Random Forest Approach for Sleep Stage Classification

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***Abstract*- Sleep is known as a primary function and one of the most essential state of human brain which plays a vital role in both health and mental in individuals lives. Sleep stage classification has become an important factor in terms of sleep disease diagnosing and treatment. Brain Computer Interface (BCI) is a computer based analysis of brain signal which records as ElectroEncephaloGraphy (EEG) signals by using electrodes placed on the scalp. BCI has become a popular technology lately and sleep stage classification using this has become a research area over the last two decades. Statistical analysis was the base for all the difference classification techniques but with the evolution of machine learning, scientists and researchers has moved to machine learning sleep stage classification differencing feature selection and classification algorithms. Also different domain such as time domain, frequency domain and etc… were come across various studies. Random Forest is used ensemble techniques in machine learning. Random forest builds multiple decision trees than one to make its predication. This study focuses on building a Random Forest sleep stage classification with higher accuracy as 91%. A comparison has performed using three different classifiers as Support Vector Machine (SVM), Multi-Layer Perceptron and K-Nearest Neighbors. Further the effect of different channels in EEG signal has been represented in the study.**

Index Terms*-) *Sleep Stages, EEG, Random Forest

I. Introduction

It is saying that human being spend around one third from their lives in sleep. This primary function of the brain plays a vital role in physical and mental health of human. Sleep is also essential in individual's learning since it eliminate fatigue and relaxes the brain. Hence adequate sleep always improves human's mental and physical health which is the main cause for a better life. Insomnia and obstructive sleep apnea may cause daytime sleepiness, irritability, depressive or anxious mood, or even death[1] since that an effective diagnosis and proper treatment with sleep-related disease is become a heavily researched topic in healthcare community. Classifying the sleep stages becomes the base for various diagnoses as it helps in classifying the cause and effect for the sleep disorders.

American Academy of Sleep Medicine (AASM) mentioned about, 5 stages of sleep which are characterized according to the distinct time and the frequency. Those are; Wake (W), Rapid Eye Movements (REM), Non REM1 (N1), Non REM2 (N2) and Non REM3 (N3) also known as slow wave sleep or even deep sleep[2]. Sleep in stage 1 is light. The eyes move slowly and muscle activity is slow. It is in stage 2 that eyes stop moving and the brain waves become slower. Deep sleep occurs in stages 3 and 4 when no eye movement and muscle activity exist [3].

Brain Computer Interface (BCI) is a computer based technique which analyze the brain signal. This is measured by ElectroEncephaloGraphy (EEG) which record spontaneous electrical activity of human brain using the electrodes placed on the scalp. Some significant characters in EEG signals; destructive, pain less, side effect less and accurate interpretation for some brain disease, makes EEG much suitable for BCI. EEG signals are classified based on signal frequency for different states. Eye ball movement, eye open and close, finger clenching are such states also called as stimuli. These signals have 0Hz – 100Hz frequency range [4].

With the evolution of technology scientists also has started being researching about BCI. Sleep stage detection can be introduced as a BCI based study. Several automatic sleep stage scoring approaches have been proposed using different feature extraction and classification methods. Sleep Stage classification technologies are varies from different statistical analysis to machine learning and deep neural networks.

Imbalanced multi-class prediction is a problem in statistical machine learning but automatic approach such as machine learning approach can classify into categories depends on the features extracted using expert knowledge from the raw signal. Another statistical learning challenge concerns the way transition rules are handled. Indeed, as the transition rules may impact the final decision of a scorer, a predictive model might take them into account in order to increase its performance[2].

In literature different categories of techniques has presented such as time-domain statistic approach, spectral analysis, time-frequency analysis, wavelet analysis and etc…[5]. Further studies have conducted by merging different signal types such as electrooculography (EOG), and electromyography (EMG) with EEG in sleep stage classification.

A non-linear analysis of EEG signals for the purpose of sleep stage classification has done by the Rajendra et al..Six non-linear parameters have chosen for the study. Those are correlation Dimension, Hurst exponent, approximate entropy, largest Laypunov entropy, fractal dimension, phase space and recurrence plot[3].

Chen et al. has performed a study to detect the sleep stages using statistical and spectral analysis of EEG signal. Further, Support Vector Machine technique has used for classification the sleep stages and maximum accuracy obtained as 86.82% [6].

A deep learning architecture has proposed by Chambon et al. and has concluded that the EMG channels improve the efficiency of the model [2].
Random Forest based approach has proposed by Pejman and Farhad[7] on the PhsyioNet dataset using statistical features. Another study has done by Umit et al. [8] which has proposed an approach for drowsiness detection. The accuracy of the study has ranged from 86.46% to 88.47%. Yuta et al. has conducted a sleep stage classification for EEG signals recorded from mice [9].
Liang et al. [10] used multistate entropy and autoregressive model parameters as features and linear discriminant analysis as classifier for single-channel automatic sleep scoring.
One channel EEG based sleep stage classification was proposed by Emina and Abdhulhamit based on Ensemble Support Vector Machine approach [5]. Also Soha has proposed another approach by using a dimensionality reduction method known as Principal Component Analysis (PCA) and Support Vector Machine classifier[11].
Several automatic sleep stage scoring approaches have been proposed by researchers over last few years, also recent practical diagnoses and clinical researchers require classification accuracy at least 95% hence still sleep stage classification has become a popular field of research. Because of the accuracy gap is still in the classification of sleep stage, the field is open for effective researchers. This study has focused on classifying the wake and four sleep stages by using an ensemble technique which is most widely used Random Forest.
The section II will describe the proposed approach and related technologies used to build the model and the next section will represent the results and interpretation.

II. METHODOLOGY

A. Dataset

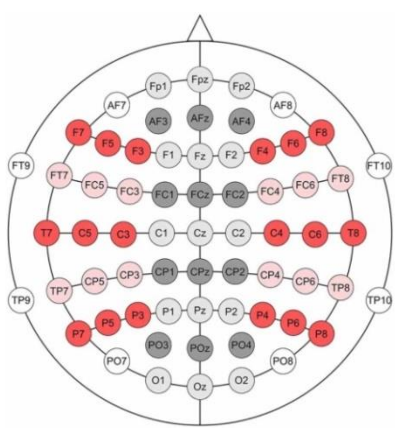

Figure 1: Electrode placement on scalp

The dataset used to build and test following model was downloaded from the https://physionet.org/. The sleep-edf database contains 197 whole-night PolySomnoGraphic (PSG) sleep recordings. The database contains two different datasets among them only the sleep-cassette dataset was taken. The EOG and EEG signals were each sampled at 100 Hz in the sleep-cassette. There were 153 PSG recordings and the relevant Hypnogram files which has recorded from 82 healthy Caucasians subject in aged 25-101. The PSG files are whole-night polysmnographic sleep recordings containing EEG, EOG, submental chin EMG, and an event marker. The EEG features were recorded from Fpz-Cz and Pz-Oz electrode locations.
Hypnogram files contain annotations of the sleep patterns that correspond to the PSGs. These patterns (hypnograms) consist of sleep stages W, R, 1, 2, 3, 4, M (Movement time) and ? (Not scored). The PSG files were in the format of EDF while the hypnograms were in EDF+ [12]. This study has used the W, 1, 2,3and 4 sleep stages in to consideration.

B. Proposed approach

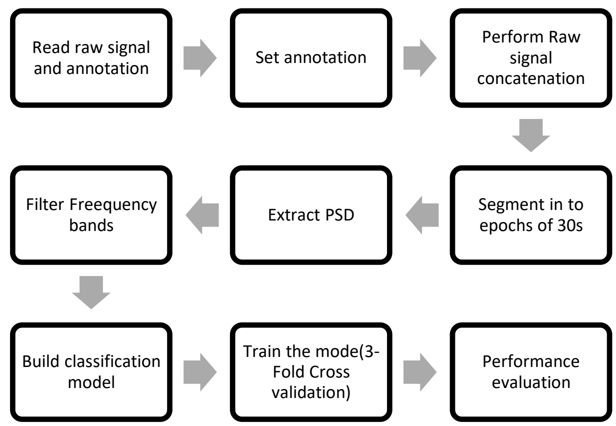

Figure 2: Proposed Approach

Two third from the data set were taken in to training and the rest were taken as test set. According to that 103 PSG files were taken in to train set and 50 were taken in to test set. As the proposed approach in Figure 2 shows the raw signals of both train and test sets were annotated using the given annotation file in the physionet dataset. The annotated raw signals concatenated in to one signal for easiness of further processing. Then raw signal segmented in to epochs of 30s and extracted the Power Spectral Density (PSD) relevant to the EEG feature, also filter the frequency band from 0.5Hz-30 Hz hence the sleep stages are falls on that frequency range as shown in Table 1. The events; Sleep stage W, Sleep stage 1, Sleep stage 2, Sleep stage 3 and 4 were extracted as the targets. The calculated PSD s for the training epochs then fed into the classification algorithm with the relevant targets for training the model. The trained model tested using the PSD s of testing epochs.
Random Forest classification using bootstrap sampling was used when building the model and the model was compared against three different classifiers. The three classifiers are; K-Nearest Neighbor, Support vector Machine and Multilayer Perceptron.

C. Random Forest (RF) Classifier

Table 1: Brain state for different frequency bands

Identifier	Frequency band	Brain State
Delta	1-4 Hz	Primarily associated with deep(slow) wave sleep
Theta	4-8 Hz	Appear as consciousness slips towards drowsiness
Alpha	8-13 Hz	Usually found over the occipital region. Indicated relaxed awareness without attention.
Beta	13-30 Hz	Associates with active thinking and active concentration.
Gamma	30-100Hz	Represents binding of different populations of neurons.

As the name implies Random forest is an ensemble of large set of decision trees which are uncorrelated to each other. Each individual decision tree in RF make the predication and the mostly voted prediction will be given as the final predication. RF improves the predictive accuracy, control over-fitting and reduce the variance rather than one single decision tree. It has the ability to handle larger input datasets when compared with other methods.

The RF allows us to perform the bagging with bootstrap sampling which is kind of a technique that samples are chosen from the original dataset with replacement. The proposed RF has built with bootstrap sampling.

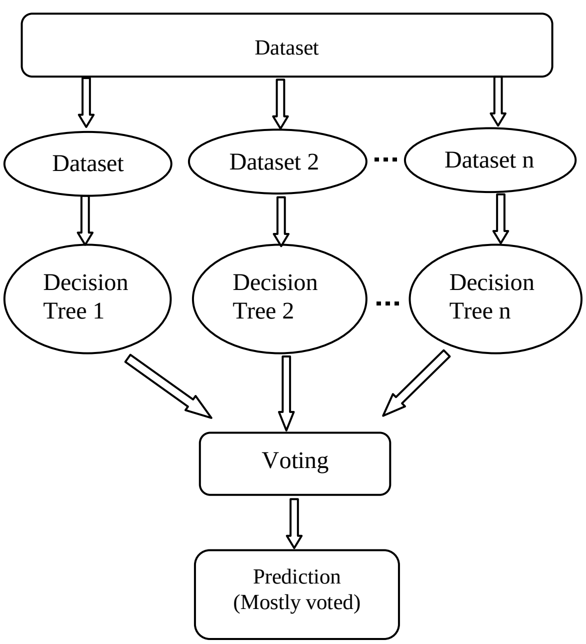

Figure 3: Architecture of Random Forest

According to the number of decision trees creating in the RF the classification accuracy might varies. In the proposed approach the bootstrap sampling has used and the evaluation done for different number of decision trees.

D. Support Vector Machine (SVM) Classifier

The SVM classifier in its algorithm find a hyper-plane in an N-dimensional feature space that has the maximum margin which can be classifying the data points distinctly. A set of mathematical functions to transform input data into required form are used in SVM classifier which are known as Kernel. The radial basis kernel function (rbf) and the sigmoid kernel function taken in to consideration in this study.

D. Multilayer Perceptron (MLP)

MLP is known as a type of Artificial Neural Network which comes under feed-forward. Every MLP has at least three layers which are known as input layer hidden layer and output layer where number of hidden layers can changed as the requirement of the problem. And each layer has built using perceptron. As Figure 4 shows each perceptron takes the input and multiplied it with the relevant weights. The weighted sum will be calculated and the final output will get through an activation function. MLP proposed in this approach has used the ReLU activation function.

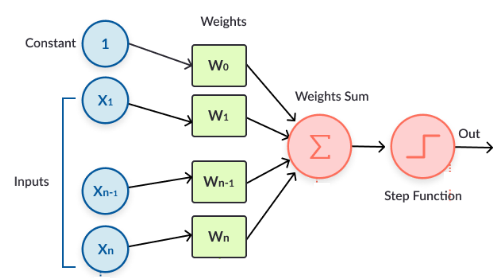

Figure 4: Structure of a perceptron

IV. RESULTS AND DISCUSSION

	Wake	Sleep stage 1	Sleep stage 2	Sleep stage 3
Wake	1843	5	5	2
Sleep stage 1	45	19	48	1
Sleep stage 2	6	25	318	76
Sleep stage 3	0	0	1	97

Figure 5: Confusion Matrix

To evaluate the built RF model test set was fed into the model. The accuracy score was around 0.91 which means the model is 91% accurate. As the Confusion matrix in Figure 5 represent, the Sleep stage W which means the Wake stage and the Sleep stage 3/4 has classified with more accurately than other stages.

The Sleep stage 1 has classified as Wake and sleep stage 2 rather than it classifying as sleep stage 1. Some of sleep stage has classified as sleep stage 1 and 2 but very few as wake.

Table 2: Accuracy score

RF	SVM	KNN	MLP
0.91	0.74	0.86	0.84

The built model using RF classifier then compared with the other three classifiers. RF model has given the highest accuracy while MLP has given the next highest accuracy.

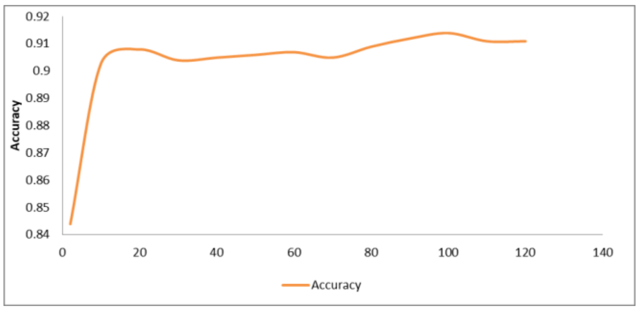

Figure 6: Effect of the number of decision trees in RF

The accuracy rate can be changed with the number of trees in Random Forest. The Figure 6 shows the accuracy ratio in to different amount of trees generated by the RF algorithm. The accuracy increase as the number of trees increase and come to its peak at 100 then start to decrease the accuracy.

To evaluate the effect of two different channels (EEG Pz-Oz, EEG Fpz-Cz) the model was tested for two different channels separately. Other than the SVM classifier it shows that the combination of the two channels; Pz-Oz and Fpz-Cz always boost the model.

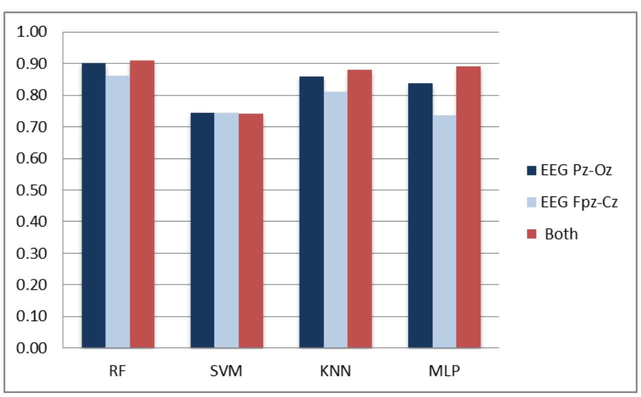

Figure 7: Effect of the Channels

Further to test the effect of different data fed into the model 3-fold cross validation was carried. For each fold the accuracy score which was defined as the ratio among the number of correctly classified data points and the number of total data points was calculated. As Figure 8 show the comparison between the different classifier in cross validation, the Random forest classifier has given the highest accuracy in 3-folds. The accuracy scores are shown in Table 3. Multi-Layer Perceptron also has given a considerably highest accuracy in 3 folds next to Random Forest.

Table 3: Accuracy Scores

	1st Fold	2nd Fold	3rd Fold
RF	0.91	0.90	0.86
SVM	0.74	0.77	0.74
KNN	0.88	0.87	0.80
MLP	0.89	0.89	0.82

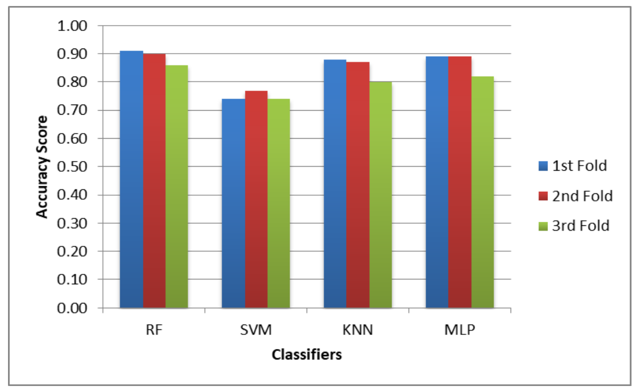

Figure 8: Result of Cross validation for different classifiers

V. CONCLUSION

Sleep stage classification has become an important in terms of sleep disease. It is said that with proper classification of sleep stages diagnose and treatment for such sleep related disease is much easier and effective. Since most of the medical aspects require more than 95% accuracy of sleep stage classification the field is still open for researchers. EEG, EMG, EOG signals has used in various researches with extracting different features and by using different channels for these studies. Lately Machine learning has used for the studies to increase the accuracy of sleep stage classification. As the methodology explained in this study, the study has focused on building up a Random Forest Classifier based model to identify the Sleep stages in EEG signals. Further the study has analyzed the effect of the number of decision trees in Random forest on the accuracy of sleep stage classification. With the increment of the number of decision trees, the accuracy also increases until a point then its start reducing. Further among the two channels (Pz-Oz and Fpz-Cz) though Pz-Oz has given higher accuracy than Fpz-Cz the combination of two channels always has given the highest accuracy. The comparison between four classifiers expose that RF has given the highest accuracy score as 91%. This result is highly depending on the dataset. In future more features can be extracted and tested with the same model created above and make a comparison about the features.

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