acquired from the two databases that the Sleep-EDF database outperforms the other. This could be due to the fact that the data in the Sleep-EDF database comes from healthy people, but the data in the SA database comes from persons who have sleep disorders. WDBN, hand-crafted features, BLSTM, and a novel pre-training approach are the four main components of the proposed model. In this study author, separated the proposed technique and used other approaches to substitute the components in the proposed method to evaluate the benefits of different elements in the proposed model to the classification performance. Support vector machine (SVM) and Hidden Markov Model (HMM) were employed to train the model instead of the BLSTM to highlight the improvement offered by the BLSTM. Six approaches were generated from the suggested two-stage model, as follows: Hand-crafted features + SVM, Hand-crafted features + BLSTM, WDBN + BLSTM, WDBN + hand-crafted features + HMM, WDBN + hand-crafted features + BLSTM, WDBN + hand-crafted features + BLSTM + pre-training process. The last method achieves the better performance when compared to the other five methods. The performance comparison of these methods by using sleep-edf database is shown in Fig.1.

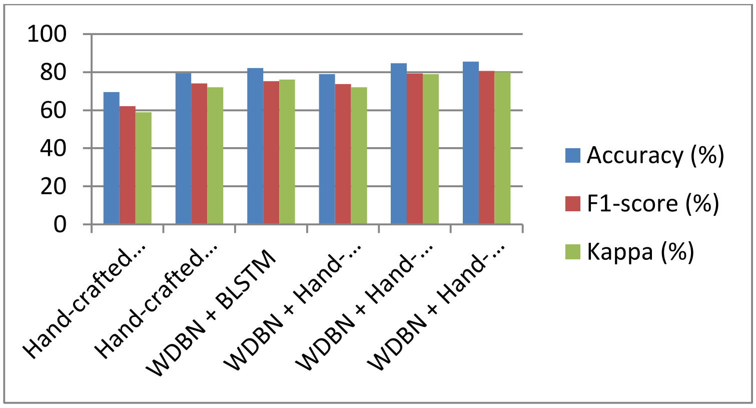

Fig.1. Performance comparison of six methods [2] from sleep-edf database

Symmetrical EEG Channels based Sleep Apnea Detection

M. A. Prucnal and A. G. Polak [13] are discussed one versus two Symmetrical EEG Channels are used to detect sleep apnea. The aim of this study was to compare the accuracy of sleep apnea identification using characteristics extracted from one versus two symmetrical EEG channels (C3-A2 or C4-A1). The PhysioBank database is used. For one and combined EEG channels, the same feature extraction and selection methods was used. For the three classes of EEG epochs, representing normal breathing, obstructive apnea and hypopnea, and central apnea and hypopnea, automated classification was performed using the k-nearest neighbours algorithm (kNN) with k = 12 and cityblock metric. The discrete wavelet transform (DWT) and Hilbert transform were used to extract features from the synchronized EEG epochs for the C3-A2 and C4-A1 channels (HT).

The non-parametric kNN classifier classifies new elements by first calculating distances between them and the training data [14-16]. The element is then assigned to the class that contains the majority of its k neighbors [17], [14-15]. Furthermore, the majority and similarity voting algorithms [16] are two extensively used approaches for classifying fresh data. For characteristics extracted from the C3-A2 channel, the ideal k (from 1 to 25) and metric (Euclidean, Spearman, or cityblock) were searched, and then applied to data from the C4-A1 channel and both symmetrical channels. When multiple classes had the same number of nearest points among the k neighbors, the class with the closest neighbors among tied groups was Favored, according to the majority vote scheme. Cross-validation was used to examine the accuracy of classification using kNN with optimal settings (leave-300-out). This technique was done 100 times with training and test sets that were chosen at random.

Compact CNN based Classification

A compact convolutional neural network (CNN) is proposed by A. M. Eldaraa, H. Baali, et al. [18] to classify the apnea and non-apnea sleep arousal categories. The PhysioNet data set is used to perform the calculation. The proposed architecture consists of three blocks. In the first block, a two-dimensional convolutional layer is used with average-pooling. In the second block, a Separable Convolution layer is used to reduce the number of trainable and decouples and in the third block SoftMax activation layer is used for classification. an accuracy, sensitivity, and specificities are calculated to measure the performance.

EEG Spectro-temporal Subframes Based Sleep Apnea Detection

A sub-frame based technique is proposed in [19] to detect the sleep apnea from EEG signals. Spectro-temporal sub frames are used instead of single whole frame of EEG signal, these sub frames are extracted from frequency band limited signals and then divide into small sub frames. Sub frames are then fed into the proposed local convolutional neural network (CNN) blocks. A physionet database [20] is used to calculate the performance of the proposed architecture, it is taken from St.Vincent's University Hospital. In the proposed methodology [19], first a specific duration frame is extracted from a given overnight EEG signal of a patient, and then each frame is divided into five spectral bands. Following that, each frame is subdivided into short-duration sub frames. In the next step, to extract the features from sub-bands a CNN is used. Afterwards, feature vectors based on sub frames are concatenated and passed through a global convolutional network. Finally, for classification, a deep neural network block is used. Three networks are used in feature extraction and classification, those are: a local convolutional neural network, a global convolutional neural network and a dense neural network classifier. Each sub frame's local features are extracted by the local section and global features are extracted by the global section. The densely connected layers optimize these to detect apnea frames. The performance of the method is evaluated in terms of accuracy, sensitivity and specificity.

Sub-frame Feature Variation based EEG Signal classification

T. Mahmud, I. A. Khan, et al. [21] proposed a unique method for automatically detecting apnea, which involves combining local fluctuations of temporal variables to discover global feature differences across a larger window. To successfully extract local feature change within one larger frame, an EEG data frame is segmented into smaller sub-frames. A fully convolutional neural network (FCNN) is presented for extracting local features from each sub-frame of a single frame. Then, a dense classifier made up of a succession of fully connected layers is trained to examine all of the local data collected from subframes in order to categorize the entire frame as apnea/non-apnea. The database is taken from St. Vincent's University Hospital to evaluate the proposed method in [21]. The suggested deep neural network in [21] the feature extraction consists of FCNN for local feature extraction and a DNN for global feature optimization.

Variational mode Decomposed EEG Signal Using a Hybrid CNN-BiLSTM

A deep fully convolutional-BiLSTM neural network is proposed in [22] for automatic detection of sleep apnea. A Variational mode decomposition (VMD) algorithm is used to increase the performance. Three sub networks are involved in the proposed network: a fully convolutional neural network, a bi-directional LSTM network, and densely connected layers. First, a FCNN is used to process each mode of EEG frame obtained from the VMD individually. To extract the temporal feature from VMD, FCNNs are used. These techniques reduce the temporal dimension of each mode's feature space while preserving the causal temporal links between the retrieved features. The output feature maps from each FCNN module are taken as an input into a multi-layer bi-directional long short term memory network (BiLSTM). The BiLSTM network is used to process the retrieved generalized sequential representations of the modes of the EEG frame acquired from the FCNN module. The resulting temporal feature vector must be converged into the final apnea incident prediction. The performance is calculated in terms of accuracy, sensitivity and specificity by taking 3-fold, 7-fold and leave-one-out cross validation techniques.

Performance Comparison and Analysis

Table I compares the performance of the various approaches presented in this review. The sleep apnea is diagnosed by using single channel EEG signal in [1] is proposed. To extract the features from EEG bands of REM (Random Eye Movement), using time-domain is discussed in the paper. The classification is done by using random under sampling boosting (RUSBoost) learning method. Performance was calculated for imbalanced and balanced classification problems by applying 2- fold, 5-fold, and 10-fold cross-validation techniques. The average accuracy of 89.9%, sensitivity of 92.7% and specificity of 85% are achieved in this proposed method. A two-stage neural network model is proposed in [12] to classification of sleep stages from EEG signals. In the first stage hand crafted features are extracted and in the second stage Bi-LSTM is used to improve the performance. Data augmentation is proposed to solve the imbalance of the samples and improve the generalization ability of the model. The performance is calculated for sleep EDF and sleep apnea patients, accuracy is achieved 85.5% and 80.3 in this proposed method.

Sleep apnea detection of one and two symmetrical EEG channels are discussed in [13] with KNN classifier and the performance is compared with three cases of C3-A2, C4-A1 and C3-A2 & C4-A1. The accuracies of these three cases, 63.8%, 64.3% and 70.3% are achieved by using the proposed method. The highest accuracy is observed in the two symmetric EEG channels. A convolutional neural network classifier is used in [18] to detect the apnea and non-apnea sleep disorders. The large class imbalance problem is overcome by applying data augmentation technique. The performance is calculated for intra-subject test and inter-subject test for the proposed method.

The spectro-temporal sub frame based CNN technique is used in [19] to detect the sleep apnea from EEG signals. The LCNN-GCNN model is used to extract the local and global features. The performance of the proposed model, achieved accuracy of 80.05%, sensitivity of 79.53% and specificity of 80.56%. The sub-frames of EEG signal is proposed in [21] to detect the sleep apnea disease. A fully connected convolutional neural network is used to extract the features from EEG data sub-frames. The performance is calculated for both frame and sub-frame techniques by using proposed method.

The sleep apnea detection of EEG signals are decomposed by variational decomposition (VMD) algorithm in [22] is proposed. The Bi-directional LSTM is used in this model. In [21], classifications of features are achieved by taking 3-fold and 7-fold cross validation techniques to improve the performance. This method provides, average accuracy, sensitivity and specificities of 93.22%, 93.25% and 89.41%.

S.No	Author	Year	Classifier	signal			Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	K(%)
1	S. Bayatfar, S. Seifpour, et al. [1]	2019	RUSBoost	EEG	Imbalanced classification problem	2-fold	89.8±0.4	92.4±0.6	85.4±0.1	- -	77.9
						5-fold	89.9±0.2	92.6±0.4	85.1±0.4		78.0
						10-fold	89.9±0.6	92.7±0.4	85.0±1.5		78.1
					Balanced classification problem	2-fold	88.0±0.4	87.4±1.9	88.6±2.1		76.0
						5-fold	88.1±0.5	87.3±1.6	88.8±1.5		76.1
						10-fold	88.2±0.7	88.6±1.7	87.9±1.5		76.5
2	C. Sun, J. Fan, et al. [12]	2019	Bi-LSTM	EEG	Sleep EDF (Healthy)		85.5	-	-	80.6	(Kappa) 80
					Sleep Apnea (Patients)		80.3	-	-	79.0	(Kappa) 74
3	M. A.	201		EEG	C3-A2		63.82±2	-	-	-	-

	Prucnal and A. G. Polak. [13]	9	KNN			.78				
					C4-A1	64.26±2.66				
					C3-A2&C4-A1	70.30±2.62				
4	A. M. Eldaraa, H. Baali, et al. [18]	2020	CNN	EEG	Intra subject test	65.28	74.68	56.92	-	-
					Inter subject test	69.49	65.29	69.82	-	-
5	I. A. Khan, T. I. Mahmud, et al. [19]	2020	CNN	EEG	-	80.05	79.53%	80.56%	-	-
6	T. Mahmud, I. A. Khan, et al. [21]	2020	CNN	EEG	Sub Frame Based Approach(different patients)	73.9-80.2	74.8-82.3	72.5-80.4	-	-
					Frame Based Approach(different patients)	67.8-71.1	68.6-73.4	65.8-70.7	-	-
7	T. Mahmud, I. A. Khan, et al. [22]	2021	CNN-BiLSTM	EEG	3 fold	90.04	89.29	90.84	-	-
					7 fold	91.01	91.19	89.95		

Conclusion

In this paper, various deep learning techniques like convolutional neural network (CNN), Bi-directional Long short-term memory (Bi-LSTM), recurrent neural network (RNN), etc., are reported to detect the sleep apnea syndrome. The performance of those techniques are compared. It is observed that the maximum accuracy and specificities are achieved with CNN + BiLSTM method.

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