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A Review of Automated Sleep Stage Scoring Using Machine Learning Techniques Based on Physiological Signals

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5.1 Introduction

Historically, the general perception of sleep is a steady state of unconsciousness. Still, the actual truth is that it has an active and dynamic life cycle during which the brain is entirely functional [1]. Indeed, a proper sleep routine can significantly improve cardiac function and maintain appropriate mental restoration, attention, consolidation, and behavior. Sleep is an essential human physiological activity. Human beings spend approximately one-third of their lifetimes sleeping. Sleeping is necessary for the body to preserve its wellness and health. Sleep deprivation causes a reduction in agility and output during the daytime, reduces concentration, and adversely affects regular circadian rhythm [2, 3]. It also leads to mental and physical impairments, affects immunity, reduces cognitive functioning, and causes other health issues. Sleep is a continuous and dynamic process with a cyclic structural framework with a time course [4].

The rapid and nonrapid eye movements are considered to be the most potential stages of sleep. These stages of sleep are distinguished by unique neural activity traits [5, 6]. REM sleep underscores heightened neural engagement, while NREM sleep triggers reductions in metabolic rate, blood pressure, heart rate, and

Intelligent Techniques for Predictive Data Analytics, First Edition.
Edited by Neha Singh, Shilpi Birla, Mohd Dilshad Ansari, and Neeraj Kumar Shukla.

Published 2024 by John Wiley & Sons, Inc.

sympathetic activity, all the while accentuating parasympathetic activity [7]. The classification of sleep stages leans on well-defined criteria endorsed by authoritative bodies. Polysomnology (PSG) is emerging as a precise standard for dissecting sleep phases. PSG involves the simultaneous measurement of a variety of parameters, including electroencephalogram (EEG), electrocardiogram (ECG), EOG, EMG, blood oxygen quality, ventilation, and respiratory effort [8]. Typically enacted within a sleep laboratory, PSG data undergoes division into 30-second epochs, each precisely categorized into one of three NREM sleep stages (N1, N2, N3), REM sleep, or a wakeful state. The American Academy of Sleep Medicine (AASM) manual [9, 10] meticulously outlines the defining characteristics of each of these five sleep stages as follows:

Stage W: distinguished by regular or increased chin muscle activity, reading eye motions, or eye blinking [11].

Stage N1: distinguished by slowly moving eyes and a high probability of awakenings or arousals. Alpha bands must not surpass half of the broad spectral band, and the amplitude of the EEG signal should be in the frequency range of 2–7 Hz and remain less than 200 mV. N1 usually accounts for 5% of total sleep time [11].

Stage N2: Amrousals and awakening stage are less seen in N2 than in N1, and slowly moving eyes begin fading. N2 is awarded if there are one or more K-complexes or spindle trains in the last 50% of the previous or early 50% of the current epoch. N2 typically accounts for half of the sleep cycle in a single night [12].

Stage N3: It accounts for predominant slow waves and delta in the EEG signal and periodic arousals or awakenings. K-complex and Spindles may arise, and N3 is assigned if slow waves account for more than 20% of the period. N3 usually accounts for 20% of overall sleep. It depicts a deep sleep mode [13].

Stage REM: The dreaming stage is distinguished by the movement of the fast eye and active brain waves of N3. In REM, arousals and awakenings are common. The EEG exhibits mixed frequency and low voltage. REM is scored as such until a transition to stage W or N3. REM sleep accounts for one-fourth of total sleep time. Rechtschaffen and Kales (R&K) and the American Academy of Sleep Medicine (AASM) are two sets of guidelines for scoring sleep stages based on polysomnography (PSG) data [13].

The inadequate understanding of the underlying physiological mechanisms that shape the physiological signs acquired during sleep is one of the hurdles in sleep stage analysis (Table 5.1). Sleep patterns are known to change with age, but the source of these changes is unknown [14, 15]. The absence of apparent causality between physiological processes and observable signs complicates data interpretation. Furthermore, new and refined correlations are being uncovered in this dynamic area of research [16]. While human experts can still make diagnoses based on medical data, computational tools can help by detecting minor

Table 5.1 Sleep phases according to respective standards alongside descriptions.

Stages	R & K	AASM	Spectral band
WAKE (W)	W	W	
NREM	S1	N1	Alpha band
	S2	N2	Theta band
	S3	N3	Delta band
	S4		
REM	R	R	

discrepancies, speeding up analysis, and lowering expenses. These models can deliver a range of outputs, from event labeling to feature extraction and even diagnosis suggestions [17].

This research highlights the significance of diverse physiological signals housing insights into sleep stages and their classification [18]. These hold promise for diagnostic purposes, treatment monitoring, and the assessment of drug efficacy. However, realizing these advantages necessitates signal measurement and effective information extraction. The multitude of digital signal processing systems available has given rise to a lack of standardized methods for information retrieval, warranting the clarification of signals that carry sufficient diagnostic information [19]. To tackle this challenge, the study delves into the analysis of information extraction techniques across a spectrum of physiological signals, thereby shedding light on the inherent data information [20].

The entire review's findings regarding sleep scoring systems are rooted in these signals. Notably, each physiological marker corresponds to a single sleep stage, leading to the search for multiple signals for potential redundant but possibly uncorrelated information. As a result, much research has been conducted to investigate the automatic assessment of sleep stages through different combinations of signals [21].

5.2 Review of Related Works

5.2.1 Electroencephalogram (EEG)

The EEG captures the electrical activity of the brain, and the patterns of activity during different stages of sleep are diverse enough that they have been utilized to establish numerous sleep stage classification systems. Time-domain (TD) features [22], spectral features (Wave bands) [23], time-frequency (TF) [24] features, and nonlinear [25] features are all ways to extract sleep-related information from EEG data. Several classification approaches, including ensemble classification methods like Random Forest and Bootstrap Aggregating, K-means, and SVM, have been employed in sleep classification research to aid medical practitioners [26, 27]. A brief analysis of EEG signals for automatic sleep stage classification is discussed [28] (Figure 5.1; Table 5.2).

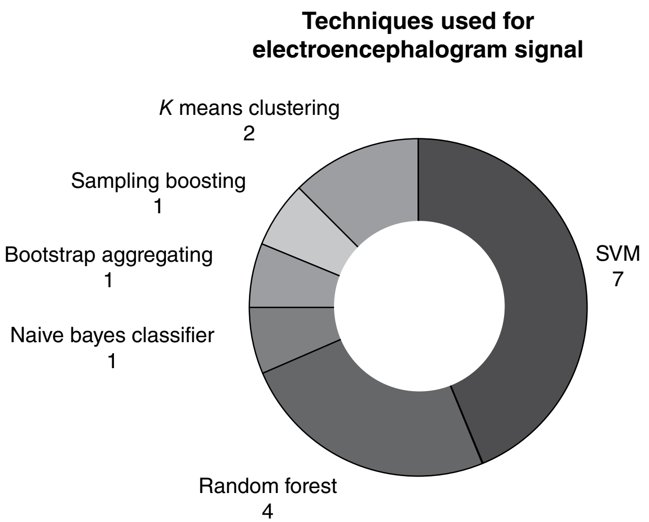

Figure 5.1 Employment of ML algorithms and alternative techniques in analyzing EEG signals.

Table 5.2 Overview of review outcomes for chosen studies employing EEG signals to aid sleep stage classification.

Existing studies	Dataset	Feature extraction and selection method	Classification method	Accuracy
[1]	Subjects: 20 Domain: healthy Age Group: 25 to 35 years	Linear evaluation technique	Support vector machine	Accuracy: Approximately 88% accuracy
[3]	EDF dataset (The benchmark Sleep)	Signal-sample-entropy and time-frequency wavelet filter	Support vector machine for a two-class problem	Accuracy: Approximately up to 98%
[2]	EDF dataset	Linear feature (Local Extrema)	Multiclass support vector machine	Accuracy: Approximately up to 98%

Table 5.2 (Continued)

Existing studies	Dataset	Feature extraction and selection method	Classification method	Accuracy
[4]	Subjects: 23 Domain: healthy adults Group: Male Age range: 23–45	Synchronization likelihood and relative entropy	Support vector machine and K-nearest neighbor technique	Accuracy: Approximately 93%
[6]	Sleep-EDF database	Nested five classes of sleep stage classification	Random forest (RFC)	Accuracy: Approximately 95%
[7]	Sleep-EDF database	Coupling techniques based on frequency features	Naive Bayes classifier	Accuracy: Approximately 94%
[8]	Sleep-EDF database	Wavelet transform techniques	Six-class classification based on Bootstrap aggregating (Bagging) from the Sleep-EDF database	Accuracy: Approximately 92%
[9]	Sleep-EDF database	Discrete Fourier Transform aka DFT	Random Forest aka RFC	Accuracy: Approximately 90%
[10]	Sleep-EDF dataset	Ensemble empirical mode decomposition	RUS Boost	Accuracy: Approximately 98%
[11]		Wavelet transform technique	Random forest aka RFC (six classes of sleep stage classification)	Accuracy: Approximately 91%
[12]	Sleep-EDF database	Time and frequency domain features and representation by entropy structural graph	K-means clustering technique	Accuracy: Approximately 96%
[13]	Subjects: 25 adults Domain: Sleep Apnea Dataset: provided by provided by St. VUHUCD	Two-stage multi-view learning approach	K-means clustering, SVM algorithm	Accuracy: Approximately 81%

(*Continued*)

Table 5.2 (Continued)

Existing studies	Dataset	Feature extraction and selection method	Classification method	Accuracy
[15]	Subjects: 25 individuals Age range: 40–60 years	Hybrid approach	RFC	Accuracy: Approximately 98%
[14]	Sleep-EDF database	Time-frequency domain features	Multiclass support vector machine	Accuracy: Approximately 88%
[16]	Subjects: 20 babies Domain: Region Croatia Age group: three months	Generalized zero-crossing methods	Support vector machine	Accuracy: 90%
[17]	Subjects: 28 Domain: Suspected Sleep Apnea Age range: 35–55	Recursive feature elimination technique	Binary support vector machine	Accuracy: Approximately 85%

5.2.2 Electrocardiogram (ECG)

ECGs without cardiac arrhythmias capture the electrical behavior of the heart, where their components can be identified individually by visual inspection. These ECG signals exhibit subtle changes consistent with autonomic nervous system (ANS) activities during sleep in particular times, e.g. prove that the decrease in volume occurs Consequently, PSG signals such as heart rate and respiratory rate change depending on the stage of sleep. These overlaps highlight the complex relationship between sleep status and physiological symptoms (Figure 5.2; Table 5.3).

5.2.3 Respiratory Effort and Electrooculography

Electrooculography (EOG) detects the REM stage by measuring the corneal retinal electrical potential, which can then be utilized to follow eye movements. The AASM recommends placing the EOG electrodes 1 cm from the left and right outside eye corners (canthus). This placement is straightforward, and patients can do it themselves, making it an effective tool for continuous sleep stage evaluation and long-term monitoring (Figure 5.3; Table 5.4).

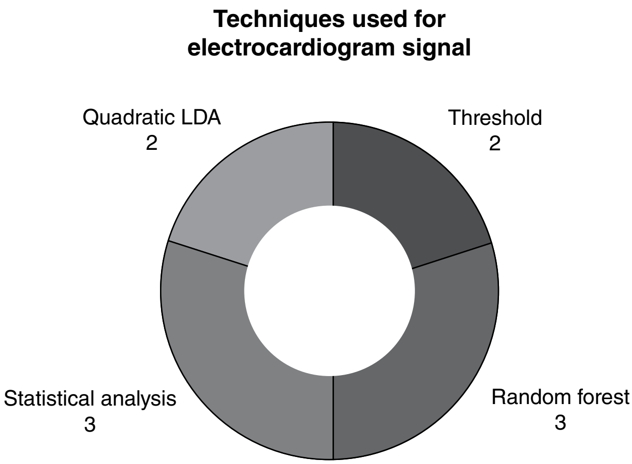

Figure 5.2 Utilization of ML algorithms and alternative techniques for analyzing ECG signals.

Table 5.3 Synopsis of review findings for handpicked studies employing ECG signals to facilitate sleep stage classification.

Wordsmith	Statistics and figures	Feature extraction and selection method	Classification method	Inferences
[18]	Dataset: CinC used for performance evaluation of the algorithm	HR statistics from ECG-derived respiration	Random Forest aka RFC	Accuracy: Approximately 87%
[19]	SLNEU database and PhyisioNet dataset	Morphological methods and techniques	Random Forest aka RFC	Accuracy: Approximately Up to 87%
[20]	Subjects: 51 (M: 37; F: 14) with obstructive sleep apnea (OSA) Surveyed at SNUH	HR parameters and statistical techniques, variability analysis	Threshold variability method	Accuracy: Approximately 88%
[21]	Subjects: 75 patients Domain: Sleep apnea Surveyed at SPTCMH	HR parameters and statistical techniques, spectral power	Statistical features	____________

(*Continued*)

Table 5.3 (Continued)

Wordsmith	Statistics and figures	Feature extraction and selection method	Classification method	Inferences
[22]	EDF sleep	HR parameters and linear statistical techniques, NL frequency domain	Random Forest aka RFC	Accuracy: Approximately 89%
[23]	Database: SIESTA Domain: Apnea-ECG	HR parameters, spectral power	Threshold variability method	Accuracy: Approximately 58%
[24]	Subjects: 71 Domain: healthy women Group: postmenopausal	HR parameters, and linear statistical techniques, NL frequency domain	Statistical analysis	Not available
[25]	Subjects: 31 Group: Male	HR parameters and linear statistical techniques from ECG-derived respiration	Quadratic linear discriminant analysis	Accuracy: Approximately up to 76%
[26]	Subjects: 37	HR parameters and linear statistical techniques	Linear discriminant analysis	Not available
[27]	Subjects: 14 Domain: Healthy	HR parameters, and linear statistical techniques, and BP parameter	Statistical analytical techniques and comparison methods	Not available

5.2.4 Multiple Signals Integration (PSG)

Using multiple physiological signals provides redundant information since essential details in one signal may be missed but discovered in another [32]. As a result, PSG, which records EEG, ECG, EOG, and EMG signals, has become the threshold standard for detecting sleep problems [33]. PSG recordings are typically produced throughout the night. A sleep hypnogram is created by manually scoring sleep stages every 30 seconds by professional sleep experts. Physiological signals combine ECG, EEG, EOG, and EMG to build automatic sleep stage scoring systems [34] (Figures 5.4 and 5.5; Table 5.5).

Figure 5.3 Application of ML algorithms and alternative techniques for EOG and respiratory effort analysis.

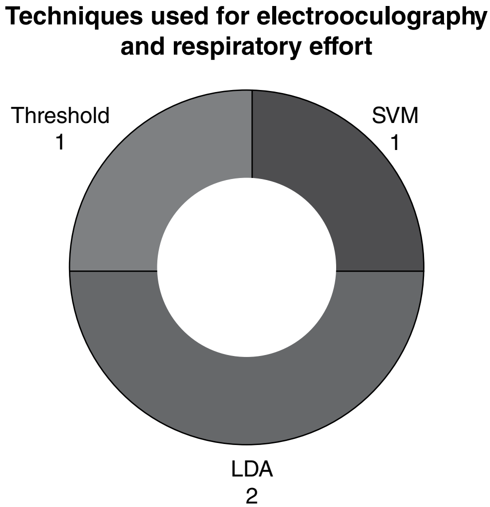

Table 5.4 Overview of sleep staging review outcomes for chosen studies utilizing EOG signals.

Wordsmith	Statistics and figures	Feature extraction and selection method	Classification method	Inferences
[28]	EOG Physio net DB	DW transform (DWT) coefficients and statistical analysis	Six classes problem approached with support vector machine	Accuracy: Approximately up to 92%
[29]	EOG	Spectral analysis	Five classes of sleep stage classification	Accuracy (Precision): Approximately 83%
[30]	Subjects: 48 Domain: Healthy (Respiratory effort)	Statistical analysis and spectral power	Quadratic linear discriminant analysis	Accuracy: Approximately 80%
[31]	Subjects: 265 Domain: Healthy (EOG)	Spectral analysis	Thresholds for percentage classes of sleep stage classification	Accuracy: Approximately 73%

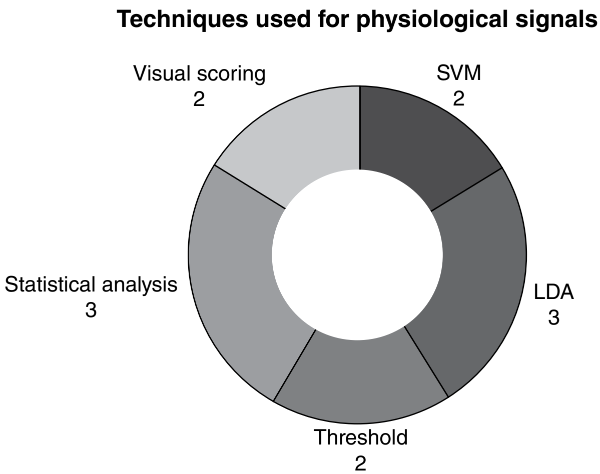

Figure 5.4 Deployment of ML algorithms and alternative techniques for processing PSG signals.

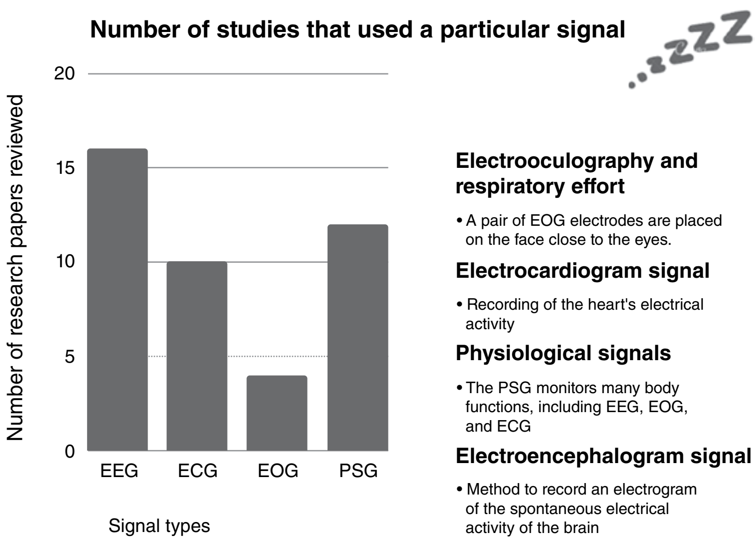

Figure 5.5 Graphical form of 42 research paper that used EOG, PSG, ECG, EEG signal.

5.3 Methodology

Preprocessing, feature selection and extraction, and classification models and algorithms are the primary steps in the quantitative sleep stage scoring procedure [42]. After feature extraction, some studies incorporate a

Table 5.5 Recapitulation of sleep staging review outcomes for chosen research incorporating multiple physiological signals.

Wordsmith	Statistics and figures	Feature extraction and selection method	Classification method	Inferences
[32]	Males: 664, i.e. (~66.67%), Females: 324, i.e. (~33.33%)	TP rate and TN rate	SVM	Accuracy (Precision): 82%
[33]	Newborns: 74 and Adults: 16: Total participants: 90	Spectral power on EEG-based signal, HR absolute HF, i.e., high-frequency component	Statistical analysis	Not available
[34]	Participants: 48	Spectral power is based on ECG signal, VM, and network analysis. Polysomnography: network analysis and time-frequency analysis	Linear discriminant analysis	Accuracy: Upto 80%
[35]	Database: sleep SIESTA	Time frequency and network analysis	Linear discriminant analysis	Accuracy: Approximately 80%
[36]	Subjects: 36 Domain: Healthy	Movement statistics, breathing rate statistics aka BR	Support vector machine	Accuracy: 81%
(Xi [30])	Participants: 115 adults; Respiratory effort, Domain: healthy	Statistical analysis	Linear discriminant analysis	Accuracy precision: Approximately 96 %
[37]	Healthy Subjects	Five-class sleep stage classification of sleep stages based on AASM rules	Statistical analysis	Not available
[38]	Participants: 230 Domain: Habitual Snorers And other 170 female participants (EEG and ECG)	Statistics and spectral power and visual scoring for PSG signals	Statistical analysis	Not available

(*Continued*)

Table 5.5 (Continued)

Wordsmith	Statistics and figures	Feature extraction and selection method	Classification method	Inferences
[39]	Participants: 542 children Domain: healthy participants from three to nine years being approximately	Five-class sleep stage classification of sleep stages based on AASM rules (visual scoring)	Visual scoring	Not available
[40]	Participants: 11 Infants; Domain: Healthy	EMG based signals	Threshold variability method	Not available
[41]	Participants: One participant having Parkinson's disease	Five-stage classification based on AASM rules (visual scoring)	Visual scoring technique	Not available

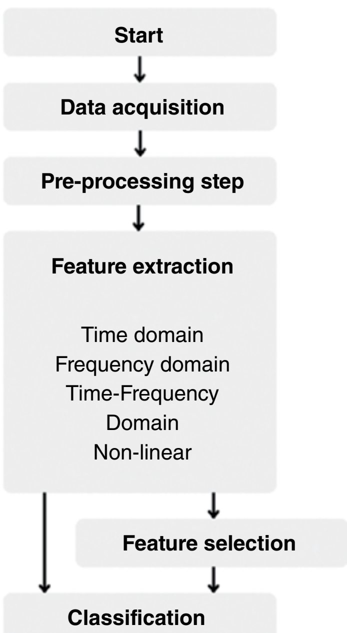

Figure 5.6 Process of automated sleep stage classification.

feature selection stage to select the most important and relevant features. The graphic below depicts the process of automatic sleep stage scoring (Figure 5.6) [43].

5.3.1 Preprocessing

Preprocessing involves cleaning raw EEG signals to remove artifacts and enhance the informative components. This is necessary to prevent incorrect or distorted results from various factors such as measurement noise, physiological variables, and pathological conditions. Despite using hardware filters while recording, outside sources can still contaminate EEG signals [44, 45].

5.3.2 Feature Extraction

Feature extraction encompasses the identification of informative attributes within a signal, which is essential for effective classification.

These derived features must possess independence and encapsulate the most distinctive data to avoid redundancy. To distill sleep stage insights from EEG recordings, a variety of signal processing techniques come into play. Extracted features are represented as in the form of either linear or nonlinear [44].

Time domain features offer simplicity and real-time adaptability as they elucidate the morphological characteristics of a signal. Frequency domain features on the contrary capture changes within EEG signals by transitioning time-based series into the frequency domain. Spectral estimation methods include parametric and nonparametric methodologies, such as periodogram and Welch, enabling the dissection of signal frequency components (Figure 5.7).

Within the nonlinear dynamics of EEG signals, nonlinear measures play a pivotal role in signal processing strategies. Notably, they find common application in feature extraction for sleep stage scoring. Entropy-based methods quantitatively gauge the irregularity and impurity of a time-domain signal [46]. In essence, lower entropy values signify more regular patterns within a signal window, while higher values indicate increased irregularity. Fractal-based methods generate a noise-like form by iteratively applying an operator on a geometric fragment. Despite their underlying rule-based behavior, certain instances exhibit noisy tendencies, adding complexity to their dynamics.

5.3.3 Feature Selection

After the feature extraction stage, some sleep stage classification methods, particularly multichannel ones, use feature selection algorithms to obtain a discriminative subset of characteristics. The goal is to reduce the number of features without sacrificing accuracy while avoiding overfitting and shortening computing time. Feature selection is handy when massive nighttime PSG records are used, and several types of characteristics are retrieved. Statistical strategies for determining the appropriate and discriminative subset of features have been developed in the literature. Sequential backward (SB) and sequential forward (SF) sampling are simple ways to examine features and determine the optimal subset. On the contrary, SF and SB sampling have limits and no backtracking. In contrast, metaheuristic algorithms such as genetic algorithm and particle swarm optimization are regularly used for feature selection [47, 48].

5.3.4 ML and DL for Sleep Disorder Detection

Recognizing the significance of sleep disorders, researchers have turned to innovative approaches, particularly ML and DL algorithms, to enhance detection methods. These computational techniques, which excel in pattern recognition

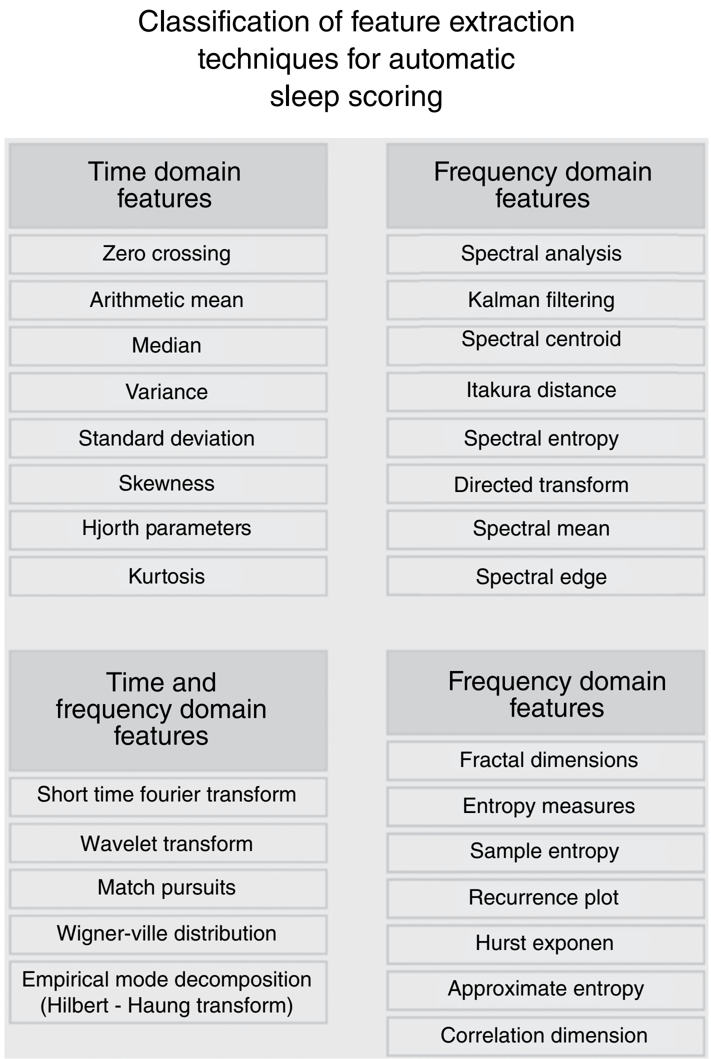

Figure 5.7 Categorization of feature extraction techniques for automated sleep scoring.

and data analysis, offer a promising means of identifying and diagnosing sleep disorders more accurately and efficiently. By analyzing extensive datasets encompassing sleep patterns, physiological signals, and other relevant parameters, ML and DL algorithms can reveal intricate patterns and correlations that might elude traditional diagnostic methods [49, 50].

5.3.4.1 Limitations of Traditional Methods

The limitations of traditional approaches for scoring sleep include the following:

Intrusiveness: Traditional methods often require patients to sleep in unfamiliar environments, affecting their natural sleep patterns and potentially leading to a phenomenon known as the "first-night effect."

Subjectivity: Manual scoring of sleep stages and events in PSG is prone to inter-scorer variability, leading to inconsistent results.

Accessibility: Sleep labs are limited in number and can be geographically distant, making it challenging for some patients to access these facilities.

Cost: PSG and related tests are expensive, involving not just equipment but also professional expertise for scoring and interpretation.

Limited Data: Traditional methods provide data from a single night in a controlled setting, potentially missing variations and fluctuations in sleep patterns over time.

5.3.4.2 Need for Automated Approaches (ML/DL)

The need for ML-/DL-based automated approaches for sleep pattern classification is essential for the following points (Figure 5.8).

Consistency and Value Chain: Machine learning (ML) and deep learning (DL) models provide methods that are practical and standardized, reducing variability among human scorers. This ensures an objective research design and assures consistent results in studies.

Noninvasive Sleep Monitoring: With sensor-enabled wearable devices, individuals' sleep patterns can be monitored in the comfort of their home. This preserves the natural sleep behavior of the subjects, allowing them to accurately replicate their typical sleep patterns.

Efficient Large-scale Studies: The automation provided by the ML and DL approaches facilitate the thorough screening of large numbers of people for sleep disorders. This early detection capability enables timely intervention and significantly reduces stress in specialty day hospitals, ultimately improving overall access to health care.

Deep-feature Extraction: ML and DL algorithms excel in extracting complex patterns that exist simultaneously across different physiological signals. This enhanced capability has the potential to reveal insights that traditional analytical methods may overlook.

Real-time Analysis and Feedback: Some automated systems provide users with real-time feedback, empowering them to make instant adjustments to improve their sleep This instant feedback this contributes to sustainable sexual improvement. Economic solutions once automated systems are developed,

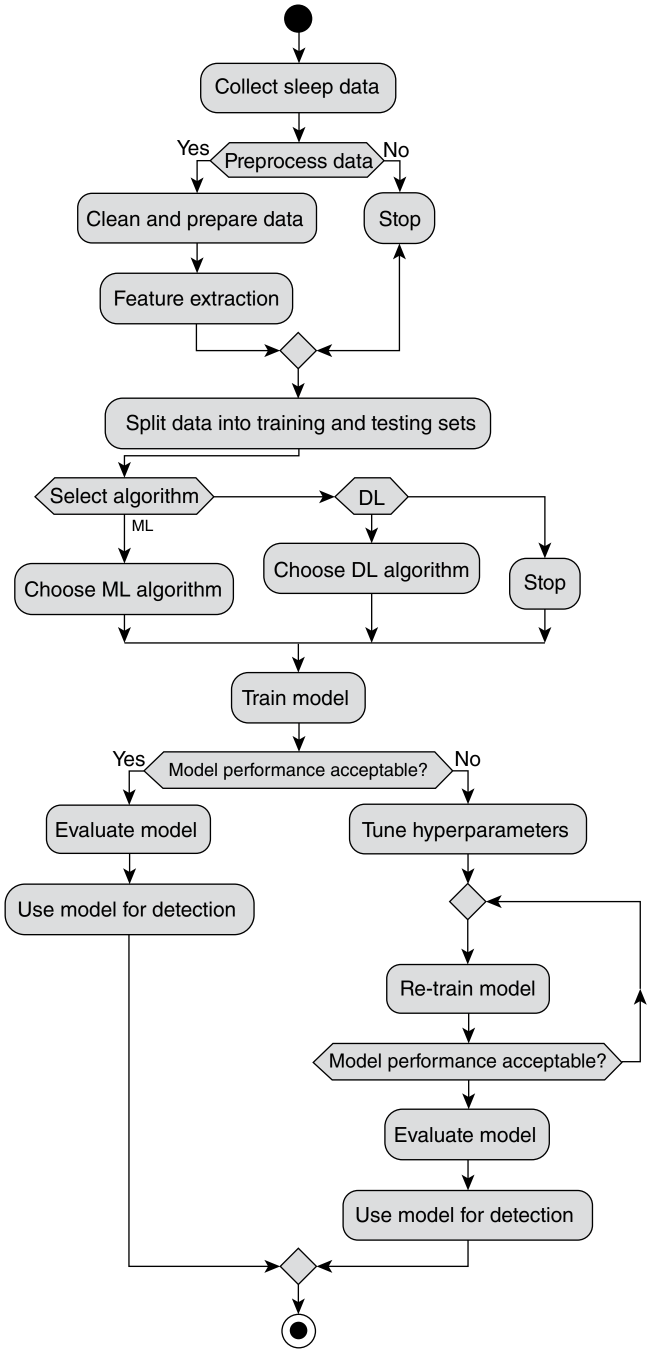

Figure 5.8 Comprehensive flowchart illustrating automatic sleep scoring through ML & DL approaches.

they offer a cost-effective alternative to hospitals with resource-intensive specialty days and repetitive testing. These potential cost savings hold significant promise for enhancing healthcare accessibility and affordability, with systems becoming notably more accessible and affordable.

Economical Solution: Once developed, automated systems offer a cost-effective alternative to resource-intensive specialty days hospitals and repetitive tests. These cost reductions can dramatically increase the affordability and availability of health care.

5.4 Conclusion

In this report, we delved into the transformative potential of ML and DL algorithms in revolutionizing sleep disorder detection. Through a comprehensive literature survey, we witnessed the remarkable impact of these algorithms on healthcare. The application of ML and DL in sleep disorder detection showcases their ability to process physiological signals from wearable devices, offering insights into disorders such as insomnia, sleep apnea, and narcolepsy. These algorithms' proficiency in deciphering intricate patterns within EEG, ECG, and other signals indicates their prowess in understanding sleep intricacies. Key to their success is feature selection, which highlights the significance of preprocessing data. The fusion of feature selection with model development has resulted in innovative models such as Deep Sleep, SleepNet, and NarcoNet. The complex architectures of CNNs and RNNs enable these models to discern sleep stages and disorder occurrences. Transitioning from model development to performance evaluation, metrics such as accuracy, sensitivity, and specificity validate the reliability of these algorithms in real-world clinical contexts. These metrics affirm the algorithms' effectiveness in addressing the multifaceted landscape of sleep disorders.

5.5 Future Work

The proposed study has led us to many avenues to contribute to our research work in sleep staging using PSG signals. In the future, we hope that some more new exciting frameworks and technology will be found by further analysis of the complications during the diagnosis of different types of sleep-related disorders. The methodology obtained in this thesis could be extended in several ways, for example:

- The performance of the proposed ensemble learning model can be extended by considering an appropriate selective aggregation technique that incorporates identifying the most effective features.

- In this thesis, we used only recordings of healthy controlled subjects and a few sleep-disordered subjects. In the future, we will focus on the large-scale sleep recordings of subjects who were affected by multiple sleep pathologies.
- Applying different wavelet decomposition techniques and other time-frequency features for a better way of analyzing discrimination of the changes in sleep behavior over the individual sleep stages.

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