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# An Efficient Method to Detect Sleep Apnea

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**ABSTRACT**

Insufficient alveolar ventilation during the course of a night's sleep results in hypopnea, which is characterized by a greater than 50% reduction in respiratory airflow. However, sleep apnea is a more serious respiratory event, such
as a complete shutdown of the breathing stream f or almost 10 seconds. For the analysis of longterm sleep data as well as the monitoring and management of its side effects and repercussions, accurate automatic algorithms for the diagnosis of sleep apnea are required. An automated deep learning-based approach is proposed for the detection of sleep apnea frames from electroencephalogram (EEG) signals. Feature extraction from such deconstructed EEG signals allows for effective analysis of the differences in the frequency spectrum brought on by apnea occurrences, regardless of the patient. To identify the occurrence of sleep hypopnea-apnea events, several deep learning approaches are used after these properties have been filtered.

## I. INTRODUCTION:

Sleep disorders can result in a considerable negative effect on our lives, which can cause insufficient sleep at night and mental tiredness during the day. Approximately 5 to 21% of adults in general, have sleep apnea, according to certain research. The two most difficult issues in sleep analysis are apnea-hypopnea detection and sleep stage scoring. Sleep apnea syndrome (SAS), is a sleep disorder in which breathing stops during nocturnal periods whenever the airflow is interrupted for longer than 10 seconds or when the average number of hypoventilations per hour exceeds 5 times. Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA), and Mixed Sleep-Apnea are the three kinds of sleep apnea (MSA). One of the most prevalent, dangerous sleep disorders is OSA. It completely closes off the upper airway and relaxes the muscles in the throat, which prevents breathing during sleep. The CSA is the process in which the brain center ceases communicating with the muscles that govern breathing, interrupting the flow of air through the lungs. The MSA is either central apnea in the second half and obstructive apnea in the first, or vice versa.

A significant portion of instances of sleep apnea go undiagnosed because sleep labs are unavailable, impractical, or expensive. In addition to respiratory airflow, chest and abdomen movement, blood oxygen signals, and wearable apnea detection equipment, suggest a cost-saving, practical, and effective detection algorithm. The EEG signal is another signal that is equally important in determining the occurrence of sleep apnea hypopnea events. Because it contains important details about the cardiorespiratory system and has the potential to be implemented in user-friendly wearables, the ECG is one of the various bio signals that is of special relevance for the identification of sleep apnea. The EEG signal contains information about sleep that is pertinent to sleep disordered breathing. Therefore, sleep disordered breathing can be treated using EEG data feature extraction and intelligent algorithms for the appropriate waveband.

Finding instances of sleep apnea-hypopnea requires a laborious and time-consuming technique. Along with the ECG, SPO2, airflow sign, and nasal pressure sign, many researchers have developed specialized physiological signals for the detection of sleep apnea events. Professional sleep analysts evaluate the data collected by the polysomnography monitor (PSG) throughout the night, including respiratory airflow, chest and abdominal movements, and blood oxygen signals, to determine the gold standard for the assessment of sleep apnea hypopnea syndrome. However, on the one hand, the pricey PSG recording equipment and the numerous electrodes have an impact on the quality of sleep at night, while on the other hand, the higher standards for qualified sleep analysts are taken into account. Therefore, the goal of this work is to find a solution to the issue that PSG data cannot be recorded in time to detect sleep apnea hypopnea syndrome because of external causes.

## II. PROBLEM STATEMENT:

Sleep apnea is a common condition in which your breathing stops and restarts many times while you sleep. This can prevent your body from getting enough oxygen. Some of the general symptoms of sleep apnea are loud snoring, gasping for air during sleep, waking up with dry mouth, morning headache, insomnia, excessive day time sleepiness, difficulty in paying attention while awake, irritability etc. This sleep apnea may lead to many complications also such as daytime fatigue, high blood pressure or heart problems, liver problems and cardiovascular problems. Hence detection of sleep apnea is very important. But the process of detecting sleep apnea is often very lethargic process. Hence this survey focuses on devising a more efficient method for analyzing sleep apnea using suitable deep learning algorithms that can process complex data and can accurately detect sleep apnea.

Here while using EEG signals, we tend to get large number of features, some of which might not be needed and thus increasing the complexity. Hence in this paper we propose a technique in feature extraction which is called as the Recursive elimination technique to get the major contributing features only. Detecting sleep apnea thus becomes important because if it is not detected efficiently, it might lead to various serious conditions.

## III. LITERATURE SURVEY:

Details regarding the literature review we conducted on our problem statement are provided in this section. The four papers' contents are listed below.

**[1]Detection of Sleep Apnea Using Sub-Frame Based Temporal Variation of Energy in Beta Band in EEG:**

Sub-framing, preprocessing, extracting the temporal fluctuation of Beta band energy, extracting statistical features, and classification are the main processes in the proposed method to detect apnea and non-apnea events. In this part, the steps are thoroughly described below.

### A. Sub-frame-based analysis:

Using frame-by-frame analysis, the task of apnea identification is carried out on each individual participant. The initial step is to split each apnea and non-apnea frame into overlapping sub-frames. There will be a total of NM m + 1 subframes for a test frame of length N when taking into account a subframe of length M with a frame shift of m samples. Since a sub-frame-based feature demonstrates significant changes in its features within an apnea frame, particularly at the transition between apnea and non-apnea events, sub-framing increases the likelihood of properly recognizing the specific apneic event. Such changes might not be able to be described by a feature that is derived from a complete frame at once. Therefore, sub-frame-based analysis is anticipated to yield better identification results than working with the complete frame.

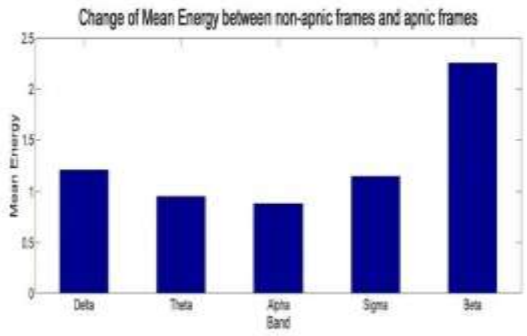
### B. Pre-processing:

The mean value is subtracted from each resulting sub-frame during preprocessing in order to eliminate the DC offset because other frequency components are more important. The frame normalizing approach eliminates unwanted amplitude variation between frames. As a result, it helps in classification of vast amounts of data.

### C. Beta band temporal variation:

Five frequency bands that EEG signal can be divided into are delta (0.25–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), sigma (12–16 Hz), and beta (1640 Hz). The beta band limited EEG signal is the primary focus of the suggested technique. The decision to use beta band energy was made for the observation that of the five previously indicated frequency bands, out of which beta band signal has the most significant influence. Regardless of whether a frame is apneic or not, the delta and other low frequency bands predominate the entire frame. The patient usually awakens if an apnea develops and causes breathing to stop. A big change is anticipated to occur in the high frequency beta band at that precise moment. This energy transfer may also occur during non-apnea occurrences, although it is mostly caused by variations in the stages of sleep and is not as abrupt as it is during an apnea event. It displays the energy change in percentage between apneic and non-apneic frames.

The figure makes it quite evident that, of the four bands, the beta band energy changes the most from apnea to non-apnea. As a result, the beta band energy in the suggested method is thought to be the most important factor in apnea identification.




## D. Feature Extraction:

In the suggested method, among other properties, Energy, Geometric mean, and Arithmetic mean are taken into account. The characteristics for a temporal variation x[n] of length N are computed as follows:

Energy = X N n=1 x[n] 2

Geometric mean = Np x[1].x[2].....x[N]

Arithmetic Mean = PN i=1 xi N

## E. Classifier:

The K-nearest neighborhood (KNN) classifiers are used in the suggested strategy. It calculates a distance function between the features of the test set's EEG pattern and K nearby EEG patterns from the training set's apnea and non-apnea groups. Based on the class labels of K closer EEG patterns in the train set, the test set's EEG pattern is categorized.

**[2] Sleep Apnea Detection Based on Rician Modeling of Feature Variation in Multi-band EEG Signal**

A proposed sub-frame-based feature extraction approach is used in each frequency band after preprocessing a particular frame of raw EEG data and dividing it into bands. then proposed subframe-based feature extraction scheme in signal with a band restriction. Modelling and statistical analysis are used to retrieve the feature vector for the classifier.Different PDFs performance criteria in the proposed method are illustrated in Fig. 2

## A. Band-limited Signal Extraction:

As the subject's state of mind and level of sleep fluctuate during sleep, so does the level of recorded EEG data stage is constantly changing in relation to time. DC offset of a frame of EEG data is removed followed by frame amplitude normalization. As a result, the energy level of various EEG frames varies significantly. In various frequency ranges, the EEG signal displays markedly distinct features. The brain sends a signal to the sleeping person to wake up and take a breath of air during an apnea because carbon dioxide builds up in the bloodstream as breathing is interrupted Such changes in neural activity level from non-apnea to apnea can cause notable variation in various frequency bands of the EEG data. The band-limited EEG signals are extracted using the five band-pass filters in the proposed method, which is expected to better preserve local information than a full-band signal.

## B. Temporal Feature Variation Pattern Extraction:

The probability of correctly identifying the specific apneic event rises with sub-framing. A short period of apnea may occur over the entire frame During the transition between apnea and non-apnea occurrences, sub-frame based derived features show sharp variations in their characteristics within an apnea frame. When apnea duration is smaller than a frame duration and frame size is sufficiently large, it is evident that there will be a transition from non-apnea to apnea, or from both.

## C. Model Fitting of the Extracted Feature Variation Pattern:

Extracted feature sequences with identifiable probability density functions from subframes of the well-known PDFs, including Gaussian, Exponential, Rayleigh, etc., can be considered. This method will give the chance to capture the differences between the statistics of data distributions in apnea and non-apnea. Out of several PDFs. To fit the feature variation pattern using Rician PDF. The third portion uses many PDFs for a thorough analysis, the feature sequence histograms and related Rician fitting of several apnea and non-apnea frames in various EEG bands. For each of the band-limited signals, examples of entropy and log-variance are shown here. The fitted Rician PDFs are different and have a large separation, as can be seen from the figure, and the histograms of feature variation pattern that correspond to apnea and non-apnea cases are very different from one another. Thus, it is anticipated that greater feature quality and a lighter computational load will be provided by PDF model fitting.

## D. Classifier:

The distance function between the features of the EEG pattern in the test set and K neighboring EEG patterns from both the apnea and non-apnea group in the training set is taken into account in the proposed method's K-nearest neighboring (KNN) classifier. The test set EEG pattern is classified based on the K closer class labels of EEG patterns.

The M-fold cross validation approach is used for performance assessment.

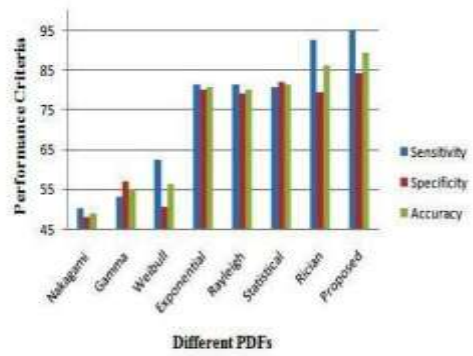



Fig 2: Different PDFs

**[3]A convolutional neural network architecture to enhance oximetry ability to diagnose pediatric obstructive sleep apnea**

The main aim of this study is to assess useful of deep learning to improve the diagnostic ability of oximetry. Here they used around 3196 blood oxygen saturation signals of children. They have made use of 20 min SpO2 segments from training set to train CNN architecture to estimate sleep apnea events, used Bayesian optimization in validation set to train CNN hyperparameters. They applied this model to three datasets from three independent databases, in which for each AHICNN they estimated Apnea hypopnea index (AHI). AHI estimated by conventional featureengineering approach, based on multi-layer perceptron (AHIMLP). AHICNN has reached highest four class Cohen's kappa than ODI3 and AHIMLP. For AHI severity, this proposal outperformed state-of-art of studies.

Methodology of this has been described below.

Proposes CNN model consists of three steps, they are signal segmentation, CNN architecture and AHI estimation.

A. **Signal Segmentation:**

In order to homogenize the frequency SpO2 recordings were down-sampled to sample rate of 1Hz. SpO2 signals of each subject divided into 20-min segments. Label each 20-min SpO2 segment of training set with annotations provided by sleep technicians.

B. **CNN Architecture:**

CNN is the deep learning technique, here used to process raw oximetry data. 20-min SpO2 segment is input to CNN architecture, it uses $\lambda C$ stacked convolution block to process input. Convolution block composed of convolutional layer, batch normalization, pooling, dropout, activation. Extraction of feature maps from input data is done by convolutional layer, after normalization is applied to normalize feature maps. Then depending on rule or threshold, use non-linear function to decide which feature maps are activated. In order to avoid overfitting dropout action was included.

C. **AHI estimation:**

Based on output YCNN m of the CNN, AHI of each patient can be estimated.

**[4] Accurate Deep Learning-Based Sleep Staging in a Clinical Population with Suspected Obstructive Sleep Apnea**

Sleep stages identification is essential in sleep disorders diagnostics. Obstructive sleep apnea is one of the most prevalent sleep disorders. Manual scoring is time-consuming, subjective and costly. They developed an accurate deep learning approach to overcome this shortcoming. This automates the classification of sleep stages and study OSA severity on classification accuracy. To develop a combined convolutional and long shortterm memory neural network, clinical dataset of patients with suspected OSA were used. Following methods are used:

To allow the comparison of proposed deep learning techniques a public dataset, Physionet Sleep-EDF is used. Combination of convolution neural network and recurrent neural network are trained in end-to-end manner to estimate sleep stages. The accuracies were calculated in an epoch-by-epoch manner. Moreover, the inter-rater agreement between manual and automatic sleep staging was evaluated using Cohen's kappa coefficient (κ) [38] and the sensitivity and specificity of identifying sleep were calculated weights are used to reweight the encoded text. A one-layer feedforward network is used to determine the final score. The cross entropy is once more employed as an objective function. MRR (Mean Reciprocal Ranking) and accuracy were the criteria used to assess this model.

## IV. CONCLUSION OF SURVEY:

Sleep apnea is a chronic disease that happens when the muscles in the throat become relaxed and block the air ways passage to the lungs due to gravity. Sleep apnea will affect the patient sleeping quality and it will make him wake several times in the night which will make him tired, sleepy and inactive during the day. Sleep apnea can happen due to relaxing in throat muscles, or it can happen due to neural problems in the brain, or it can be mixbetween the two. The patient himself may not know that he has sleep apnea, so it is important to build a model that detectsleep apnea. So herewe develop suitable deep learning model that would be able to analyze medical condition with best possible accuracy.

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