JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review on Machine Learning Based Approaches for Automatic Sleep Disorder Detection

Prof. Mahendra Nivangune

(Professor, Sinhgad Academy of Engineering Kondhwa, Pune)

Vrushali Jenekar[1], Asmita Kurandale[2], Ojasvi Mhatre[3]

[1, 2, 3] (Students, Sinhgad Academy of Engineering Kondhwa, Pune)

Abstract-The Word Sleep apnea (SA) in the term of Obstructive sleep apnea (OSA) is becoming the most ordinary respiratory disorder during sleep, which is distinguish by stopping of airflow to the lungs. These interrupt in breathing must last for more than 10 seconds to be considered an apnea event. Apnea occurrence may occur 5 to 30 times an hour and may occur up to four hundred times per night in those with severe Sleep Apnea. The most frequent night symptoms of SA can mainly include the activities like snoring, nocturnal arousals, sweating, restless sleep and many more. Moreover, sleeping disorders, symptoms of sleep apnea do not occur just during the night. Daytime symptoms also can range from morning headaches, depression, impaired concentration and excessive sleepiness which cause mortality from traffic and industrial accidents. This survey paper aims to bring the different techniques to identify sleep apnea syndrome by using the different features of an individual, because dependent features have been found most effective and efficient to detect the sleep apnea disorders. In this paper a comparative analysis has been prepared between the different techniques used.

Keywords: ***Sleep Apnea,*** **Obstructive** ***sleep Apnea (OSA), Convolution Neural Network (CNN)***

I. INTRODUCTION

Sleep apnea is a potentially serious sleep disorder that occurs when a person's breathing is interrupted during sleep. Sleep apnea is a potentially serious sleep disorder that occurs when a person's breathing is interrupted during sleep. Sleep apnea is a potentially serious sleep disorder that occurs when a person's breathing is interrupted during sleep. Actually, Sleep Apnea is not a issue to be taken gently, since it is related with a major
risk factor of health implications and expand cardiovascular disease and sudden death.

Sleep Apnea Syndrome→Medical Definition

Sleep Apnea Syndrome: SAS is a sleep disorder characterized by breathing stops during sleep. Breathing stops for more than 10 seconds is said to be apnea. It is diagnosed as SAS by a professional physician using data from specialized instruments.

The severity of symptoms is as follows: if the apnea is happened
• 5 to 14 times per hour is mild;
• 15 to 29 times per hour is moderate;
• more than 30 times per hour is severe.

OVERVIEW OF SLEEP STAGES AND THE CLASSIFICATION STRUCTURE

There are five stages of sleep that has been proved: stage 1, stage 2, stage 3, stage 4, rapid eye movement (REM) [8]. To facilitate the assessment of sleep apnea, only two categories are essential: deep sleep (DS) and light sleep (LS). The average DS and LS distribution of normal people and sleep apnea patients is represented in following figure;

LS is responsible for body relaxation normally before DS. However, sleep apnea patients suffer from long term LS renders inefficient sleep quality. Moreover, lack of DS also renders insufficient sleep. Therefore, in this paper, LS and DS are newly defined based on the conventional sleep stages:

- **LS: Sleep stage 1:** typically soon after "sleep action"; body is not inhibited yet; breath slow down; blood pressure and brain temperature decreases.
- **Sleep stage 2:** slower heart rate than sleep stage 1; brain starts to emit large waves; more metabolic functions slow down.
- **DS: Sleep stage 3 & 4:** brain waves become slow down and larger than sleep stage 2; most potential sleep disturbances can be ignored.
- **REM:** eyes move rapidly; dreams usually happen; increase of heart rate.

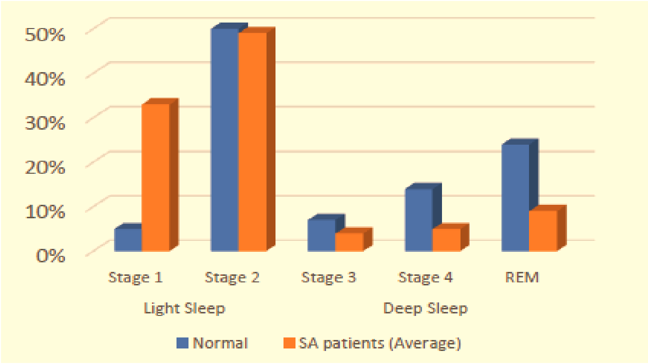


Figure: - Average distribution of sleep stages for normal people and sleep apnea patients.

II. EXISTING SYSTEM

Existing system has used SVM, for classification and they used heart rate variability & Oxygen Saturation was considered in detecting OSA which is providing 82% of accuracy. The combination of K-Means and K-NN algorithm using the term Re-weighting achieves the accuracy of least 88%.

DISADVANTAGE

- Takes more time for computation of the results.
- SVM classification accuracy is very low
- Considering the ECG signals as they are not as accurate as ECG wave interpretation.

III. LITERATURE REVIEW

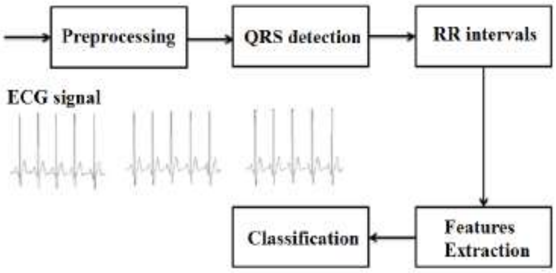
METHOD: - OSA severity classification using a Deep Learning (DL) approach
DESCRITION:-A heap of one-dimensional Convolutional Neural Networks (1-D CNNs) with 256, 128 and 64 units, separately, for programmed highlight parceled them into 10 equivalent measured subsamples to such an extent that there were 10 subsamples with 100 examples in each. For each subsample, it at that point stays 900 examples from the aggregate. Extraction [6]. Each CNN layer is trailed by group standardization; the amended straight unit initiation work just as the maximum pooling process with pool size equivalent to 2 so as to separate just significant highlights from the yield of its past layer. After model improvement, we assessed our primary classifier utilizing exactness, particularity, affectability and F-score.

METHOD: - SaO2
DESCRITION:-The study assessed analysis of a comprehensive feature set based on blood oxygen saturation (SaO2) from nocturnal oximetry in order to evaluate sleep quality. The three features of SaO2 signal which are delta index, central tendency measure and oxygen desaturation index are evaluated. Central tendency measure accuracy was higher than those provided by delta index and oxygen desaturation index.
ADVANTAGES: - central tendency measure the sensitivity was 90.1% and the specificity was 82.9%.

METHOD: - HEART RATE VARIABILITY (HRV)
DESCRITION:-Based on spectral components of heart rate variability (HRV), frequency analysis was performed in [9] to detect sleep apnea. Using Fourier and Wavelet Transformation with appropriate application of the Hilbert Transform, the sensitivity was 90.8%. In addition, in [10] a bivariate autoregressive model was used to evaluate beat-by-beat power spectral density of HRV and R peak area.
ACCURACY: - where the sleep apnea classification results showed accuracy higher than 85%.

METHOD: - Electrocardiogram (ECG) signal
DESCRITION:-Many studies show that detection of OSA can be performed through the Electrocardiogram (ECG) signal due to cyclic variations in the duration of a heartbeat. This consists of bradycardia during apnea followed by tachycardia upon its cessation [9, 11]. In our previous published research, we developed a model based on a linear kernel Support Vector Machines (SVMs)using a selective set of RR-interval features from short duration epochs of the ECG signal. The results show that our automated classification system can recognize epochs of SA with a high degree of accuracy.

PROCESS:-



ACCURACY: - accuracy, approximately 96.5%

METHOD: - Electroencephalographic (EEG)
DESCRITION: - Electroencephalographic (EEG) arousals are seen in EEG recordings as an awakening response of the human brain. EEG arousals were defined according to the American Sleep disorders Association (ASDA) report [4]. Principal features of EEG arousals in the time series were: appearance of arousal response longer than 3 s; and existence of sleep period lasting at least 10 s immediately before arousal responses. In recorded EEG time series for patients with OSAS, EEG arousals occur by the resumption of ventilation immediately after the apnea interval, and have crucial meanings in the clinical diagnosis of OSAS. Obstructive apnea is defined as total cessation of airflow at the nose and mouth, lasting at least 10 s and associated with ongoing thoracic and abdominal efforts to inspire. Waveforms of airflow pressure and airflow temperature are almost flat during the apnea interval.
The method consists of four procedures: data acquisition; parameter calculation; detection of pathological events; and detection of EEG arousals.

Table-I: Comparison of Different Approaches and Performance Analysis of Previous Work

Authors	**Data input**	**Features**	**Classifiers**	Performance Results (Acc* %)
Md Juber Rahman et al., (2018)	Apnea ECG database Physionet	• 17 features of time and frequency domain • Poincare plot	Ensemble classifier	87.5
Serein AIRatrout and Abdulnasir Hossen (2018)	MIT database	Wavelet packet decomposition of heart rate variability	Linear SVM	93.34
Gregoire surrel et al., (2018)	Apnea ECG database Physionet	R-R intervals	Time domain analysis SVM	88.2
Heenam Yoon et al., (2018)	45 healthy subjects from hospital	R-R intervals From ECG signals	Threshold heuristic rules And 5 fold cross validation	89.97

IV. PROPOSED METHODOLOGY

The attempt is made to develop a system that helps to analyse and detect the Presence of the apnea and hypopnea in the individual using CNN. A convolutional neural network (CNN) is a kind of deep neural network that can automatically learn effective feature representation from training data and has been successfully applied in many fields. In this system we have considered 12 features that are mainly responsible for the sleep apnea.
There are some dependent variables or Predicted variable that helps to get the factors that mostly dependent on key variables that mainly includes Apnea-Hypopnea Index (AHI), Central apnea, Oxygen Desaturation and Hypopnea.

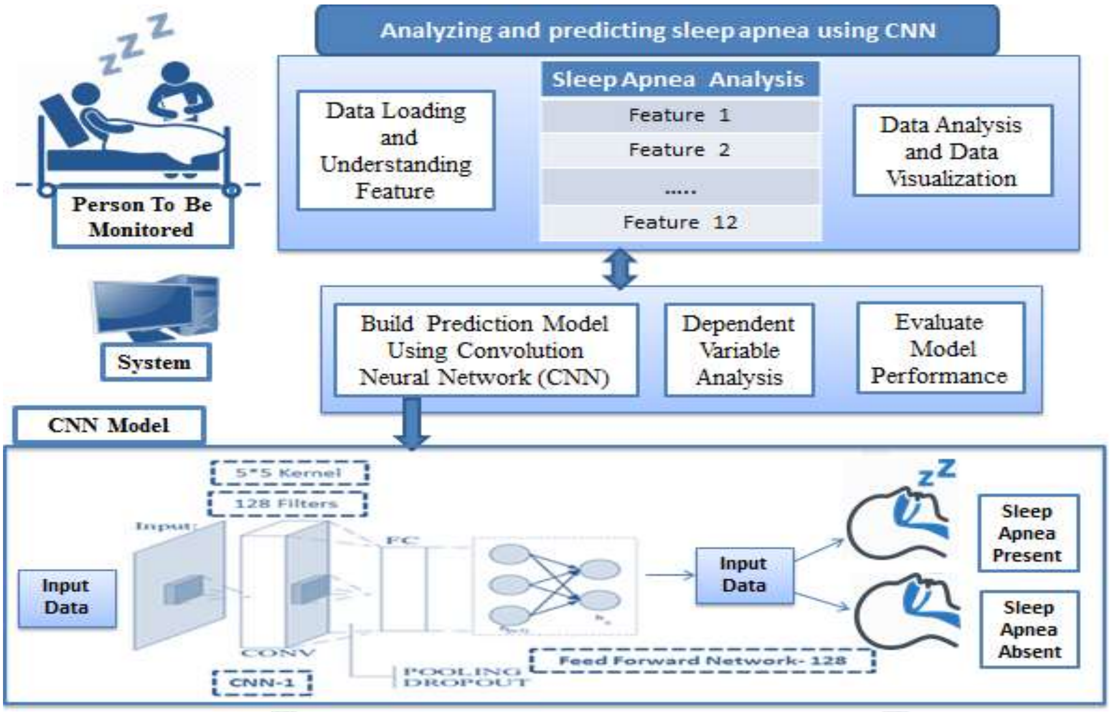


Figure: - System Architecture

V. CONCLUSION

Over the last decades, obstructive sleep apnea syndrome detection has attracted lots of interest for the researchers. In this present review paper, we have analyzed papers from an engineering and medical background. It is observed that OSA disorder identification is difficult, because of the complex medical data sets and the OSA includes changes in it as well. In this survey paper shows that there is an interconnection between the parameters in the dataset and obstructive sleep apnea syndrome events. Based on the same data, mostly machine learning approaches like Support vector machine classifiers and so on are used in order to differentiate between sleep apnea disorder signals to normal breathing parameters. Various automated models, techniques and algorithms were developed for the detection of obstructive sleep apnea syndrome events based on features, which helps in selecting the best detection technique or algorithm for identifying the sleep apnea syndrome events with high performance results while implementing in various real time home applications.

REFERENCES:

[1] T. Sugi, F. Kawana, M. Nakamura “Automatic EEG arousal detection for sleep apnea syndrome 2009 Elsevier Ltd. All rights reserved.

[2] Ali Jezzini, Mohammad Ayache, Lina Elkhansa,Zein al abidin Ibrahim, "ECG Classification for Sleep Apnea Detection," 2015 International Conference on Advances in Biomedical Engineering (ICABME), pp. (pp. 2476-2486). IEEE., 2015.

[3] Yuan, Y., Jia, K., Ma, F., Xun, G., Wang, Y., Su, L., & Zhang, A. (2018). variable Sleep Stage Classification Mistreatment Hybrid Self-Attentive Deep Learning Networks. 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM).

[4] Li, X., Cui, L., Tao, S., Chen, J., Zhang, X., & Zhang, G.- Q. (2018). HyCLASSS: A Hybrid Classifier for Automatic Sleep Stage grading. IEEE Journal of medical specialty and Health science, 22(2), 375–385.

[5] Li, Y., Pan, W., Li, K., Jiang, Q., & Liu, G.-Z. (2018). slippy Trend Fuzzy Approximate Entropy as a completely unique Descriptor of vital sign Variability in impeding apnea. IEEE Journal of medical specialty and Health science, 1–1.

[6] Phan, H., Andreotti, F., Cooray, N., Chen, O. Y., & De Vos, M. (2018). Joint Classification and Prediction CNN Framework for Automatic Sleep Stage Classification. IEEE Transactions on medical specialty Engineering, 1–1.

[7] Alvarez D, Hornero R, Marcos JV, del Campo F. 2010. Multivariate analysis of blood oxygen saturation recordings in obstructive sleep apnea diagnosis. IEEE Transactions on Biomedical Engineering 57:2816-2824

[8] Azarbarzin A, Moussavi Z. 2013. Snoring sounds variability as a signature of obstructive sleep apnea. Medical Engineering & Physics 35:479-485

[9] DeChazal P, Heneghan C, Sheridan E, Reilly R, Nolan P, O’Malley M. 2000. Automatic classification of sleep apnea epochs using the electrocardiogram. Vol 27 (Cat 00CH37163): IEEE. In: Computers in cardiology 2000. 745-748

[10] Young T, Peppard P, Palta M, Hla KM, Finn L, Morgan B, Skatrud J. 1997. Population-based study of sleep-disordered breathing as a risk factor for hypertension. Archives of Internal Medicine 157:1746-1752

[11] Khandoker AH, Palaniswami M, Karmakar CK. 2009. Support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings. IEEE Transactions on Information Technology in Biomedicine 13:37-48

[12] Md Juber Rahman, Ruhi Mahajan, Bashir I. Morshed. (2018). Severity classification of obstructive sleep panea using only heart rate variability measures with an ensemble classifier. IEEE EMBS international conference on biomedical and health informatics, pp. 33-36.

[13] Serein AI-Ratrout and Abdulnasir Hossen. (2018). Support vector machine of wavelet packet spectral features for identification of obstructive sleep apnea. International conference on electrical and electronics engineering, pp. 380- 383.

[14] Gregoire surrel, Amir Amimifar, Francisco Rincon, Srinivasan Murali and David Antienza. (2018). Online obstructive sleep apnea detection on Medical wearable sensors. IEEE transactions on biomedical, circuits and systems, Vol-12, no4, pp. 762-773.

[15] Heenam Yoon et al, (2018). Slow-wave sleep estimation for healthy subjects and OSA patients using R-R intervals. IEEE journal of biomedical and health informatics, vol-22, no-1, pp. 119-128.