

# Automated Sleep Stage Classification using Machine Intelligence Techniques: Physiological Signals, Sleep Data Presentation, and Models

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**Abstract.** Advancements in clinical practice has led to the classification of sleep stages (SSC) establishing an essential step up for physicians when evaluating sleep patterns and diagnosing sleep disorders. Nevertheless, the conventional method of sleep stage classification heavily relies on the manual efforts of sleep experts, presenting a time-consuming and labor-intensive process. To overcome this challenge, computer-aided diagnosis (CAD) emerges as a promising tool to assist sleep experts, facilitating the assessment and decision-making procedures. Particularly, in recent times, CAD integrated with artificial intelligence, notably employing machine learning (ML) and deep learning (DL) techniques, has gained widespread traction in SSC. DL offers enhanced accuracy and cost efficiency, thus making a substantial impact. This study systematically reviews research on SSC employing ML and DL methods (ML-DL-SSC). It examines various critical aspects of ML-SSC and DL-SSC, including signal and data representation, data preprocessing, deep learning models, and performance evaluation. Specifically, the paper aims to address three primary inquiries: (1) What signals can ML-DL-SSC utilize? (2) What are the diverse approaches to representing these signals? (3) What are the efficacious ML and DL models? By elucidating these queries, this paper endeavors to offer a comprehensive overview of ML-DL-SSC. This review explores the latest ML and DL approaches for sleep scoring and the challenges in integrating automated scoring into clinical practice along with the ability to achieve accuracy higher or similar to manual scoring, highlighting the potential of deep learning to improve sleep disorder diagnosis by analyzing a combination of different signals like polysomnography(PSG) and other varieties of data.

**Keywords:** Sleep disorders, Automated sleep-scoring systems, Machine Learning, Deep Learning, Polysomnography (PSG) Signals

## 1 Introduction

Sleep, which takes up almost one-third of a person's life and is essential to survival, is the most basic biological process [86]. Regrettably, sleep disturbances are common in

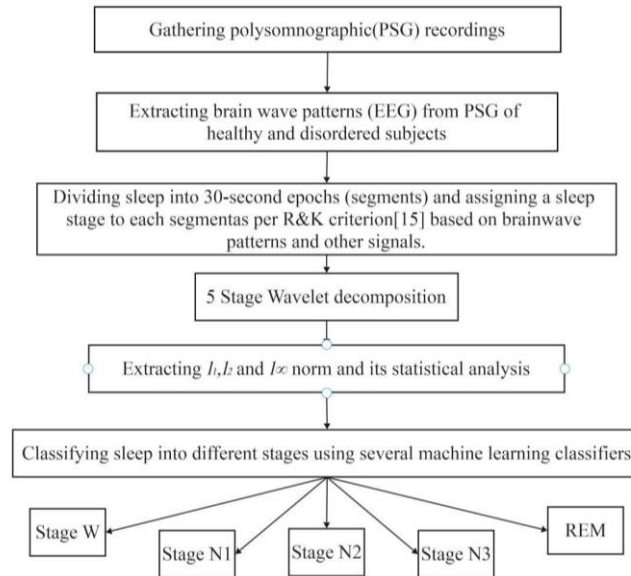
today's world. According to a 2022 global survey with almost 500,000 participants, the COVID-19 pandemic caused a 40.5% increase in the prevalence of sleeplessness in the general population [87]. Numerous **Psychiatric disorders** are intimately linked to sleep problems [88]. For example, Zhang et al.'s research revealed a relationship between the degree of dementia and the decreased fraction of deep sleep in Alzheimer's patients [89]. Furthermore, Baglioni et al (2011) reported that insomnia doubled the likelihood of depression in those without depressive symptoms [90]. Sleep disorders are a widespread health concern, and diagnosing them typically involves an overnight test called polysomnography (PSG) that records various body signals. Sleep scoring, the process of analyzing these signals to identify sleep stages and disturbances, has been a challenge due to its time-consuming nature and variations in expert scoring. Recently, deep learning algorithms have been explored as a potential solution to automate scoring. This text discusses the complexities of PSG and the challenges in adopting automated scoring in clinical practice, with a focus on deep learning techniques and their potential to overcome these challenges.

Sleep is vital for our physical and mental well-being. It helps our bodies recover, strengthens our brain connections, and enhances our learning and memory. Modern lifestyles and traumatic experiences, especially in childhood, can lead to sleep problems. Studies show that a significant percentage of adults experience sleep issues, which can impact their quality of life and productivity. Sleep problems also have economic consequences, costing billions of dollars globally. Mainly, the two main sleep stages are Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM), each with unique characteristics. Sleep experts use a gold standard test called Polysomnography (PSG) to monitor these stages, but it's a complex process with room for interpretation. This is where computational methods come in, assisting experts in analyzing sleep data and potentially improving diagnosis.

### 1.1 Visual scoring procedure

When experts visually score a person's sleep, they divide the sleep recording into 30-second chunks and assign a sleep stage to each chunk. If more than one stage appears in a chunk, they pick the stage that takes up the most time in that chunk. Originally, there were seven sleep stages, but in 2007, they were reduced to five stages: wakefulness, light sleep (N1), deeper sleep (N2), deep sleep (N3), and REM sleep. They also got rid of a stage for movement. Experts use brainwave patterns (EEG), among other signals, to determine these stages. Sleep stages cycle through the night, and a full cycle takes about 90 to 110 minutes.

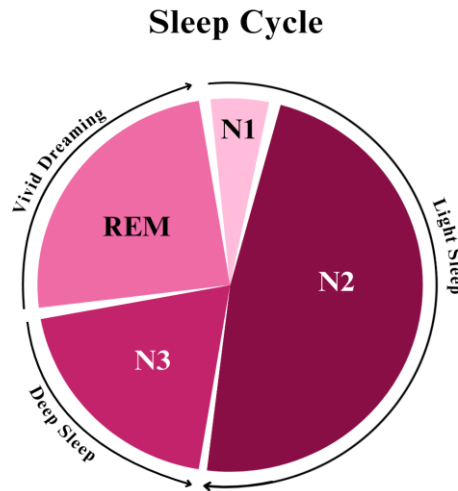
Sleep scoring involves dividing sleep into 30-second segments and assigning a sleep stage to each segment based on brainwave patterns and other signals. There are five main stages, and these stages repeat in cycles throughout the night. The process helps experts understand a person's sleep pattern and quality.



**Fig. 1.** Flowchart of visual scoring procedure

When experts analyze someone's sleep, they break it down into different stages. There are five main stages:

1. **Wakefulness (Stage W):** This is when you're awake, and it's identified by certain brainwave patterns and eye movements.
2. **Light Sleep (Stage N1):** It's a light sleep stage, and it's easy to wake up from. Brainwaves are slower, and there might be occasional bursts of activity.
3. **Deeper Sleep (Stage N2):** This stage is deeper than N1, and it's harder to wake up from. Sleep spindles and K complexes can appear in brainwaves.
4. **Deep Restorative Sleep (Stage N3):** This is the really deep and restorative sleep stage. Delta waves dominate in brainwaves, and it's tough to wake up from.
5. **REM Sleep (Rapid Eye Movement):** This is when you dream. Brainwaves are active, but your body is relaxed. You can wake up more easily during REM.



**Fig. 2.** Flowchart of Sleep Cycle

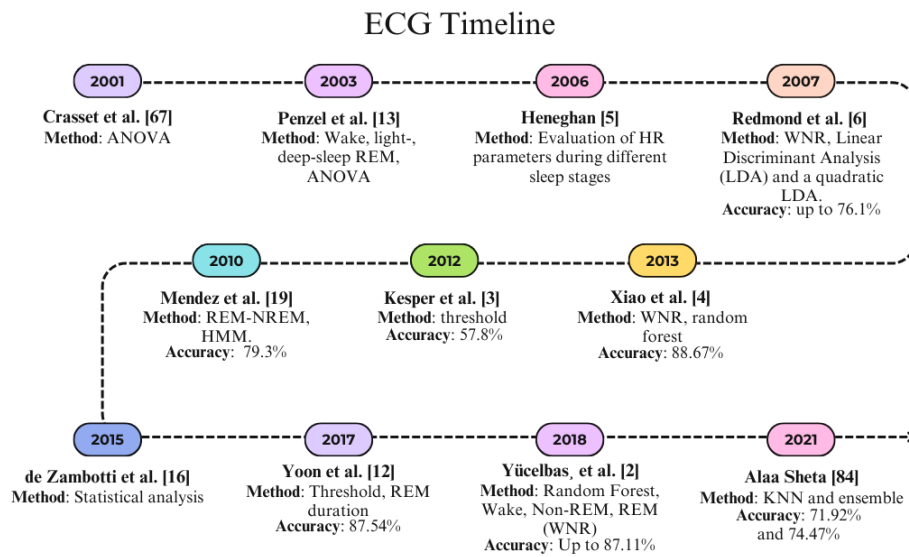
The process of determining these stages can be complex because there are many factors to consider. Different experts might interpret the same sleep recording differently, especially when there are transitions between stages. So, scoring sleep isn't always straightforward, and it can be more challenging for people with sleep disorders. For example, mixing up N2 and N1 or N3 won't have a big impact, but mistaking wakefulness for another stage can affect the overall analysis. Studies have shown that experts sometimes disagree on these stage transitions. This happens because the rules are trying to fit sleep into fixed categories, but sleep is a continuous process with subtle changes.

## 2 Sleep Stages Classification Using Machine Learning Models

### 2.1 Electrocardiogram (ECG):

Human heart electrical actions are monitored through ECG signals. These signals are used to analyze and diagnose different heart conditions. The signals show the electrical actions of heart rhythms. ECG signals are organized to a great extent and each signal can be spotted visually in the absence of any signs of heart infection. There are two kinds of ECG signals: nonstationary and nonlinear. To get physiology data, the Nonlinear boundaries will be utilized such as guess entropy, fractal aspect, connection component, biggest Lyapunov type, and Hurst. Doctors use ECG signals to monitor the electrical activity of the heart. These signals help them diagnose various heart conditions by showing the rhythm of the heart's electrical actions. [1]. ECG signals were utilized to distinguish the wake (W), non-fast eye development (NREM), and quick eye development (REM) phases of the sleep data. ECG signals were used to tell

apart the different stages of sleep: wakefulness (W), non-rapid eye movement (NREM), and rapid eye movement (REM). [2]. Moreover, Yucelbas, et al., Xiao et al., and Kesper et al. stated that though ECG s somewhat complex, it is also equally accurate as compared to PSG signals [2-4]. Redmond et al. have validated ECG-based sleep staging by comparing it with EEG-based sleep staging [5,6].



**Fig. 3.** ECG research timeline with classification methods and accuracy

The Autonomic Nervous System is responsible for regulating various involuntary bodily functions including Sleep stages. The Autonomic Nervous System helps control things your body does without you thinking about it, like the different stages of sleep. [7]. During REM (Rapid Eye Movement) sleep, there are specific changes in respiratory patterns compared to those observed during NREM (Non-Rapid Eye Movement) sleep. Due to decrease in lung tidal volume, a frequent and irregular pattern is exhibited in respiratory rate during REM phase of sleep. During REM sleep, breathing patterns change compared to when you're in deep sleep. Your breaths become shorter and more irregular because your lungs don't fill up as much with air. [8]. Heart Rate Variability (HRV) is a measure of the variation in time between every heartbeat. The regulatory of HR signals are estimated using many measures of HRV [9,10]. heart rate (HR) and heart rate variability (HRV) show specific patterns that are very diverse during different stages of sleep. Due to sympathetic and parasympathetic activities, HR and its variability grow during the Rapid Eye Movement stage of sleep [11,12]. It shows drastic differences between NREM and REM stages when HRV parameters are calculated with various factors like time and frequency domains and nonlinear analysis

[13,14]. Many such works are also done like Trinder et al. had made analysis on autonomic activities on sleep with the help of heart rate variability measurements. Trinder and colleagues analyzed how the body's automatic functions, like heart rate variability, relate to sleep. [15]. Also, de Zambotti et al. analyzed the cardiac autonomic function and stated the effects of alcohol on sleep. De Zambotti and colleagues looked at how alcohol affects the way our heart and nervous system work during sleep. [16]. For the extraction of rest stage data, Penzel and al. have applied detrending change as well as photodynamic analysis. To gather data on rest stages, Penzel and his team used methods like detrending change and photodynamic analysis. Detrending change helps remove any trends or patterns that aren't related to the rest stages, while photodynamic analysis involves studying data related to light exposure during rest. [13]. Moreover, of HR was compared with pulse rate variability by Liu et al. [17] Moreover they explored that heart rate variability and pulse rate variability exhibits similar features. And it is important to mention that measurement of pulse rate variability is easier than heart rate variability [17]. Analysis of changes in sleep stages in postmenopausal women was carried out by Virtanen et al and their team looked at how the different stages of sleep changed in women after they went through menopause [18]. Also, a real time Decision support system (DSS) was also proposed by Mendez et al. for HR based sleep stage scoring [19]. Moreover, KNN and different ensemble techniques were applied to get the accuracy of 71.92% and 74.47% respectively by the work done by Alaa Sheta [84].

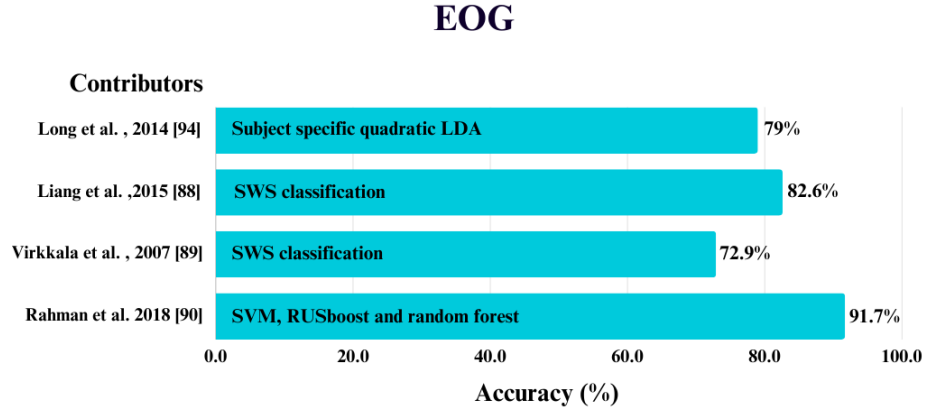
**Table 1.** A summary of results of research work in sleep stage scoring using ECG signals.

Author	Data	Feature extraction method	Classification method	Classification results
Alaa Sheta, 2021 [84]	Physionet's CinC challenge-2000 database	Ensemble	KNN	71.92%
Yücelbas, et al., 2018 [2]	Sleep laboratory of Necmettin Erbakan University database and PhysioNet	Morphological methods	Random Forest, Wake, Non-REM, REM (WNR)	Up to 87.11% accuracy

Yoon et al., 2017 [12]	Twenty-one healthy subjects (male: 12, female: 9) and 30 subjects (male: 25, female: 5) with Obstructive Sleep Apnea (OSA) recorded at Seoul	HR parameters, Spectral power, variability measurements	Threshold, REM duration	87.54%
Mendez et al., 2010 [19]	24 subjects	HR statistics Spectral power	REM-NREM, HMM	79.3%
Redmond et al., 2007 [6]	31 male subjects	ECG derived respiration and HR statistics	WNR, Linear Discriminant Analysis (LDA) and a quadratic LDA	up to 76.1%
Redmond and Heneghan, 2006 [5]	37 subjects	ECG derived respiration and HR statistics. EEG sleep staging for comparison	Evaluation of HR parameters during different sleep stages	Not reported
Penzel et al., 2003 [13]	64 patients with symptoms of excessive daytime sleepiness and arterial hypertension	HR statistics, spectral power	Wake, light-, deep-sleep REM	Not reported

## 2.2 Electrooculography (EOG):

EOG stands for "Electrooculogram," which measures and records the electrical activity generated by eye movements. EOG is derived from continuously measuring the standing potential of retina and cornea, and it is a valuable tool for tracking and analyzing eye movements. These signals provide very curtailed information for detecting Rapid Eye Movements. According to the rules and guidance of AASM [20], the EOG electrodes are placed at a position of lateral right from 1 cm and at left outer canthi. This position of EOG electrodes is straightforward and is followed by many patients [21]. Long-term monitoring and assessment of the continuous sleep phase is a key factor that depends on user-led signal acquisition. In that context, Virkkala et al.'s work is important because it indicates the presence of information on NREM sleep stages in EOG signals [22]. Rahman et al.'s use of the EOG sleep scores may significantly impact classification accuracy [23]. Moreover Liang et al. in 2015 also uses SWS classification to give an accuracy of 82.6%. Long et al. uses Subject-specific quadratic LDA to give a significant amount of 79% accuracy for classifying EOG signals. A recent work of Alihan SUIÇMEZ in 2022 shows that lesser sleep stage studies have been conducted in the past 10 years using EOG signals [85].



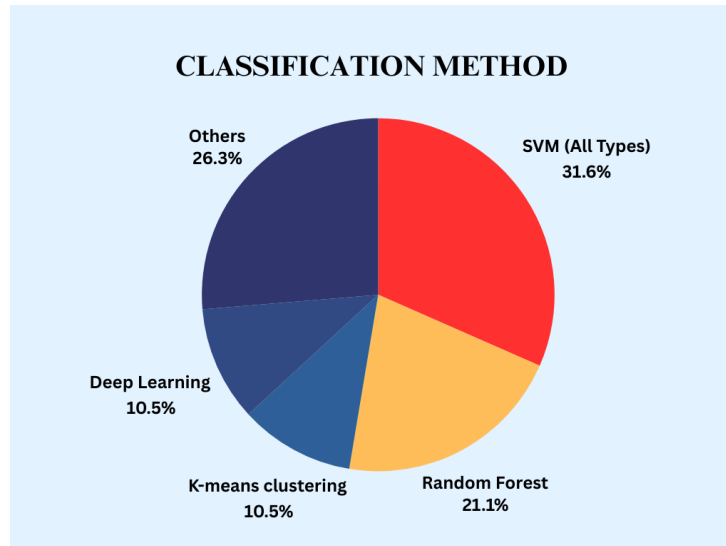
**Fig. 4.** Accuracy of research work that is using EOG signals with classification methods

Sleep is very important as it activates and regulates processes with restorative functions for physical and mental conditions [24]. Human nocturnal sleep objectives can also be widely accessed with the help of respiratory information [24-26]. Respiratory effort are amplitude by Long et al. to established classification system on automated sleep stages [27]. They used a subject-specific feature normalization to enhance the classification accuracy. As regards monitoring the long-term health of sleep due to changes in physiological parameters resulting from aging, this type of individualized intervention is a major topic.

### 2.3 Electroencephalogram (EEG):

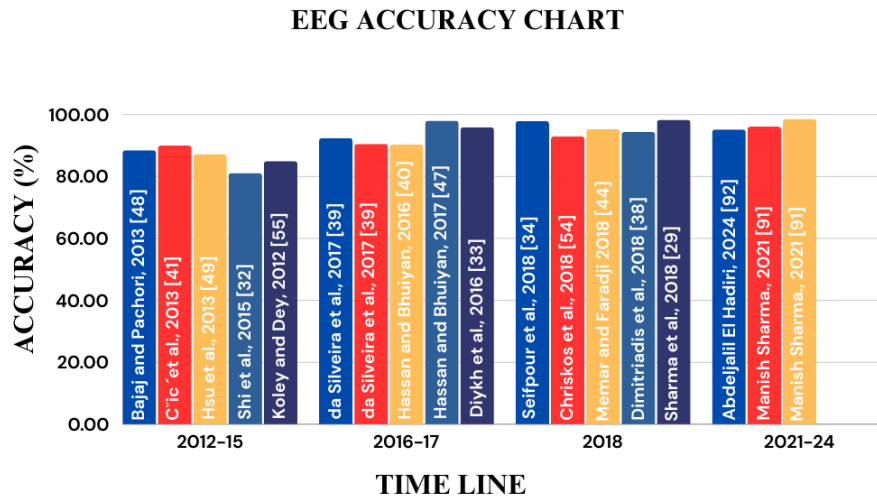
In EEG the electrical activity of the brain is tracked using numerous sleep staging classification systems [29-32]. From EEG signals various signal processing techniques have been in use to gather sleep-related information, which includes: spectral features [37-39], time-frequency features[35,40,41], non-linear features [42,43], and time-domain features [33-36]. Machine Learning Classification methods have been used to help practitioners in decision-making. From reviewing sleep classification studies, some of the widely used classification methods are K-mean classification [33], support vector machine (SVM) [41], Also Ensemble Learning Classification techniques have shown improved results, some of them are Random forest [44], Bootstrap Aggregating [45], Artificial Neural Network (ANN) [46], The below figure shows the amount of work done using EEG signals for given classification methods.





**Fig. 5.** Amount of work done for EEG signals using different classification methods

Hassan and Bhuyian analyzed EEG signals to develop a sleep classification system that used the Ensemble Empirical Mode decomposition technique and the RUS Boost classifier with an average accuracy of 88.1% for the six-class problem [47]. When they used the tunable-Q factor wavelet transform technique with the help of Random Forest Classification [40], the average rises to 90.4%. Li, Wen, and Diykh analyzed EEG signals using time-domain features using a k-mean classification algorithm to identify six sleep stages which give 95.9% accuracy. Bajaj and Prachori [48] analyzed EEG signals using time-frequency features and multiclass least square SVM classifier for the six-class problem, which gave an average accuracy of 88.5%. Hsu et al. analyzed EEG using energy features and recurrent neural classifier, which gave an average accuracy of 87.2% [49]. Seifpour et al. [34] analyzed novel multi-class sleep stage classification using symbolic analysis concepts and developed a new time-domain feature named Statistical SBLE. They achieved an average accuracy of 90.6% for six-stage classification and 97.% average accuracy for two-stage classification. In recent few years, various classification methods was used to accuracy of 98.6% in EBooT and 96.1% in KNN by Manish Sharma [91]. Also, a sleep stage classification based on non-linear data shows an accuracy of 95.2% for RF-PCA model by Abdeljalil El Hadiri [92].



**Fig. 6.** Bar graph showing the accuracy result of different research work that uses EEG signals

#### 2.4 PSG And Combination Of Signals :

Polysomnogram (PSG) is a combination of Physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and electromyogram (EMG)[27]. PSG recordings are carried out entire night [23,69]. Sleep experts manually score on 30 30-second epoch using a Polysomnogram in the entire night [22]. R.S.T Leung analyses autonomic functions with the help of PSG signals to study the effects caused by OSA on sleep stages [74]. On analysing the sleep attack pattern of a patient with Parkinson's, Tracik and Ebersach found that by refraining from passing through three stages, a rapid transition can be possible directly from stable wakefulness to the S2 stage [75]. Khushida et al. compared the reports with sleep patterns which were extracted from Polysomnogram [76], where they couldn't distinguish between subjective and objective sleep staging. Montgomery-Downs et al. had studied the changes in sleep pattern of children. [77] and Long et al. analyzed sleep and wake states [78] using actigraphy and respiratory effects. Furthermore, their studies emphasize on the non-linear concepts of dynamic warping for improving classification results.

**Table 2.** A summary of review results on combination of physiological signals for sleep stage scoring

Author	Data	Feature extraction method	Classification method	Classification results
Tripathy et al., 2018 [82]	MIT-BIH polysomnographic database	From RR: recurrence quantification analysis and dispersion entropy	Deep neural network	95.71
Helland et al., 2015 [80]	EEG, ECG and respiratory signals from the SIESTA database	HR: statistics. PSG: Time / frequency, and network analysis	LDA, Wake, REM and REM	80%
Willemsen et al., 2014 [79]	36 healthy subjects	HR statistics and spectral power, Breathing Rate (BR) statistics	SVM WNR	81%
Long et al., 2014 [78]	Actigraphy and respiratory effort, 115 healthy adults	Statistical analysis of dynamic wrapping of body movement	LDA, binary problem for comparing features to a PSG study	95.7%
Estévez et al., 2002 [83]	11 healthy infants	EEG sleep spindle detection EOG REM detection and EMG muscle tone	Threshold WNR	Not reported
Kushida et al., 2001 [76]	Full PSG 100 patients with sleep disorders	Visual scoring of wake and sleep states	Threshold	77%

Kirjavainen et al. analyzed respiratory and body movement signals and its combined study is used for wakefulness and sleep stages in adults and infants [81]. The body movements can be measured with the help of a novel sensor-enhanced bed. The above figure summarizes the findings of automated sleep based on a combination of signals and PSG where accuracy has been reported.

### 3 Discussion

The use of machine learning, particularly deep learning, to score and analyze sleep patterns from physiological data (like PSG, which monitors various body signals during sleep). using computer programs, and machine learning algorithms, to help score sleep stages accurately. These algorithms are getting quite good, with an average accuracy of around 85%, which means they agree well with human experts who visually score sleep.

Deep learning, a type of machine learning, is becoming popular because it can learn directly from raw data without needing a lot of prior knowledge or complex mathematical rules. It's like a black box that figures things out on its own. Some deep learning algorithms can even learn how to handle problems like artifacts (unwanted signals) in the sleep data.

It depends on things like the characteristics of the dataset used for training the algorithm. The data must be diverse and representative of different types of sleep patterns and people. If the dataset is too limited or biased, the algorithm may not perform well on new data from different sources.

When evaluating deep learning for sleep scoring, it's not just about getting high accuracy. The dataset used must be diverse and resemble real-world sleep patterns. Very high accuracy can sometimes mean the algorithm is just memorizing the data it was trained on and not really understanding sleep. So, researchers need to be careful and use diverse datasets to get reliable results.

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The joint analysis of three signals EOG, EEG and ECG affirms that merging them can improve the performance of SSC systems. Multimodal methods, which use EEG to monitor brain activity, ECG for tracking heart rate variability, and EOG for detecting eye movements, offer a more reliable and precise classification of sleep stages. Mostly multimodal approach reduces the reliance on any single signal, therefore minimizing the weaknesses of individual modalities and providing a more comprehensive understanding of the body's physiological states during sleep.

### 3.1 Limitations

Calculate a person's heart rate (HR) from ECG signals by identifying the R wave in the ECG, which marks each heartbeat, and then measuring the time between these R waves (called RR intervals). But, it's much easier and more efficient to directly measure HR without using ECG. Direct HR sensors are efficient because they can easily detect the R wave, making it simpler and requiring fewer tools than using ECG. The process of detecting the heartbeat isn't always well-documented and is often a secret of the

companies that make these sensors. So, it's hard to be sure that the HR measurements from these sensors give the same RR intervals as those calculated from ECG, especially for small changes in the signal that show different sleep stages. The difficulties in using direct HR sensors are because the way they detect heartbeats isn't always clear. Researchers usually stick to ECG signals to calculate RR intervals, even though it might not be the most efficient method.

### 3.2 Future Work

#### **Future Directions for DSS in Sleep Medicine:**

**Develop Transparency and Trust:** Provide user-friendly decision support system (DSS) methods that can catalyze clinicians towards faster decision-making and assist patients with intuitive visualizations to gain their trust.

**Adaption and Learning:** Enhance the algorithms for dynamic learning and ad staying updated to evolve with new research techniques, findings, and patient-specific conditions.

**Sensor Technology:** As the paper mentions patient comfort is essential for long-term monitoring, and advancements in sensor design for unobtrusive and comfortable sleep monitoring are required.

**Heart Rate (HR): Based Scoring Innovation:** Research and Investigate to refine HR-based sleep scoring, assessing its applicability across diverse patient demographics and further enhancing it by seamless integration with the Internet of Health Things (IoHT) for comprehensive real-time monitoring.

**Real-time Analysis with Feedback:** Real-time analysis is crucial for controlling the therapeutic process effectively. Further research can focus on developing real-time analysis algorithms that provide immediate feedback to both patients and healthcare providers using various Artificial Intelligence and Deep Learning advancements. This can facilitate timely interventions and adjustments in treatment plans.

**Data Rate Considerations:** As different physiological signals have varying rates of data, further research should explore their data rates on communication and storage infrastructure to ensure seamless handling of information

**EOG signals:** Research statistical approach for feature extraction methods on EOG signals to get higher accuracy and alternative approach for sleep stage classification and sleep disorder detection.

## 4 Conclusion

This work explains EEG-based schemes which are most commonly used methods for SSC due to their ability to capture brainwave activity, which is directly related to sleep stages. EEG is effective at identifying transitions between light sleep (N1, N2) and deep sleep (N3), as well as detecting REM sleep through the presence of rapid eye movements. The accuracy of EEG-based classification methods, such as Random Forest and Support Vector Machine (SVM), typically ranges from 88% to 95% in detecting sleep stages. However, EEG signals can be prone to noise and require precise electrode placement. While ECG-based SSC methods evaluate autonomic nervous system through heart rate variability (HRV), giving insights of physiological changes during different sleep stages, Although ECG-based methods may not reach higher accuracy levels compare to EEG, they are useful in detecting cardiovascular irregularities associated with sleep disorders. Lastly EOG signals have promised lesser efficiency but allows detection of rapid eye moment (REM). Also, this paper discusses machine and deep learning techniques for classifying sleep stages automatically. These techniques, in contrast to traditional methods, may automatically extract latent and advanced complex features from sleep data, obviating the need for further feature extraction stages. The signals, datasets, data representation strategies, preprocessing approaches, deep learning models, and performance evaluations in sleep stage classification are all thoroughly examined in this work. This review provides a well-reasoned argument for the importance of physiological signals in sleep monitoring. It effectively highlights the potential of DSS systems to improve the reliability of sleep stage scoring while reducing the need for human interpretation and addressing issues of fatigue-related errors.

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