Drowsiness detection by analysis of EEG signal with the help of Machine Learning

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***Abstract*—Electroencephalogram (EEG) signals give physiological indications of mind whether you are resting or prepared to do some work, think or dream. To understand these things it is essential to aggregate some EEG motion from the human cerebrum. Among all open physiological indications of the cerebrum, EEG is economical and adaptive. The aim of this work is detecting drowsiness of a person by analyzing EEG signal with the help of Machine learning. For this, we examining the EEG signal and we extract the features. Here three different types of features such as time, frequency-based features and sub-band based features are extracted. Total we extract 66 features from each epoch of individual subject in order to classify drowsiness and alertness. Here we considered total 30 persons and we used the Random forest as the classifier techniques to predict the drowsiness states. With these all parameters, with different ratios of active and drowsy training samples our experimental results show more than 95% accuracy.**

***Index Terms*—EEG, drowsiness, features, Subbands and classification**

I. INTRODUCTION

Unusual sleep amid daytime, falling asleep at an inappropriate time during work is called drowsiness or tiredness. Which can decrease the working capability and energy levels resulting the person to be irritable and shows poor judgment and sleep apnoea. Few of the reasons for this is medicine reactions, poor rest amount and some other therapeutic conditions like inappropriate levels of sugar and narcolepsy. Drowsiness could be more dangerous during driving, working in accident prone areas of factories etc. As per National Highway Traffic Safety Administration (NHTSA) announcement, more than one lack police reports shows road vehicle accidents were happened because of driver drowsiness [1], [2]. In India, during 2017 statistics it was 4, 80,652 road accidents and more than hundred thousand of people have died. Keeping in mind the end goal to handle these issues, to improve the alertness of person in all his important activity by measuring and alerting his drowsy condition during working time. Drowsy driving can be recognized by visual, non-visual and vehicular tracking methods [3]–[6]. In visual method of drowsy detection, a camera can be used to capture the driver face and gather the visual features like head movements and eye blinking sequences [3]. But the real time drowsy detection in such method is not possible as the cognitive state cannot be detected before the captured image is processed. Further, the driver may feel uncomfortable when the camera is focused towards his face and body during all-times of driving. In the non-visual method of drowsy detection method, wearable bio sensors are used to record the electroencephalogram (EEG) signal of the driver and are processed in real time by extracting the features of the EEG and ECG signals [4], [5]. In vehicular drowsy detection method, researchers detect the level of drowsiness of the driver by measuring the driving performance index. The physical deviation of the vehicle from its reference line decides the cognitive state of the driver [6].

In case of non-visual, bio signals are recorded through sensors and processed further for drowsy detection. This is done by few biosensors connected through in wired / wireless manner to the processor. The wired connection makes the driver uncomfortable by restricting his movement due to the wires connected. However, Lin et al provides solution by setting new remote sensors in a non-intrusive system [7]. Although physiological features such as brain signals, heart pulses, blood pressure and eye blinking rate are highly correlated with sleepiness, but the physiological signal activity produced by the brain has been found to be more reliable to determine sleepiness as the brain is always dynamic whether the person is in sleep or alert or think or even dream state [4]. Human brain is complex both in structure and Functionality. Bashashati et al [8] and Freedman et al [9] have suggested that to perceive brain activities EEG (Electroencephalogram), PET (Positron Emission Tomography), MEG (Magneto-encephalography), or FMRI (Functional Magnetic Resonance Imaging) technologies are usually used. Among all these cerebrum methods EEG is the most flexible procedure in the event of both therapeutic and non-medical due to following reasons:

- EEG specifically measures neural action.
- EEG has a high time determination and can catch the

physiological changes fundamentally, the intellectual procedures much better compared to other cerebrum imaging methods, (for example, MRI or PET scanners).
- EEG is economical, light weight and additionally versatile (adaptable to gather the signal in true condition).

Electroencephalography (EEG) is the process of gathering and monitoring electrical motions of cerebrum. To record such electrical movements few electrodes were placed on or beneath the head [10]. This technique is used in many research areas like cognitive, human robot interaction and detect seizure risk in epilepsy and also in sleep related problems. EEG is especially helpful in cognitive science. It discloses the changes in brain state accordingly with different experimental conditions. It works with high accuracy due to its high sampling rate. This helps us to disclose much about the sequence of mental procedures. Maximum of research work related to the psychological study is centered on the quickness and accurateness of subject response like how long a subject takes the respond to a particular stimulus. EEG can develop this strategy for cognitive processing by showing us what occurs in the brain previously, amid and after a particular reaction.

Machine Learning technique is the study of allowing PCs to learn, without being expressly customized [11]. Any ML issues can be related to any one of two classifications, such as supervised and unsupervised learning. Drowsy detection is possible by any of the methods. Authors of [12], [13] have presented drowsy detection by unsupervised methods whereas authors of [14]–[16] have proposed drowsy detection by supervised method. The rest of the paper is organised as follows. Existing work related to drowsiness detection using multi-channel EEG and single-channel EEG is illustrated in Section 2. EEG data acquisition and getting required epochs from available EEG data is shown in Section 3. Whereas Section 4 describes our proposed work and experimental results. Finally, Section 5 concludes the paper.

II. Related work

Automatic drowsiness detection by analysing EEG signal and machine learning techniques is possible by the supervised learning and unsupervised learning methods. In the unsupervised approach of drowsiness detection, the acquired data does not require a label to prepare training dataset on whether the driver is in an active state or sleepy state at each time moment. It considers baseline shifts and differences in EEG spectra during recording conditions in different driving sessions.

Pal et.al [12] and Hung [13] have proposed EEG based drowsiness detection in unsupervised approach by creating alert model. A virtual driving environment was setup by the authors for recording the EEG data of the driver. The authors used the power spectrum of alpha and theta subbands and considered first few minutes of driver EEG signal as the active state to predict the drowsiness of a driver. In the supervised approach, it is necessary to label the acquired dataset as the train data and subsequent test data can be predicted to be in an alert state or drowsy state. Yeo et al [17], Lin et al [15] have proposed EEG based drowsiness detection using supervised approach by using classification model. In these cases, the data acquisition is done through a various number of EEG channels. Yeo et al [17] utilized 32 channels EEG information and Support Vector machine (SVM) classifier to predict the drowsiness of a person with a much better accuracy. The authors extracted EEG sub-bands like delta, theta, alpha and beta by the Fast Fourier Transform (FFT) method and features dominant frequency, average power of dominant peak, center of gravity frequency and frequency variability are extracted from each of the sub bands for further analysis and estimation. Similarly, Khushaba et al [18] used 3 channel EEG signals along with other bio-medical signals such as EoG (Electrooculography) and ECG signal for drowsy detection. Though multichannel EEG signal can provide better accuracy for drowsy detection, but it is expensive and not suitable for real time detection of the driver's alert state. Further, multi-channel data acquisition needs the driver to wear a cap fitted with several electrodes onto it, making him highly uncomfortable. On the contrary, a single channel device can be just a small knob on the head as in Fig:1.

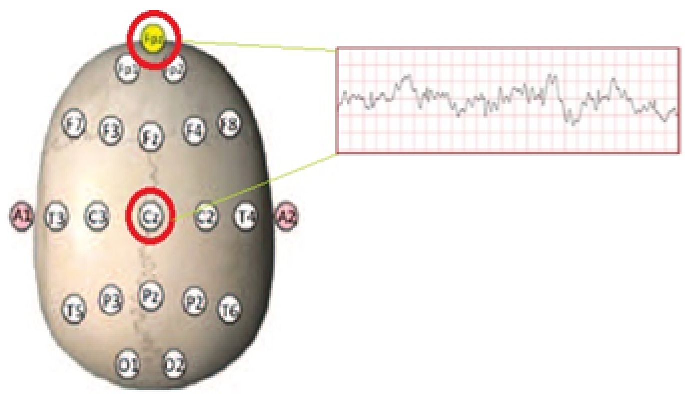

Fig. 1. Data acquisition channel.

Authors of [19]–[21] have presented drowsy detection by utilizing single channel EEG information and multiple classifier methods. Jalilifard et al [19] utilized 52 features and Kdtrees classification algorithm to predict the drowsiness of a person with better accuracy. The authors extracted EEG subbands using Short Time Fourier Transform (STFT). Similarly, Garcés et al [20] utilized STFT, linear discriminative analysis to reduce the features, and neural network classifier to determine the sleepiness of a person. Likewise, Aboalayon et al [21] used Butterworth bandpass filter to mine the EEG sub-bands and SVM classifier to predict the drowsiness of a person with better accuracy 92.50%. The authors Lin et al [15] and Tripathy et al [16] find the drowsiness of a person using alpha and theta bands, by calculating Mahalanobis distance (MD). These authors used FFT, to extract the alpha and theta bands. Finally, they combine alpha, theta MD along with some constant α, was set from 0.1 to 0.9 to compute Combined Mahalanobis distance (MDC). If the MDC value is greater than threshold value consider as person is in drowsy.

Cohen [22] explains digital signal processing methodologies to analyze EEG signals. Especially in case of extracting required subbands, there are some signal processing techniques like Fourier transforms and digital filters, Wavelet Transform and empirical mode decomposition (EMD) etc.

The key novelty of this work is to recognize the sleepiness by using a feasible set of features, effectively and essentially usable techniques i.e., FFT, and an efficient classification strategy. The test comes about on an assortment of subjects confirm over 95% of classification accuracy of the proposed work.

III. EEG DATA ACQUISITION

Human cognitive states can be broadly considered in two phases. i.e. in awake or in sleep stage. Drowsy stage is the stage when a person transit from the awake stage to sleep stage for a very short span of time(may be for few seconds) but very frequently. Thus recording of EEG signal at drowsy state is a challenging task. This requires a virtual reality setup for recording of the data by allowing a subject to stay in a monotonous state for a longer time period so that he may feel drowsy or go to the sleep state.Thus for the current work we have tried to collect the EEG data from physionet.org which is a standard organization of MITBIH depicted by researchers for the investigation and analysis of sleep stages [23]. The available data has been recorded for different duration's for different subjects. During acquisition of EEG data from brain, subject is either be in awake state or be in any of one sleeping state. However, we have modeled the data as a series of alternate awake and sleep state as shown in Fig.2.

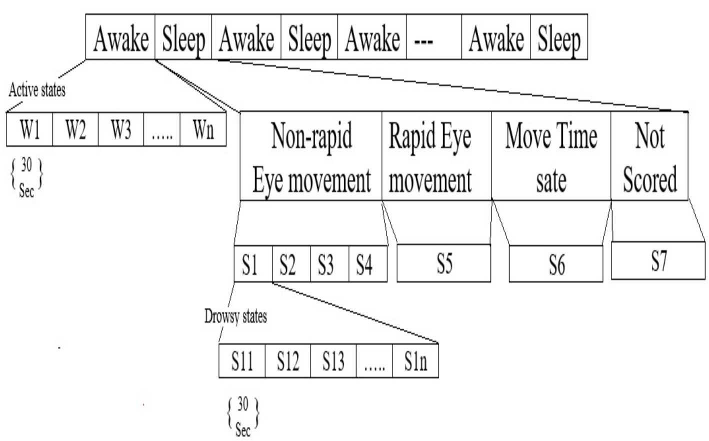

Fig. 2. System diagram for gathering wakeup states and drowsy states.

The figure explains that, human sleep stage can be partitioned into 7 different stages as S1 to S7. The initial stage of the sleep state, i.e. the S1 stage is usually considered as the drowsy state as this state lies in between the awake and the deep sleep stage of a person. Thus the recorded data contains several epochs of 30 seconds duration each for the awake stage (W) and the S1 stage as indicated in the figure 2. The number of slots (or epochs) in the awake stages vary from person to person. The same is also true for the S1 stage.

Let A be a all awake states W of a person

$$A_i = \{\, w_i \mid w_i \in W \,\}$$

Let D be a all sleep states S_1 of a person

$$D_i = \{\, s_{1i} \mid s_{1i} \in S1 \,\}$$

Thus for the current research, we consider all the epochs present in the W stage and the S1 stage of a person P and is indicated as:

$$P_i = A \cup D = \{\, X \mid X \in A \ or \ X \in D\}$$

IV. PROPOSED DATA AND SYSTEM MODEL

Thus, the EEG recorded data is gathered for 30 persons for analysis and prediction. The different stages of processing of the gathered data of 30 persons are shown in Fig.3.

The recorded data is preprocessed by the Independent Component Analysis (ICA) method before further processing. The ICA helps in removing the ocular artifacts by considering signal amplitude distribution over time [24], [25]. After the ICA of the data it is fed to the feature extraction stage. The tenacity of feature extraction in the present study was to extract a set of features that optimally distinguish 'alert' EEG from 'drowsy' EEG. In this phase, we have extracted the features in time domain, frequency domain and also few features were extracted from the sub bands. Time domain features can speak about morphological qualities of an EEG signal. They are basically interpretable and appropriate for many real-time applications like finding epileptic problems etc. In the current work we have extracted total 12 features in time domain. They are Energy, Entropy, skewness, Kurtosis etc. for further analysis and classification. Fast Fourier transform (FFT) is used to gather frequency based EEG sub-bands. FFT for Continuous time signal $x(t)$ (i.e., EEG) is $X(f)$ which is obtained as below:

$$X(f) = \int_{\infty}^{-\infty} e^{-j2\pi f t} dt$$

Frequency based features are the multipurpose features, which are repetitively utilized for describing changes in EEG signals for every particular reaction. We have used total 9 features like Center of Gravity Frequency(CGF), Frequency Variability (FV), and Median frequency (MF) etc. for further processing and classification. In addition, various discriminating features from time and frequency domain and some more features are extracted from EEG subbands (δ, θ, α, β and γ). In this proposed algorithm EEG sub-bands extracted by the Fast Fourier Transform (FFT) and 9 features are calculated from each subbands. Such as Energy, Mean, Co-variance, Mahalanobis distance [15] and sum, mean, min, max and median of local maxima (peaks) of each sub-band frequency. Thus, total 66 features were extracted in the current

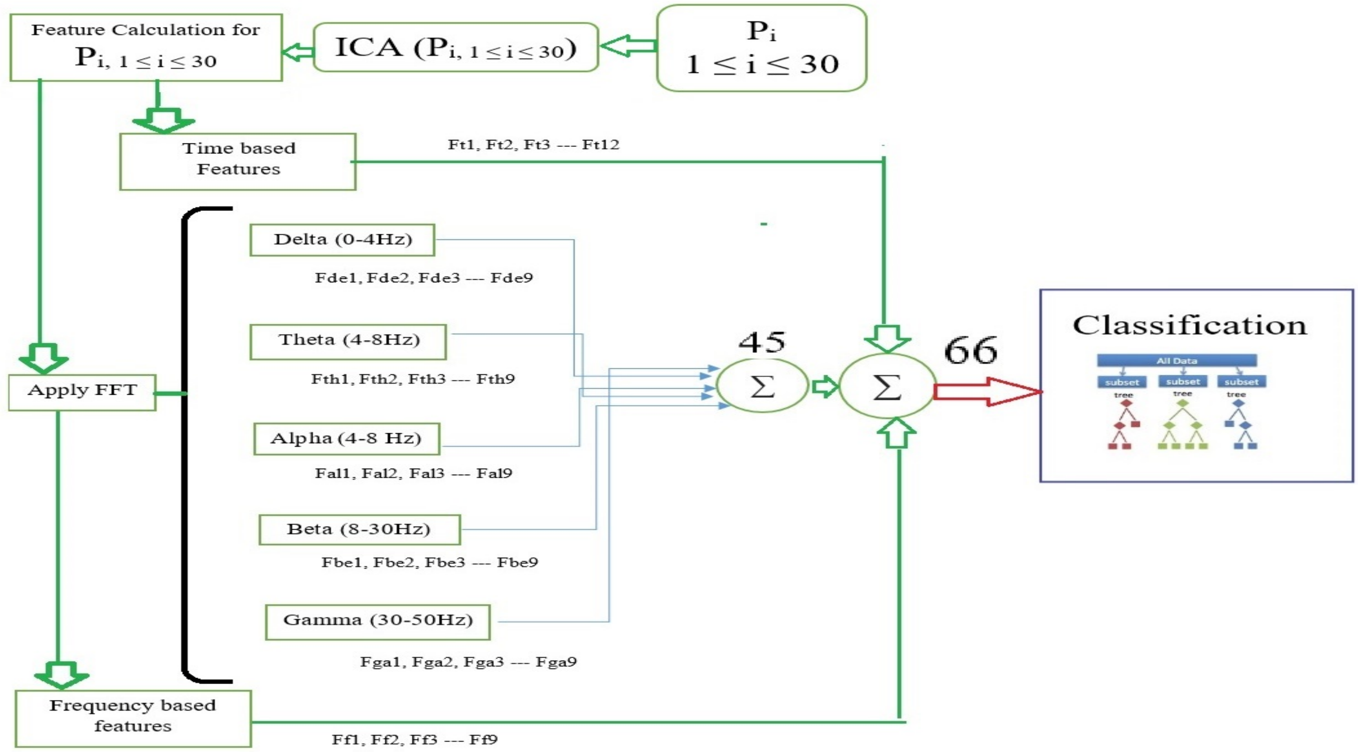

Fig. 3. Stages of signal analysis for proposed drowsiness detection.

work and fed to a supervised learning classifier for detecting the drowsiness of a person. We tested our model using the SVM, Random Trees, Rep Tree and Hoeffding Tree classifier for advanced validation of our proposed classifier. Weka (version 3.8.1) has all these machine learning algorithms, implemented using java and it is General public licensed open source software.

These 66 features in this drowsiness detecting model are based on the observations in the multiple researcher's works on different applications. Using available past data (in-sample) forecast the future (out of sample) by training the model. To train and evaluate the model using in-sample data there are some training methodologies. The initial idea of training methodology is, provide all available data (in-sample) for training and also for a testing purpose. Here the model gives maximum training accuracy but it was overly complex and overfit the training data. To overcome this, another alternative is Train-Test split. Here the in-sample data is split into the two groups such as training and testing. Evaluate the model by testing set, before that the model is trained on the training set. Here the resulting evaluation matric is known as testing accuracy and it was a better estimate of out-of-sample and it is not overly complex as like initial idea and it helps to avoid overfitting. However, there is a drawback in this alternative method, i.e., its testing accuracy can change a lot depending on which observations happen to be in the testing set. This leads to the testing accuracy is a high variance estimate of out-of-sample accuracy. This could solve by creating a bunch of different train and test splits of in-samples and repeating the second procedure on each test-train split and then averaging of testing accuracy leads to the less variance on out-of-sample. This procedure is called cross-fold validation. Here the datasets features were classified into train and test sets by putting fold cross validation as 10. So, the available in-sample data (let say N, for our experiment it vary from subject to subject) is split into 10 folds and each fold contains N/K Samples. Take any of one fold as a testing set and the union of remaining 9 folds as the training set and calculate the testing accuracy. Repeat the same thing by considering another one fold as a test and remaining as a train set till all of the folds included one time in the test process as implemented in [26]. The average of all these outcomes is considered as the final result of a classifier.

The accuracy results of single subject (subject id: SC4151E0) with different active and drowsy epoch ratios of various classifiers are summarized in Fig 4:

Similarly, the average accuracy results of 10 subjects with different active and drowsy ratios of these classifiers are summarized in Fig 5:

From the results it is clear that the random forest classifier gives better results in case of single subject and also in case of multiple subjects. So we choose random forest as classifier for further work process. Thus for detail study of the various awake and sleep epoch ratios, we have computed the average accuracy of a group of subjects (may be multiple of 5) with

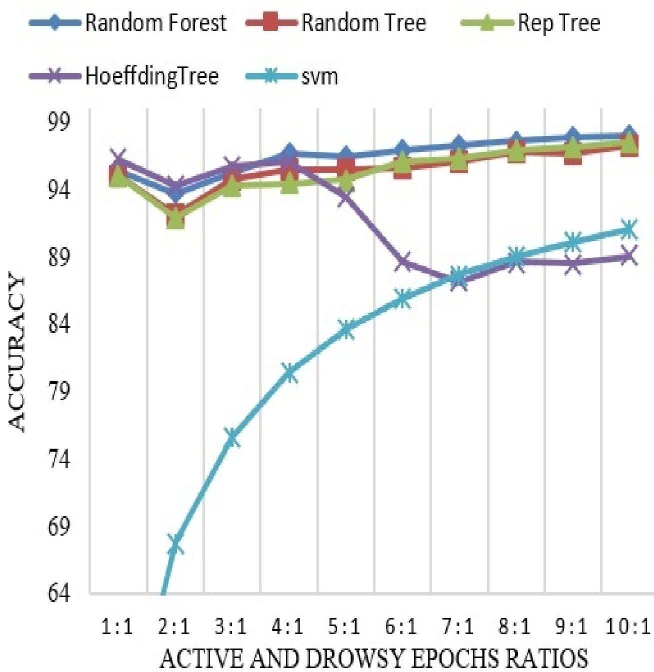

Fig. 4. Comparison of multiple classifier results of proposed drowsiness detection model with respect to different active and drowsy states of single subject.

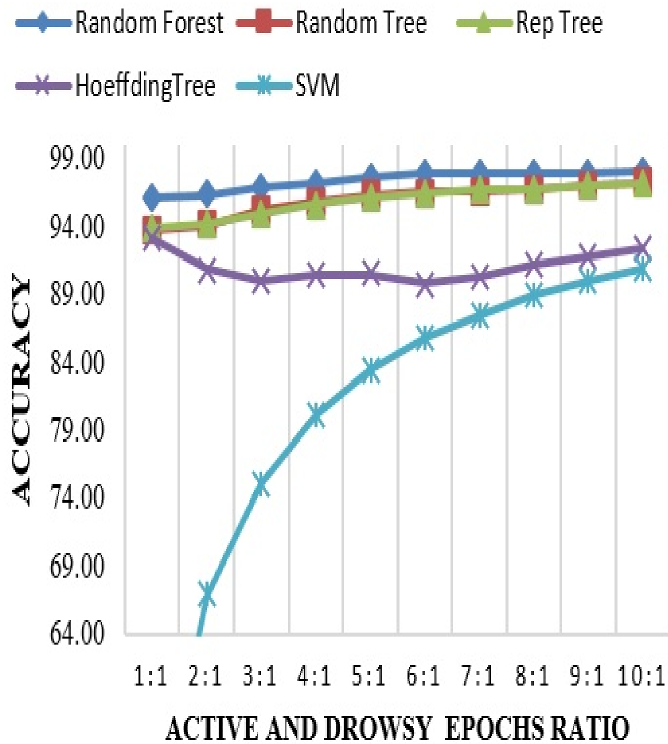

Fig. 5. Comparison of multiple classifier results of proposed drowsiness detection model with respect to different active and drowsy states of 10 subjects.

changing ratios as in fig 6. It clearly indicates the accuracy levels of different number of subjects in multiple ratios of active and drowsy states. Here active drowsy ratios are in 1:1 to 10:1. In case of less number of subjects (i.e., minimum of 5 subjects) a high number of active states and less number of drowsy states features give more accuracy. In case of more number of subjects (i.e. 30) more accuracy found at 6:1 ratio of active and drowsy samples.

Conclusion

Use of EEG signal for real time drowsy detection is a common phenomenon. It gives a better accuracy of detection in comparison to the visual and traffic monitoring method of drowsy detection. However, getting the data for drowsy state of a person is a challenging task. Thus small epochs of 30 seconds durations are considered from the awake stage and the sleep stage of a person. And with appropriate method of artifact removing, it is fed to the feature extraction and classification stage. Random forest method is chosen for classification as it proves to be more efficient in terms of accuracy calculation.

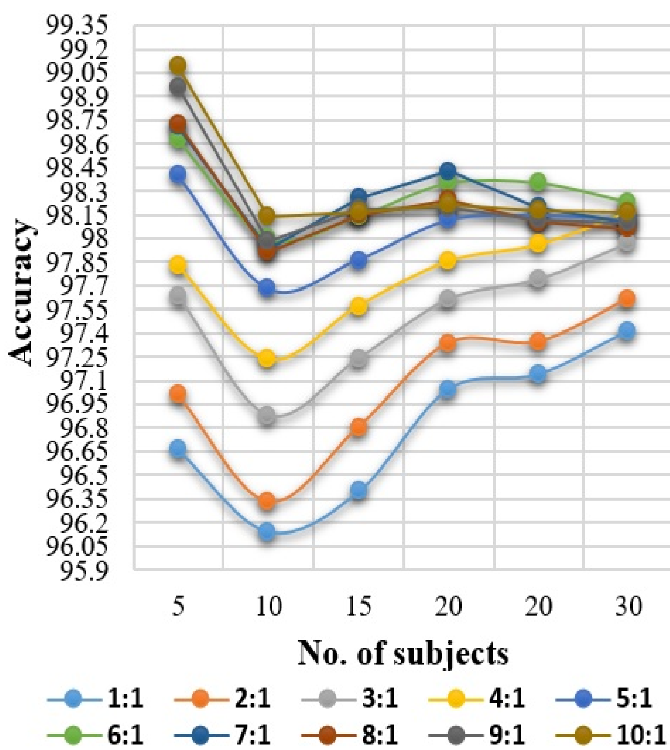

Fig. 6. Random forest classifier average accuracy levels for group of persons with various ratios of awake and sleep stage epochs.

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