ISSN No:-2456-2165

Sleep Stage Classification for Prediction of Human Sleep Disorders by Using Machine Learning Approach

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Abstract:- Sleep is a fundamental need of human body. In order to maintain health, sufficient sleep is must. Efficiency of sleep is based on sleep stages. Sleep stage classification is required to identify sleep disorders. Sleep stage classification identifies different stages of sleep. In this paper, we used Stochastic Gradient Descent(SGD) a machine learning algorithm for sleep stage classification. In feature extraction, Power Spectral Density(Welch method) is used. We acheived 89% overall accuracy using this model.

Keywords:- *sleep stage classification, SGD, PSD Welch, machine learning etc.*

I. INTRODUCTION

Sleep is a basic need of human life. About one-third human lifespan is covered by sleep. Sleep has the direct connection to human health.[1] Sleep irregularities are increasing, in today's stressful and busy life. Sleep deficiency may cause sleep disorders like obstructive sleep apnea, parasomnia, narcolepsy, etc. A group of conditions in sleep disorders shows lack of good sleep on a regular basis. They are come with a health problem or by too much stress. So diagnosis of correct sleep disorder is much important. Sleep disorders are diagnosed by getting the duration of sleep. During sleep, physiological information has been recorded and that information is analysed for the diagnosis of sleep disorders. Physiological information contains continuous time signals which are distinguished as sleep stages.[2]

Basically sleep is categorized into two sleep stages as Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM).[3] During NREM stage of sleep, brain activity is low and eyes don't move back. During REM sleep, brain activity is high. In this stage, a person dreamed and only his/her eyes and breathing muscles are active. Generally a person goes through 4 to 6 sleep cycles at night of 90-120 minutes each. Every cycle contains 3 NREM stages and 1 REM stage and it continues. According to American Academy of Sleep Medicine (AASM), stages of sleep are categorised in 5 stages as Awake(W), NREM1, NREM2, NREM3 and REM[4].Those NREM stages are varying in depth of sleep. As in NREM1 stage sleep is lighter, in NREM2 stage sleep is deeper and in NREM3 stage sleep is slow wave sleep. In REM stage, eye movements are rapid and increased in breath. Dreams occur in this stage.

For making sleep stage classification, Polysomnography (PSG) is used. PSG refers to the study of human sleep while sleeping. It is a test used to monitor sleep stage and to diagnose irregulation in sleep waves. Electrical signals have been recorded during PSG.[5] These recordings of signals are called polysomnograms (PSGs). PSGs are group of Electroencephalogram (EEG), electrooculograms (EOG), electromyograms (EMG), electrocardiograms (ECG), oxygen saturation and respiration. In all of these signals, EEG signals are most important because EEG signals contains most of the brain activity during sleep which reflect the nature of sleep. EEG signals are easily used to diagnosis of sleep disorders. Those signals are divided into 30s epoch and is assigned to one of the particular sleep stage from 5 sleep stages. The scoring procedure takes place by analysing the signals using their frequency waves.[6]

Following table shows the frequency ranges of EEG signals of each sleep stage.

Sleep Stage	Brain Waves	Frequency Range (Hz)
Awake(Eyes Opened)	Beta	13 to 30
Awake(Eyes Opened)	Alpha	8 to 12
NREM1	Theta	4 to 8
NREM2	Sleep Spindles	12 to 14
	K-complex	0.5 to 1.5
NREM3	Delta waves	0 to 4
REM	Sawtooth Waves	Mixed

Table 1:- Frequency range of EEG signals

ISSN No:-2456-2165

II. RELATED WORK

In sleep stage scoring, EEG sleep stages are classified automatically. The process of automatic classification of sleep stages by using EEG signals is complex and difficult problem to solve. This section provides a brief work of various techniques which are used in previous papers.

Michael Sokolovsky et al. designed a deep convolutional neural network architecture which implies over single EEG channel. The data of EEG and EOG signals from multichannel PSG are used. This architecture contains different levels of layers separated by pooling layer. Classification accuracy of this model is 81% as calculated from the confusion matrix[7]. CNN consist of three main processing layers: Convolution layer, pooling layer and fully connected layer. In convolution layer, linear transformation is applied to gain each individual component of data vector. In pooling layer, aggregation function is used to control over fitting of the parameters in the network. And in fully connected layer, Non-linear activation function is applied on the input of previous layer. In this approach publicly available physionet database is used. Two EEG signals and one EOG signals are segmented into 30-5 epoch and overlapping 150-5 or 5 epoch are taken for further process. This architecture contains multiple stages with layers. Pooling layers seperates each convolutional layers. There are seven layers in this model, from which six convolutional layers are in the first level, fifth and sixth level single convolutional layers and in the final level two fully-connected layers are there.

Three types of datasets are used for noval multiclass EEG based model[8]. First is physionet sleep EDF database which is publically available, EEG and EOG databse is contained by this database. Second database is provided by St.Vincent's University Hospital and University College Dubin(UCDDB).It is also available on physionet. It contains two EEG and two EOG signals. Expanded sleep-EDF dataset(XSEDFDB) is the third dataset used and available on physionet. Different types of features has been extracted here. Standard deviation, Maximum-Minimum distance, Normalized line length, Normalized spectral entropy are some of the features extracted. From all of the features best feature has been selected by using Kruskal-Wallis Test. Kruskal-Wallis Test tests the normality of the features. It is the one way analysis of variance(ANOVA). After removing statistically non-significant features minimal-redundancy-maximal relevance (mRMR) algorithm is applied to select best features. For classification purpose Random Forest Algorithm is used.

A method introduced by Huaming Shen et al [9] is state space based sleep stage classification. This model consists of two phases: first is offline training phase and second is identification phase. In offline training phase, preprocessing has been done on EEG signals and gets divided into segments of equal duration. Then different orders of state space models are estimated with each EEG segment. The most suitable classifier and order of state space model is obtained according to the training results. In identification phase, with extracted features and selected classifier, sleep stage classification is done. The input databse in this model are sleep EDF physionet database and dreams subjects database.

III. METHODOLOGY

In this section, machine learning method which is applied for sleep stage classification is described in detail. As shown in the figure the implementation of the entire system started by the pre-processing of the PSG signals followed by time–frequency analysis and feature extraction. The extracted features were then used to train and test the classifier; finally the performance of the entire procedure was evaluated.

A. EDF Database

This standard EDF Database is taken from [10] which is specifically recorded for sleep study. This database contains whole night study of 153 people. Each dataset contains PSG signals and hypnogram signals in it. This PSG signal contains EEG(Fpz-Cz and Pz-Oz), EOG horizontal, Respiratory oro nasal, EMG submental Temporory rectal and event marker. Hypnogram file contains the sleep pattern annotations which are related to PSGs. These patterns (hypnograms) consist of sleep stages W, R, 1, 2, 3, 4, M (Movement time).

B. Pre-processing

Some artifacts are presents in signals which may lead to wrong results. To remove them preprocessing is necessary. In preprocessing, signals are filtered to eliminate undesired background signals, noise, physiological factors. The input PSG signal is filtered to eliminate undesired background signals and events are extracted from annotations. These extracted events are decomposed into 5 sleepstages namely Sleep stage 1, Sleep stage 2, Sleep stage 3, Sleep stage R and Sleepstage W. Here, PSG signals are segmented into 30s of epoch with each epoch corresponding to a single sleep stage[11].

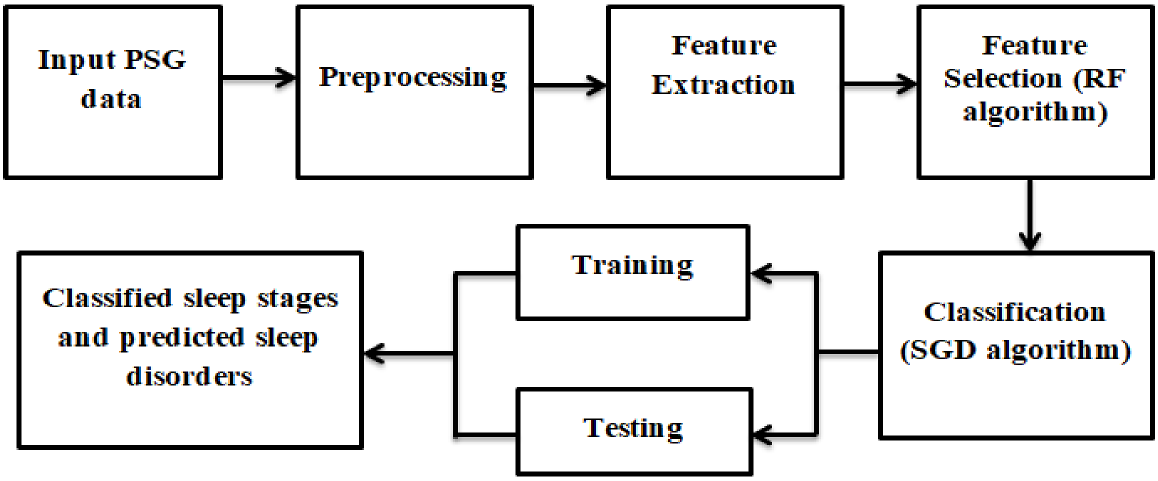

Fig 1:- Flowchart of sleep stage classification process

C. Feature Extraction

Extracting informative, descriptive, discriminative and independent features is a complex step to prepare a suitable set of values for a classifier[8]. This work employs a mixed approach (i.e., time–frequency analysis) to extract features from the EEG signal. The feature of sleep stage for classification is calculated 30 seconds as one epoch. First, we use the power of EEG signal for each frequency bands. Power Spectral Density using Welch method[12] is used for feature extraction. Welch method computes a modified periodogram for each segment and then averages these estimates to produce the estimate of the power spectral density. Because the process is wide-sense stationary and Welch's method uses PSD estimates of different segments of the time series Time–frequency analysis techniques are effective in analyzing non-stationary signals whose frequency distribution and magnitude vary with time.

D. Feature Selection

Feature selection takes place after feature extraction to find discriminative subset of features. Feature selection is used to obtain higher accuracy with minimum number of features(without redundancy). Random Forest algorithm[13] is used for for feature selection because it is highly accurate and generalize better. A random forest classifier is an ensemble of decision trees in which each tree is trained on a random subset of data points (bagging) and a random sampling of features is performed at each node of the tree. The samples not used for training per tree are called out-of-bag samples and will be used to assess the performance of the classifier.

E. Classification

We train a model for automatic sleep stage classification using Stochastic Gradient Descent(SGD) of machine learning algorithm[14]. Then we use the model to training and testing. SGD is one of the algorithms of machine learning. It is a supervised learning model for data analysis. SGD Classifier supports multi-class classification by combining multiple binary classifiers in a "one versus all" (OVA) scheme. For each of the K classes, a binary classifier is learned that discriminates between that and all other K−1 classes. At testing time, we compute the confidence score (i.e. the signed distances to the hyperplane) for each classifier and choose the class with the highest confidence. Stochastic gradient descent (SGD) tries to lower the computation per iteration, at the cost of an increased number of iterations necessary for convergence.

IV. RESULTS AND DISCUSSION

We train a model for automatic sleep stage classification through machine learning using the physionet sleep EDF dataset. We use Python and SGD for machine learning for evaluating. We evaluate the performance results of confusion matrix for analysing parameters like recall, precision and f-score[18]. Figure shows results of obtained confusion matrix.

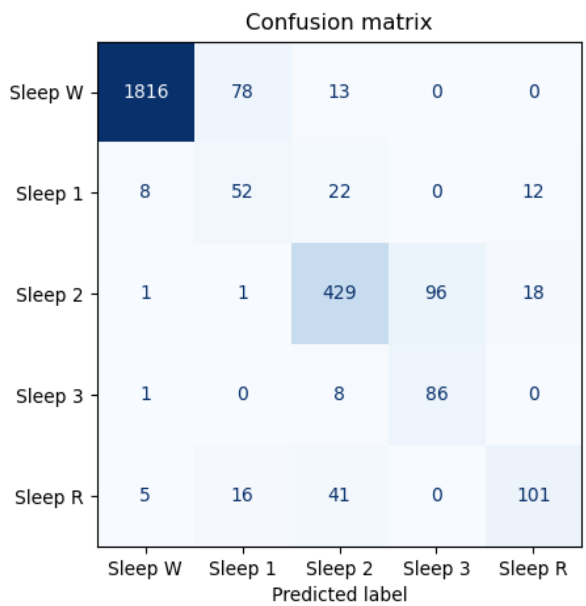

Fig 2:- Confusion matrix

ISSN No:-2456-2165

Overall accuracy is obtained by this model is 89%. Very good individual class performance was attained on sleep stages W, N2 and REM in terms of precision(99%, 84%, 77% resp.), recall(95%, 79%, 62% resp), and f-scores(97%, 81%, 69% resp.). The worst performing classes by the same metrics were N1 and N3 stage, as reflected, also, in a lowered overall f-score. Class W is accurately classified whereas class N1 need some improvement. Following table shows obtained values of precision, recall, f-score, sensitivity.

Sleep Stages	Precision	Recall	F-score	Sensitivity
W	0.99	0.95	0.97	0.95
N1	0.35	0.55	0.43	0.55
N2	0.84	0.79	0.81	0.78
N3	0.47	0.91	0.62	0.90
R	0.77	0.62	0.69	0.61

Table 2:- Achieved values of precision, recall,f-score and sensitivity

It is realistic to expect such poor sensitivity in the NREM1 stage, which reduces the overall classification accuracy in this work. The most accurately classified sleep stage was wake, with approximately 95.22% sensitivity of wake stage epochs correctly classified. Stages N1, N2 and N3 follow, with approximately 55.31%, 78.71% and 90.52% sensitivity of epochs correctly classified for each stage, respectively. Then, Stage R achieved an average sensitivity of 61.96% for correctly epochs classified. However, the lowest sensitivities exist in the N1 stage detection (55.31%), while the average specificities achieved for REM (98.86%) are high and close to the other sleep stages.

Sleep stages are used to identify various sleep disorders. Each sleep disorder belongs to their respected sleep stage. In following figure, we predicted some sleep disorders according to obtained events of each sleep stage[16].

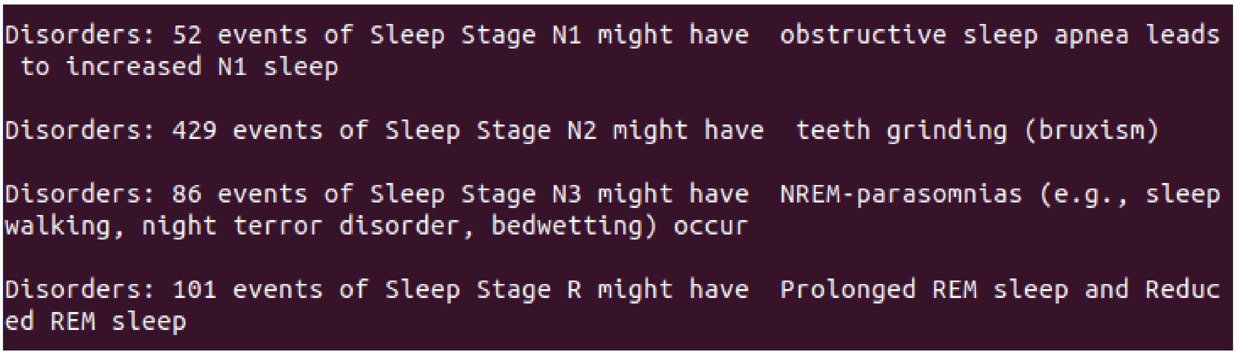

Fig 3:- Result of predicted sleep disorders

V. CONCLUSION

In day to day life, sleep is very active state because brain activity increases during sleep and if required sleep is not fulfil then there is chances of sleep disorders. Sleep disorders are find out by doing the polysomnography consist of various signals and by using those signals sleep stage classification is done. In our work we used SGD algorithm for sleep stage classification. SGD can converges faster because it performs updates more frequently. Overall accuracy acheiveed by this model is 89%. In our system, we shows sleep disorder according to the identified sleep stages which is not included in any other existing system.

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