BIO-ELECTRONIC-INTELLIGENCE BASED SLEEPING STAGES CLASSIFICATION

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DOI: http://doi.one/10.1729/Journal.23688

Abstract: **The marvellous phenomenon of sleep that consistently takes place for about one third part of a human being life-cycle had been a subject of mystery for many physicians over century. The research to know its lifecycle leads to the primary bifurcation of its occurring stages. The specialists of this field often use the visual inspection of neurological signals to map the scoring of sleeping stages with the help of EEG signals. Usually, EEG signals for this task are further divided into five wave bands i.e. delta, theta, alpha, beta & gamma. To filter and classify these five wave bands further ahead into sub bands Butterworth band pass filter is used. The gained sub band features will be then fed to the machine learning classifiers. This time-consuming task often possesses its limitations leading to the delay of result generation process. These limitations generated the demand for development of Dynamic classification of sleep stages (DCSS). Classification of sleeping stages leads to the knowledge for accessing that channels of neurological fluxes caused via various brain waves that could possibly help in the monitoring and diagnose of sleep disorders associated with sleep cycle. To get dynamic results modern Machine Learning Algorithms & improved statistical procedures are needed to be applied. This review paper aims at presenting the need and approach for dynamic and deliverable technique to classify and detect sleep stages with sleep dataset using modern statistical procedures over single-channel EEG signals.**

Keywords: EEG; DCSS; Machine Learning Algorithms; sleep stages; sleep disorders.

Introduction:

The pleasure of performing in physical activities comes backed up from sleep oriented mental rest. Brain is a complex organ the functionality of which is totally affected from the sleep cycle. Sleeping disorders include excess sleeping, wake conditions, neural impulse triggered leg movements etc. Such crucial implementations of disturbed sleep cycle can cause anxiety, depression, laziness & many other associated issues. Medical science already had a sleep-based research branch that is involved in practising and solution of clinical problems. Dynamic classification of sleep stages is initial and most important step in detection of sleep disorders. The key role is being played by PSG recordings that are being taken while the subject is sleeping at the hospital overnight. The most usually followed PSG recordings are combination of Electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG) and Electrocardiogram (EDG) recordings. **DCSS** is a concept that characterizes the stages of sleep. For this particular purpose several monopolar and bipolar montages are used. The bipolar montages helps in generating the referential input & output chain to study the effect of horizontal and vertical eye movement over electromagnetic waves in brain and thus gathering the associated frequency of waves through EEG signals as shown in figure below.

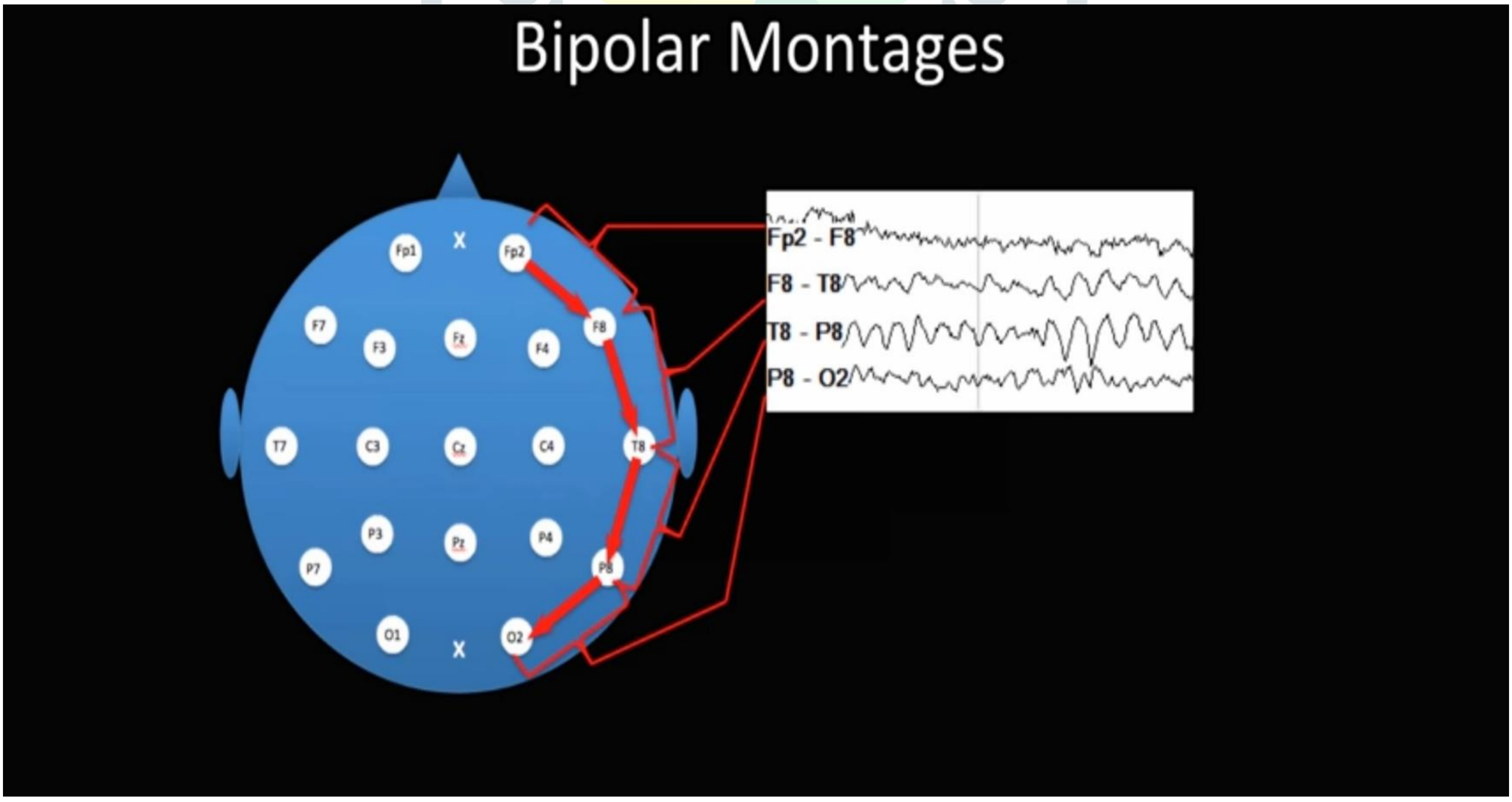

Figure 01: Associated Bipolar Montages with electrode placement

The simultaneous registration of EEG in several areas of the cortex of the large hemispheres, EOG, EMG muscles of the head, neck, limbs, etc., as well as the use of a number of other printing techniques allows to distinguish several brain conditions in the process of transition from wakefulness to sleep. In this continuum can be highlighted: 1) active wakefulness - desynchronized EEG, fast, low-voltage electrical activity; 2) wakefulness in a relaxed state - predominance in the EEG alpha rhythm; 3) falling asleep - a lowered index of alpha activity, the appearance of theta-rhythm; 4) shallow sleep - further reduction in the frequency of EEG, the appearance of delta waves and sleepy spindles at a frequency of 12 - 15 Hz; 5) moderately deep sleep - delta waves and K-complexes; b) Deep sleep - a high index of delta waves; 7) Paradoxical sleep - the appearance of rapid eye movements, EEG of active wakefulness, decreased tone of some muscles.

The duration of *nap stage* is 10-15 minutes. Next, a transition to the II stage is noted, which is characterized by the appearance of the so-called vertex potentials in the central frontal sections with a maximum in the central vertex region. Vertex waves have a morphology in the form of a single or biphasic acute wave followed by a slow wave. Despite the classical morphology and localization of vertex potentials, cases of their asymmetric spread to neighbouring departments are possible, which often alarms researchers. It is also necessary to differentiate vertex potentials with benign childhood epileptiform patterns (DEPD), which may have similar morphology and localization in the vertex sections. However, the morphological features of DEPDs - finer and sharper adhesions, as well as their chronological confinement - DEPD, as a rule, are found in the waking state and in the deeper stages of sleep, in contrast to vertex waves, it allows to exclude a diagnostic error.

Physiologically sleep patterns include nap stage, superficial stage of sleep, deep sleep stage and delta sleep stage. The *nap stage is* characterized by a gradual replacement of the alpha rhythm, low-amplitude slow-wave activity of the predominantly theta range with an amplitude emphasis in the fronto-central sections in combination with a moderate increase in the beta-wave index. Periodically, at this stage, the appearance of rhythmic high-amplitude bilateral slow waves, as a rule, of the theta range, with a pronounced amplitude predominance in the front sections, often having a pointed character - the so-called sawtooth rhythm, is noted. In the structure of the sawtooth rhythm, an alternative regional amplitude predominance in one of the hemispheres can be detected, which sometimes creates the illusion on the EEG of periodic regional slowdown. There is a theory that this EEG pattern is a manifestation of genetically determined brain excitability. Differences between the schemes proposed to date and the DCSS are related to the separation of some of the described stages into several sub-stages as shown in figure 02.

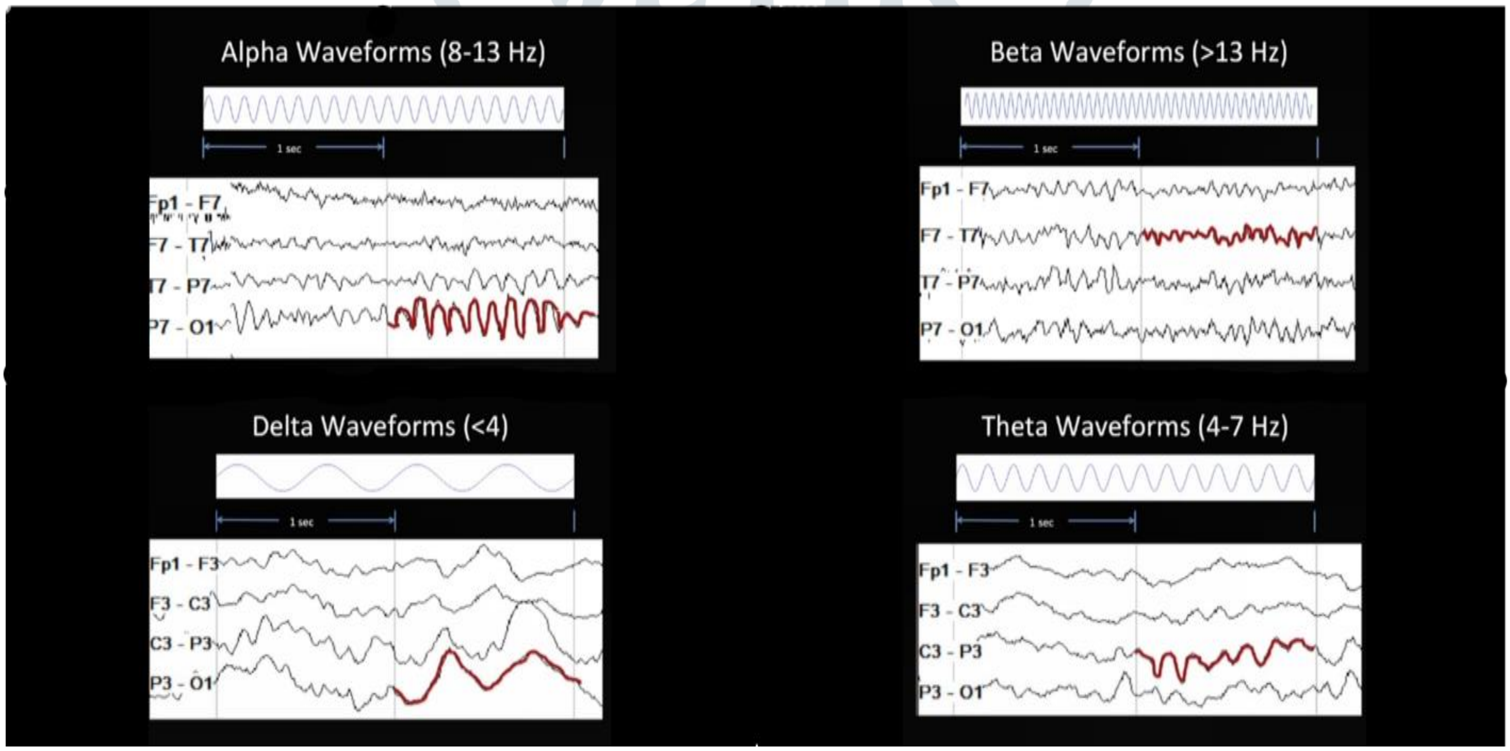

Figure 02: Separated sub band samples of EEG signals into alpha, beta, delta and theta waveforms.

The superficial stage of sleep is characterized by the appearance of the classical pattern of this stage - the "sleep spindles", first described by Loomis in 1938. This pattern is a group of rhythmic low-amplitude waves with a frequency of 12.5-15.5 Hz and an amplitude of 20-40 μ-V, forming spindle-shaped flashes with a specific localization in the central sections with spread to the frontal sections. With the transition to stage III, some slowdown of the carriage spindles to 10 Hz may be noted, as well as their more diffuse distribution. Also characteristic of the second stage is the appearance of K-complexes, which are short flashes of slow waves with an amplitude predominance in the vertex region, as well as the fronto-central section arising from external stimuli. Morphologically, the K-complex consists of an initial acute component, followed by a slow wave with a frequency of 1 Hz in combination with fast-wave potentials. Often K-complexes are associated with carotid spindles. At some forms of epilepsy, the appearance of atypical "epileptiform" K-complexes, in the structure of which a spike component is noted in the middle of the outbreak, is possible. During the second stage of sleep, other physiological island-wave sleep transits that are similar in morphology to epileptiform changes can be recorded. These include the so-called 6-14 Hz positive spikes, which are groups of low-amplitude waves with a frequency of 14-17 Hz and / or 5-7 Hz, arc-shaped, found over the temporal sections of both hemispheres. Periodically indicated arcuate commissures may have a tendency to diffuse distribution, and their interhemispheric asymmetry may also be noted. Positive occipital sleep transit (POSTS) - are positive acute potentials localized bi-occipitally as shown in figure 03.

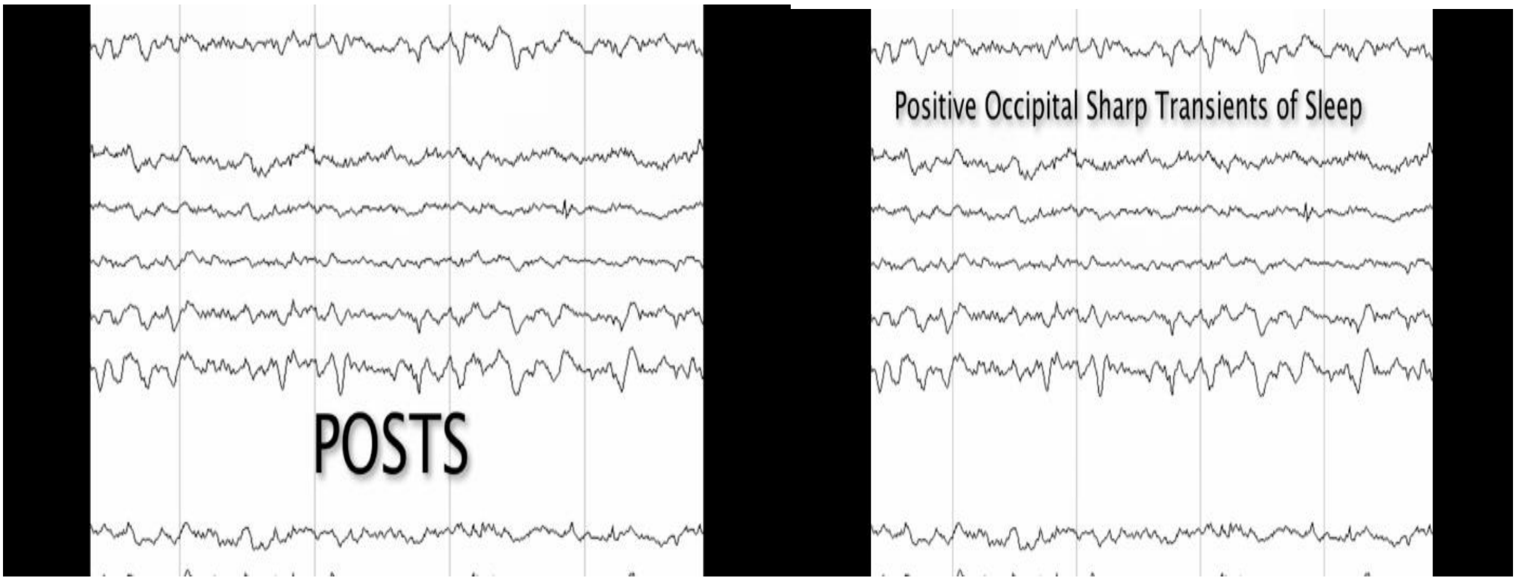

Figure 03: Visualisation of POSTS in EEG segments.

It is noted, as a rule, in adults in the stages of shallow sleep. Transition to *deep sleep stage is* characterized by an increase in the index of slow-wave activity up to 50% with the preservation of K-complexes and sleep spindles. With a further increase in the index of diffuse slow waves and the blocking of K-complexes and sleep spindles, a transition to delta sleep stage sleep is noted.

Related Work:

The research over sleep stages dates back to centuries in various civilizations. The first reference of which leads its traces back to the time of Vedas of Hindu mythology. In modern era back to the decades the human civilization was using each and every possible technological update to understand and modify the accuracy of the sleep stages classification. The importance in need of accuracy over classification of sleeping stages needs transition according to technological updates in this research era. The division of human sleep in the REM & NREM facilitated further classification leading to the separation of NREM in 4 crucial stages in which several neural networks of brain remain inactive and eyes remain closed; this particular state of partial unconsciousness generate a less complicated neural network of brain [1]. Mora et al. [2] stated that effective classification of the cycles of sleeping can act as helping hand in treatment of disorders related to sleep. Estrada et al. depicted a different and important paper that suggested that even the awake stage can be used to record sleep score even if it is not the part of the sleep cycles. The relation establishes itself here with unconsciously aroused state of human brain [3].

Depicting the data Chih-En and Sheng-Fu stated that around 33% of world population might be suffering from insomnia itself [4]. Recently the extraction of brain signals with the help of EEG, ECG, EOG & EMG have shown very crucial details in stepping over treatment of sleep dysfunctions [5]. Thus, generally sleep stage classification can be helpful on details of restoring the energy level of human body via a psychological recovery process or by reversing the fatigue caused by wakefulness stage of human body [6]. Recording of sleep scoring overnight is a very lengthy and time-consuming process and then categorizing the whole data is even more messy. Therefore need and application of automated methods for analysing the typical EEG signals might be fruitful [7]. Rechtschaffen and Kales (R&K) shall be well quoted for their milestone initialization sleep stage classification work [8]. SVM used for symbolic representation of EEG signals had also been used for the automated feature extraction to over an accuracy of 70% and 77% respectively [9][10]. Discrete Wavelet Transform (Maximum Overlap) and SVM classifiers are also a great combination to detect sleep/awake condition (95.0%) and sleep stage classification (93.0%) in various multiple classes [11].

Methodology:

The seldom innovation of this research work is to facilitate the physicians to use an automated technique that can be implemented over hardware for real time diagnosis of sleep stages and thus a more effective treatment of sleep disorders. Our procedure that will help in detecting drowsiness, sleep apnea and various sleep disorders will start as the initial decomposed classification of EEG signals frequency bands in alpha, beta, gamma, delta and theta sub bands using band pass filter (IIR BUTTERWORTH). After then two different and new features will be extracted by each frequency band separately. And finally some known Machine Learning classifiers will be used to identify most efficient classifier among W, REM & NREM sleep stages. Since the proposed classification method uses automated classifiers it is most dynamic method used till date over single EEG channel. Figure 04 depicts the opted procedure to implement DCSS system.

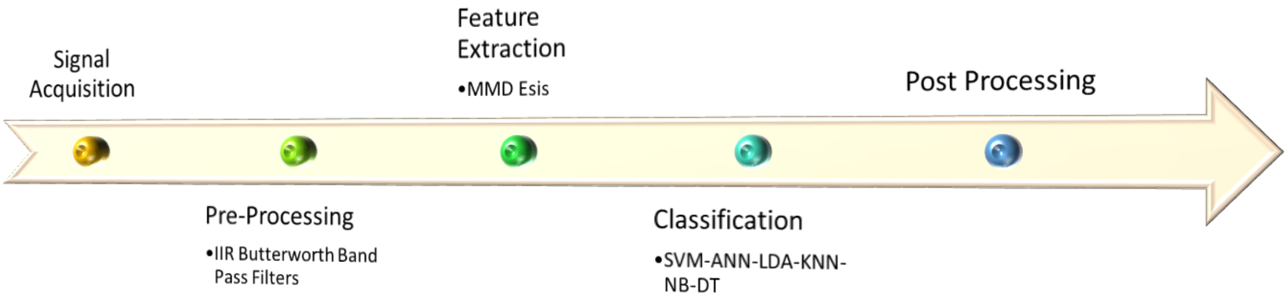

Figure 04: Proposed DCSS system procedure.

Dataset and Machine Learning and Classification: Five plus one machine learning classifiers containing Support Vector Machines, Decision Tree, Neural Networks, K-Nearest Neighbours, Naïve Bayes and Linear Discriminant Analysis along with Statistics Toolbar in MATLAB 2020a. The dataset being picked up by us is most widely used dataset used for sleep related researches. It is widely known as PhysioNet portal of Sleep-EDF database. It is having a collection of 61 mature subjects both male and female recorded over 24 hours at the sampling rate with 100 Hz frequency. Rechtschaffen and Kales states that the recordings contain oro-nasal respiration, rectal body temperature & hypnograms with event marking signals. The related hypnogram files have sleep patterns having stages wake, stage 1, stage 2, stage 3, stage 4, rem, movement time(M) and (?). Here question mark(?) states that it has not been recorded. Illustrating the purpose different classed stages of EEG signals and used input is presented in table and figure given below.

Stages	Wake	Stage 1	Stage 2	Stage 3	Stage 4	REM
Total	5961	3522	7175	4321	1900	897

Table 01: Various sleep stages with their respective sleep epochs

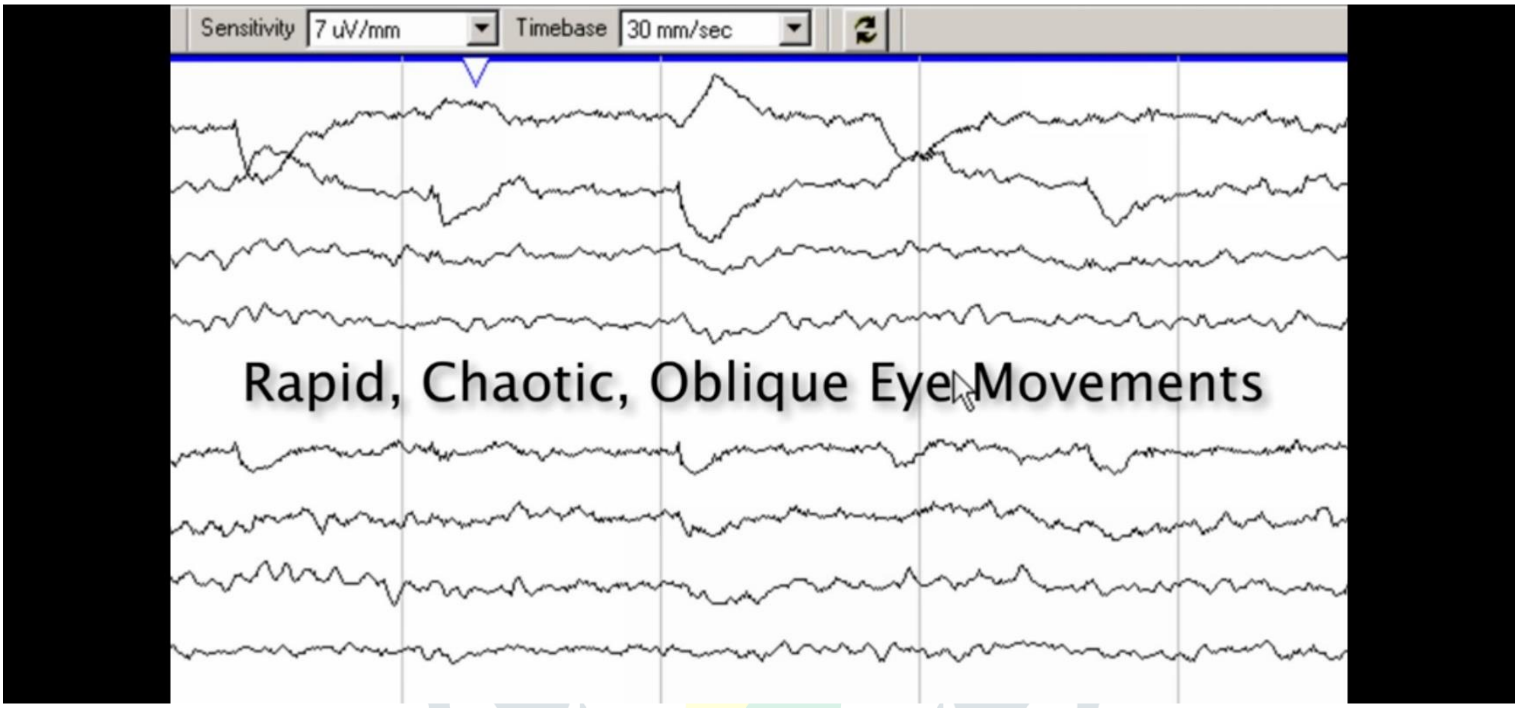

Figure 05: Various sleep stages with their respective sleep EEG samples

Conclusion:

The area of sleep research will become revolutionarily accurate with the help of Machine Learning Technology and the modern statistics toolboxes. Although the merger between the unfolded layers of biological aspects of the brain with the modern analysis procedures is taming the accuracy in results quickly. In this paper, we have demonstrated the possibility of the accuracy enhancing technique in EEG datasets to un-dig the mystery behind the response of traditional behaviour of brain signals with the process as proposed in figure 03.The proposed procedure will represent the improved sensitivity, specificity and accuracy after the DT will be performed on the extracted features.

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