DYNAMIC CLASSIFICATION OF SLEEP STAGE: EEG BASED ML ACCURACY ENHANCEMENT

Naveen Singh, Sumit Kumar Srivastava, Akash Jaiswal, Manisha Yadav and Shri Om Mishra

Department of Electronics and Communication IET

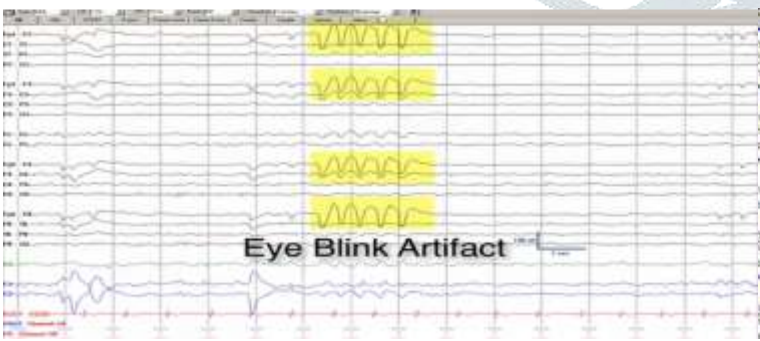
Dr Ram Manohar Lohia Avadh University, Ayodhya (U.P.), India

Abstract: Energy is single phenomenon that impacts the sleep quality of humans by manipulating its quality. The analysis of sleep study and its associated factors helps gathering the data about the sleep disorders in association with the PSG recordings. This work focuses on a methodology for study of wave bands from various dynamic sleep stages based on polysomnographic recordings (PSG) and associated solely EEG energy signals. EEG signals from Physionet-Sleep dataset is picked and utilized aiming to automated identification of five crucial sleeping stages. The initial steps include filtering of EEG signals to obtain five EEG rhythms & the calculated energy from each sub bands to precisely train typical classifiers.

***Keywords*: EEG, DCSS, Physionet Database, Dynamic Classification of sleeping stages, Energy.**

Introduction

Sleep is a boon to humankind that positively impacts the overall physical & mental health to restorative stage [1]. Eventually nightlong analysis of human sleep & associated behaviors during various sleep stages helps in needed diagnosis of sleep disorders & various other mental health issues. Various sleep associated trails can impact to memory associated ladders like learning, memorization, mental abilities, etc. Analyzing and mapping the intensity of patients sleep cycles throughout the whole night helps in calculation of diagnosis significance accuracy and hence measured implementation steps to treatment. Sleep is a naturally remounted sequential process comprising of five different stages, whose progress can be measured over cyclical trails. The sleep cycle in humans with wake cycles included various different stages starting with awake stage then an important non-rapid eye movement process cycle also referred as NREM (NREM is having further crucially divided and equally important components as transitional sleep referred as N1 stage followed by a light sleep cycle termed as N2 and then a final deep sleep stage termed as N3. A further division of N3 sometimes comprises of a slow wave sleep stage N4) and finally a rapid eye movement cycle referred as REM. These different sleep stages are monitored with the use of different activities involving respiratory, neural & cardiac data during sleep & it is very useful towards assessment of sleep-in potential. Various parameter recordings that are crucial for this assessment involves Eye blink & Eye fluttering artifact as shown in figure below-



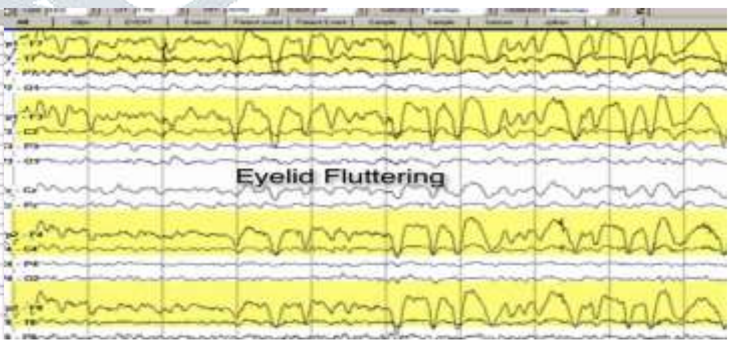


Figure 01& 02: EB artifact- Neural activities recorded using EEG & Eyelid Fluttering- Atlas of adult Electroencephalography

The appropriate footsteps while approach of recognizing, source identifying & elimination of artifact is a crucial procedure to minimize the probability of misinterpretation of the EEG recordings and to limit the potential for unnecessary clinical consequences. These are some important procedures to be followed before using ML classifiers to reach desired research motive. Apparently, the recordings are bifurcated into short intervals of time (30s), called epochs, which are finally rearranged into the various sleep stages. The process systematically takes place in a pre-equipped clinic or hospital, by a well-trained sleep specialist who operates over the PSG recordings and identifies the sleep-related patterns over time.

Different approach and different methods have been tested based on the PSG recordings by ISRUC[6,10,11] also with the Siesta dataset [12-14]. Taking in concern the ISRUC database, a number of previously done studies have been concerned [2,3,15-17] that on one hand used the maximum overlap Discrete Wavelet Transform (MODWT) for EEG signal decomposition [2,15,17] and on other hand filters [16] and thus uniquely collected an extensive set of features. Also, then most unique and different features were taken and applied to train a Support Vector Machines (SVM) [2,3,15,17] and in another case a Bayesian classifier [16]. The present paper uses an EEG-based more precise method for classification of sleep stages. The presented method performs evaluation over the energy of the obtained EEG rhythms from the Physionet sleep Dataset aiming to train a set of classifiers and differentiate the 5 stages of sleep. Results obtained from the different-class problems and their procedures are presented.

Methodology

The quoted & presented method consists of two simple stages: first one feature extraction and another one classification in different classes. Butterworth filters are implemented to read EEG recordings, obtained from patients from database, focusing on the extraction of the to be measured energy in each sub-band. Then to test several classifiers the extracted featured vector is used to test & train several classifiers. Design of the filter and steps to extract features are then implemented with the help of MathWorks MATLAB platform, followed by most important classification step is performed with various other simulation softwares. The followed flowchart of the preproposed method is displayed in Figure 03.

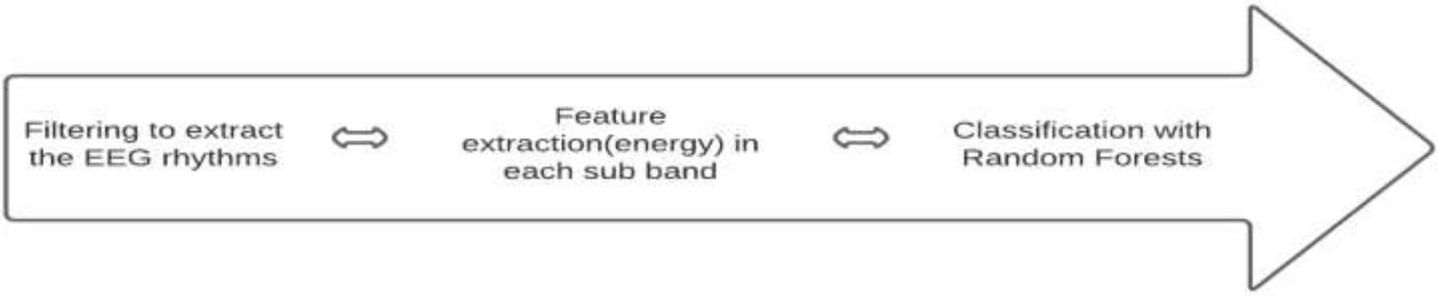


Figure 03: Flowchart of the proposed methodology.

Dataset

The dataset used for this work is the Sleep-EDF dataset on Physionet website [3]. This dataset contains PSG recorded data taken during the sleep over night for an average of eight hours, and is a collection of 61 PSGs taken from 1987–2014 including the previous Sleep EDF (extended) database recordings previous to 1990. The data recordings contain data from 20 healthy subjects given numbers from 00 to 19, which contains ten male & ten female participants having ages between 25 and 34. These polysomnographic recordings contains EEG Fpz-Cz, EEG Pz-Oz, EOG horizontal, submental chin EMG and most critical and useful event marker signals. The whole sleep-edf database contains 197 whole-night PSG sleep recordings, containing EEG, EOG, chin EMG, and event markers. Here we are taking the evaluation over EEG recording majorly. Many records also contain respirational data with the help of chest percussion artifact as shown in figure 04 & body temperature.

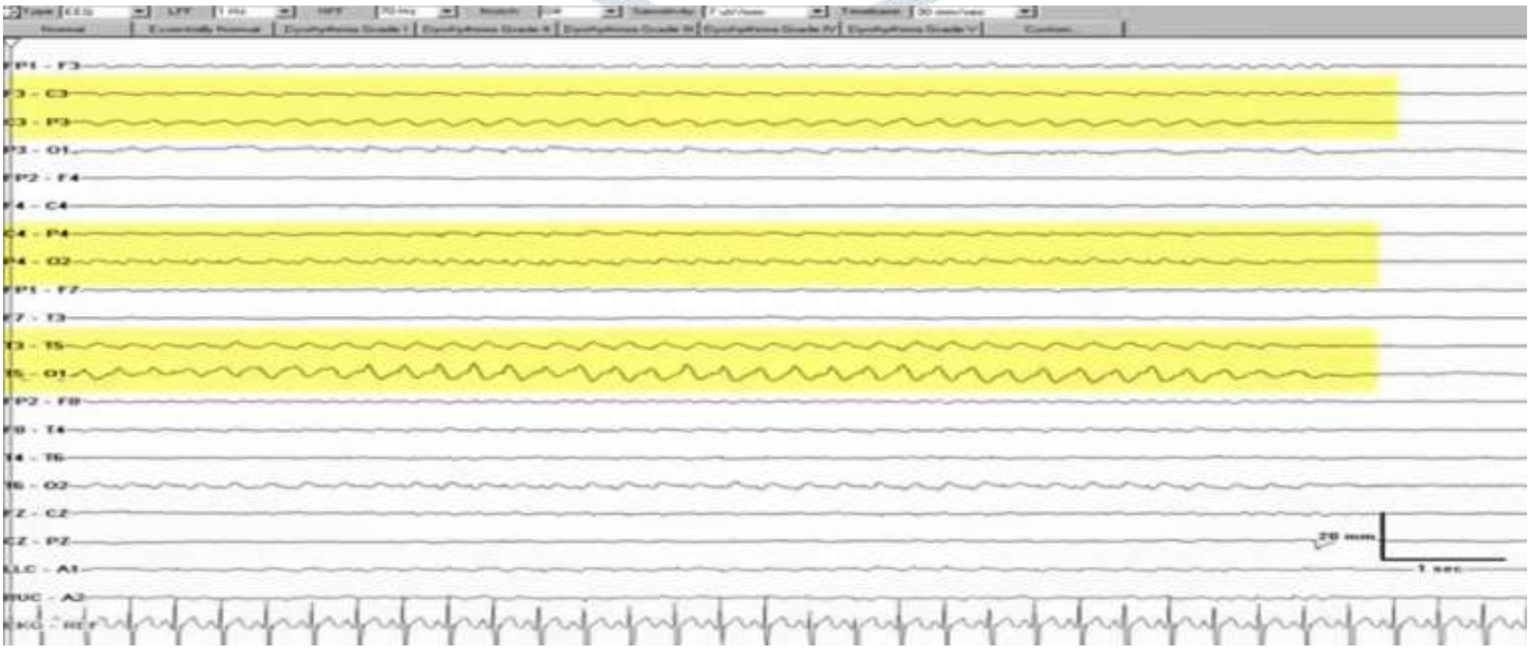


Figure 04: Chest Percussion Artifact.

For the illustrated purpose, Figure 05 represents fews samples of five different stages of EEG signals, which were deployed as inputs to the designed filters. Table 01 shows the number of wake, Stage 1, Stage 2, Stage 3, Stage 4 and REM epoch.

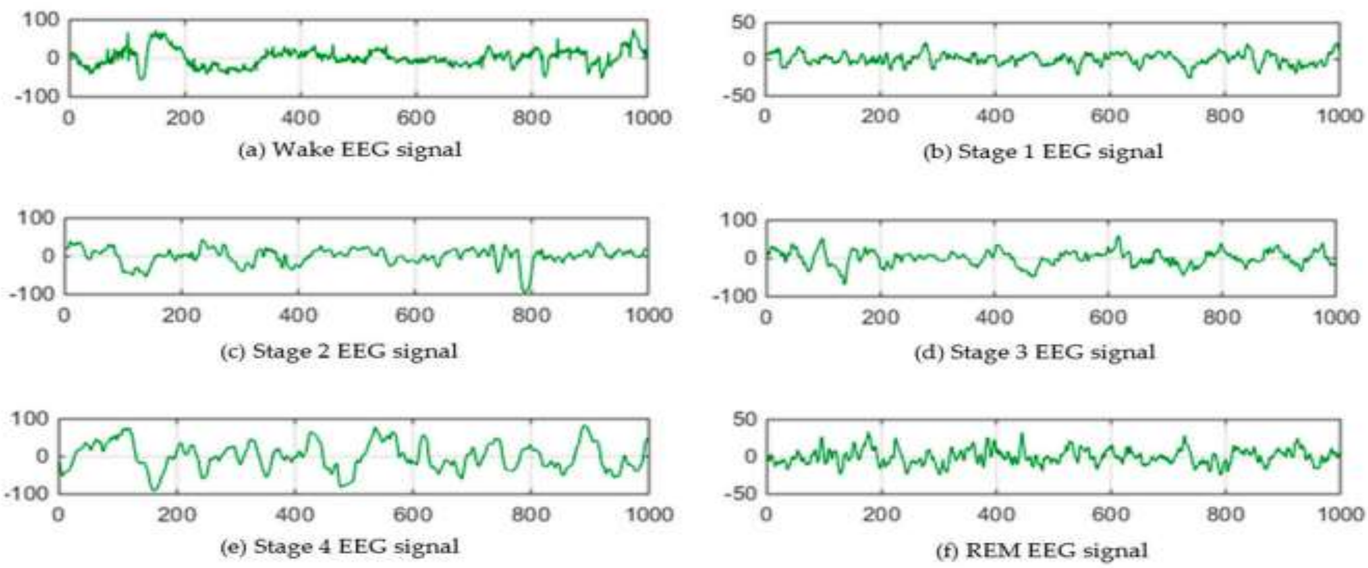


Figure 05: EEG signal sample(a) Wake (b)Stage 1 (c)Stage 2 (d)Stage 3 (e)Stage 4 (f)Rapid Eye Movement

Stage	W	S1	S2	S3	S4	REM
Total	5961	3552	7175	4321	1900	897

Table 01: Number of epochs during various sleep stages.

Feature Extraction & Classification

In procedure to extract the data in the various frequency sub-bands, Butterworth filters are designed and applied over every EEG signal. Hence from each sub band of interest energy is extracted, respective to the EEG rhythms. As every EEG signal stores data from main 6 channels, a feature vector of 30 characteristics (5 sub-bands * 6 channels) is deployed as input to train the Machine Learning classifiers. The five well-known classifiers are used over proposed method for dynamic sleep staging.

Naive Bayes

Naïve Bayes [18] is a moderate classifier that operates over decision rule making and probability classification. The basic assumption behind the operation of this classifier is that the features comprising the feature vector are independent with statistical nature. Naive Bayes operates on the Bayes decision theory & the aim is to minimize the error classification over error probability & the maximization of posterior probability. The classifier adopts the Gaussian assumption, meaning that each marginal is described by two parameters (mean and variance), hence minimizing the complexity in computation & the data related needs.

Decision Tree

A Decision Trees classifier perform over the rules that are decision focused. The top node of tree root is attached with different nodes through links also called the branches. The repetition of the procedure occurs until zero further links exist for connection making with other nodes. Taking in account the classification's architecture a single link only to be followed over every time & the following node becomes the root node of the next sub-tree till time when no other decision can be made. Thus, Decision Trees is a fully focused decision base classifier [19].

K-Nearest Neighbor

The k-Nearest Neighbor [20] is a supervised, instance-based & non parametric classifier & hence one of the simplest ML algorithms used for the purpose of the classification. According to this method, an instance is classified to its utmost relative class depending on the vote its k nearest neighbors. This approach is a better technique when there is very minimal or few or mostly no knowledge of the distribution of the data is available. SVM [21] is a technique for linear and nonlinear classification problems. The input features are represented into a higher-dimensionally (usually much higher than the original) spaced feature aiming to be linear separated. This projection is performed by the kernel function. The space distinguishing the data is called decision hyperplane & the distance from the hyperplane is called margin. The goal for training an SVM is to identify the optimal separating hyperplane with the largest margin, focusing over the better generalization of the classifier. Here, the radial basis function is taken as kernel function.

Results & Discussion

To train and test the used classifiers we are using ten-fold cross-validation technique. The chosen classifiers deployed to the quoted method in this study include SVM, NN, KNN, NB, SVM and DT, which falls in the category of the most commonly used ones in DSSC. The performance of these classifiers can be obtained by the computation of accuracy, sensitivity and specificity using TP, FP, FN and TN values, where TP refers to true positives, TN is true negatives, FP is false positives and FN is false negatives. The proposed methodology achieves an average classification sensitivity, specificity and accuracy of 89.06%, 98.61% and 93.13% respectively, when DT performed the training and testing of the extracted features.

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	91.20	96.44	91.26	86.89	98.65	66.33	93.29
	Sp	98.59	91.09	98.10	98.70	99.63	98.94	
30	Se	91.07	95.85	90.96	86.16	97.42	76.27	93.18
	Sp	98.89	97.91	98.13	98.87	99.55	98.40	
50	Se	91.47	95.06	90.83	87.61	97.64	72.23	92.92
	Sp	98.58	98.16	98.11	98.72	99.32	98.59	

Table 02: Decision Tree performance results: Acc: Accuracy; Se: Sensitivity; Sp: Specificity.

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	92.50	96.79	91.72	86.89	98.14	36.33	92.31
	Sp	97.34	97.48	97.89	99.02	99.63	99.18	
30	Se	94.14	95.76	92.65	86.89	97.14	39.69	92.59
	Sp	97.46	97.93	97.77	99.15	99.64	99.03	
50	Se	94.67	96.93	91.40	82.89	96.81	37.48	92.32
	Sp	97.36	97.64	97.41	99.04	99.68	99.31	

Table 03: SVM performance results.

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	90.73	96.45	90.70	84.68	97.28	33.14	91.45
	Sp	97.55	96.61	97.40	98.77	99.53	99.46	
30	Se	89.33	96.69	92.73	84.74	97.32	36.76	91.91
	Sp	97.86	96.86	97.35	96.25	99.44	99.11	
50	Se	87.93	96.84	94.30	82.71	97.21	40.01	91.75
	Sp	98.04	96.64	97.26	99.32	99.40	98.97	

Table 04: NN performance results.

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	90.49	95.23	85.17	85.90	94.22	40.89	89.72
	Sp	96.53	96.28	97.75	98.28	99.45	98.98	
30	Se	86.28	92.47	90.96	82.99	94.58	45.57	89.49
	Sp	96.95	97.33	96.80	98.58	99.53	98.09	
50	Se	87.56	95.23	83.42	87.83	93.79	41.58	88.94
	Sp	96.56	95.33	98.19	97.98	99.59	98.65	

Table 05: KNN performance results.

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	76.05	85.90	84.47	69.40	96.18	48.98	83.95
	Sp	97.87	95.29	94.72	98.32	97.00	96.96	
30	Se	77.68	84.34	85.31	69.77	94.92	51.37	83.84
	Sp	97.63	95.56	94.67	98.44	96.67	97.07	
50	Se	74.06	85.24	85.17	66.96	96.31	48.70	83.34
	Sp	97.73	95.41	94.45	98.28	96.65	96.92	

Table 06: NB performance results

Sleep EEG Stages

Test Percentage		S1	S2	S3	S4	Wake	REM	Acc
20	Se	89.40	95.70	43.56	56.88	81.16	0	74.60
	Sp	93.81	80.17	93.77	98.74	99.79	99.97	
30	Se	88.25	94.31	42.45	54.68	81.26	0	74
	Sp	93.88	79.88	93.43	98.51	99.85	100	
50	Se	88.26	96.26	40.87	60.03	82.62	0	74.87
	Sp	93.66	79.37	95.12	98.64	99.87	100	

Table 07: LDA performance results.

Taking in account the overall procedure we are having the, the sensitivity, specificity and accuracy results for DT were relatively high for all sleep stages. In terms of classification accuracy, the DT is followed by the SVM (92.37%), NN (91.70%) and KNN (89.38%). Taking errors as a serious concern in the classification of each sleep stage, the mainly related classification errors are caused to epochs N1 and REM, that can also be found in previous studies [2,3,16,]. The probability to the occurrence of these errors is due to the similarity between the EEG patterns taking place meanwhile in Rapid Eye Movement stage and N1 stage (slow eye movement) [16]. Also, the applied filters bifurcate the EEG signals into particular frequencies of desired interest that correspond to the EEG rhythms. Hence, the increased value of accuracy can be accurately explained due to the smaller number of subjects and more data extracted taken from the experiments and then from the combination of EEG signals

Conclusion

Sleep studies are mainly performed for the research, data collection, diagnosis & treatment of sleep related clinics and pathologies. Experts perform the sleep scoring for the review of the PSG recordings and obtain the data from energy bands from different sleep stages. For past few decades scientific research has been focused on sleep staging classification, aiming to facilitate & provide the required aid to the sleep experts in sleep scoring and therefore. In this work, a new method based on EEG is used for dynamic sleep stage classification focused on the energy extracted from the EEG rhythms is presented to Butterworth filters & then applied to EEG signals to extract the frequencies of interest and results showed 93.136% accuracy with Decision tree. In the future, more classifiers will be used & to examine and the improved results with several advance selection methods will be calculated.

References

1. Estrada, E.; Nazeran, H.; Nava, P.; Behbehani, K.; Burk, J.; Lucas, E. Itakura distance: A useful similarity measure between EEG and EOG signals in computer-aided classification of sleep stages. In Proceedings of the 27th IEEE Annual International Conference of Engineering in Medicine and Biology Society, Shanghai, China.

2. Li, Y.; Yingle, F.; Gu, L.; Qinye, T. Sleep stage classification based on EEG Hilbert–Huang transform. In Proceedings of the 4th IEEE Conference on Industrial Electronics and Applications (ICIEA), Xi'an, China.

3. Aboalayon, K.A.; Faezipour, M. Multi-class SVM based on sleep stage identification using EEG signal. In Proceedings of the IEEE Healthcare Innovation Conference (HIC), Seattle, WA, USA.

4. Huang, C.-S.; Lin, C.-L.; Ko, L.-W.; Liu, S.-Y.; Sua, T.-P.; Lin, C.-T. A hierarchical classification system for sleep stage scoring via forehead EEG signals. In Proceedings of the IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB), Singapore.

5. Huang, C.-S.; Lin, C.-L.; Yang, W.-Y.; Ko, L.-W.; Liu, S.-Y.; Lin, C.-T. Applying the fuzzy c-means based dimension reduction to improve the sleep classification system. In Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ), Hyderabad, India.

6. Lee, Y.-H.; Chen, Y.-S.; Chen, L.-F. Automated sleep staging using single EEG channel for REM sleep deprivation. In Proceedings of the Ninth IEEE International Conference on Bioinformatics and BioEngineering, Taichung, Taiwan.

7. Hassan, A.R.; Bhuiyan, M.I.H. Automatic sleep scoring using statistical features in the EMD domain and ensemble methods.

8. Khalighi, S.; Sousa, T.; Pires, G.; Nunes, U. Automatic sleep staging: A computer assisted approach for optimal combination of features and polysomnographic channels. 9. ¸Sen, B.; Peker, M.; Çavu¸so ˘glu, A.; Çelebi, F.V. A comparative study on classification of sleep stage based on EEG signals using feature selection and classification algorithms.

10. Radha, M.; Garcia-Molina, G.; Poel, M.; Tononi, G. Comparison of feature and classifier algorithms for online automatic sleep staging based on a single EEG signal. In Proceedings of the 36th IEEE Annual International Conference of Engineering in Medicine and Biology Society, Chicago, IL, USA.

11. Hassan, A.R.; Bashar, S.K.; Bhuiyan, M.I.H. On the classification of sleep states by means of statistical and spectral features from single channel electroencephalogram. In Proceedings of the IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI), Kochi, India.

12. Hassan, A.R.; Bhuiyan, M.I.H. Computer-aided sleep staging using complete ensemble empirical mode decomposition with adaptive noise and bootstrap aggregating. Biomed. Signal Process.

13. Ge, J.; Zhou, P.; Zhao, X.; Wang, M. Sample entropy analysis of sleep EEG under different stages. In Proceedings of the IEEE/ICME International Conference on Complex Medical Engineering, Beijing, China.

14. Kuo, C.-E.; Liang, S.-F. Automatic stage scoring of single-channel sleep EEG based on multiscale permutation entropy. In Proceedings of the IEEE Conference on Biomedical Circuits and Systems (BioCAS), San Diego, CA, USA.

15. Liang, S.-F.; Kuo, C.-E.; Hu, Y.-H.; Cheng, Y.-S. A rule-based automatic sleep staging method. In Proceedings of the 33rd IEEE EMBS Annual International Conference of the Engineering in Medicine and Biology Society, Boston, MA, USA.

16. Rodríguez-Sotelo, J.L.; Osorio-Forero, A.; Jiménez-Rodríguez, A.; Cuesta-Frau, D.; Cirugeda-Roldán, E.; Peluffo, D. Automatic sleep stages classification using EEG entropy features and unsupervised pattern analysis techniques.

17. Lan, K.-C.; Chang, D.-W.; Kuo, C.-E.; Wei, M.-Z.; Li, Y.-H.; Shaw, F.-Z.; Liang, S.-F. Using off-the-shelf lossy compression for wireless home sleep staging. J. Neurosci. Methods 2015, 246, 142–152. [CrossRef] [PubMed]

18. Estrada, E.; Nazeran, H.; Ebrahimi, F.; Mikaeili, M. EEG signal features for computer-aided sleep stage detection. In Proceedings of the 4th International IEEE/EMBS Conference on Neural Engineering, Antalya, Turkey, 29 April–2 May 2009; pp. 669–672.

19. Estrada, E.; Nazeran, H. EEG and HRV signal features for automatic sleep staging and apnea detection. In Proceedings of the 20th IEEE International Conference on Electronics, Communications and Computer (CONIELECOMP), Cholula, Mexico.

20. Leistedt, S.; Dumont, M.; Lanquart, J.-P.; Jurysta, F.; Linkowski, P. Characterization of the sleep EEG in acutely depressed men using detrended fluctuation analysis.

21. Redmond, S.J.; Heneghan, C. Cardiorespiratory-based sleep staging in subjects with obstructive sleep apnea. IEEE Trans. Biomed. Eng.

22. Alvarez, D.; Hornero, R.; Marcos, J.V.; del Campo, F.; Lopez, M. Spectral analysis of electroencephalogram and oximetric signals in obstructive sleep apnea diagnosis. In Proceedings of the 31st IEEE Annual International Conference of the Engineering in Medicine and Biology Society, Minneapolis, MN, USA..

23. Correa, A.G.; Leber, E.L. An automatic detector of drowsiness based on spectral analysis and wavelet decomposition of EEG records. In Proceedings of the 32nd IEEE EMBS Annual International Conference of the Engineering in Medicine and Biology, Buenos Aires, Argentina.

24. Gurudath, N.; Riley, H.B. Drowsy driving detection by EEG analysis using wavelet transform and k-means clustering.

25. Correa, A.G.; Orosco, L.; Laciar, E. Automatic detection of drowsiness in EEG records based on multimodal analysis.

26. Kumari, K. Review on drowsy driving: Becoming dangerous problem.

27. Tsai, P.-Y.; Hu, W.; Kuo, T.B.; Shyu, L.-Y. A portable device for real time drowsiness detection using novel active dry electrode system. In Proceedings of the 31st IEEE EMBS Annual International Conference of the Engineering in Medicine and Biology Society, Minneapolis, MN, USA.

28. Yu, S.; Li, P.; Lin, H.; Rohani, E.; Choi, G.; Shao, B.; Wang, Q. Support vector machine based detection of drowsiness using minimum EEG features. In Proceedings of the IEEE International Conference on Social Computing (SocialCom), Alexandria, VA, USA.

29. Fraiwan, L.; Lweesy, K.; Khasawneh, N.; Fraiwan, M.; Wenz, H.; Dickhaus, H. Time frequency analysis for automated sleep stage identification in fullterm and preterm neonates.

30. Fraiwan, L.; Lweesy, K.; Khasawneh, N.; Wenz, H.; Dickhaus, H. Automated sleep stage identification system based on time–frequency analysis of a single EEG channel and random forest classifier. Comput. Methods Progr. Biomed.

31. Ebrahimi, F.; Mikaili, M.; Estrada, E.; Nazeran, H. Assessment of itakura distance as a valuable feature for computer-aided classification of sleep stages. In Proceedings of the 29th IEEE EMBS Annual International Conference of the Engineering in Medicine and Biology Society, Lyon, France.