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The Role of Electroencephalography in Advancing Sleep Research

Zahra Zia, Ahsen Ejaz, Kai Liang Lew *, Cheng Zheng, Suleiman Aliyu Babale, Tetuko Kurniawan, and Chia Shyan Lee

***Abstract* – Electroencephalography (EEG) is fundamental in sleep research, providing critical insights into cerebral activity and significantly contributing to the diagnosis of sleep disorders. This study examines recent progress in EEG-based sleep research, emphasizing cutting-edge methods for sleep staging and disease identification. The amalgamation of machine learning and deep learning methodologies, encompassing hybrid models such as CNN-LSTM, has markedly improved the precision of sleep stage categorization and automated analysis. Enhancements in signal quality and dependability, especially by improvements in artifact removal methods like wavelet-enhanced independent component analysis (ICA), have further advanced these developments. The implementation of multimodal strategies, wearable EEG technology, and AI-enhanced systems has broadened the sphere of sleep monitoring beyond clinical environments, rendering it more accessible and individualized. This article examines the use of EEG in detecting sleep disorders, including insomnia, obstructive sleep apnea, and narcolepsy, by identifying biomarkers and abnormalities in sleep architecture. Emerging research underlines the promise of clinical EEG, marking it as a transformational tool for both study and therapy. Nonetheless, obstacles persist in domains such as noise reduction, biomarker standardization, and scalability. Future directions include merging EEG with imaging modalities like fMRI, developing wearable technology, and employing advanced AI for individualized sleep health management. In particular, EEG is highlighted as a transformational and promising tool for promoting sleep medicine through novel, accessible, and effective solutions.**

Keywords— Electroencephalography (EEG), Sleep Staging, Machine Learning, Sleep Disorders, Artifact Removal 9.

I. Introduction

The integration of machine learning and deep learning into sleep research has paved the way for significant advancements in the analysis and understanding of sleep disorders. These technologies, especially when applied to EEG signals, enable more precise and automated sleep staging, providing valuable insights into various sleep-related conditions. This review delves into the growing role of these

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advanced techniques in enhancing the diagnosis and treatment of sleep disorders, highlighting their potential to transform clinical practices and research in sleep medicine.

There have been several previous studies on how Metaheuristic algorithms can auto-mate sleep staging, which traditionally requires perusal of polysomnography (PSG) data by human notchers. For example, in a study, machine learning based scoring was shown to use a manual scoring and actigraphy, random forest classifier outperformed on around-the-ear EEG signals.It promises big things for large scale sleep studies [7]. A second study developed a convolutional neural network based algorithm, Sleep Stage Machine Learning that performed at human level in we highlight the potential for rapid, accurate diagnostic based only on EEG signals. Sleep staging has been extensively improved in terms of accuracy and computation speed by deep learning.

Sleep stages were then classified with a deep learning based network combining attention mechanisms and bilateral LSTM, beating state of the art methods [12]. Similarly, sleep staging was studied using a combination of convolutional and recurrent neural networks that achieved accuracy similar to inter scorer agreement in international sleep centers[20], and another used a residual based attention model which successfully improved performance by decomposing EEG signals into different frequency bands with considerable efficiency gains[30]. Combining modalities of EEG and ECG was shown to improve sleep staging accuracy. In a study, it was proposed a method combining EEG and ECG features, which obtained exceptionally high classification performance and suggested that EEG features are more effective for wake stage classification and ECG features for deep sleep stages [22].

Sleep staging has been extensively improved using deep learning in terms of accuracy as well as efficiency. Classifying sleep stage was also addresses by a deep learning network incorporating attention mechanisms and bidirectional LSTM that achieves high accuracy and outperforms traditional methods[12], and a combination of convolutional and recurrent neural networks for sleep staging giving an accuracy close to the inter-scorer agreement in international sleep centers[20], followed by a residual-based attention model that allows decomposition of

EEG signals into different frequency bands with a leading efficiency gain[8]. Sleep staging accuracy has been improved by including EEG and ECG multimodal features. A method combining EEG and ECG features is proposed in a study, which achieves high classification performance and suggests that EEG features are more effective for wake stage classification and ECG features are more effective for deep sleep stages [30]. EEG based methods have also been used to detect sleep disorders such as obstructive sleep apnea (OSA). The EEG-Cloned collaborative learning network was developed for concurrent sleep staging and OSA event detection to reduce model complexity and increase performance [10]. A second study was about automatic sleep staging in a clinical population with suspected OSA and high accuracy, and showed the possibility of cost efficient diagnostic integrations [22].

The main goal is to combine the more recent advances in EEG analysis and their application on the studies of sleep. However, during recent years, we have seen a great trend for applying nonlinear analysis methods for EEG signals during sleep, which are more detail about intrinsic dynamics of EEG signals during sleep, such as fractal and entropy approaches [8], and meanwhile multitier spectral analysis that makes more clear and more accurate spectral estimates enabling a better visualization of the oscillatory structures of the sleep EEG [18], these have effectively improved the spacial accuracy of sleep EEG is a non-invasive brain recording procedure which can give information on sleep architecture and sleep abnormalities. Brainwave patterns during various sleep stages are widely used to detect and to diagnose different forms of sleep disorders [9]. EEG's capacity to record real time brain activity provides an ideal means for identifying sleep disorders that affect an individual's physical, mental and emotional well being[17].

EEG is used to diagnose sleep disorders since it detects the electrical activity of the brain at night. It allows you to identify abnormal brainwave patterns that indicate particular sleep disorders. EEG can such as location for example it can detect presence of sleep apnea through interruption of patterns and changes in brain activity [13]. Like this, it can be used to diagnose REM sleep behavior disorder by observing strange electrical activity in REM sleep stages [35]. Analysis of EEG data at a fine level provides the means for accurate diagnosis and treatment of sleep disorders, with customized treatment strategies.

Non-invasive sleep monitoring has become a need as the demand for a comfortable, easy to access diagnostic tool increases. Because EEG is a nonintrusive method of continuous brain activity monitoring, during sleep, EEG serves this role quite well [19]. To enable real time monitoring outside of clinical settings, portable EEG devices has been developed serving as a friendly alternative to classic polysomnography [5]. The major advantages of EEG to sleep monitoring are its high temporal resolution and its capacity to record detail patterns of brain activity. For instance, high density EEG offers both spatial and temporal resolution in understanding of sleep physiology and related disorders [36]. In addition, recent technological improvement in EEG, such as single channel EEG system and automated sleep stage scoring can enhance sensitivity and specificity of sleep disorder diagnosis [1].

II. Background on EEG and Sleep

A. EEG Fundamentals

Electrodes placed on the scalp measure brain electrical The brain electrical activity is measured with electrodes placed on the scalp. Brain waves (Delta, Theta, Alpha, Beta) and their uses in sleep studies. EEG is the placement of electrodes on the scalp to study electrical activity by the brain. The signal from these electrodes measures circumstances in which voltage fluctuations occur as the results of ion current fluxes in the neurons of the brain, especially during synaptic excitations of dendrites of the pyramidal neurons in the cerebral cortex. They are then amplified and recorded for analysis. EEG is a safe and repeatable procedure and can be used in many people, including children and adults [35]. Figure 1 shows the setup of an EEG cap with electrodes that measure brain electrical activity.

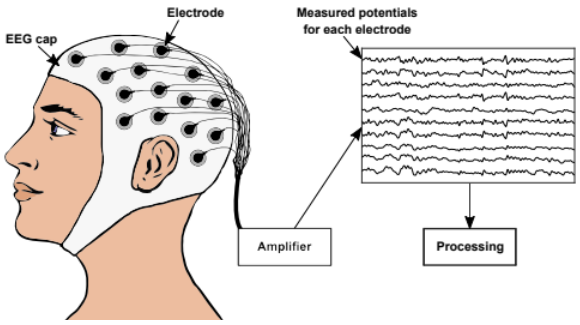

FIGURE 1. The image illustrates the setup of an EEG cap with electrodes that measure brain electrical activity. The signals are amplified and processed for analysis, displaying waveforms for each electrode [6]

EEG records different types of brain waves, each associated with specific states of consciousness and brain activities:

Delta Waves (0.5-4 Hz): And these are the slowest of brain waves, occurring mainly in deep sleep (non REM sleep). Often often they are crucial for restorative sleep served as biomarkers for the depth of sleep [35].

Theta Waves (4-8 Hz): They are associated with light sleep and relaxation. In addition, they participate in the transition of wakefulness and sleep and in memory processing [29].

Alpha Waves (8-12 Hz): One that is seen when a person is awake but not really thinking or concentrated like when you are meditating. Sleep studies can take alpha waves also into sleep during which is referred to as alpha delta sleep and is associated with unrefreshing sleep and chronic fatigue [23].

Beta Waves (12-30 Hz): This is active thinking, problem solving, focus fast waves. Brain slows down from unstructured beta wave activity during sleep, moving into deeper sleep stages [31].

For sleep studies, these brain waves are important; they are used to identify different sleep stages and sleep disorders diagnoses. EEG is good at predicting what stage of sleep you are in as well as giving an insight to any neurological changes that happen during sleep.

B. Sleep Stages and EEG Correlation

Sleep stage correlates to EEG markers are vital to interpret sleep physiology and research. The first EEG markers of NREM and REM sleep stages make these stages easily identifiable and distinguishable from each other.

NREM Sleep Stages and EEG Markers Stage 1 (N1): This is the lightest stage of NREM sleep, characterized by the presence of theta waves. EEG studies show that theta bursts are prominent in this stage and may help trigger down states (DS) in subsequent stage [17]. Stage 2 (N2): This stage is marked by sleep spindles and K-complexes. Sleep spindles are burst-like signals that reflect thalamocortical oscillations and are crucial for sleep architecture and cognitive functions [21]. K-complexes are large waves that occur in response to external stimuli and are thought to protect sleep [14].

Sleep disorders such as insomnia, sleep apnea, narcolepsy, and restless legs syndrome (RLS) significantly impact individual's quality of life and cognitive function. Monitoring brain activity and identifying specific patterns in this case are determinants that EEG is a very valuable tool in diagnosing these disorders. Figure 2 shows the samples of EEG pattern in five sleep stages

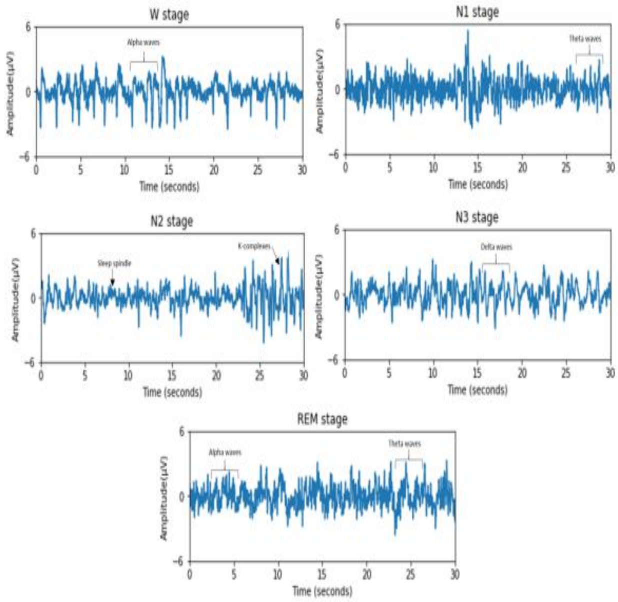

FIGURE 2. Samples of EEG pattern in five sleep stages [39]

By inducing synchronization between the hemispheres of the brain, binaural beats—auditory illusions produced by providing slightly different frequencies to each ear—have been shown to improve the quality of sleep. Research has indicated that exposure to delta frequency binaural beats, such 3 Hz, might enhance overall sleep characteristics and lengthen the duration of deep sleep. Furthermore, mood enhancements, such as a decrease in anxiety and aggression, have been linked to auditory stimulation using delta binaural beats. These results imply that binaural beats might be used as a non-invasive way to enhance mood and sleep[41]. Lim et al.'s study investigates the use of augmented reality (AR) for memory training, which might have an effect on the quality of sleep. Reduced cognitive impairments from sleep deprivation and increased sleep efficiency have been associated with cognitive activities, including AR-based therapies. According to research, AR can improve cognitive performance and mitigate the consequences of sleep deprivation. Including AR-based training in regular activities may improve sleep and memory[42].

C. EEG Markers in Sleep Disorders

Insomnia is difficult going to and staying asleep and early morning awakenings characterize insomnia. Altered sleep spindles, which are vital for the stability of sleep as well as cognitive function, may be found in EEG studies of insomnia.

Sleep Apnea is an interruption in breathing that repeatedly occurs while you are asleep, which produces broken sleep patterns and excessive daytime sleepiness. Reduced delta activity during NREM sleep is observed in EEG recordings in patients with sleep apnea, suggesting deficient restorative sleep. Also, apnea episodes at high frequency cause frequent arousals leading to increases in alpha wave intrusions, indicating disrupted sleep continuity. These markers are crucial for distinguishing the sleep apnea's effect on mental activity [32].

Narcolepsy is a neurological disease that impacts the event of wakefulness and REM sleep, making REM sleep onset typically very fast. Compared to EEG and PSG analysis in narcolepsy, we observe distinct EEG and PSG patterns too, such as early REM sleep transitions, disrupted theta rhythm and irregular alpha activity during wakefulness. EEG is a valuable tool for diagnosis of narcolepsy because these abnormalities correlate with symptoms such as excessive daytime sleepiness and cataplexy [17].

Restless Legs Syndrome (RLS) is the periodic limb movements during sleep and restless legs syndrome are conditions associated with one another. Studying RLS patients with EEG studies have shown enhanced beta and alpha waves during a PLM that suggests heightened cortical arousal and discomfort. They disrupt the progression of normal sleep stages and therefore lead to fragmented and poor quality of sleep [32] [17].

III. EEG ANALYSIS TECHNIQUES IN SLEEP STUDIES

A. Signal Processing Techniques

Artifacts and removal of artifacts is the first step of effective preprocessing of EEG data. Manual inspection is the basis of traditional techniques which are accurate, but labor-intensive and sub ejective. This challenge is addressed by modern approaches via automated and semi automated methods. For example, the study" Artifact Removal from Sleep-Disordered EEG by Wavelet Enhanced Independent Component Analysis" presents a hybrid method of wavelet transforms and independent component analysis (ICA). Then [33] this method divides up the artifacts from NG neural signals by using features like kurtosis, skewness and entropy. Figure 3 shows the EEG acquisition with electrode placement and denoising.

Filtering techniques is used to preprocess-in utilizes the filters to clean up EEG data, removing frequencies that are unnecessary. For instance band pass filters are used to isolate the frequency range of interest to our brain activity which is routinely between 0.5 Hz and 40 Hz. Fast-pass filters suppress high frequency noise such as muscle activity, while low pass filters eliminate slow wave artifacts such as that caused by electrode drift. Usually these filters are used with other preprocessing steps to ensure complete artifact removal. The adaptive filtering techniques have attracted interest for their ability to adapt filter parameters to the signal characteristics. In particular, these techniques are well suited to sleep studies in which EEG signals show large variations among sleep stages [33].

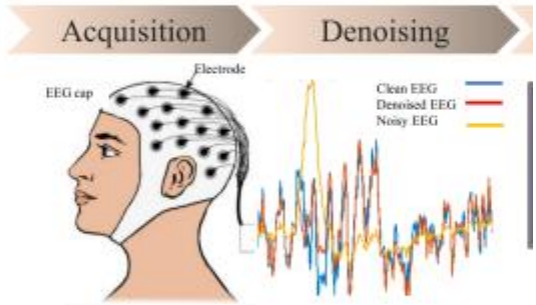

FIGURE 3. EEG acquisition with electrode placement and denoising showing clean (blue), denoised (red), and noisy (yellow) signals [6].

Advanced Artifact Removal Techniques involve application of machine learning and statistical methods. In the study the wavelet enhanced ICA approach highlighted classified components as neural or art factual. The signal components are classified by statistical metrics, such as kurtosis and entropy, which quantify irregularity and randomness of signal components. The reduction of the need for manual intervention improves efficiency and oblectivity [33]. In addition, principal component analysis (PCA) methods of blind source separation are also employed. In summary, these methods represent noise within EEG data and decompose the EEG data into underlying components for the selective removal of the noise. While PCA has limitations in separating overlapping artifact sources, as compared with ICA, ICA is preferred in many instances to deal with overlapping artifact sources.

B. Feature Extraction and Analysis

Spectral Power and Frequency Analysis in EEG Studies: It is known that spectral power distribution is the key for EEG signals identification of dominant frequencies in different sleep stages, e.g. delta waves in deep sleep or theta waves in light sleep. These frequency components are analyzed though Fast Fourier Transform (FFT) and convert the raw EEG signal from the time to the frequency domain [10].

Time-frequency analysis of EEG using wavelet transforms can be used to analyse EEG signals in non stationary states such as sleep. Regarding capturing characteristics of NREM sleep, sleep spindles and K-complexes [16] and both high and low frequency signals, the wavelet approach will be beneficial.

EEG coherence measures the phase relationship between signals from different parts of the brain, helping to assess the connectivity and synchronization between brain regions. This is particularly useful for understanding the network dynamics during sleep and

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detecting disruptions that may indicate disorders like insomnia or sleep apnea [16].

C. Machine Learning Algorithms for Sleep Stage Classification

Many machine learning (ML) techniques, such as Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs) have been well exploited in EEG analysis of sleep stage classification. EEG signals are used by these algorithms to find distinctive patterns which correspond to different sleep stages, i.e. NREM and REM. For example, SVM is a powerful classifier that is good for high dimensional data, e.g. EEG signals but Random Forests have robustness with combining multiple decision trees for even more accurate predictions [24] [27]. Figure 4 shows the distribution of the utilization of different sleep datasets used in studies.

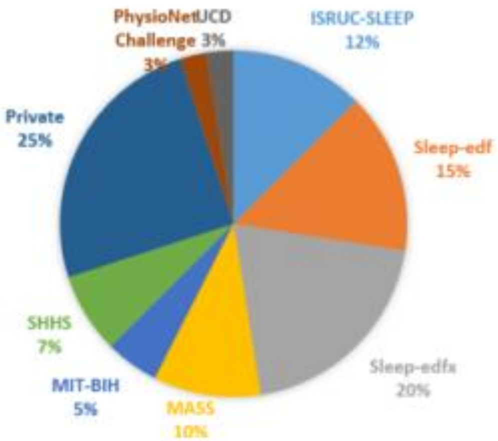

FIGURE 4. The distribution of the utilization of different sleep dataset in studies employing ML techniques for sleep stage classification [39]

Deep learning techniques in sleep studies used the integration of CNN and LSTM models to get the better results in sleep stage classification accuracy in hybrid architectures [38]. These CNN and LSTM based models leverage the feature extraction capabilities of CNNs on EEG signals, and the superior temporal behavior of LSTMs, to improve the overall classification performance. In addition to being valuable for sleep stage classification, such models can improve sleep disorder diagnosis [26].

The application of ML and DL models creates great promise for automating the study of sleep studies, reducing human error, and improving the efficiency of diagnosis of sleep disorders. Lastly, these technologies can be used to develop personalized treatment plans according to individual sleep patterns, which moves the field of sleep medicine forward [26].

IV. Applications Of Eeg In Sleep Studies

EEG holds broad applications in sleep studies and is an indispensable diagnostic and understanding tool for a wide range of types of sleep disorders and for evaluation of cognitive and psychiatric conditions.

A. Diagnosis of Sleep Disorders

Diagnosis of disorders such as sleep apnea, insomnia, narcolepsy and restless legs syndrome are all dependent on EEG. This can help identify important markers of sleep fragmentation in insomnia, lack or absence of or reduced REM sleep in narcolepsy, and abnormal sleep in sleep apnea. These disorders are associated with specific EEG features like slow wave activity (SWA), sleep spindles and disorganized sleep architecture (disrupted sleep architecture), which help to more accurately diagnose and develop treatment strategies [25].

B. Impact of Sleep Deprivation

EEG is also crucial when attempting to understand how sleep deprivation affects the brain. It helps us understand how EEG patterns are changed, by showing reduced slow wave activity (SWA) and rebound of REM sleep following deprivation. These patterns are altered, and linked to cognitive impairments including poor memory retention, attention deficits, and poor decision making ability [37].

C. Memory and Cognitive Function During Sleep

EEG is crucial to us understanding the role of sleep in memory consolidation and cognitive function. For example, sleep spindles and slow waves have been found to be critically involved in the consolidation of both declarative and procedural memory. Specifically, we used EEG to assess how these sleep features support learning processes and cognitive performance during NREM and REM sleep [15].

D. Sleep and Psychiatric Disorders

EEG is also used to probe the connections between sleep and psychiatric conditions, such as depression, schizophrenia and anxiety. Patients with psychiatric disorders frequently have an abnormality in sleep architecture, including disruptions of REM sleep. Studies in patients with depression have found that the REM sleep can be altered in very specific ways which could play a role in the cognitive and emotional disturbance seen in depression. EEG provides important information on the neurophysiologic changes underlying these disorders and can guide treatment choice [3].

V. Case Studies: Practical Implementations of EEG-Based Sleep Research Techniques

These EEG sleep studies applications show its essential part not only in understanding basic sleep processes but also in diagnosing, and altering on numerous disorders influencing sleep and thinking health.

A. Sleep Staging in Large-Scale Population Studies Using Wearable EEG and AI

To understand the various sleep patterns and what problems they treat, sleep staging is extremely important. Much of the work is burdened by use of traditional polysomnography (PSG) which is costly, labor-intensive, and intrusive. To overcome such limitations, wearable EEG headbands were combined with AI based sleep staging models in this study. In the study, 1,000 individuals between the age of 18 and 65 had dry EEG headbands monitor them for six months. A hybrid deep learning model comprised of convolutional neural networks (CNN) for spatial feature extraction and long short term memory (LSTM) networks for sequential sleep pattern detection was utilized to analyze the collected data. EEG data preprocessed through wavelet transform and independent component analysis (ICA) to remove muscle artifacts, eye movements and background noise was fed in [8]. An EEG bandpass filter (0.5–40 Hz) was used to filter out unnecessary EEG frequencies for sleep classification[6]. PSD analysis enabled estimation of activity in different frequency bands, whereas the wavelet decomposition was able to detect sleep spindles and other general sleep indicators[23]. The datasets containing 10,000 PSG labeled EEG recordings are used to validate the trained CNN-LSTM model[27]. Classification achieved an 89% accuracy over manual PSG based scoring results[22]. In stage N2, alpha intrusions were correlated with poor sleep quality and fragmentation, and multimodal EEG-ECG integration improved classification of deep sleep by 7%, with an indication of sleep abnormalities linked to cardiac[18]. Particularly, this study emphasizes the scalability and accessibility of wearable EEG for long-term home-based sleep monitoring. Manual sleep staging is automated using AI based classification, which reduces the manual workload and is feasible for large scale population studies and personalized sleep analysis.

B. EEG-Based Detection of Sleep Apnea Using AI and ICA Preprocessing

Obstructive sleep apnea (OSA) is a condition of catastrophic bites in which the airway repeatedly becomes obstructed producing fragmented sleep and oxygen desaturation. An auto OSA diagnosis based on PSG requires respiratory as well as oxygen saturation sensors, but recent work has been directed towards EEG OSA based auto apnea event detection. The goal of this study was to investigate the utility of using an AI enhanced EEG based approach to detect apnea related events which relies on no additional sensors, while simultaneously demonstrating the potential of EEG signals to detect apnea events in OSA patients versus healthy controls with 0.400 participants (250 patients with known OSA, 150 healthy controls)[30]. In this work full night EEG recordings from clinical sleep labs were analyzed as EEG micro-arousals and sleep stage transitions that associate to apnea episodes were searched. Noise and nonneural artifacts are removed from the recordings using ICA and wavelet enhanced preprocessing[5]. The delta, theta and alpha band activity were examined using spectral power analysis and K-complexes and EEG arousals, representing EEG arousals indicative of sleep disturbances were identified using advanced feature extraction[10]. This detection task was performed using a CNN based feature extractor with Transformer based architectures for sequential pattern recognition. It was shown that conventional PSG based classifiers can not outperform this model with a 92% detection accuracy[13]. Among other things, such as reduced delta power in stage N3 in severe OSA patients were correlated with lower sleep efficiency whereas increased alpha wave intrusions from REM sleep were associated with oxygen desaturation episodes[32]. In addition a predictive apnea risk index was developed to aid in the early diagnosis of OSA without requiring inpatient PSG[21]. By highlighted the possibility of conducting EEG based, non invasive apnea detection without use of respiratory sensors and with the ease of home based screening this study. Faster and cheaper OSA detection using AI-assisted EEG analysis improves access to diagnosis and treatment of sleep disordered breathing in the long term[15].

C. EEG Biomarkers for Insomnia and Cognitive Impairment

Chronic insomnia is a very common sleep disorder and is accompanied by cognitive impairments such as memory deficits or executive dysfunction. This study examined EEG based biomarkers in individuals with primary insomnia to investigate relationship of insomnia and neurocognitive decline. The investigators had 80 chronic insomniacs and 60 healthy age matched controls who were enrolled in the study, followed for 6 months with full night EEG monitoring. After sleep, memory retention, attention, and problem solving were tested with cognitive testing[40]. Spectral and connectivity based feature are extracted from the EEG recordings. Significantly lower sigma activity (12–15 Hz) was found in insomniacs compared to controls, which may be translated as reduced sleep spindle density[39]. Sleep spindles are important for memory consolidation and cognitive function. Additionally, the connection of the thalamocortex was found to be less effective and correlated to a lack of memory[28]. Increased beta activity (15–30 Hz), a biomarker of hyperarousal, is well described in insomniacs was observed using time frequency wavelet decomposition[11]. Impaired cognitive performance results when sleep spindles in insomniacs fall by 30%. Better working memory and better retention of new information, in turn, was shown to be linked with lower spindle density[29]. When participants showed elevated beta activity, they showed higher anxiety levels, which is some support for the former hyperarousal model of insomnia[19]. This implies that EEG biomarkers can assist in predicting cognitive impairment and also help in early intervention of at risk individuals.

D. AI-Based Home Sleep Disorder Screening Using Portable EEG Devices

The study recruited 150 subjects who were thought to have sleep disorders using a single channel EEG headband with dry electrodes[20]. The recorded EEG data was transmitted to an AI system in the cloud to be automatically analyzed. AI models were able to identify abnormal sleep patterns in 82% of the cases and then were PSFG validated further[7]. Early REM transitions were successfully detected by the EEG analysis in individuals suspected of having narcolepsy and patients with high frequency micro arousals were identified as having possible insomnia related sleep disruption[35]. Interventions aimed at areas highlighted in the reports increased sleep efficiency by 15% at month 2 after conditioning on these recommendations[36].

VI. Practical Challenges in Implementing EEG-Based Sleep Research Techniques

While many efforts have been made in EEG based sleep research, there are still many challenges that prevent EEGs from widespread implementation. There is a lot of noise contamination, variability of sleep patterns, and absence of large quality datasets to build accurate, generalizable AI models. Further, the clinical EEG systems are costly and as it relates to the privacy of the data there are ethical concerns which makes it hard to monitor sleep at home. To address these challenges, we need to improve the ability of the multimodal integration, develop a standardized biomarker and regulatory allow AI based sleep analysis.

A. Noise and Artifact Contamination in EEG Signals

The EEG signals are very susceptible to noise generated by EMG, EOG and electrical interference. As a result, it is challenging to get clean data for sleep staging as well as for disorder detection. In a study using portable EEG to monitor home-based sleep, as much as 30 percent of the data could not be used because of noise caused by muscle contractions and body movement. When data quality was low, even the most advanced artifact removal techniques such as ICA and wavelet decomposition failed to distinguish genuine neural activity from artifacts[10].

B. Variability in Sleep Patterns Across Individuals

From age, lifestyle, medication use, neurological conditions, sleep architecture varies greatly between people. This is one of the reasons why it is difficult to create generalizable AI models for sleep stage classification. Applying a deep learning model trained on young adults (18–30 years) for sleep stage classification to older adults (50+ years) resulted in a 25% drop in accuracy. The model had not been trained on older individuals, who had fewer sleep spindles and disturbed slow wave sleep (SWS)[22].

C. Limited Availability of Large, High-Quality EEG Datasets

Many ML models need a large number of annotated EEG recordings, yet sleep datasets are limited and noisy, and tend to consist of only particular populations. As seen in a study on AI sleep apnea detection, current public EEG datasets used for the study were recorded under controlled lab conditions, which turned out to be less realistic in terms of home use. These datasets were too noisy to train models with, its apparent, as they were not good in the home environment, where patient movement was high and noise was high[18].

D. Difficulty in Standardizing EEG Biomarkers for Sleep Disorders

EEG based diagnostic tools can not be standardized due to the lack of universal biomarkers of sleep disorders such as insomnia, sleep apnea, and narcolepsy. Different EEG biomarkers for insomnia related hyperarousal are reported in different studies. In some experiments, increased beta activity is reported, whereas in others spindle activity is reduced. This inconsistency prevents the development of an AI driven, insomnia diagnostic model[11].

E. High Cost and Limited Accessibility of EEG Sleep Monitoring Devices

However, clinical EEG systems are quite expensive and restrict home based sleep monitoring to only a few number of people. Both inexpensive wearable EEG devices usually lack signal quality and resolution similar to lab based systems. Low cost wearable EEG was compared using clinical PSG EEG and it was found that wearable headbands had 40% lower signal quality which in turn resulted in misclassification of sleep stages. High density EEG setups also were extremely demanding in calibration and, consequently, impractical for non-expert users [29].

F. Ethical and Privacy Concerns in AI-Based EEG Sleep Monitoring

In particular, huge data sets are needed for AI driven EEG analysis, which involves the issue of ethics in data privacy, security and informed consent. One concern was of home based sleep tracking, using AI to analyze EEG data, which involved storing a user's data on the cloud server. If not properly anonymized, participants worried about how the information related to their sleep patterns and neurological data could be used by insurance companies or third parties[19].

G. Lack of Clinical Validation for AI-Based Sleep Analysis

Most models of AI based EEG sleep analysis do not have regulatory approval because they aren’t clinically validated. An automatic sleep scoring model using deep learning was able to perform well in laboratory settings but was not accepted for clinical use due to poor performance in hospital settings as compared to trained sleep technologists. REM sleep was misclassified in 20 percent of cases and sleep disorder diagnosis was delayed[7].

VII. Recent Advances In Sleep Stage Classification Using EEG

Recently EEG based sleep stage classification has progressed a lot, especially when combined with machine learning techniques. As documented in studies, algorithms like Support Vector Machines.

Classifying sleep stages can be very effective using (SVM), Random Forest and Convolutional Neural Networks (CNN). Furthermore, the classification performance is further improved by utilizing combination of deep learning methods such as CNN-LSTM hybrids, which further emply additional information using both convolutional and sequential models. More recently, these hybrid models have been applied very well to sequential data, like EEG signals, for better sleep stage identification [2]. Figure 5 shows the mind map of classification advances in sleep study.

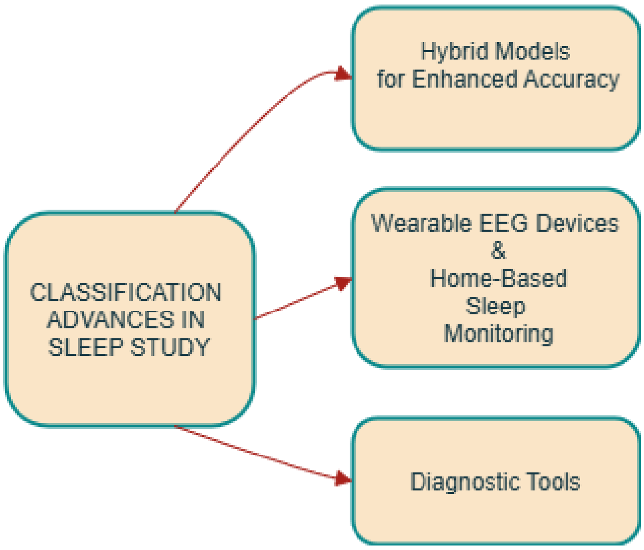

FIGURE 5: The mind map illustrates Classification Advances in Sleep Study

A. Hybrid Models for Enhanced Accuracy

The use of hybrid such as CNN-LSTM introduces something special due to the combination of the feature extraction strength of CNN with the temporal sequence modelling construct of LSTMs. The performance of these models is better compared to traditional methods particularly on challenging sleep stage classification tasks. These advancements are critical for automating sleep data analysis, reducing manual scoring, and speeding and improving the ability to diagnose sleep disorders [4].

B. Wearable EEG Devices and Home-Based Sleep Monitoring

The introduction of wearable EEG devices has been a major shift in sleep research, enabling continuous, home based sleep monitoring. As the devices become more prevalent these days, these devices are becoming more important in the sleep medicine as they provide a less intrusive and can be more readily availed these devices are provided to diagnose sleep disorders like sleep apnea and insomnia. Wearable devices and integration to machine learning models for real time data analysis makes the advent of improved patient care and personalized sleep treatment with great promise [2].

C. The Role of AI in Improving Diagnostic Tools

Deep and machine learning algorithms, which are the use of AI, are revolutionizing the landscape of diagnostic in sleep medicine. Through the application of these technologies to EEG data, such systems have been developed to more accurately identify sleep disorder and sleep stage. Today these AI driven systems are widely used in clinical and at home settings, promoting easier access to clinical tools and allowing for the detection of such disorders as insomnia, narcolepsy and sleep apnea [2][4].

VIII. Challenges And Limitations

A. Technical Limitations

EEG signals are extremely sensitive to noise and artifacts from many possible sources, including eye movements, muscle activity and electrical interference. These artifacts can greatly compromise the accuracy of sleep related measurements. Furthermore, EEG signals also have the inherent complexity that makes them difficult to interpret (i.e. subtle differences between sleep stages or disorders [6]).

B. Data Interpretation

Standard EEG markers for sleep disorders have proved difficult due to inter–individual variability of brain activity. Even within the same sleep stage, signal patterns are varied enough to make a universal reference for clinical diagnostic difficult. This inconsistency may add to the confusion of EEG data interpretation, leading towards misclassification, or even missed diagnosis [19].

C. Scalability and Accessibility

However, the high cost of equipment and special training needed for interpreting the data impedes widespread clinical adoption of EEG technology. In addition, wearable EEG devices will continue to emerge, but their accuracy and reliability for use in the home still need to be improved. Such limits the scalability of EEG based sleep monitoring for broader public use [19] [28].

IX. Future Directions

Sleep is becoming an important focus in sleep research, which has led to the integration of EEG with other imaging methods, such as fMRI. EEG has high temporal resolution, thus yielding the pixel on a millisecond scale. On the other hand, fMRI provides superior spatial resolution and can localize neural activity within the brain with greater accuracy than can old techniques. If researchers combine the two, they will get a more complete picture of how the brain works in sleep. This hybrid approach is needed to chart the neural bases of diverse sleep phenomena including sleep spindles and slow wave sleep, both of which are presumed to contribute to cognitive and memory consolidation.

According to one notable study, they explored the neural correlates of sleep spindles, which correlate with cognitive skills, such as fluid intelligence, while simultaneously electromyography (EMG) and functional magnetic resonance imaging (fMRI). By analyzing time-locked sleep spindles (a classic marker of sleep in the EEG) with fMRI, we have found that sleep spindles are time-locked to specific brain activations, in turn suggesting how sleep contributes to its cognitive functions. By mapping these spindles directly to brain regions, we gain insight into how the brain plays a role in memory consolidation and learning during sleep. Improvement of sleep-based treatments [19] and development of biomarkers for cognitive disorder can be achieved with such findings. Also, EEG and fMRI combined can elucidate sleep disorders. Brain activity, however, may be disrupted in the sleep of insomnia, narcolepsy, or sleep apnea. Instead of EEG alone, researchers were able to pinpoint changes in the brain regions associated with disrupted sleep patterns by combining both EEG and fMRI. And in particular, this dual approach could be especially useful for identifying novel biomarkers that are undetectable by either method alone. Table 1 shows future directions in sleep research, highlighting the integration of EEG-fMRI, AI, and wearable devices for enhanced disorder detection, treatment, and at-home monitoring.

EEG-fMRI integration in sleep re-search has the potential for the diagnosis as well as beyond this, and this has the potential to be their best application so far. Then, as machine learning and more sophisticated computational approaches continue to grow, these hybrid data sources might appear to be combined with AI models that can predict and track sleep disorders over time. It could help more personalized, more effective treatments.

In addition to using non-invasive home monitoring systems. Their in vivo applications and potential for at home sleep monitoring, which reduces clinical settings dependency, thus continuous data collection, represent a promising direction of wearable EEG devices. It is likely to aid further accessibility to sleep diagnostics and improve the ability of more people to manage their sleep health at home [3].

TABLE 1. Future directions in sleep study

Future directions	Details	Impact
EEG-fMRI Hybrid Approach	Combining EEG's temporal resolution with fMRI's spatial resolution for sleep analysis.	Comprehensive understanding of sleep's role in memory and cognitive functions.
Neural Correlates of Sleep Spindles	Analyzing sleep spindles with EEG-fMRI to link them to cognitive skills like fluid intelligence	Insights into memory consolidation and learning during sleep.
Improvement of Sleep Treatments	Using EEG-fMRI to improve treatments and develop biomarkers for cognitive disorders.	Better-targeted treatments for sleep and cognitive disorders.
Detection of Sleep Disorders	Identifying sleep disruptions in disorders (insomnia, narcolepsy, sleep apnea) through EEG-fMRI.	More accurate identification and personalized treatment of sleep disorders.
AI and Machine Learning Integration	Using AI to analyze hybrid EEG-fMRI data for sleep disorder prediction and tracking.	Personalized, real-time management of sleep disorders.
Non-invasive Home Monitoring Systems	Development of wearable EEG devices for at-home sleep monitoring.	Increased accessibility to sleep diagnostics and home-based management.

X. Conclusion

EEG has proven its status as a fundamentally indispensable tool in sleep research and diagnostic neurology. Because it is such a great way to capture on the brainwave dynamics involved in sleep architecture its ability to monitor for insomnia, sleep apnea, narcolepsy, etc. is invaluable. The rapid advances in machine learning, deep learning, and signal processing have significantly improved EEG's ability to perform high accuracy sleep stage classification and to detect very subtle anomalies, opening the door to automated, large scale sleep studies.

Despite these advancements, challenges remain, particularly in minimizing noise, standardizing biomarkers, and making EEG technology more accessible for home-based use. Emerging wearable EEG devices and the integration of EEG with complementary imaging modalities like fMRI hold promise for providing deeper insights into sleep processes and their neurophysiological underpinnings. These innovations have the potential to revolutionize diagnostics and treatment, particularly by enabling personalized sleep interventions and continuous monitoring solutions.

Looking ahead, the convergence of EEG with artificial intelligence and hybrid diagnostic models is expected to redefine sleep medicine, making it more precise, efficient, and accessible. By addressing technical and practical limitations, future research can unlock the full potential of EEG, empowering both clinicians and individuals to better understand and manage sleep health. Ultimately, EEG's evolution will not only enhance the diagnosis and treatment of sleep disorders but also contribute significantly to our broader understanding of brain function and its impact on overall well-being.

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CONFLICT OF INTERESTS

No conflict of interests were disclosed.

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Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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