A review of automated sleep disorder detection

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Abstract

Automated sleep disorder detection is challenging because physiological symptoms can vary widely. These variations make it difficult to create effective sleep disorder detection models which support human experts during diagnosis and treatment monitoring. From 2010 to 2021, authors of 95 scientific papers have taken up the challenge of automating sleep disorder detection. This paper provides an expert review of this work. We investigated whether digital technology and Artificial Intelligence (AI) can provide automated diagnosis support for sleep disorders. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines during the content discovery phase. We compared the performance of proposed sleep disorder detection methods, involving different datasets or signals. During the review, we found eight sleep disorders, of which sleep apnea and insomnia were the most studied. These disorders can be diagnosed using several kinds of biomedical signals, such as Electrocardiogram (ECG), Polysomnography (PSG), Electroencephalogram (EEG), Electromyogram (EMG), and snore sound. Subsequently, we established areas of commonality and distinctiveness. Common to all reviewed papers was that AI models were trained and tested with labelled physiological signals. Looking deeper, we discovered that 24 distinct algorithms were used for the detection task. The nature of these algorithms evolved, before 2017 only traditional Machine Learning (ML) was used. From 2018 onward, both ML and Deep Learning (DL) methods were used for sleep disorder detection. The strong emergence of DL algorithms has considerable implications for future detection systems because these algorithms demand significantly more data for training and testing when compared with ML. Based on our review results, we suggest that both type and amount of labelled data is crucial for the design of future sleep disorder detection systems because this will steer the choice of AI algorithm which establishes the desired decision support. As a guiding principle, more labelled data will help to represent the variations in symptoms. DL algorithms can extract information from these larger data quantities more effectively, therefore; we predict that the role of these algorithms will continue to expand.

Keywords: Sleep disorders; Automated detection; Deep learning; Machine learning; Sleep apnea; Insomnia: Artificial Intelligence, Biomedical signals processing, Sleep disorder detection;

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1. Introduction

Sleep is a biological activity initiated and controlled by the human brain [1]. Sleeping maintains the physical and mental health of an individual. The human body heals and rebuilds itself during sleep, removing metabolic waste that has built up during wakefulness [2]. Sleep also reorganises memory and supports long-term memory formation [3]. Considering the immense benefits of sleep for human beings, it is essential that everyone gets enough sleep. Insufficient or poor-quality sleep disrupts the body's circadian rhythm, increasing the risk of developing health problems, including serious diseases like cardiovascular disease, cognitive impairment, and memory deterioration. This negatively impacts daily activities, such as study or work, and may lead to decreased appetite, reduced work productivity, and an increased accident probability [4–7]. Sleep deprivation also disrupts the body's circadian rhythm, the changes in life activities within 24 hours [8], increasing the risk of developing health problems, including serious diseases like cardiovascular disease, cognitive impairment, and memory deterioration. Figure 1 depicts the sequence of physiological processes within 24 hours [9].

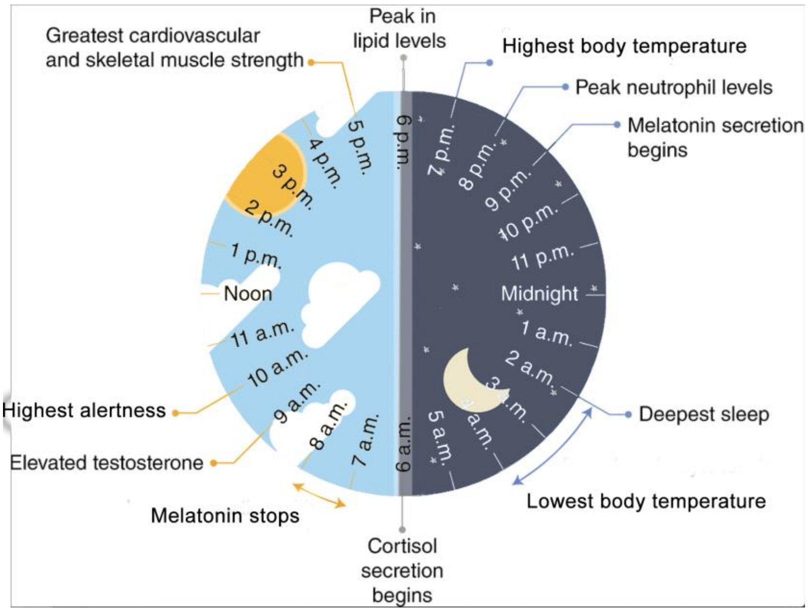


Figure 1: Circadian rhythm.

Sleep stage classification plays a vital role in the assessment of sleep quality. Most often the classification processes follows the American Academy of Sleep Medicine (AASM) standard [10], which is a modification of the classification rules originally developed by Rechtschaffen and Kales's (R&K) [11]. The AASM rules define characteristic features for five distinct sleep stages:

- W (Wakefulness): stage W is characterised by alpha (8-12 Hz) and beta (16–30 Hz) waves;
- N1 (NREM 1): stage N1 is scored when theta (4-8 Hz) waves are evident, and vertex sharp waves may be present;
- N2 (NREM 2): stage N2 is scored when high voltage biphasic waves (K-complexes) and sleep spindles (12-16 Hz) are noted, and theta waves are present;
- N3 (NREM 3): stage N3 is characterised by high amplitude (>75 μV) delta (0.5–4 Hz) waves;
- REM: stage Rapid Eye Movement (REM) is scored when theta and sawtooth (2-6 Hz) waves are evident, and alpha waves may be present.

Current studies illustrate that sleep disorders constitute a health burden for all societies [12]. Sleep disorders, such as Periodic Limb Movement Disorder (PLMD), Rapid eye movement Behavioural Disorder (RBD), bruxism, obstructive sleep apnea, and insomnia [13–15] affect a wide range of people daily due to their detrimental physiological effects and high prevalence [16, 17]. Between 10% and 30% of people have insomnia, which means they have trouble initiating and/or maintaining sleep [18]. Bruxism is tooth grinding [19] and it is the second most common sleep disorder with a prevalence of 8% to 10%. The main symptom of PLMD, the third most prevalent sleep disorder, is repetitive limb movement during sleep. Sleep apnea and hypopnea are sleep breathing disorders, and they have a prevalence of 3% to 7% and 2% to 4%, respectively. In sleep apnea, breathing stops and starts repeatedly during sleep due to a blockage in the airway or a problem with breathing control [20–22]. The disorder can occur at all ages, leading to cognitive dysfunction due to a disruption of the brain's normal processes during sleep. It is also proven to be a risk factor for cardiovascular diseases. Therefore, adequate treatment can reduce the comorbidity rate [23]. REM behaviour disorder (RBD) is characterised by the patient acting out their dreams. During this activity, patients may hurt themselves or their partners. Narcolepsy and Nocturnal Frontal Lobe Epilepsy (NFLE) are less common sleep disorders with a prevalence of 0.025% to 0.05% and 0.018% to 0.019%, respectively. People who are diagnosed with narcolepsy have difficulty staying awake, with excessive daytime sleepiness and other features including hallucinations, sleep paralysis, and cataplexy. NFLE is a form of epilepsy that affects patients during sleep.

Sleep disorders are diverse and require disease-specific treatment [24, 25]. Furthermore, sleep is personal, and the impacts of sleep disturbance are individual for each human being. Hence, objective disease detection is required for an individual diagnosis. Early detection may lead to better management and treatment of sleep disorders [26, 27]. Traditional diagnosis processes need highly trained sleep physicians and clinical scientists to manually analyse and interpret the results. This manual evaluation might suffer from inter- and intra-observer variability and is resource-intensive [28]. Based on automated sleep disorder detection, diagnosis support systems can improve cost efficiency and reduce inter-and intra-operator variability. However, disorder diagnosis support is a challenging problem due to the individuality and variability of symptoms.

This review investigates whether digital technology and Artificial Intelligence (AI) allow us to automate sleep disorder diagnosis support. We have reviewed the state-of-the-art scientific literature on AI for sleep disorder detection giving us the necessary overview and background to discuss approaches for automated sleep disorder diagnosis and treatment support. The following list details the contributions of our work:

- We provide an expert review of 114 scientific studies from 95 articles.
- The review delivers a comprehensive overview of application areas and technology used.
- We discuss the difference between Machine Learning (ML) and Deep Learning (DL) in detail.
- We also attempt to look into the future by discussing the individualisation of sleep disorder detection.
- The attempt to look into the future is informed by establishing the limitations of the reviewed articles.

The remainder of this paper is organised as follows. The next section provides some medical background on sleep disorders. Section 3 describes the article search methods. The discovered articles were reviewed, and Section 4 presents the review results. Section 5 provides our interpretation of these results focusing on limitations and potential future work. Finally, concluding remarks are presented in Section 6.

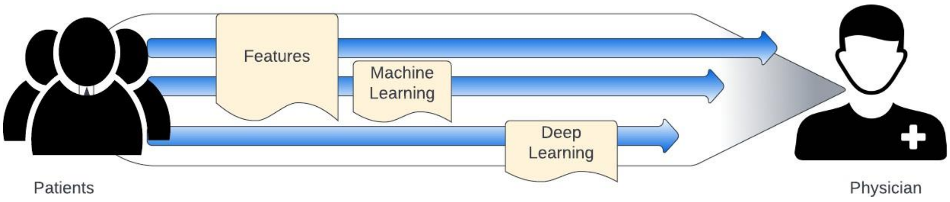


Figure 2: Information flow diagram.

2. Background

In recent years, problems concerning real-time diagnosis and treatment monitoring of sleep disorders have attracted the attention of many researchers [29]. This section provides some background on the medical need for sleep disorder detection, and we discuss some technology that can be used for automated sleep disorder detection.

2.1. Automated detection

In a medical setting, physiological signals are often used to provide objective evidence that leads to a sleep disorder diagnosis. Polysomnography (PSG) analysis is the gold standard for sleep disorder detection [30, 31]. However, PSG recordings require many wires and electrodes, making the measurement setup time-consuming, and uncomfortable for the patient [32]. Further, PSGs are recorded in sleep laboratories, which can cause disruption of sleep due to changes in the environment, known as the first-night effect, potentially leading to inaccurate diagnostic information. Portable PSG-based methods, which can be used in the home environment, might be a solution to the problem caused by the first-night effect [33]. Furthermore, manual analysis processes are resource-intensive and prone to inter-and intra-operator variability [34]. Automated sleep disorder detection aims to address these drawbacks by incorporating objective decision-making into remote monitoring ecosystems. For patients, this has the added benefit that the data acquisition can be accomplished in the home environment, which is usually more comfortable for the patient.

Automated sleep disorder detection requires AI models that assign meaning to data [35]. The data comes in the form of physiological signal measurements or medical imaging. This data is processed in one of three ways, and each way opens a distinct information channel from the patient to the sleep physician [36, 37]. The first channel is established through feature extraction [38]. Linear or nonlinear algorithms are used to extract one or multiple parameters from the measurement data. The extracted features are 100% explainable, given that the algorithm code is available. However, it is difficult to track these parameters; therefore, they are rarely used for scientific publications. One way to address this problem is to use ML algorithms that take features as input and produce a class label as output. This class label can be used for sleep disorder detection. The explainability of ML-based systems is lower when compared to features alone because labelling depends on weights and other parameters that are established during a training phase. DL represents a direct information extraction channel without incorporating feature extraction [39]. DL is the least explainable detection method because feature extraction and labelling are automated. Figure 2 shows the three distinct information pathways from patient to sleep physician.

ML is still the dominant problem-solving AI technique. ML algorithms are characterised by learning patterns with adjusting parameters to improve results. Most ML models require supervised learning based on labelled data. In contrast, unsupervised learning discovers data clusters and automatically assigns labels to them [40–42]. Thus, the algorithms can create powerful tools for understanding relationships in normal datasets [43]. Over the years, a wide range of ML algorithms has been proposed, including Artificial Neural Network (ANN), Kernel Extreme Learning Machine (KELM), Naive Bayes (NB), Hidden Markov Models (HMM), Linear Discriminant Analysis (LDA), K-Nearest Neighbour (KNN), Logic learning machine (LLM), Feedforward Neural Network (FNN), and Logistic Regression (LR). In general, designing decision support systems with these algorithms is time-consuming, and their performance depends on the features extracted. Also, model performance may decrease as the data volume increases [44].

DL is currently gaining a lot of attention because of its ability to extract knowledge from large datasets, which is an advantage when compared to ML algorithms [45]. DL models, such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) can be used to improve classification performance using Electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), and Electromyogram (EMG) signals for identifying sleep disorders, such as sleep apnea, insomnia, bruxism, narcolepsy, and nocturnal frontal lobe epilepsy [17, 46].

2.2. Material

Medical practitioners initiate the sleep apnea diagnosis process by conducting a primary investigation, such as pulse oximetry or cardiorespiratory polygraphy. Physicians may recommend a sleep study to provide objective evidence for a clinical diagnosis when the primary investigation is inconclusive due to the presence of other sleep disorders, either behavioural or pharmacological [30, 47]. To conduct a sleep study, the subject will be sent to a sleep laboratory where whole night PSG recordings are captured. A PSG recording contains multi-modal and multi-channel signals, including EEG, ECG, EMG, EOG, Cardiorespiratory Polygraph (CPR), Nasal Airflow (NA), Photoplethysmogram (PPG), Oxygen Saturation (SpO_2), Partial pressure of oxygen (PaO_2), and Partial Pressure of Carbon Dioxide ($PaCO_2$). EEG signals are most often used for scientific research on sleep disorder detection because they record electrical brain activity from which sleep staging is derived. ECG signals measure the electrical heart activity, EOG signals monitor eye movements, and EMG signals monitor muscle tone.

A range of physiological signals and medical images have been used as input to AI models for sleep disorder detection [48]. Automated detection sleep apnea as been successfully evaluated using gas exchange data by Vimala et al. [49]. Deviaene et al. [50], Vaquerizo-Villar et al. [51], and Gutiérrez-Tobal et al. [52] used pulse oximetry to establish sleep disorder detection systems. Some experiments use single lead signals, like ECG [53]. A wide range of time- and frequency-domain features can be extracted during the design of an ML model. The result tends to be more efficient and low-cost. Many researchers conducted their experiments with the MIT PhysioNet Apnea-ECG database [54–58]. The MIT PhysioNet dataset, from Phillipps University, is popular for ECG based sleep apnea detection [59]. It contains 70 apnea, and 35 non-apnea ECG recordings in each training and testing set. Its signal was segmented 100 samples per second, nominally 200 A/D units per millivolt. The St. Vincent's University Hospital / University College Dublin Sleep Apnea Database (UCDDB) contains 25 full overnight PSGs from patients referred to the Sleep Disorders Clinic at St Vincent's University Hospital, Dublin, for sleep apnea and snoring detection. Table 1 provides a summary of benchmark datasets for sleep disorder detection. Some other public datasets are involved in those papers, such as the Shiga University of Medical Science hospital (SUMS), the Rio Hortega University Hospital dataset (RHUH), from universities or hospitals.

2.3. Related reviews

During the preparation of our review, we discovered four reviews related to sleep status and sleep disorder detection. Figure 3 provides a graphical representation of the distinctness between the individual studies. In their review, Abdel et al. [65] focused on sleep apnea diagnosis support based on Internet of Intelligent Things (IoIT) technology. IoIT establishes a distributed measurement environment that channels physiological signals to a central server for analysis. In most cases, this analysis will involve some kind of AI model which automates sleep apnea detection. Buongio et al. [66] reviewed sleep stage classification based on ECG signals. A comprehensive review from Heyat et al. [67] documents progress on insomnia detection. Campabadal et al. [68] reviewed sleep

Table 1: Benchmark datasets.

Database	Data	Origin	Properties
MIT physioNet [60]	70 ECG recordings	Phillipps University	100 Hz sampling frequency, nominally 200 A/D units per mV.
Cyclic Alternating Pattern (CAP) [61]	108 standard PSG recordings	Sleep Disorders Center of the Ospedale Maggiore of Parma	Multi-channel EEG, ECG, EMG, EOG, SpO_2 and respiratory signals, including Respiratory Event Index (REI), Accelerometry Derived Respiration Index (ADR).
UCDDB [62]	25 standard PSG recordings	University College Dublin dataset	Apnea/Hypopnea Index (AHI) values in a range of 1.7–90.9. 128 Hz sampling frequency.
Sleep Heart Health Study (SHHS) [63]	standard PSG from 6441 subjects	American National Heart Lung & Blood Institute	C3/A2 and C4/A1 EEGs, 125 Hz sampling frequency.
The Wisconsin Sleep Cohort [64]	standard PSG from 2570 subjects	National Sleep Research Resource	Multi-channel EEG (O1-M2 and C3-M2 have been collected in most of the subjects), ECG, EMG, EOG, SpO_2, and respiratory signals. 100 and 200 Hz sampling frequency

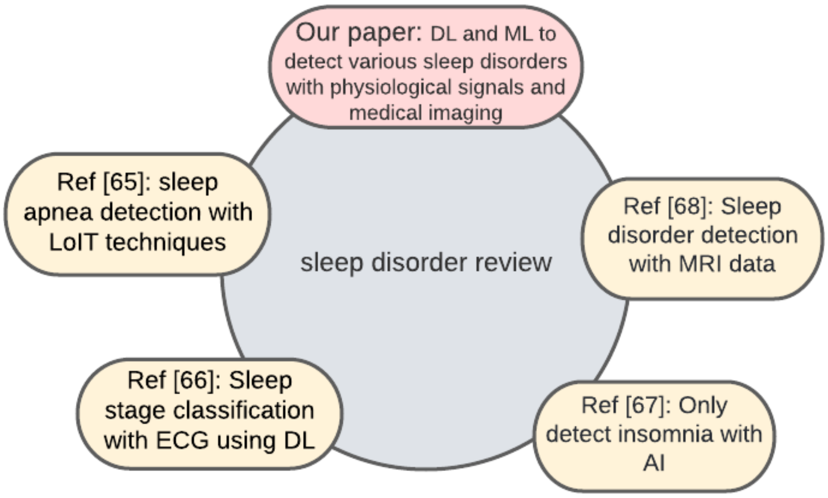


Figure 3: Comparison with other published review articles related to sleep disorders.

behaviour disorder classification methods. All reviewed studies were based on Magnetic Resonance Imaging (MRI) image data. In contrast to these established reviews, our approach focused on automated sleep disorder detection with AI models. We did not restrict the type of data used to provide objective information during the detection process. Neither did we place any restrictions on the type of AI. Therefore, we established a comprehensive review of automated sleep disorder detection.

2.4. Sleep disorders

2.4.1. Sleep apnea

Obstructive Sleep Apnea (OSA) is the cessation of breathing caused by a blocked airway during sleep. It is estimated that around 11% of middle-aged people suffer from OSA [69, 70]. The symptoms range from loud snoring and erratic breathing to gasping when sleeping. These events may cause neurological and cardiovascular complications, including poor memory or hypertension, heart failure, and even death [5, 71]. OSA is more frequent in men [72]. In addition, several factors increase the risk of developing OSA, such as obesity, craniofacial abnormalities, smoking, or family history [73].

2.4.2. Hypopnea

Hypopnea is a less severe form of sleep breathing disorders and is defined as a reduction in airflow, associated with a drop in oxygen saturation or arousal from sleep [74]. Although airflow is compromised in both sleep apnea and hypopnea, the airway is completely blocked during sleep apnea events and only partially blocked during hypopnea events [46]. Hence, a limited amount of air can still pass through the airway during a hypopnea event. The symptoms include snoring, gasping, choking, and breathing difficulty during sleep, resulting in tiredness due to repeated sleep disruptions. The AHI is the number of sleep apnea or hypopnea events divided by the monitoring period.

2.4.3. Insomnia

Insomnia is defined as an individual's inability to fall asleep and/or stay asleep and is the most prevalent sleep disorder in human beings. Ethnological studies established the prevalence of insomnia at nearly 30% [75, 76].

Insomnia can cause secondary co-morbidity, such as depression, stroke, seizures, weak immune system, obesity, diabetes mellitus, hypertension, heart disease, and anxiety [76]. It may also increase accident risk, degrade performance at work, reduce sex drive, and cause memory loss. Insomnia can be short-term (acute), or long-term (chronic) and can be categorised as primary or secondary, the former being sleep difficulty with no underlying health conditions, whereas the latter is related to a medical disease [6].

Symptoms of insomnia may include drowsiness during the day, tiredness, irritability, concentration or memory problems, and, most importantly, difficulty falling asleep [77, 78].

2.4.4. REM sleep behaviour disorder

RBD was first described in 1986 and is characterised by extreme behaviours during REM sleep [79] and causes the loss of normal skeletal muscle atonia during REM sleep and generates prominent motor activity accompanying dreaming [80]. The behavioural content is usually a dynamic or violent dream in which a person is attacked or flees a situation. The behaviours seen in RBD typically occur more than 90 minutes after a person enters sleep [79]. Physical behaviour, such as running, punching, hitting, jumping out of bed, and kicking, can be frustrating and dangerous to the bed partner. Several studies have shown a strong relationship between RBD and neurodegenerative disease, especially Parkinson's disease, multiple system atrophy, and dementia [81, 82].

2.4.5. Narcolepsy

Narcolepsy is a rare sleep disorder that causes a person to fall asleep uncontrollably and at inappropriate times [83]. The central nervous system is deficient in the neurotransmitter hypocretin, which controls sleep and wakefulness. Patients with narcolepsy may experience hallucinations and sleep paralysis due to REM intrusion into wakefulness or a sudden loss of muscle tone in response to emotional triggers known as cataplexy [30, 77]. The main symptoms are excessive daytime sleepiness, sleep attacks, cataplexy, sleep paralysis, and excessive dreaming during the night. There is no cure for this disorder, but improving sleeping habits and taking medications to control symptoms are recommended to decrease the disease burden [84]. Narcolepsy is a life-long, debilitating condition in which patients are likely to experience difficulty in engaging with daily activities, such as study or work, and maintaining or establishing relationships.

2.4.6. Periodic limbs movement disorder

The symptoms of PLMD are repetitive, stereotypical movements of the limbs, most commonly the lower limbs. Unfortunately, the cause of PLMD is still unknown, although reduced dopamine in the basal ganglia is implicated, and genes have been identified, suggesting genetic inheritance [85, 86].

2.4.7. Nocturnal Frontal lobe epilepsy

Frontal lobe epilepsy is a rare neurological disorder. It is characterised by brief, recurrent seizures that originate in the brain's frontal lobe. It mainly occurs during sleep [87], and most patients are diagnosed before 20 years of age. The brain's frontal lobe performs various functions related to memory, alertness, personality, awareness, and anxiety. As a result, individuals with frontal lobe epilepsy exhibit various symptoms resembling psychosis or sleep disturbances.

Seizures usually last no more than 30 seconds and can include features such as repetitive movements, explosive vocalisations, urinary incontinence, unusual behaviours, abnormal postures, and head and eye deviation [88].

Genetic, lesional, and cryptogenetic nocturnal frontal lobe epilepsy types have been described. It can be a benign clinical entity, although some severe, drug-resistant forms have been described [89].

2.4.8. Bruxism

Bruxism is a term that encompasses different jaw muscle movement phenomena, including teeth rubbing, clenching, and tightening or pushing of the jawbone [90]. It may occur during the daytime but also during sleep.

Bruxism can lead to worn or cracked teeth, broken dental restorations, failed dental implants, muscle hypertrophy, jaw muscle pain and fatigue, headaches, toothaches, interference with bedmates'

Table 2: Databases and Boolean search strings used to select the papers.

Database	Boolean string [Title/Abstract]	No. of Studies
Pubmed	“Apnea”/“Insomnia”/“Hypopnea”/“RLS”/	517
IEEE	“Parasomnia”/ “excessive”/“Sleep breathing disorder”/ “Deep learning”/“Machine learning”/	370
Direct Science	“Periodic limb movement disorder”/“Automated detection”/	759
Google Scholar	“Sleep awake disorder”/“Sleep disorder”	451

sleep, and reduced overall quality of life. The cause of bruxism is still uncertain; however, genetic factors and stress are likely to play a role in the disease formation [90]. Many people are unaware of sleep bruxism, so it is difficult to estimate the prevalence. Furthermore, there are no gender differences, but it is more frequent in younger people [91].

3. Search Methods

The search methodology for our review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2021 guidelines. We have used the following databases to source papers. We have used the following core databases to source papers: IEEE Xplore Digital Library, Pubmed, NCBI, Science Direct, and Google Scholar [92]. Most search results were relevant to AI techniques for automated sleep disorder detection. Table 2 provides the Boolean strings that were used to achieve the search results from the selected databases. Figure 4 depicts the complete 2021 PRISMA workflow that consists of individual searchers and filtering activities. We have structured the paper selection process into three different phases (identification, selection, and inclusion) according to the PRISMA guidelines. During the identification stage, we discovered 2309 papers related to sleep disorder detection. In the selection phase, we removed 2214 papers according to the criteria outlined in Figure 4. In the inclusion phase, we conducted an expert review of 95 papers. Some papers included more than one study, i.e., the authors detected different sleep disorders with their AI model [69, 93, 94], so a total of 112 studies were used for analysis. Two authors carried out the different tasks outlined in the PRISMA phases cooperatively. The filter results were discussed with all eight authors.

4. Results

Figure 5 illustrates our categorisation of the sleep disorder studies that were reviewed for this study. The subsequent sections cover sleep apnea, insomnia, and RBD.

4.1. Sleep apnea

The pie chart in Figure 5 shows that most sleep disorder studies focus on sleep apnea. Sleep apnea was detected based on ECG, EEG, and PSG signals, and some studies used more than one signal. Snoring sounds were also considered for sleep apnea detection [95–98].

Figure 6d provides an overview of the algorithms used for sleep apnea detection. More than half of the studies adopted ML, followed by DL. Few studies used a hybrid approach by combining ML and DL algorithms. Figure 6a presents the distribution of ML classifiers. We found that 18 studies used Support Vector Machine (SVM), which takes up the biggest share, followed by Extreme Learning Machine (ELM). Furthermore, Figure 6c shows that there are 14 DL studies, with CNN being the most popular DL algorithm, followed by Long Short-Term Memory (LSTM).

Figure 7 shows the classifier performance for sleep apnea detection. The figure allows us to compare the average Accuracy (ACC) results of each classifier, and this might indicate which of them performs best. Gated Recurrent Units (GRU), a DL algorithm, achieved the highest ACC of 99.00% for sleep apnea detection. In contrast, with an ACC of just 71.00%, the NB algorithm reported the

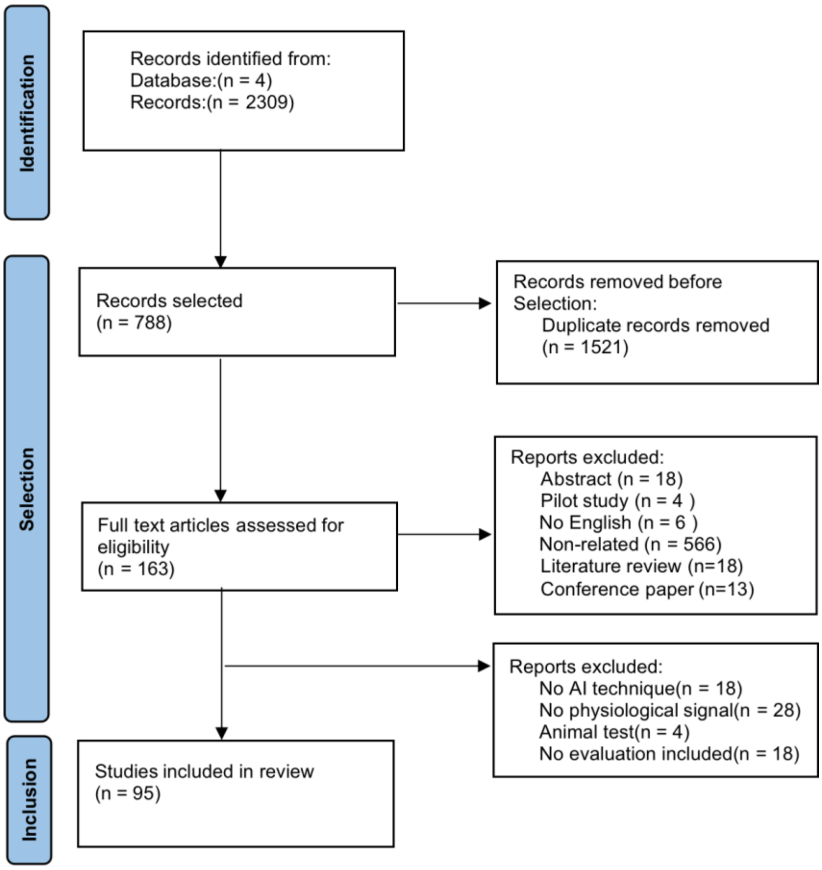


Figure 4: PRISMA flow diagram.

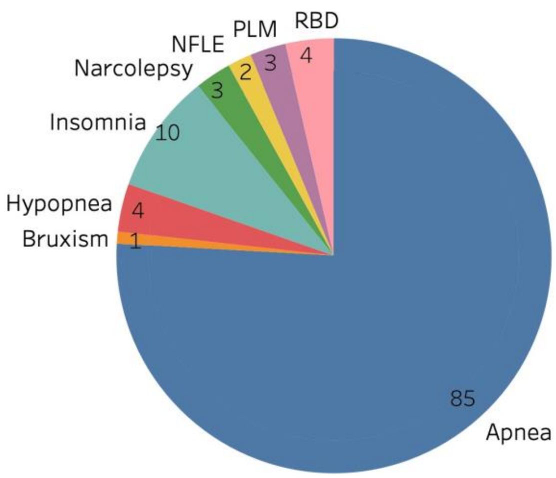
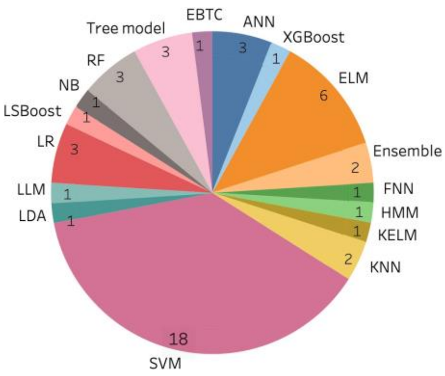
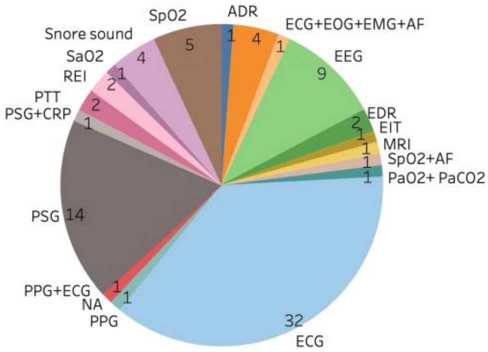


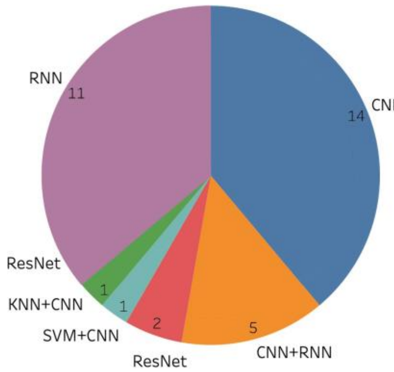
Figure 5: Distribution of sleep disorders.



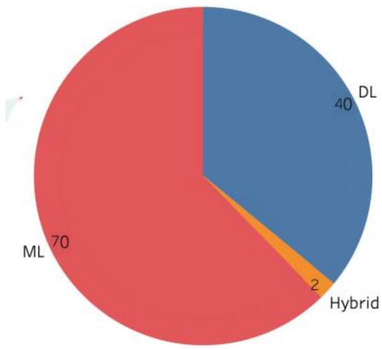
(a) Distribution of ML algorithms for sleep apnea detection.



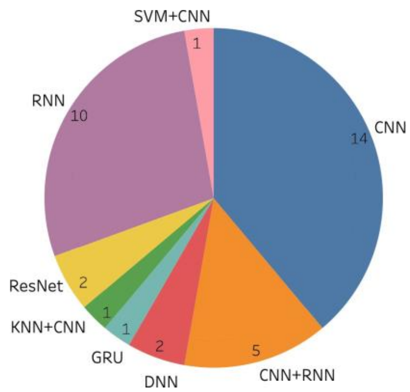
(b) Distribution of signals used for sleep apnea detection.



(c) DL and Hybrid classifier distribution in sleep apnea detection solutions.



(d) Distribution of AI algorithms used for sleep apnea detection.



(e) DL and Hybrid classifier distribution in sleep apnea detection solutions.

Figure 6: Sleep apnea-related distribution diagrams.

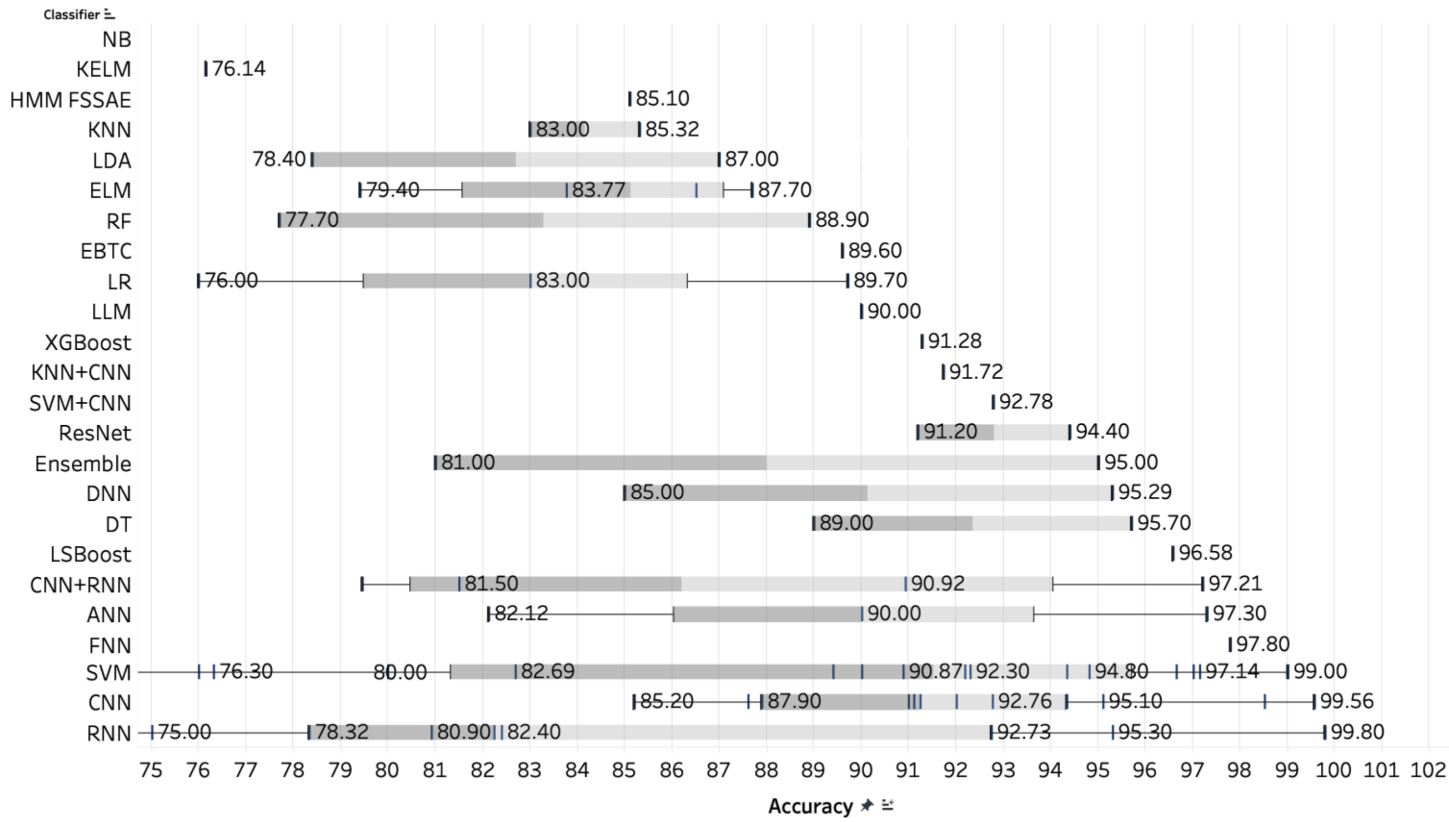


Figure 7: Average classification ACC for sleep apnea detection obtained with different classifiers.

lowest classification performance for all reviewed sleep apnea detection models. Listing the model performance in Figure 7 reveals another important characteristic: the three least performing models belong to ML [99].

Table 3 summarises seven studies with the best ACC for sleep apnea detection among all the reviewed sleep apnea papers. Erdenebayar et al. [46] conducted experiments to detect sleep apnea on their own ECG dataset. They applied a LSTM classifier to extract features, which enhanced the ACC significantly [46]. During our review, we encountered papers using less frequently used signals, including REI, Pulse Transition Time (PTT), ECG-Derived Respiration (EDR), Electrical Impedance Tomography (EIT), Airflow (AF). Bricout et al. [30] automated sleep apnea detection with a small dataset of 28 subjects and achieved 100% Specificity (SPE). Table A.11 summarises of all the reviewed studies on automated sleep apnea detection.

It is known that the dataset dimension influences the model performance. For this reason, Table 3 also shows the dimension of the training set as a percentage of the total dataset and the number of folds when the cross-validation technique was used.

4.2. Insomnia

The second most often studied sleep disorder is insomnia. Figure 8b shows that EEG was the most commonly used signal to detect insomnia. Only two DL models were used for insomnia detection. The first of these models was CNN, and the second model was a combination of CNN and LSTM. The pie chart in Figure 8a illustrates that SVM and Random Forest (RF) were the two most common classifiers for insomnia detection. The average ACC is lower than for the DL classifier CNN+LSTM or the ML classifier Ensemble Bagged Trees Classifier (EBTC). Figure 9 summarises the ACC values obtained using various AI algorithms for automated insomnia detection. EBTC and multiple classifiers have the highest ACC. Table 4 summarises all studies the reviewed insomnia detection studies. Sharma et al. [103, 104] achieved the highest ACCs with the EBTC classifier for the CAP

Table 3: Details of studies with top ACCs. RIP represents the respiratory inductance plethysmography, and SpO2 is the oxygen saturation.

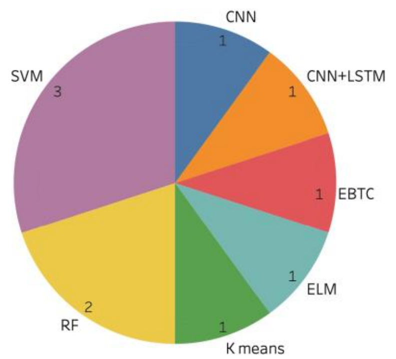
Author, Year	Signal	Classifier		ACC %	Dataset	Size	No. Folds	Dimension training set %
		Type	Algo.					
Erdenebayar et al., 2019 [46]	ECG	DL	RNN	99.00	Own	82 apnea patients	-	80
Bricout et al., 2021 [69]	Standard PSG recordings (thoracic and abdomen RIP, Nasal airflow, SpO2, ECG)	ML	Tree model	89.00	UCDDB	28 subjects	Leave one out Cross validation (LOOCV)	96
Romero et al., 2019 [98]	Sound	DL	Deep Neural Network (DNN)	95.29	Own	31 male and 13 female participants	-	66
Jafari et al., 2013 [100]	ECG	ML	SVM	94.80	Own	164 subjects	-	66
Almuhammadi et al., 2015 [101]	EEG	ML	SVM	97.14	MIT PhysioNet Apnea	70 ECG recordings	-	80
Erdenebayar et al., 2019 [46]	ECG	DL	CNN	98.50	Own	86 patients	-	80
Faust et al., 2021 [102]	ECG	DL	RNN	99.80	MIT PhysioNet Apnea	35 records	10	90

dataset.

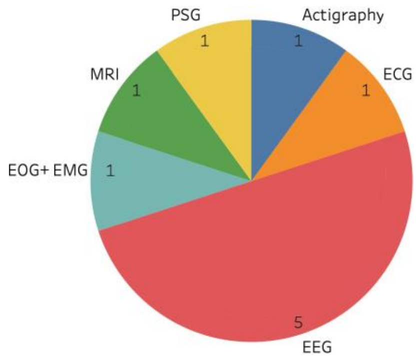
In 2021, Li et al. [105] proposed optimal bi-orthogonal wavelet-based features to identify insomnia. Their study discriminated between healthy and insomnia cases from the CAP sleep dataset [106]. The highest classification ACC of 95.60% and a Kappa value of 0.97 were achieved using the N3 deep sleep stage. They proposed that deep sleep can be used instead of the entire overnight sleep recordings if sleep scoring is performed; otherwise, all EEG epochs, irrespective of their sleep scores, need to be combined and used to identify insomnia [107].

An optimal antisymmetric biorthogonal wavelet filter bank has been used by Sharma et al. [77] to minimise the joint duration-bandwidth localisation of underlying filters during insomnia detection. The -norm feature was computed from various wavelet sub-bands coefficients that were extracted from ECG signals. The norm features were fed to supervised ML classifiers to train and test models for automated insomnia detection. This work used ECG recordings of seven insomnia patients and six normal subjects from the publicly available CAP sleep database.

Authors created ten different subsets of ECG signals based on annotations of sleep stages, namely wake (W), S1, S2, S3, S4, REM, Light Sleep Stage (LSS), Slow-Wave Sleep (SWS), non-REM, and W+S1+S2+S3+S4+REM for the automated identification of insomnia [108]. Their ECG-based REM sleep stage detection system showed the best performance with an ACC of 97.87%, F1-score of 97.39%, and Cohens kappa value of 0.9559 for KNN with the ten-fold cross-validation strategy. SVM yielded the highest value of 0.99 for the area under the curve with the ten-fold cross-validation corresponding to the REM sleep stage [77].



(a) Number of articles published using AI techniques for automated insomnia detection.



(b) Number of published articles using physiological signals for automated insomnia detection.

Figure 8: Insomnia-related distribution diagrams.

4.3. REM behaviour disorder

Based on our article search strategy outlined in Section 3, we discovered only four automated RBD detection studies. The bar chart in Figure 10 provides an overview of the detection performance reported in these four papers. Sharma et al. [109] used EEG and EOG+EMG to detect RBD with an ML algorithm, the latter achieved a better result. Cooray et al. [79] were the only authors to use DL and reported outstanding ACC, SPE, and Sensitivity (SEN), of 96.00%, 98.00%, and 83.00% respectively. Table 5 summarises all the studies discovered on REM sleep disorder detection.

4.4. Hypopnea

Table 6 provides a summary of all studies for automated hypopnea detection. All the discovered studies used DL algorithms. Erdenebayar et al. [46] took two ECG experiments targeting on hypopnea with different classifiers, namely GRU and CNN. These classifiers were trained and tested on the same dataset. GRU achieved slightly better results with ACC, SPE, and SEN 97.00%, 97.00%, and 97.00%, respectively, than the same index of CNN at 96.40%, 96.00%, and 96.00%.

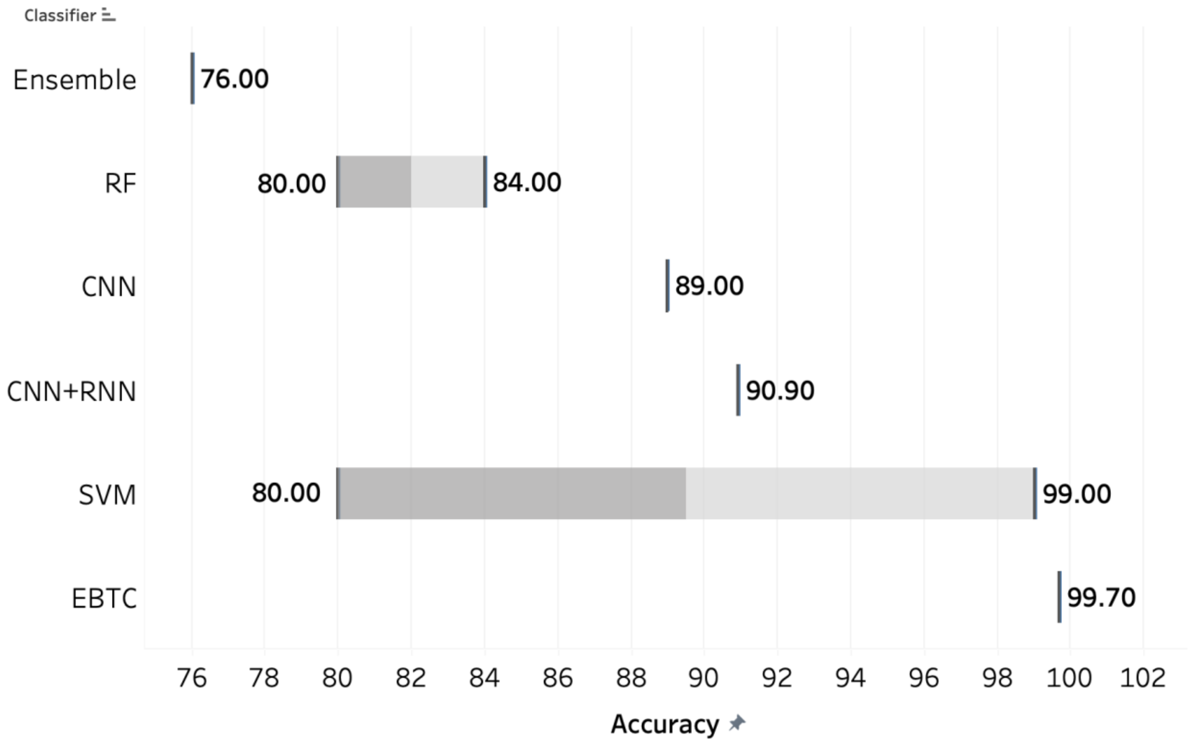


Figure 9: ACC (%) obtained using various AI algorithms for automated insomnia detection.

Table 4: Summary of the studies conducted on the topic of automated insomnia detection.

Author, Year	**Signal**	**Classifier**		**ACC**	**Dataset**	**Size**
		Type	Algo.	%		
Sharma et al., 2022 [77]	EOG +EMG	ML	EBTC	99.70	CAP	108 PSG recordings
Sharma et al., 2021 [109]	ECG	ML	SVM	99.00	CAP	108 PSG recordings
Wei et al., 2018 [76]	EEG	DL	CNN+ RNN	90.90	Own	44 Subjects
Atianashie et al., 2021 [6]	EEG	DL	CNN	89.00	MIBIH PSG and CAP	108 PSG recordings
Sharma et al., 2021 [109]	ECG	ML	ELM	76.00	CAP	108 PSG recordings
Hamida et al., 2015 [78]	ECG	ML	K means	-	Own	18 patients
Angelova et al., 2020 [103]	Standard PSG (accelerometer data)	ML	RF	84.00	Own	21 patients, 24 normal
Kusmakar et al, 2021 [104]	Actigraphy	ML	RF	80.00	Own	80 patients
Lee et al., 2021 [110]	MRI	ML	SVM	80.00	Own	19 patients, 21 normal
Shahin et al., 2018 [111]	EEG	ML	SVM	-	Own	54 patients,61 normal

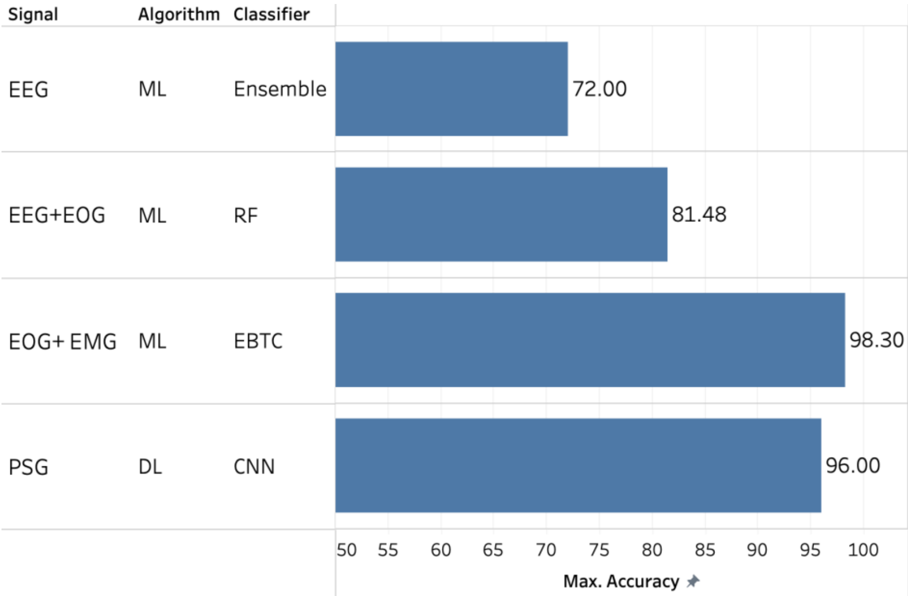


Figure 10: REM behaviour disorder detection performance.

Table 5: Details of automated RBD detection studies.

Author, Year	Signal	Classifier Type	Classifier Algo.	ACC %	Dataset	Size
Cooray et al., 2019 [79]	PSG (EEG - EOG - EMG)	DL	CNN	96.00	Own	53 patients, 53 normal
Sharma et al., 2021 [77]	EEG	ML	ELM	72.00	CAP	108 PSG recordings
Sharma et al., 2021 [109]	EOG +EMG	ML	EBTC	98.30	CAP	108 PSG recordings
Cesari et al., 2021 [112]	EOG +EEG	ML	RF	81.48	Own	158 PD patients

Table 6: Details of automated Hypopnea detection studies.

Author, Year	Signal	Classifier Type	Classifier Algo.	ACC %	Dataset	Size
Erdenebayar et al., 2019 [46]	ECG	DL	CNN	96.40	Own	86 hypopnea patients
Erdenebayar et al., 2019 [46]	ECG	DL	RNN	97.00	Own	86 hypopnea patients
Drzazga et al., 2021 [93]	REI	DL	RNN	80.66	Physionet sleep database	1000 PSG recordings

Table 7: Details of automated Narcolepsy detection studies.

Author, Year	**Signal**	**Classifier**		**ACC** %	**Dataset**	**Size**
		Type	Algo.			
Sharma et al., 2021 [109]	EEG	ML	ELM	78.00	CAP	108 PSG recordings
Sharma et al., 2022 [77]	EOG +EMG	ML	EBTC	96.70	CAP	108 PSG recordings
Christensen et al., 2015 [113]	EEG	ML	HMM	89.20	Own	13 subjects

Table 8: Details of automated PLMD detection studies.

Author, Year	**Signal**	**Classifier**		**ACC** %	**Dataset**	**Size**
		Type	Algo.			
Sharma et al., 2021 [109]	EEG	ML	ELM	84.00	CAP	108 PSG recordings
Sharma et al., 2022 [77]	EOG +EMG	ML	EBTC	97.50	CAP	108 PSG recordings
Kye et al., 2017 [114]	PSG (accelerometer data)	ML	KNN	96.62	Own	13 patients

4.5. Narcolepsy

Sharma et al. [77] contributed two papers that propose AI models to classify narcolepsy. One of their studies analysed EEG signals with an ELM classifier. This combination achieved a low ACC of 78%. After the initial study results, they combined EMG and EOG. This signal combination was analysed with an EBTC classifier. Ultimately, this increased the ACC to 96.70%. A study by Christensen et al. [113] achieved an ACC of 89.20% based on EEG signals. Table 7 provides a summary of all selected narcolepsy studies.

4.6. Periodic limb movement disorder

Only two research groups studied PLMD detection. Sharma et al. [77] achieved the highest reported ACC of 97.50% for PLMD classification with a multi-signal approach using EOG and EMG from the CAP dataset together with an EBTC classifier. Kye et al. [114] achieved 96.62% ACC with PSG as input signals. Table 8 provides a summary of the three studies focused on PLMD detection.

4.7. Nocturnal frontal lobe epilepsy

Sharma et al. [77, 109] conducted two studies to detect NFLE with ML classifiers based on signals from the CAP database. Their results indicate that ML approaches can achieve NFLE detection with high ACC. Given that a combination of EOG and EMG resulted in higher classification ACC when compared to EEG alone, it seems that multiple signals can improve the classification performance. Table 9 provides a summary of the two studies on automated NFLE detection.

4.8. Bruxism

Heyat et al. [115, 116] conducted two studies for bruxism classification. In the first, they developed a Decision Tree (DT) to classify bruxism with the ECG signals, obtaining 81% ACC [115]. In the second study, they designed an automated method to detect bruxism with ECG signals using a Hybrid Machine Learning (HML) classifier [116]. In their study, they combined more than ten

Table 9: Details of automated NFLE detection studies.

Author, Year	Signal	Classifier		ACC %	Dataset	Size
		Type	Algo.			
Sharma et al., 2022 [77]	EOG +EMG	ML	EBTC	97.50	CAP	108 PSG recordings
Sharma et al., 2021 [109]	EEG	ML	Ensem-ble	84.00	CAP	108 PSG recordings

Table 10: Details of automated Bruxism detection studies.

Author, Year	Signal	Classifier		ACC %	Dataset	Size
		Type	Algo.			
Heyat et al., 2019 [115]	EEG	ML	DT	81.25	CAP	224 EEG segments
Heyat et al., 2020 [116]	ECG	ML	HML	94.00	CAP	936 ECG segments
Lai et al., 2019 [117]	EEG +ECG +EMG	ML	DT	97.21	CAP	244 EEG segments

classifiers with complicated parameters. Their method has an effective performance of 94.00% ACC, and they claimed the proposed model is suitable for home monitoring devices. Table 10 provides a summary of the single bruxism study. Lai et al. [117] achieved the highest bruxism detection ACC of 97.21% with a DT model that analysed EEG, ECG, and EMG signals.

5. Discussion

In our study, we have presented an overview of all sleep disorder detection approaches reported in 95 scientific papers. During the review, we found eight types of sleep disorders for which automated detection systems have been established during the last 11 years (from 2010 to 2022). Sleep apnea and insomnia were the most studied fields, and all other sleep disorder topics attracted fewer than 4 papers.

We have analysed conventional ML and DL techniques for sleep disorder detection. Figure 11 shows the number of sleep disorder studies published within one year, from 2010 to 2022. The graph shows that more articles have been published in recent years. This indicates that the topic has gained increasing relevance. Colour coding was used to present the frequency of DL, ML, and Hybrid algorithms. It is noted that ML dominated the field of automated sleep disorder detection until 2018. DL became popular from 2018 onward [118]. As such, DL is much more process-centric when compared with ML approaches, which depend on skilful human interaction during feature generation and selection. Being process-centric has another implication, namely the interchangeability of algorithms. The performance of ML methods depend on the combination of features and classification algorithm. Hence, there is always an element of uncertainty, and many investigators adopt a trial-and-error approach where they test a range of different classification algorithms. The process-centric nature of DL results in the fact that most frameworks, which facilitate the creation of DL models, are much more plug-and-play rather than trial and error. The plug-and-play nature of the frameworks enables a skilled designer to create hybrid models by combining two or more DL algorithms or even ML and DL algorithms. Indeed, such hybrid models are a new trend for automated sleep disorder detection.

Sharma et al. [109] conducted a 6-class sleep disorder study using multiple signals from the CAP dataset. They aimed at general sleep disorders, such as bruxism and NFLE, with only one or two

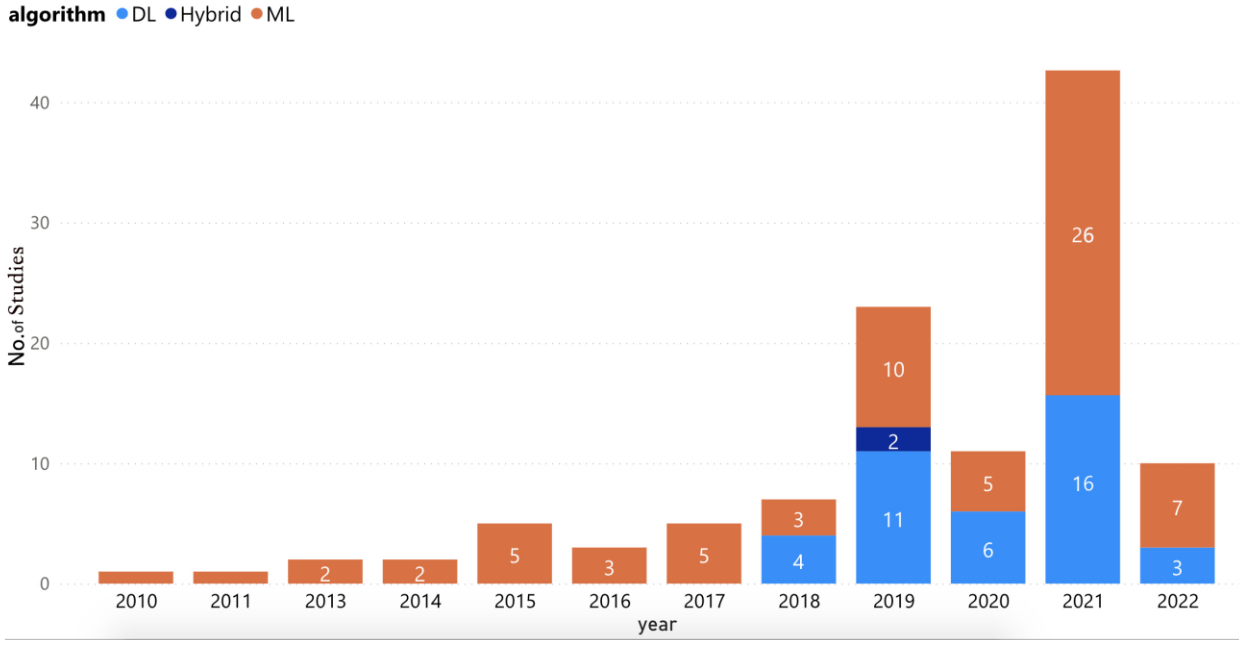


Figure 11: Year-wise distribution of AI methods used for automated sleep disorder detection.

studies in the recent decade. The CAP dataset consists of 108 PSG recordings and was used in many similar studies. Sharma et al. combined two signals and built a model, all targeted sleep disorders achieving high ACC.

It can be noted from this review that automated sleep apnea and insomnia detection attracted the most research work within the area of automated sleep disorder detection. Sleep apnea can be life-threatening and lead to debilitating co-morbidities. Hence, more research has focused on this disorder. Also, it can be diagnosed using a wide range of physiological signals, such as ECG, PPG, Heart Rate Variability (HRV), snore sound, and SpO_2. The fact that medical imaging was not used for sleep apnea detection is hardly surprising because time-domain signals allow us to observe and analyse how sleep apnea events unfold. According to the pie chart in Figure 6b, 32 studies automated sleep apnea detection studies were based on ECG signals. Many ECG benchmark datasets are available because these signals are routinely captured as part of overnight PSGs. Furthermore, the autonomic nervous system links ECG signal morphology to the breathing pattern. More specifically, sleep apnea events alter the beat-to-beat interval of the human heart. These changes can be detected with AI models for sleep apnea diagnosis support. Another important vital of ECG signals is that they can be measured in the home environment. Unfortunately, it is difficult to measure EEG in the home environment because the instrumentation effort is significantly higher when compared to ECG. The high instrumentation effort is necessary to control and if possible, reduce noise. This makes EEG signal analysis less practical for sleep apnea detection in the home environment. Nine studies indicated that EEG morphology analysis can be used for sleep apnea detection, however EEG is more difficult to measure in the home environment when compared to ECG because the instrumentation effort is significantly higher Nine studies focused on that signal type indicate that EEG morphology analysis can be used for sleep apnea detection. PSG measurements involving multiple channels are even less practical for sleep apnea detection in the home environment than EEG signals alone. The 15 studies that used the complete range of PSG signals aim to automate diagnostic pathways in sleep clinics.

Figure 6e indicates that DL and hybrid models, such as CNN, LSTM, and a combination of both, have been proposed for automated sleep apnea detection. Faust et al. [102] have used LSTM models to obtain high accuracy for sleep apnea detection based on HRV signals. This result is significant because it shows that considering the beat-to-beat intervals is sufficient to detect sleep apnea reliably.

This will reduce bandwidth and processing requirements, bringing down the cost of wearable devices for sleep apnea detection at home. The pie chart in Figure 6a indicates that studies, which relied on ML techniques for sleep apnea detection, achieved the best results with SVM algorithms. Therefore, this technique has become a benchmark method for ML-based sleep apnea detection models. ELM algorithms were reported as the best classification methods by six studies.

For insomnia detection, 5 out of 10 studies have used EEG signals, see Figure 8b, from which, we can derive that the EEG signal morphology reflects insomnia. Having only one study based on ECG signals indicates that the link between insomnia and ECG morphology is much weaker when compared to EEG. fMRI images were also used for insomnia detection. With their study, Lee et al. [110] established that fMRI can be used to discriminate between normal and insomnia subjects.

Eight studies incorporated ML for automated insomnia detection, one used a hybrid model, and only one relied on a DL model, as indicated in Figure 8a. Three research studies achieved the best insomnia detection performance with SVM classifiers. Therefore, these classifiers should be used as reference standards for ML-based insomnia detection. Two studies report their base results with the RF classifier.

There are several differences between the ML and DL models, which can explain their different performances. First, ML models require expert-led feature engineering to generate results, which DL models do not need. The most important among these is the features extraction stage, which generates the input data. Furthermore, to train the ML models, a trial-and-error phase is required, in which the operator finds the data structure that generates the best results. Instead, the DL models generate the features that enhance the achievement of the task, such as the detection or classification. Furthermore, DL systems require ‘nore data to achieve good performance, which certainly extends the computational cost and training time. Indeed, ML models can be trained on Central Process Units (CPUs), while DL models benefit from using Graphics Processing Units (GPUs).

In the analysed AI models, there are some data-related limitations. Indeed, there is a delicate interplay between the available data and the processing methods that can be used to extract relevant knowledge from the data. DL methods handle significant data volumes better than traditional ML techniques [39]. However, there are four distinct limitations of DL: 1) the computational complexity of DL algorithms is higher when compared to traditional ML. 2) This effect is magnified by the fact that there is more data. Specifically, a measure of computational complexity is the number of complex multiplications for an atomic data quantity, say an image or a signal block. More images for training and testing linearly increase the computation requirement. 3) DL models are considered black boxes. It means that the model generates the output without explaining how the individual neurons work together to arrive at the result. For this reason, the DL results should be considered independent opinions that might help with clinical tasks and processes. 4) DL algorithms require hyperparameter tuning. Despite attempts to automate this process by either predicting or evaluating the values, hyperparameter setting is usually done with trial-and-error. Unfortunately, the trial-and-error approach involves training the network for some epochs. Repeating this training multiple times for different settings requires significant processing time that needs to be spent in addition to the final training time. On the upside, DL algorithms scale well, i.e., more processing resources result in a speedup. Hence, it is possible to control the processing time. However, there is a trade-off between resource and time investment. Looking towards the extremes, big data and computationally complex algorithms might not be affordable for some research groups because the hardware is expensive for DL training and testing. A potential solution might be cloud-based processing, which can train and test the AI model more effectively.

Another data-related issue is that sleep disorder symptoms are not always present. Sleep apnea, NFLE, and RBD detection might produce heavily skewed data. More specifically, the non-disorder class has more data than the disorder class. The problem arises when AI models are trained and tested with such data. The problem is best illustrated with an example. Let’s assume a sleep apnea detection scenario where only 20% of the data was measured during sleep apnea. A particularly lazy AI model could identify all samples as normal and thereby achieve an ACC of 80%. Such a system would be completely insensitive, and therefore it would be useless in a practical scenario. That indicates the need for a balanced dataset to generate unbiased AI models. Data augmentation is a way of increasing the amount of data for the smaller classes, usually the disordered class is the smaller one. Doing so might correct the problems introduced by skewed data. However, using augmented data means the model is trained and tested with synthetic data. This synthetic data has similar properties as measurement data, and it was created with some algorithm. AI models might learn properties introduced by the augmentation algorithm and thereby identify augmented data that belongs 100% to the disorder class. This is a particular problem for deep networks with the ability to learn the most subtle relationships.

Sleep analysis and sleep disorders detection have attracted great interest over the years. Indeed, several review articles have been presented to discuss sleep disorders, the system for the diagnosis, the automatic classification or detection models. Vivien Abad et al. [119] presented an overview of the principal sleep disorders, such as insomnia, circadian cycle disorders, and excessive somnolence disorders, analysing any pharmacological and non-pharmacological therapies. In their review, Abdel et al. [65] focused on sleep apnea diagnosis support based on IoIT technology. A comprehensive review from Heyat et al. [67] focuses on insomnia detection, and another group published a review on bruxism detection [120]. Campabadal et al. [68] reviewed sleep behaviour disorder classification methods based on MRI image data. Buongio et al. [66] presented an overview of the sleep stage classification based on ECG signals. Also, Faust et al. [121] reviewed automated sleep stage scoring, presenting all physiological signals that give clinical information for the classification of sleep stages. In contrast to these established reviews, our approach focused on automated sleep disorder detection with AI models. Instead, our work amplified the previous reviews, including a description of eight sleep disorders without any restriction about the type of AI or the data used to provide clinical information.

5.1. Limitations

We face challenges comparing the performance of proposed sleep disorder detection methods because the study setup might have involved different signals or different datasets [122]. However, in our work, there are some limitations. First, a data-related limitation arises from the selection process, leading to training and testing data for AI algorithms. Especially some personal datasets of small size have few subjects, and their data collection method is dissimilar from common public datasets [123, 124]. https://www.overleaf.com/project/6227e97500547e32b96126e5

Furthermore, we have compared the performance of models which were trained with a different ratio between the training and test set. Indeed, the dimension of the training and test set is known to influence the accuracy value and the model performance. For this reason, the performance could also be influenced by this division and the type of model used. Moreover, the pre-processing techniques play an important role in influencing both the signals and the model performance. Although this knowledge, in our work, we have focused on the ML and DL models, their limitations and differences, and not on the pre-processing techniques.

5.2. Future work

Future work should eliminate the burdens of current learning systems and AI techniques. We believe that collecting physiological signals of sleep disorders can benefit a wide range of patients worldwide [125]. Some physiological signals, such as HRV, PPG, and ECG, can be extracted with portable devices that are low-cost and real-time [126, 127]. And there is a limited number of studies on the automated detection of bruxism, NFLE, and narcolepsy. Further steps can involve more relative studies and experiments to detect these diseases [128]. On the other hand, AI has been highlighted as a potential decision-making tool due to the low measurement complexity and can reflex medical practitioners' decisions. Furthermore, we can exploit AI algorithms while doctors can label data in the newly added datasets [107]. It is even feasible to conduct data mining from data itself and get knowledge to remove the current defects [129].

Furthermore, future work could investigate explainable AI techniques which may be used. This approach could be useful for establishing hybrid diagnosis processes where human experts and AI models work cooperatively on clinical tasks.

In the future, it might be possible to substitute ECG measurements with HRV [36] and PPG [130] to detect sleep apnea. As such, the substitute measurements capture only the beating activity of the heart. This results in a significantly lower data rate when compared to ECG. Therefore, these signals are easier to communicate and process. This has the potential to reduce costs for the healthcare provider. The fact that HRV and PPG signals require only moderate instrumentation effort makes the sensors more convenient for patients when compared to ECGs. This might help with patient compliance.

The field of sleep disorder detection should move towards disease prediction and prevention. A first step towards that goal is to detect mild or early-stage disorders. We have already seen the first attempts in this direction with hypopnea detection. Hypopnea detection is essential because this disorder might lead to sleep apnea [30]. Hence, automated hypopnea detection might lead to adequate treatment of this sleep disorder, preventing patients from developing sleep apnea.

Competition is an important driver of scientific studies on sleep disorder detection. Good publications strike a delicate balance between uniqueness and competition. Combining both requirements can result in novel processing methods that outperform standard methods. These studies should be based on publicly available databases to establish an undisputed claim for novelty and performance. Not only does this foster competition, but it will also help to validate proposed models. Therefore, we expect to see more and more extensive databases in the future. It might even be possible to have a database indicating the best results for a particular dataset.

From an abstract or philosophical perspective, we understand that more public databases are needed to increase extractable knowledge, which might lead to better AI models for medical decision support. These databases should also be geographical, ethnically, and temporally diverse to reduce potential bias. Furthermore, a wide range of experts should be employed to establish the ground truth.

Measurement methods and the resulting data are also important factors for the practicality of proposed sleep disorder detection systems. A lower data rate and a straightforward measurement setup improve practicality. In the future, it might be possible to find systems that offer practical solutions for sleep disorder detection in the home environment. Moving away from the sleep lab and into the home environment would allow us to do significantly more measurements in the comfort of a patient's home. Another significant aspect is that the environmental impact of sleep disorder monitoring at home is lower when compared to sleep lab-based approaches [131]. Such a scenario becomes practical when the patient or a carer can initiate the measurement, and the resulting data is automatically analysed with an AI model. Sleep disorder detection in a home environment imposes firm restrictions on the technologies used for measuring, communicating, and processing signal data. The measurement setup should aid patient-led data acquisition. The measurement system should be capable of monitoring one night (12 h) without user intervention, and the data should be communicated in real-time to a central server for processing. Such a real-time uplink reduces the need for internal buffering, thereby extending the monitoring duration. In other words, an internal sensor buffer fills up, and if that happens, the device needs to travel to a central facility for data readout and processing. ECG and HRV signals are possible solutions that meet the firm requirements of sleep disorder detection in the home environment.

Furthermore, future works could investigate the preprocessing stage and how it affects the final model performance.

6. Conclusion

The world is facing sleeplessness. Automated detection of sleep disorders might be a way of addressing this problem. This paper documents our efforts to establish the extent of current knowledge on automated sleep disorder detection. The review focused on eight common sleep disorders for which automated detection methods were proposed. We found 95 relevant papers published in the past 11 years, which were reviewed to establish methods, signals, and performance. For methods used, we detected a shift from ML to DL. The signals used to show the automated detection models depend on the sleep disorder. We have analysed this aspect deeper for the two most prevalent problems of sleep apnea and insomnia. ECG signals are predominately used for sleep apnea detection, and EEG signals are used for insomnia detection. Another important trend became apparent during the focused review. A significantly higher proportion of DL systems were used for sleep apnea detection compared to insomnia detection.

Stepping back from the technical details of signals and systems, our findings support the idea that sleep is an individual process. 24 distinct algorithms were used to analyse 20 different signals or indeed signal combinations. This diversity of methods and signals clearly documents the challenge faced by practitioners in the area of automated sleep disorder detection. It seems that we are far from proposing that one method works best, even for individual sleep disorders. This calls for further research. This research should be conducted on large publicly available databases to foster competition amongst research groups and method validation. The research should focus on signals that can be measured easily in the home environment, such as ECG and HRV. Establishing signal acquisition in the home environment will enable us to investigate disease progression and sharpen AI-based detection methods. This might lead to disease prediction and automated intervention in the form of lifestyle change suggestions. We need to work harder on automated sleep disorder detection so the world can sleep well.

7. Acronyms

LR Linear Regression
AASM American Academy of Sleep Medicine
ACC Accuracy
REI Respiratory Event Index
AF Airflow
SpO_2 Oxygen Saturation
ANN Artificial Neural Network
AHI Apnea/Hypopnea Index
AI Artificial Intelligence
CAP Cyclic Alternating Pattern
CNN Convolutional Neural Network
CPR Cardiorespiratory Polygraph
CPU Central Process Unit
DL Deep Learning
DNN Deep Neural Network
DT Decision Tree
EBTC Ensemble Bagged Trees Classifier
ECG Electrocardiogram
EDR ECG-Derived Respiration
EEG Electroencephalogram
EIT Electrical Impedance Tomography
ELM Extreme Learning Machine
EMG Electromyogram
EOG Electrooculogram
FNN Feedforward Neural Network
GPU Graphics Processing Unit
GRU Gated Recurrent Units
HML Hybrid Machine Learning
HMM Hidden Markov Models
HRV Heart Rate Variability
IoIT Internet of Intelligent Things
KELM Kernel Extreme Learning Machine
KNN K-Nearest Neighbour
LDA Linear Discriminant Analysis

LLM Logic learning machine
LOOCV Leave one out Cross validation
LSS Light Sleep Stage
LSTM Long Short-Term Memory
LR Logistic Regression
ML Machine Learning
MRI Magnetic Resonance Imaging
NA Nasal Airflow
NB Naive Bayes
NFLE Nocturnal Frontal Lobe Epilepsy
OSA Obstructive Sleep Apnea
PLMD Periodic Limb Movement Disorder
PPG Photoplethysmogram
PTT Pulse Transition Time
PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSG Polysomnography
RBD Rapid eye movement Behavioural Disorder
REM Rapid Eye Movement
RF Random Forest
RNN Recurrent Neural Network
SEN Sensitivity
SHHS Sleep Heart Health Study
SPE Specificity
SWS Slow-Wave Sleep
SVM Support Vector Machine
UCDDB St. Vincent's University Hospital / University College Dublin Sleep Apnea Database
SUMS Shiga University of Medical Science hospital
RHUH Rio Hortega University Hospital dataset
PaO_2 Partial pressure of oxygen
$PaCO_2$ Partial Pressure of Carbon Dioxide
ADR Accelerometry Derived Respiration Index
SaO_2 Arterial Oxygen Saturation
NR Not Reported

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Appendix A. Apnea detection studies

Table A.11: Details of apnea detection studies.

Author, Year	Signal	Classifier		ACC %	Dataset	Size
		Type	Algo.			
Tapia et al., 2020 [132]	EEG	DL	RNN	80.90	Own	EEG extracted from 19 PSG recordings
Qin et al., 2021 [5]	ECG	DL	CNN	91.10	MIT PhysioNet Apnea	70 ECG recordings
Chang et al., 2020 [22]	ECG	DL	CNN	87.90	MIT PhysioNet Apnea	70 ECG recordings
Urtnasan et al., 2021 [20]	ECG	DL	CNN	94.33	CAP	108 PSG recordings
Erdenebayar et al., 2019 [46]	ECG	DL	CNN	98.50	OWN	86 patients with SA
Yueet al., 2021 [28]	PSG	DL	ResNet	91.20	Own	405 PSG recordings
Erdenebayar et al., 2019 [46]	ECG	DL	GRU	99.00	Own	86 patients
Steenkiste et al., 2018 [133]	PSG	DL	LSTM	75.00	SHHS	6441 individuals
Vanet et al., 2020 [124]	PSG	DL	LSTM	72.80	Own	25 subjects
Drzazga et al., 2021 [93]	REI	DL	LSTM	82.40	SHHS + MIT PhysioNet Apnea	5804 recordings + 25 recordings
Drzazga et al., 2021 [93]	REI	DL	LSTM	78.32	SHHS + MIT PhysioNet Apnea	5804 recordings + 26 recordings
Wang et al., 2019 [94]	ECG	DL	CNN	87.60	MIT PhysioNet Apnea + UCDDB	70 ECG recordings +25 PSG recordings
Vanet et al., 2020 [124]	ECG	DL	LSTM	72.80	Own	25 patients
Faust et al., 2021 [102]	ECG	DL	LSTM	99.80	MIT PhysioNet Apnea	70 ECG recordings
Panindre et al., 2021 [125]	ECG	DL	LSTM	82.24	MIT PhysioNet Apnea	70 ECG recordings
Eldaraa et al., 2020 [16]	ECG + EOG + EMG + AF	DL	CNN	69.49	MIT PhysioNet Apnea	70 ECG recordings

Atianashie et al., 2021 [6]	EEG	DL	CNN	92.00	MIT PhysioNet Apnea + CAP	70 ECG recordings + 108 PSG recordings
Shahid et al., 2021 [107]	MRI	DL	CNN	85.20	Own	50 head MRI datasets
Wu et al., 2021 [134]	NA	DL	CNN	91.23	Own	night-time PSG recordings of 500 subjects
Tuncer et al., 2019 [34]	PSG	DL	CNN	92.76	Own	100 subjects
Thorey et al., 2019 [128]	PSG	DL	CNN	91.00	Own	52 PSG recordings
Vaquerizoet et al., 2020 [51]	SpO_2	DL	CNN	95.10	Own	46 preprocessed SpO_2 signals
Wang et al., 2019 [135]	EDR	DL	ResNet	94.40	Own	30 overnight recordings are used for training and 5 for testing
Almutairiet al., 2021 [136]	ECG	DL	CNN + LSTM	90.92	MIT PhysioNet Apnea	70 ECG recordings
Zarei et al., 2022 [43]	ECG	DL	CNN + LSTM	97.21	MIT PhysioNet Apnea +UCDDB	70 ECG recordings + 25 PSG recordings
Iwasaki et al., 2021 [122]	ECG	DL	CNN + LSTM	Not Re-ported (NR)	SUMS	57 subejects
Banluesombatkul et al., 2018 [137]	ECG	DL	CNN + LSTM	79.45	Own	545 subjects
Bernardini et al., 2021 [138]	ECG + SpO_2	DL	CNN + LSTM	81.50	MIT PhysioNet Apnea	70 ECG recordings
Li et al., 2018 [139]	ECG	DL	DNN	85.00	MIT PhysioNet Apnea	70 ECG recordings
Romero et al., 2019 [98]	Snore sound	DL	DNN	95.29	Own	31 male and 13 female participants
Cheng et al., 2022 [95]	Snore sound	DL	LSTM	95.30	Own	33 patients and 10 normal people

Srinivasulu et al., 2021[58]	ECG	ML	EBTC	89.60	MIT PhysioNet Apnea	70 ECG recordings
Hassan et al., 2015 [123]	ECG	ML	ELM	83.77	MIT PhysioNet Apnea	70 ECG recordings
Sard et al., 2019 [140]	ECG	ML	ELM	86.50	MIT PhysioNet Apnea	70 ECG recordings
Sard et al., 2016 [57]	ECG	ML	LDA	87.00	MIT PhysioNet Apnea	70 ECG recordings
Sadr et al., 2014 [106]	ECG	ML	ELM	87.70	MIT PhysioNet Apnea	70 ECG recordings
Sharma et al., 2021 [109]	EEG	ML	Ensem-ble	81.00	CAP	108 PSG recordings
Sadr et al., 2015 [141]	SpO_2	ML	ELM	79.40	MIT PhysioNet Apnea	70 ECG recordings
Pant et al., 2022 [55]	ECG	ML	Ensem-ble	94.52	MIT PhysioNet Apnea	70 ECG recordings
Li et al., 2021 [105]	ECG +SpO_2	ML	FNN	97.80	Own	148 apnea patients, 33 healthy
Feng et al., 2021 [142]	ECG	ML	HMM	85.10	MIT PhysioNet Apnea	70.00 ECG recordings
Tripathy et al., 2018 [118]	EDR	ML	KELM	76.14	MIT PhysioNet Apnea	70.00 ECG recordings
Piorecky et al., 2021 [37]	ECG	ML	KNN	85.32	MIT PhysioNet Apnea+ UCDDB	134 patients,24 healthy
Piorecky et al., 2021 [37]	PSG	ML	KNN	83.00	Own	477 PSG recordings
Sadr et al., 2016 [143]	PSG	ML	LDA	78.40	MIT PhysioNet Apnea	70.00 ECG recordings
Skotko et al., 2016 [44]	PSG	ML	LLM	90.00	Own	130 patients
Ferre et al., 2019 [144]	PSG	ML	LR	76.00	Own	90 patients

Alvarez et al., 2010 [17]	Arterial Oxygen Saturation (SaO_2)	ML	LR	89.70	Own	148 consecutive patients(115 males and 33 females)
Akhter et al., 2018 [97]	Snore sound	ML	LR	83.00	Own	91 patients 108,228 Snore episodes
Gutierrez et al., 2019 [52]	SpO_2	ML	LSBoost	96.58	SHHS+RHUH	non at-home PSG recordings of 5,804 individuals+at home PSG recordings322 patients
Cai et al., 2019 [99]	ECG	ML	NB	71.00	Own	60000 signal samples
Pepin et al., 2020 [70]	PSG	ML	Ensem-ble	95.00	Own	376 consecutive adults with suspected apnea
Nakayama et al., 2019 [56]	PSG	ML	RF	NR	MIT PhysioNet Apnea+SUMS	70 ECG recordings +57 patients
Ramachandran et al., 2021 [145]	PSG	ML	RF	88.90	MIT PhysioNet Apnea	70 ECG recordings
Deviaene et al.,2019[50]	SpO_2	ML	RF	77.70	Own	975 patients
Sharma et al., 2021 [77]	ECG	ML	SVM	90.87	Physionet's CinC challenge-2000 database	35 subjects
Prabha et al., 2017 [25]	ECG	ML	SVM	80.00	Own	15 patients and 17 healthy
Jafari et al., 2013 [100]	ECG	ML	SVM	94.80	MIT PhysioNet Apnea	70 ECG recordings
Ramesh et al., 2021 [127]	ECG	ML	SVM	68.60	Wisconsin Sleep Cohort (WSC) dataset	1500 subjects
Memis etal. et al., 2017 [31]	ECG+ SpO_2	ML	SVM	96.64	MIT PhysioNet Apnea	70 ECG recordings
Wang et al., 2020 [146]	EEG	ML	SVM	94.33	Own	30 apnea patients
Vimala et al., 2019 [49]	EEG	ML	SVM	99.00	MIT-BIH Polysomno-graphic Database	14 subjects
Thacha et al., 2021 [26]	EEG	ML	SVM	92.18	CAP	108 PSG recordings

Belloet al.,2021 [24]	EEG	ML	SVM	82.69	UCDDB	25 PSG recordings
Almuhammadi et al., 2015 [101]	EEG	ML	SVM	97.14	MIT PhysioNet Apnea	70 ECG recordings
Onargan et al., 2021 [40]	EEG	ML	SVM	76.00	MIT PhysioNet Apnea	70 ECG recordings
Vahabi et al., 2021 [1]	EIT	ML	SVM	97.00	ImageNet dataset	15 subjects
Mencar et al., 2019 [129]	PaO_2 + $PaCO_2$	ML	SVM	NR	Own	313 patients
Behar et al., 2013 [126]	PPG	ML	SVM	92.30	Own	856 recordings
Selvaraj et al., 2014 [27]	PSG	ML	SVM	89.40	Own	53 healthy and untreated patients
Balci et al., 2022 [41]	PSG	ML	SVM	76.30	Own	19 subjects
Alvarez et al., 2020 [147]	SpO_2+AF	ML	SVM	94.80	Own	239 patients
Bricout et al., 2021 [69]	ADR	ML	Tree model	89.00	Own dataset	28 subjects
Sharma et al., 2021 [77]	SpO_2	ML	Tree model	95.70	MIT PhysioNet Apnea	70 ECG recordings
Liu et al., 2020 [48]	PSG	ML	XGBoost	91.28	MIT PhysioNet Apnea	70 ECG recordings
Pinho et al., 2019 [54]	ECG	ML	ANN	82.12	MIT PhysioNet Apnea	70 ECG recordings
Acharya et al., 2011 [30]	ECG	ML	ANN	90.00	Own	450 sets of apnea ECG data
Mitilineos et al., 2021 [96]	Snore sound	ML	ANN	97.30	Own	2500 sound excerpts
Tuncer et al., 2019 [34]	PTT	Hybrid	SVM + CNN	92.78	MIT PhysioNet Apnea	70 ECG recordings
Tuncer et al., 2019 [34]	PTT	Hybrid	KNN + CNN	91.72	MIT PhysioNet Apnea	70 ECG recordings