Effects of EEG-Sleep Irregularities and Its Behavioral Aspects: Review and Analysis

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Abstract. Sleep is one of the important sections for humans for maintaining daily activities full of concentration and attention. Maintaining the proper sleep patterns is strongly related to physical, mental, cognitive, and physiological well-being. On the other hand, poor sleep patterns may lead to several diseases, and also affects both physiological and cognitive functions, which causes worsened general health condition of the subjects. For that reason, it's important to understand the sleep behaviour of the subjects and analyze the changes in sleep characteristics becomes one of the research perspectives, where we need to find the different major reasons and causes, which are directly or indirectly responsible for sleep deprivation. All these reasons arise more demands for a brief comparative analysis on the sleep monitoring system. The proposed chapter is mainly focused on the different methods and procedures for analyzing the changes the sleep behaviour in the different stages of sleep and also we have briefly focused upon how the age factor and gender of the subjects may disturb the sleep quality. It also offers a systematic review of how the Artificial Intelligence techniques make easier during the sleep stages classifications. Another important aspect of this chapter is a brief analysis of the different bio-signals and their clinical characteristics with concern to measure the sleep irregularities.

Keywords: Sleep Stages, Scoring Procedure, Polysomnography, Sleep Parameters, Artificial Intelligence

1 Introduction

Sleep is the basic requirement for human life for functioning different internal and external parts of the body and it plays an important role in properly maintaining an individual's memory concentration, immunity system performance, learning ability, and physical movement [1-9].In general, sleep is an active and regulated process and it majorly responsible for creating an essential restorative function, so that it helps to a proper balance between physical and mental health [10]. For the human body, sleep is a universal recurring and dynamic state and its physiological changes reflect our daily lifestyles in diverse ways. According to the different scientist's views, one human can cover one-third of sleep in life [11]. It has been reported from different sleep studies that proper sleep helps to strengthen the mind, motor functioning and it directly improves the performance at job places [12]. According to the statistics of the Institute of Medicine, it has found that 50 to 70 million Americans were affected by various types of sleep problems [13]. It has been reported from the Centre for Disease Control and Prevention that the people of the United States of America, consume less than 7 hrs. of sleep at night. Deprivation of sleep causes many times created other health issues in the human body such as heart disease, obesity, diabetes, and other neurological disorder and additionally sometimes it has also reflected that sleep disturbances cause the balance between memory consolidation, mental restoration, and behavior [14]. The major boosting reached in this sleep research with the invention of electroencephalography in the year 1930. It has been found for the first time from EEG signal in the year 1937 that the sleep behavior is not a homogenous procedure, but it consists of different sleep stages [15]. According to sleep experts, sleep is linked to metabolic function and obesity [16], and its negative impact is put on our health with subject to cognition processes such as vigilant attention and public health [17-18]. Sleep deprivation causes to one person feel drowsy and unable to concentrate on the job appropriately. The term drowsiness is considered sleepiness, where one subject can need to fall asleep. It has been seen in recent years that the drowsiness factor caused a huge loss towards society in terms of life. It has been observed that due to drowsiness, road accidents increased globally. According to a report from US National Highway Traffic Safety Administration, the death was caused due to drowsiness and as a result, 100,000 vehicles crashes. It has been seen also that due to drowsiness, the maximum accident happened due to "Drift-Out-Of-Lane" crashes [19]. Sleep is an important part of human health function. As per the report from the National Institute of Health, sleep plays an important role in human daily routine, and its importance is equally like food and water for survival. The proper sleep staging is directly connected to maintaining good health physically and mentally, and also it is strong associated with proper cognitive and physiological well-being. On the other hand, it is also seen that poor (or) disordered sleep patterns may cause serious health issues like impairments of cognitive function which consequences degradation of the health conditions[20]. All these reasons demand proper analysis on the sleep stages, changes in sleep behaviour with regards to the individual sleep stages, and investigation on the possible treatment solutions. Some of the existing studies also observed that changes in lifestyles continuously, and stress on the job sectors may also one of the important cause for the poor sleep patterns, which affects directly the workability of the subjects and threatens the daily routine of the people's and public safety [21]. Apart from all these direct risks, sometimes traumatic childhood experiences may also increase the risk of sleep disorders in adulthood [22]. From the Willemen T et al. study, it has found that around 27.6% population of Italian had sleep problems [23].this public health issue also directly link with the economic condition of the country. Wickwire E.M. et al. [24] reported that around $100 billion per year spend on the diagnosis of different sleep-related disorders. Ozminkowski R.J. et al. mentioned that the direct (or) indirect investment for the diagnosis of sleep-related disorders is $1000 in 6 months which is quite more incomparable to the subjects without sleep problem patient's treatments [25]. It has been reported from the different summary that, different types of sleep-related disorders report a significant increasing public health risk and medical attention [26].In the late 1950, polysomnography (PSG) was originated and treated as one of the gold standards to analyze sleep patterns and to detect the different sleep-related disorder. The changes physiological activities during REM and N-REM sleep stages are presented in Table 1.The behaviour of each sleep stages are described as follows:

1. Wake Stage (W): During this stage, one subject is completely awake and the person is able to doing his/her day to day activities. Generally time period of this sleep stage is about 14-16h approximately for a person [27] (Fig. 1).

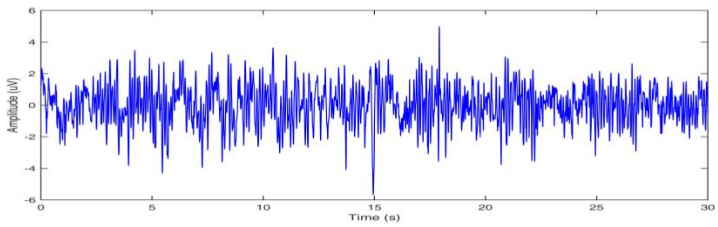

Fig. 1. Typical EEG signal behaviour in: Wake stage (W)

2.NREM Stage1 (N1):It is the transitional stage in between wake and sleep.It is called as light sleep stage, where one person can easily awaken from sleep.In this stage, the eye movements are slow, muscles are relaxes, and the heart rhythms are gradually slows down[27](Fig. 2).

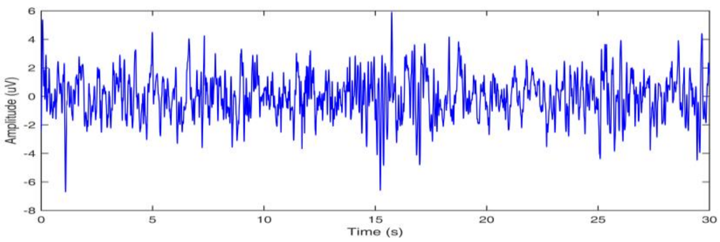

Fig. 2. Typical EEG signal behaviour in: NREM sleep stage1 (N1)

3. NREM Stage2 (N2): This sleep stages becomes deeper sleep stage in comparable to N1 sleep stage, where one person brain activities slows down, body temperatures drops and the movements of eyes are seizes. But sometimes occasional bursts of brain waves were appeared [27] (Fig. 3).

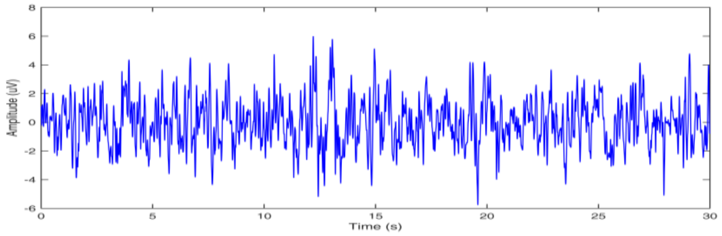

Fig. 3. Typical EEG signal behaviour in: NREM sleep stage2 (N2)

4. NREM Stage (N3): During this stage, one person completely goes in to deeper sleep and the brain waves are completely dominated by slow delta waves, which are in smaller in size. The major symptoms of a person in this stage are sleep walking and night terroring [27] (Fig.4).

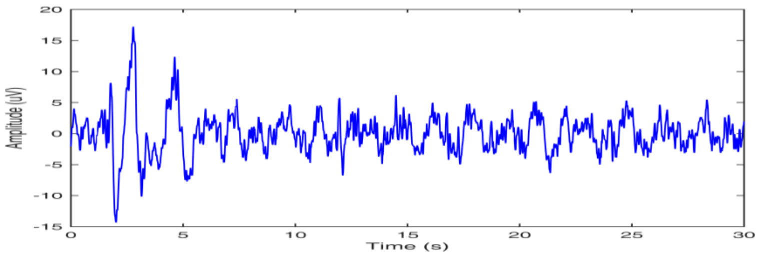

Fig. 4. Typical EEG signal behaviour in: NREM sleep stage3 (N3)

5. REM Stage (R): During this sleep stage, the movements of eyes are rapidly changes and maximum time's arousals are occurred. The brain behaviour of this sleep stage is quite similar to the wake sleep stage [28] (Fig.5).

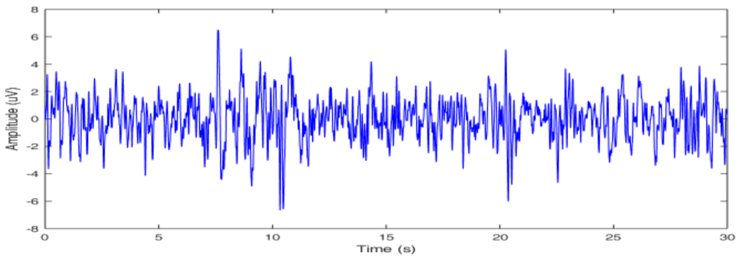

Fig. 5. Typical EEG signal behaviour in: REM sleep stage (R)

Table 1.Changes physiological behaviour

Physiological Behaviour	NREM	REM
Brain Behaviour	Decreases incomparable to wakefulness	Increases

Heart Rhythm	Stable	Fluctuating
Blood Pressure	Stable	Fluctuating
Nerve Functioning	Stable	Increases
Movements of muscles	Absent	Present
Respiration	Stable	Fluctuating
Blood Circulation	Decreases	Increases in comparable to the NREM
Body Temperature	Stable	Fluctuating
Dreams	Absent	Present
Swallowing	Decreases	Decreases
Cerebral blood flow	Decreases	Increases
Muscle tone	Mild	Absent

2 Medical background

Sleep state scoring is one of the primary steps towards the diagnosis of any types of sleep-related problems and different mental diseases. In a clinical system, sleep analysis takes more importance for the identification of sleep irregularities during sleep. During sleep stage analysis, we need to take consider various physiological signals such as electroencephalogram, electrooculogram, electromyogram, and electrocardiogram. Sleep staging is one of the essential parts of the diagnosis related to different sleep-related disorders such as sleep apnea syndrome [29]. The important point of research work is the proper evaluation of sleep-related diseases. Therefore proper monitoring, screening, analysis of the changes of sleep behavior through whole night sleep recording is an important issue for the health world. The various causes are responsible for sleep deprivation and the same details are described in the Table 2.

Table 2.Reasons for sleep disruption

Category	Factors being
Life styles	Habitual Drinking Alcohol
	Shift wise Duty
	Drug abuse
Environmental	Excessive surrounding noises
Psychosocial	Anxieties, Worriedness, Parents of young baby, Family members with chronic disorders, serious illness
Sleep-related disorders	Insomnia Periodic Limb Movement Disorder Obstructive Sleep Apnea Narcolepsy Parasomnias

Health conditions	Diabetes Certain medications Chronic neurological disorders

Sleep stages scoring has been processed according to two sleep standards which were edited and published by Rechtschaffen and Kales standard (R&K) [30] and the American Academy of Sleep Medicine [31]. According to R&K rules, each sleep epoch is segmented into the 30s and classified as awake (W), non-rapid eye movement sleep stages (N-REM1, N-REM2, N-REM3, and N-FREM4 and rapid eye movement. In the year 2007, AASM releases new sleep standards with minor revisions on existing R&K sleep rules, according to AASM rules the NREM sleep stages are segmented into three sleep stages that are N-REM1, N-REM2, and N-REM3. Amongst all physiological signals, EEG signals are considered as most of the cases, because it derives directly the brain-behavior of the subject which helps in the further diagnosis process [32]. With help of EEG recordings, we have found different characteristics of the sleep behavior from different sleep stages during sleep. EEG waves distinguishing the brain activities with help of sub-bands such as delta, theta, alpha, and beta. Each sleep stage is characterized with certain EEG sleep patterns such as in the REM sleep stage, maximum waveforms are in nature of low-amplitude, mixed-EEG frequency, saw-tooth wave-like patterns, low-EMG patterns, high fluctuated EOG behavior from both the eyes. Similarly in the N-REM1 sleep stage, alpha patterns are found and its frequency ranges of 2-7 Hz. In this stage, the EMG level is lower than with compared to awake stages. In the N-REM stage2; in general, two different types of events have occurred such as sleep spindles, which occurred with the frequency range of 12-14 Hz and k-complexes. N-REM stage3 and N-REM stage4 are considered as deep sleep, low-frequency waves are seen, which frequency ranges are less than 2 Hz, sometimes in this part also sleep spindles are seen. Generally, the PSG signals contain the combinations of the signals information such as brain activation through EEG signal, eye movements information's through EOG signal, and muscle-skeletal information's through EMG signal, heart rhythms using ECG signal, breathing information using respiratory airflow, oxygen saturation. The general procedure of the PSG test is patients need to be admitted overnight into the hospital, during that period bio-physiological signals are recorded. This entire process is called sleep scoring or sleeps staging. During sleep scoring, the main objective is to analyze the complete information from the different electrophysiological signals. The main objective is to analyze the sleep stages properly and the arousals, respiratory events, cardiac events have to be correctly identified. Majorly the three bio-signals: EEG, EOG, and EMG signals used for the analysis of the sleep characteristics. The existing sleep stages process with the manual visual inspection is quite tedious. Sometimes this process may create produce the wrong sleep scoring analysis due to more human interpretation during the sleep recordings and other important reasons is that variations on the sleep experts may also produce different sleep scoring results. To overcome all these differences, there should be a requirement for the automated sleep staging system using a computer-aided-system. The different researchers proposed different techniques and methods for automated sleep staging systems, reported very good sleep staging accuracy. It has been seen that AI plays a crucial role in developing and upgrading for the diagnosis of various types of sleep-related disorders. Artificial intelligence and its subset techniques recently more attracted and performed well in number of fields such as engineering [33-35], healthcare [36-39], and psychology [40].

3 Visual Scoring Procedure

It is one of the approaches for monitoring sleep behaviour and its characteristics. The obtained polysomnography record of sleep is generally segmented into 30s epochs. During the visual inspection, each epoch is annotated with a sleep stage. sometimes, it has been seen that two(or) more sleep stages being co-existed with a single epoch, in that cases that epoch be aligned to that particular sleep stage, which covers the major portions of the 30s epoch. The entire sleep scoring procedure was followed by R&K sleep scoring rules and these rules are widely adopted worldwide until 2007. After that AASM updated the existing sleep manuals, which were edited by R&K in terms of sleep scoring rules and the interpretation of PSG results. According to the AASM manual, the stages of sleep restricted up to five sleep stages that is wake stage, N1 stage, N2 stage, N3 stage, REM stage, Movement Time(MT) stage was abolished. Most of the time, it has been seen that sleep experts recommended the EEG signals for monitoring the sleep behaviour, because it provides meaningful information directly from the brain activities, which helps to analyze the sleep irregularities during sleep.

EEG signal is generally represented in terms of its frequency components. Each frequency sub-band presents different characteristic waveforms. These are δ rhythms (0.5-4Hz),θ rhythms (4-8Hz),α rhythms (8-12 Hz), and β rhythms (12-35Hz).The waveform in the frequency range 0.5-2 Hz and peak to peak amplitude >75μv are considered as slow wave activity. Sometimes during N2 and N3 sleep stages, sleep spindles (distinct wave patterns in the range of 12-14Hz, continue for more than 0.5s), k-complexes (the sharp negative waves followed by the positive waves, which continues up to 0.5s), all these wave-patterns are seen during the different stages of sleep. The main intention of sleep stages is to recognize the EEG frequency components and analysis the sleep patterns, but sometimes it is also observed that applying these rules may create unnecessary complexity. In general, sleep progresses from the wake stages through the REM stage then begins again with the wake stages. The process takes 90-110 min for each iteration. The human sleep cycles have shown REM sleep and a longer period of NREM sleep. The sleep stage characteristics according to AASM sleep scoring rules are briefly summarized in the following list. The changes sleep behaviour in the different signal sub bands for healthy controlled and sleep disordered subjects are shown in Figures 6 and 7 respectively.

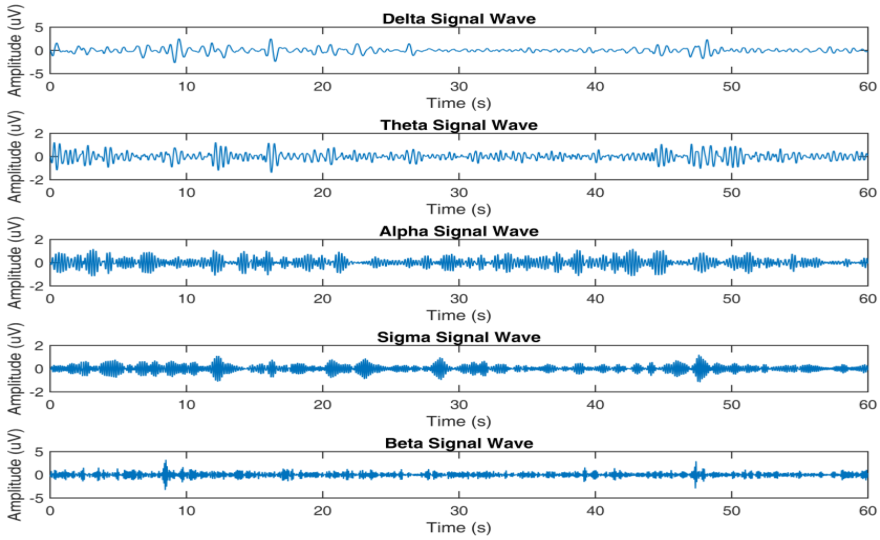

Fig. 6. Changes sleep behaviour:Healthy Subject

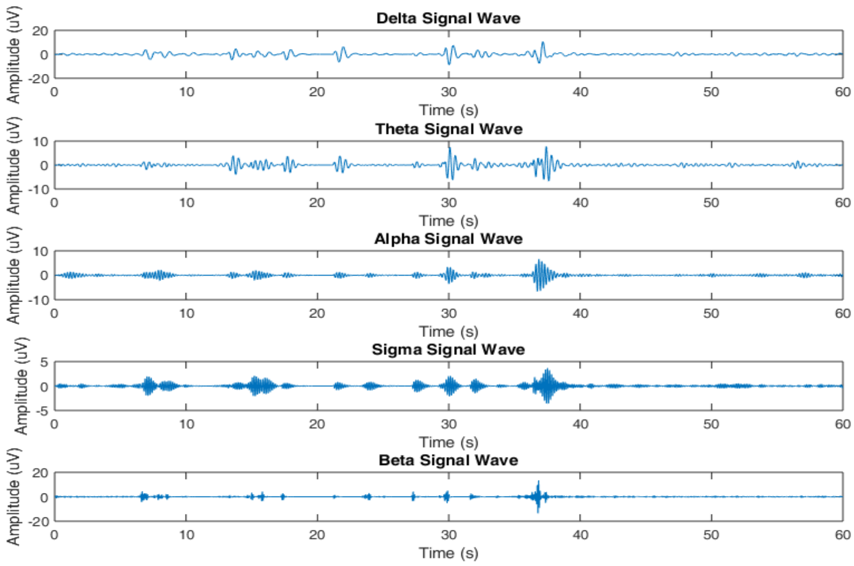

Fig. 7. Changes Sleep Behaviour:Sleep disordered subject

4 AI and Sleep Staging

In this section, we discuss some existing applicable methods of diagnosis various types of sleep-related disorders and the globe. The main intention of this section is to explore the different strategies and technique's effectiveness with subject to the sleep staging and also focuses upon the latest updates on the different sleep disorders. The main objective of this section is to presents the different ideas, which can speed up the treatment and diagnosis process. The effectiveness of AI tools depends on the proper analysis and classification of the sleep stage patterns. The different approaches and steps taken during sleep staging analysis through AI-based methods to overcome the risk of sleep-related disorders are presented in the structural framework shown in Figure 8.The first most important step in the preparation of the data, which is highly necessary for popularly understanding sleep behaviour. In this phase, we briefly discussed his/her medical information, daily routine activities, professional and social lifestyles, and the other various set of information to be transformed into the data, which can be understood by the machine easily. The main objective of understanding the sleep recordings includes understanding the sleep characteristics. Before the sleep records to be processed further, we need to be eliminating the contained signal compositions from raw data. On the other hand, we can say that it is a process, where we acquiring, analysis and preprocessing data. During this process, human intervention takes place, and experts analyze sleep behaviour and its patterns.

Sleep expert's interpretation is highly impacting during this section because their knowledge and experiences concerning monitoring sleep behaviour are not available in ML solutions. Generally, ML techniques depend upon the structured data. Another common challenge during handling the huge record like PSG signals, which causes the model to overfit [41]. Therefore, the feature extraction step is more helpful in the traditional ML algorithms to overcome overfitting issues, when handling the huge amount of sleep records [42]. The human interpretation is required during the extraction of hand-crafted features from the sleep record in ML techniques. The extracted features fed into the classification models such as the SVM (or) RF classifiers. Sometimes these feature extraction process covering the PSG signals recordings into a low-dimensional vector, which makes a loss in the information [42].For all these mentioned reasons, ML techniques are limited for classifying the multi-class sleep stages classification with high accuracy and precision.

However deep learning techniques are well suitable for managing enormous (or) complicated recordings.DL is a subset of ML; it consists of several layers of the algorithm, which helps to interpret the data. The main important thing with DL methods is training the PSG signals without any feature reduction techniques [43]. It automatically extracts the feature from the input PSG signals without any interpretation.DL models handle the large volume of data and make accurate predictions. It also considers that feature which is more helpful during the inference and neglects the other ones. Therefore DL techniques are more preferences incomparable to the ML techniques while dealing with the high-volume of PSG signals.

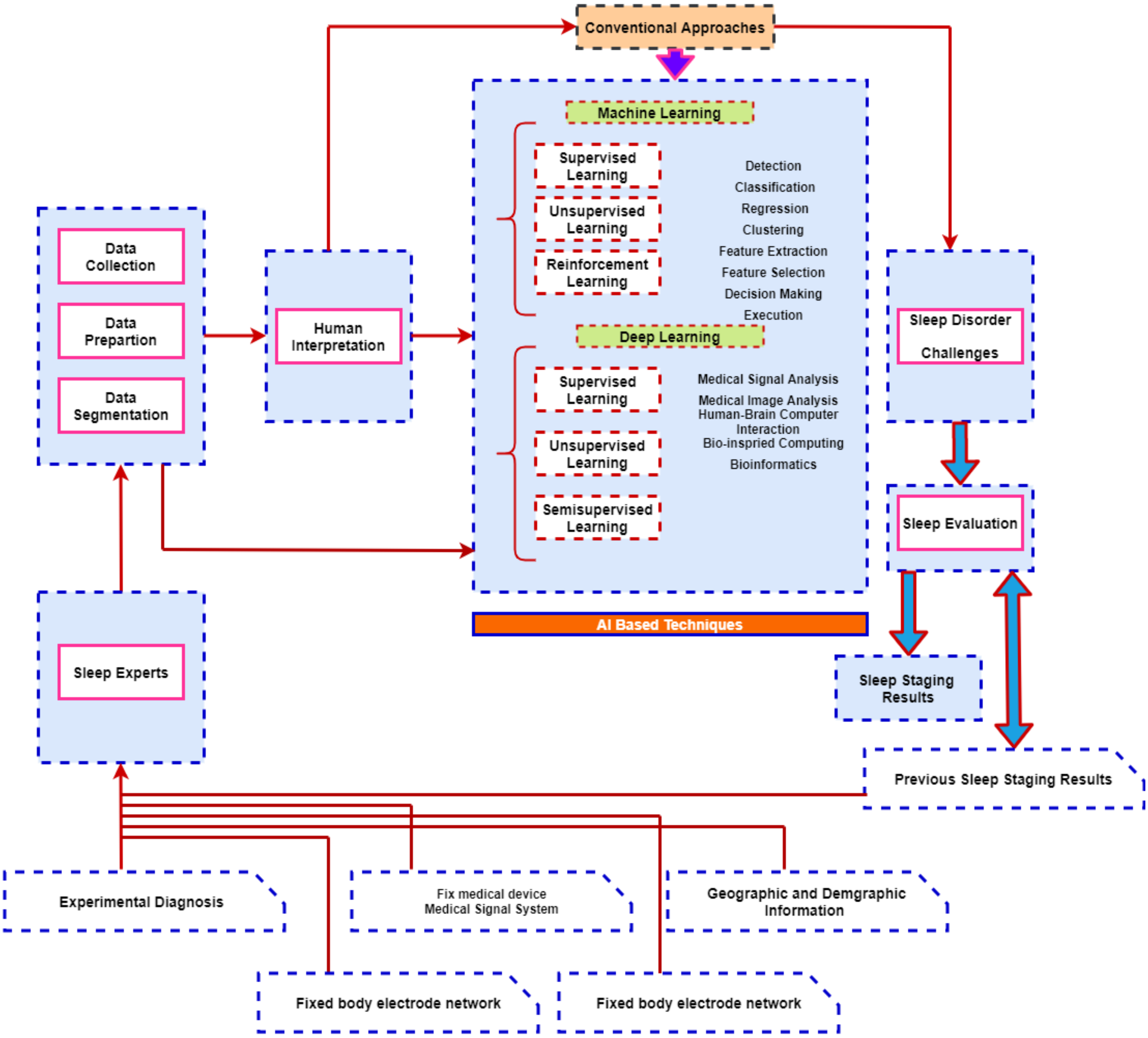

Fig. 8.AI Based Structural Framework

AI and its supporting tools are widely applied during sleep staging.Accordingly, these solutions to be categorized into 3 parts that are high-risk, outbreak and comfortable, and recognizing and diagnosis. The AI-based sleep staging system presents in Fig, 9, which is specifically desired for analysis and classification of sleep-related disorder.

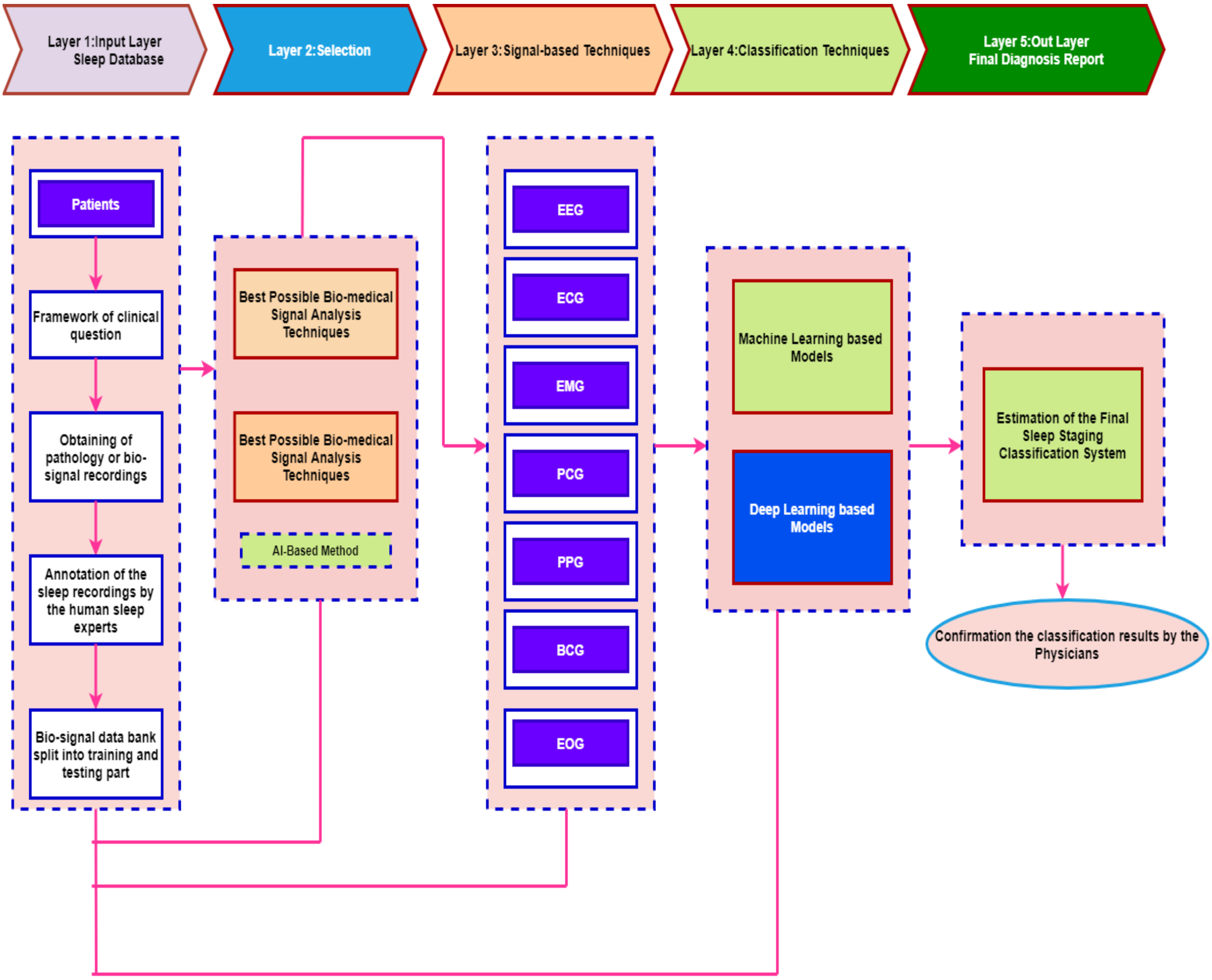

Fig. 9.AI Based Structural Framework

The entire procedure is presented into 5 layers. The initial layer is called the input layer, which is to associate the database, and this layer is specifically designed for collecting the sleep recordings. A high configuration system is used during the data preparation for further processing. The next layer is the selection layer, which is specifically designed by AI-based techniques for discontinuing sleep stage characteristics. If the obtained techniques are confirmed by the clinicians, the recommended suggestions are taken in the third layer by obtaining the required signals. For each subject, the bio-signals are recorded for some time. Generally the most widely used bio-signals during the sleep staging classification are ECG,EMG, Phonocardiography (PCG),Photoplethysmography(PPG),Ballistocardiography(BCG), and other bio signals like EOG, respiratory signals, blood pressure, and skin temperature. The fourth layer is specifically focused upon preprocessing the signals by remaining the irrelevant artifacts and segmentation the recorded signals to better analyze the changes in sleep characteristics. Finally, in the fifth layer, we used the learning algorithms for classifying the sleep stages patterns using ML and DL models. At last, the evaluation results may decide regarding the treatment process. The authors [44]-[46] discuss that sometimes, the subjects complain regarding his/her sleep quality. But for non-complementary subjects, we must discuss his/her Sleep_Onset_Latency (S_{OL}), Wake_After _Sleep _Onset (W_{ASO}), Total_ Sleep_ Time (T_{ST}), Sleep_Efficiency (S_E) for being analysis the sleep behaviour. Some additional parameters are also considered together such as the distribution of sleep epochs per individual sleep stage, the time and quality of sleep and there is also analysis of the pathological events like PLMD and SDB. It has been seen from the existing contribution that, several parameters have been used during the assessment of sleep quality.

4.1 Analysis of Human Sleep behaviour using Sleep Variables

Every human have its own internal physiological process, which are repeated every 24 rounded hours. It has been seen that from the last 60 years the sleep studies involved the huge amount of sleep technicians, physiologist, and sleep experts. In general the two sleep standards such as R&K and AASM standards were widely used during sleep scoring rules. Finally, the required sleep parameters during the investigation of the sleep quality are described in Table 3. For characterizing the sleep behaviour, both the sleep manuals followed the certain variables. According to the R&K sleep standards, there are four conventional parameters are used: S_{OL}, T_{ST}, W_{ASO}, and S_E.The different possibilities approaches with regards to assessment the sleep quality is shown in Figure 10.

S_{OL}: The time taken from the wake stage to sleep stage

W_{ASO}: It computes the total awakening periods in minutes during the sleep hours. It can be computed as

$$W_{ASO} = \sum_{i=1}^{N_A} D_{AW}$$

Where N_A=Number of awakening periods in between the sleep onset and sleep offset

D_{AW}=The duration of the ith awakenings

T_{ST}: It represents the total sleeping time from the sleep onset to the wake stage again. It represents the actually sleeping time.

$$T_{ST} = T_B - (S_{OL} + W_{ASO})$$

Where T_B=Total sleep time in bed

S_E: It is the ratio in between T_{ST} and T_B

$$S_E = \frac{T_{ST}}{T_B}$$

Table 3.Required Sleep Parameters during Sleep Staging

Variable	Definition
Total_Sleep_Time	It is the time between starting sleep time and ending sleep time.
Total in Bed	It represents the total in bed
First in Bed Time	Time when the subject went first time to bed
Final out in Bed Time	It is the time, when the subject leaves from the bed definitely
Sleep onset	The first time the subject falling to asleep
Sleep offset	It is the time in which the subjects awakes from the sleep
Number of Awakenings	It is the total number of awake per night
Number of Arousals	It is the total number of arousals per night
Total sleep time in Bed	It is the total time in bed by the subject
Total recording time	Total time in between light on and light off
Sleep interval	It is time in between first sleep and last sleep
N1 (%)	It is the ratio of time spent in between the N1 sleep and TST
N2 (%)	Ratio of time spent in between N2 and TST
N3 (%)	Ratio of time spent in between N3 and TST
REM (%)	Ration of time spent in between REM and TST

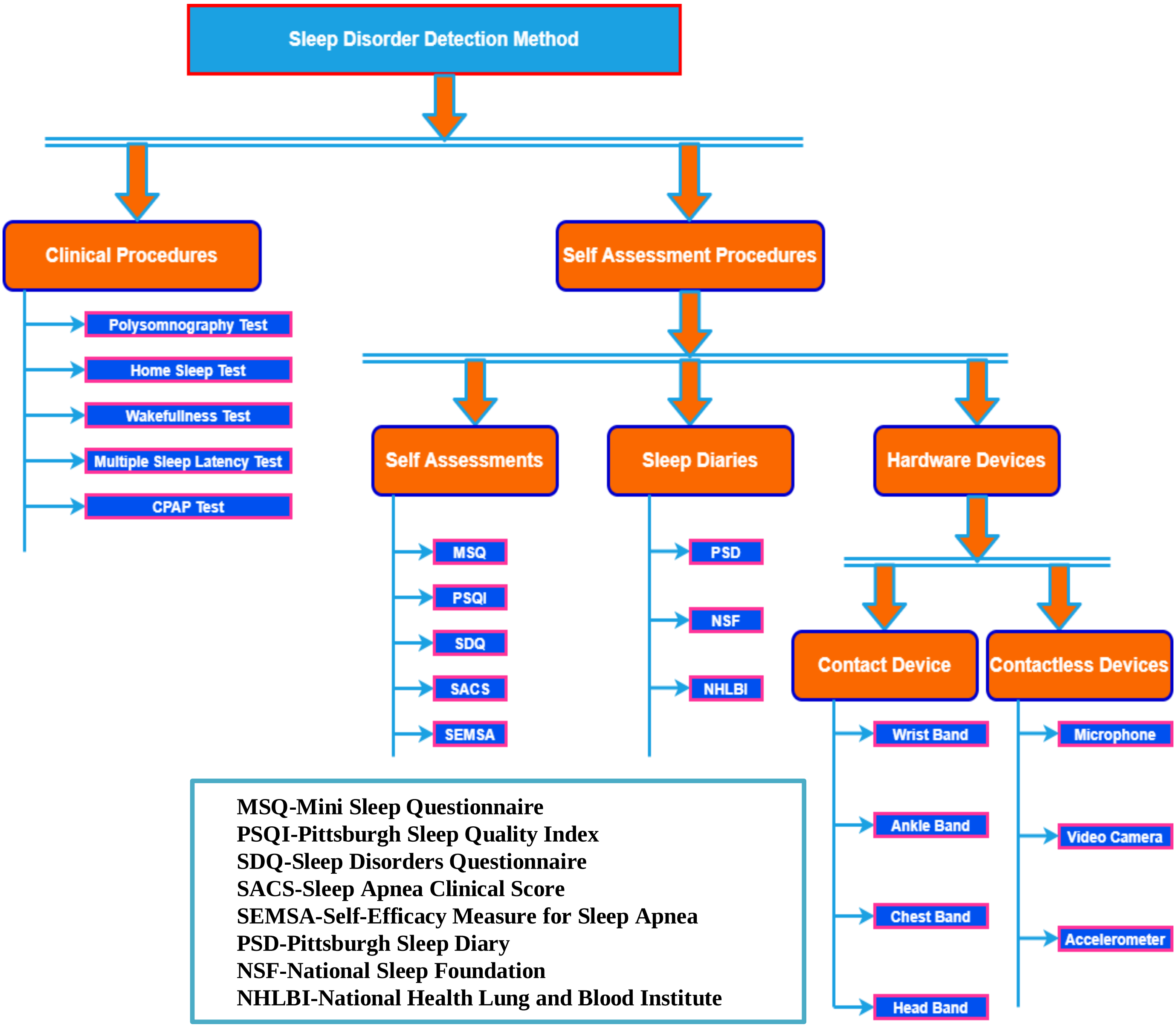

Fig. 10. Sleep detection procedures

4.2 Characteristics of Bio-Signals

The required biomedical signals are recorded for a central period of time. The physiological bio signals is highly non-stationary and heterogeneous [47-48].

Technical Characteristics

Generally, the human body is one of the complex cognitive physiological processes, where the bio-signals are changes dynamically concerning time and reflect the different behaviour during every stage of sleep.All the bio-signals having electrical activities and conductance, also measures their temperature, pressure, sound, acceleration [49-50]. The characteristics of the different bio-signals are described in the Table 4.

Table 4.Bio-signals characteristics parameter

Bio-signals	Channels	Frequency Range (Hz.)	Amplitude	Electrode placement
EEG	1-6	0.5-100	2 to 200 μv	Scalp
ECG	1-12	0.05-150	0.1 to 5 μv	Surface
EMG	1-32	5-2000	0.1 to 5 μv	Needle
EOG	1-2	1-100	10 to 3500 μv	Contact
PPG	1	0.25-40	-10 to 10 μv	Finger Tips
PCG	1	10-400	-2 to 2 μv	Surface
BCG	3	1-20	-0.05 to 0.05 μv	Surface
Skin temperature	1	1-200	-50 to 50 μv	Surface

Clinical Characteristics

According to the existing findings, the majority of the outcomes used three bio-signals such as EEG, ECG, and EMG signals for analyzing the sleep behaviour of the subject. Despite observing these existing statistics, we also required that some recent studies are based on EEG signals.The different ways of clinical procedure for diagnosing the different sleep-related disorders are presented in Table 5.The clinical properties of the different bio-signals are briefly described below:

EEG: It helps to measure brain activities during sleep. It measures the electrical activity of the brain. During the monitoring of the brain's behaviour, electrodes like a cup or disc shape are placed on the scalp. Those fixed electrodes are pick up the brain's electrical signals and these signals are called an electroencephalogram. Generally, the EEG signals are highly used during the diagnosis of the different types of neurological disorders, sleep-related disorders, epilepsy detection, brain tumor identification, and brain hemorrhage. In two different ways, we obtain the recording details from the brain either fixing the electrodes in the scalp or mounted a special band on the head. Three different types of EEG recordings are acquired such as routine EEG, where we have received the details of the recordings from the fixed 20 electrodes on the scalp. The second type is sleep EEG, where the EEG is recorded with the heart rate, airflow, oxygen saturation, and limb movement. The final last type is ambulatory EEG, in which we collected the recording details from the subject throughout the whole day by fixing a small portable EEG recorder. The main advantage with regards to the EEG signal is, it supports the non-invasive techniques, hardware implementation also very low incomparable to the other techniques and which also allows for better analysis of the auditory stimuli [51].

ECG: It is recorded non-invasive manner. Majorly it helps to provide information regarding changes in the heart rhythms and heart rate. This information makes it easier clinically to analyze the changes in sleep behaviour with concern to the abnormal heart rate [52-53]. Sometimes it has also been observed from the subjects also were affected with the different heart-related dreams; they could not complete their proper sleep cycle because of irregular heartbeat and pattern changes in the irregular manners.

EMG: The importance of this signal is, to get information about the muscle movement information, which directly helps to analyze the abnormal body movements during the sleep hours which is also one of the causes to diagnose the sleep patterns. It is also recorded from the subjects in non-invasive manners [54].

EOG: It helps to capture the information about the movements of the eyes, which also helps to analyze behaviour of different sleep-related disorders. This information was obtained from the two-eyes using a fixed electrode on both the left-eye and right-eye [51].

PCG: General this signal is captured information about the different occurring sounds produced during the sleep. It is one of the best and significant ways to analyze the various sleep problems [53].

PPG: It is recorded in a non-invasive manner using an oximeter device. The recorded PPG data are high in complex nature because their complexity depends on the skin thickness. It also helps during sleep staging by getting the information from the heart and treated as one of the best detection during the sleep staging process [55].

Table 5.Laboratory test for diagnosis the sleep-related diseases

Clinical Procedures to assess the sleep-related diseases
Conduct the polysomnography test
Primary diagnostic workshop due to the initial causes of the sleep disturbances
Sleep latency test
Standard EEG test and video-EEG monitoring system
Actigraphy test
PSG test using Video monitoring
Electromyogram test for analysis the restless leg syndrome
Upper airway imaging techniques for obstructive sleep apnea

Wakefulness test	
Clinical test of the diagnosis of the various types of the sleep-related disorders	

Some of the existing contributions on sleep study using different bio-signals are discussed with concern to the used dataset, feature extraction, and classification model and the same information is presented in Table 6.

Table 6.Sleep studies using different bio-signals

Existing Study	**Input**	**Feature Extraction**	**Classification Model**
Selected Recent Existing Sleep Studies based on EEG signal			
Mousavi et al., [56] 2019	Sleep-European Data Format(S-EDF) dataset	Time and frequency domain features	DL
Michielli et al.,[57] 2019	S-EDF		
Sharma et al.,[58] 2018		Time-frequency localized wavelet filter bank	SVM
Seifpour et al., [59] 2018		Statistical behaviour	Multi-class SVM
Chriskos et al.[60] 2018	23 Healthy male adults	Synchronization likelihood and Wavelet entropy	SVM,NN,KNN
Memar and Faradji et al.[61] 2018	S-EDF UCDDB XESEDF DREAMS	Nested Five-Fold cross validation and subject-wise cross validation	RF
Pillay et al.[62] 2018	16 preterm and new born	Multiple time and frequency domain features	HMMs and GMMs
Hassan and Subasi et al.,[63] 2017	S-EDF DREAMS	Tunable-Q wavelet transform	Bagging
Based on ECG signal			
Yucelbas et al.,[64] 2018	Sleep centre, Erbakan University and PhysioNet	Morphological Methods	RF
Yoon et al.,[65] 2017	21 Healthy subjects and 30 subjects with obstructive sleep apnea	Statistical parameters, Spectral power	
Liu et al.,[66]	75 sleep apnea sub-	Time domain statisti-	Statistical

2017	jects and obtained from Shandong Province of Traditional Chinese Medicine Hospital	cal parameters	analysis
Based on EOG signal			
Rahman et al.,[67] 2018	EOG, PhysioNet Database	Discrete Wavelet Transform	SVM, RUSBoost and RF
Based on PSG signal			
Tripathy et al.,[68] 2018	MIT-BIH Polysomnography	Variance, Entropy	DNN
Takatani et al.,[69] 2018	16 Adults and 74 new born	EEG spectral power	Statistical analysis
Lerman et al.,[70] 2017	125 women under medication of Joint disorder	Sleep parameters	Multiple regression analysis
Rosipal et al.[71] 2015	148 Subjects Healthy controlled		Probabilistic sleep model
Orff et al.,[72] 2012	137 women subjects with different medical conditions		Multivariate analysis of variance

From Table 5, it has been found that the different approaches taken on the sleep staging methods and also highlight the different sleep parameters with concern to medical and psychology backgrounds. During sleep staging, the sleep parameters are derived in two ways, one related to the sleep stages, and the other is derived variables. In the sleep stages part, the information collected from stage 1, Stage 2, Stage 3, Stage 4, Slow wave sleep, and REM sleep.In the other hand, the derived variables contains the information with regards to total sleep time (hrs.), sleep period times (hrs.), sleep onset latency(epoch),sleep efficiency, number of awakenings and sleep offset.

4.3 Non-REM Sleep

EEG signal is more effective towards the analysis of sleep behaviour in the NREM sleep stages. For a better analysis of the individual sleep stages characteristics during NREM sleep, the best way in the spectral analysis of the EEG signal. EEG signals are analyzed, by decomposing the entire signal into the different frequency sub-bands (from 0.5-45 Hz). The recorded EEG signals are segmented into different frequency bands with different ranges of frequency levels for better discrimination of the sleep stages. For better discrimination in between the wake and REM sleep stages, we divided into two different waveforms as $\boldsymbol{\beta 1}$(13-20 Hz), and $\boldsymbol{\beta 2}$ (20-30 Hz).It has been reported that waveforms have a significant impact on the classification of sleep stages so that we divided them into $\boldsymbol{\gamma 1}$(30-40 Hz) and $\boldsymbol{\gamma 2}$(40-49.5 Hz) waveforms.

4.4 Sleep Diaries and Questions

In the earlier days, to understand the sleep-related problem, subjectively analysis was conducted to gather the data about the sleep and its quality. Till now the debate is going on to find out the best way of sleep behaviour monitoring. The main difference found in the subjective way of analysis from the PSG test is obtaining the different self-request questions for analysis of the sleep behaviour. There should be followed several mechanisms to understand and validate the self-report assessment. The two approaches such as sleep diaries and PSQI for maintaining the day-to-day basis the sleep behaviour but sometimes it has been seen that this way of sleep behaviour monitoring for the elderly subjects may lead to some errors because of their continuous changes the memory cognition. The general format of the self-assessment and daily sleep diaries contains the information about the different sleep parameters.The sleep diaries provide information about the sleep schedule and awakening in the nighttime. Majorly sleep diaries used during the clinical reasons, only maintaining intervention effects and maintain the actigraphy data. On the other part, sleep questions are one of the low cost-effective approaches for collecting information about the sleep and sleep pattern, sleep problems, and its behaviours.Mainly all these discussions to be mentioned during the subjective self-assessment process and analysis of their strength and weakness. The brief presentation regarding subjective self-assessment questionaries' and sleep diaries and the sleep quality information.

5 Sleep patterns Clinical Age

The sleep behaviour of the subject in general changes concerning the age factor. The sleep requirements are different from infancy to adulthood and it has been observed that their sleep patterns are quite different with concern to their initiating and maintaining of sleep efficiency. It has been found that the quality of sleep degrades with declines of the age factor. Sometimes age factor takes an impact role to understand the sleep characteristics.

5.1 Newborns

For newly birth children, the sleeping time is quite larger across the day (or) night. The sleep experts identify the two stages REM and NREM for the first two to three weeks and with the age of the three months old, the four sleep stages are seen. Majorly two types of sleep phases are appeared one is quite sleep and active sleep.During the active (REM) sleep, the baby makes noises and crying, also functioning small movements of the limb and fingures.In the other hand, the quite(NREM) sleep, the baby being still and does not perform ant types of movements [75]. Sometimes the sleep patterns changed with the great demand in the social cues. Once the baby step with age of three months, its sleep cycles becomes as it is like the adults and all the four stages (N1, N2, N3 and REM) are appeared. With the age of 3 months, now the sleep cycle comes into normal process, begins with the NREM sleep stage, and decreases the REM sleep stage [76]. By the age of 1 year old, the infant is typically taken 14 to 15 hours per day, the majority of the sleep part happened in the evening time and one or two naps happened during the daytime [77].

5.2 Young Children

Since there are some few studies conducted with regards to the young children and its sleep behaviour. It has been found that, the sleep amount quite decreased for the young children as the age of the children increases. The major reasons behind the decreasing in sleeping time are involvement in the social and cultural environments. [78].The several social and cultural factors may cause the changes in sleep patterns in daytime like school time schedule [79].

5.3 Adolescents

According to the different sleep studies, the sleep requirements for adolescents require 9 to 10 hrs. of sleep each night. The 8th standards students of the USA takes around 7 to 9 hrs. of sleep [80]. It has been also found that high school or college students were deprived. Due to the development of pubertal activity, SWS and sleep efficiency of the subject decreases [81]. Most of the subjects in this category spent more time in sleep stage2.basically these changes happened due to the hormonal changes in the body. In this group increasing the age of subjects, decreasing the sleep period [81].

5.4 Adults

In general, the sleep architecture for adults continuously changes with increases of the age across adulthood. Two major things to be observed during sleep for the adult category subjects are early wake time and reduced sleep time [82]. According to the age factor of the subject, older adults having age range from 60 to 70, are typically awakes before 2 hrs., than young section adults having age ranges from 20 to 30[83]. The number of awakenings occurred for young adults but it remains close to the REM sleep stages, then sleep remains consolidated. Generally, the arousals occurred during the REM phase of sleep for adults.

5.5 Gender Differences

Some of the research studies systematically based on the gender-based changes in sleep behaviour and circadian rhythms. The changes different sleep characteristics also been found in infants [84], childhood [85], and adolescents [86].In general, the adults have consumed more time in the N1 sleep stage and experience more awakenings [87]. It has been seen that women were taken larger slow-wave sleep patterns incomparable to the men. Sometimes they also complain regarding the difficulty in falling asleep and awakening from midsleep. On the other hand, the general complaints with regards to men are excess daytime sleepiness. During the menstrual time, the sleep cycle complexity influences women subjects [88]. Some of the good findings works already existing with regards to difficult sleep problems during pregnancy time and the postpartum period [89].

5.6 Elderly People

Sleep problem has directly affected concerning all individuals, irrespective of the subject age; however, this ratio is somehow increased for the elder subjects. Generally, the older population sleep patterns got break continuously [90]. The SWS segments continuously change concerning the subject's age. It has been found that, changes the sleep behaviour affect both the male and female category genders differently. Age with 70 having female gender spend around 20% time of sleep in N3 and N4,but this same ratio for male genders subjects were around 5%.

6 Chapter Outcome and Conclusion

Monitoring the different sleep-related disorders is highly one of the important research for both health and industrial sectors. Millions of populations were suffered from different types of sleep-related diseases, which remain neglected in terms of proper diagnosis and treatments. Most of the developing countries have not good health resources to fulfill the demands of the clinical settings to diagnosis such disorders. Based on different reports, millions of the populations were suffered from different types of disorders, which alternatively affects the professional and social lifestyles. Mainly it has been observed that the lack of awareness is one of the major challenges. The major concern in the present situation is that to require proper technology and diagnostic tool for good management in the diagnosis process. Advanced techniques and procedures may help to reduce the gap between the traditional and automated sleep staging process. This automated sleep monitoring system able to enhance the changes in sleep characteristics during different stages of sleep. Recently this process makes easier due to emerging bio-medical signal processing techniques and devices that can able to support accurately identify sleep irregularities and also measure sleep quality.

In this present chapter, we have discussed an overall view of how sleep plays important role in our life. This chapter provides information about how sleep problem affects the social and professional life of one person and also we have given some statistics results for awareness to readers how a sleep problem nowadays considered as one of the global health challenges. Further, we also put some information about how the different physiological signals are the most important towards analysis the brain behaviors and activities. This chapter gives basic outlines with regards to changes in sleep characteristics during different sleep stages and also we briefly discussed sleep deprivation with concern to the age factor of the subjects.

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