A systematic review on automatic identification of insomnia

Article *in* Physiological Measurement · January 2024

DOI: 10.1088/1361-6579/ad2059

8 authors, including:

Manisha Ingle
Visvesvaraya National Institute of Technology

Manish Sharma
Institute of Infrastructure Technology Research And Management

Kamlesh Kumar
Institute of Infrastructure Technology Research And Management

Prince Kumar

A Systematic Review on Automatic Identification of Insomnia

Manisha Ingle[1], **Manish Sharma**[2], **Kamlesh Kumar**[2], **Prince Kumar**[2], **Ankit Bhurane**[1], **Heather Elphick**[3], **Deepak Joshi** [4], **U. Rajendra Acharya** [5]

[1]Department of Electronics and Communication Engineering, Visvesvaraya National Intitute of Technology Nagpur, Nagpur-440010, Maharashtra, India
dt22ece003@students.vnit.ac.in; ankitbhurane@ece.vnit.ac.in

[2] Department of Electrical and Computer Science Engineering, Institute of Infrastructure Technology Research and Management, Ahmedabad 380026,India;
manishsharma.iitb@gmail.com; kamlesh.kumar.19e@iitram.ac.in (Student);
prince.kumar.19e@iitram.ac.in (Student)

[3] Sheffield Children's NHS Foundation Trust, Sheffield, UK; h.elphick@nhs.net

[4] Indian Institute of Technology Delhi Hauz Khas, New Delhi, Delhi 110016;
joshid@cbme.iitd.ac.in

[5] School of Mathematics, Physics and Computing, University of Southern Queensland, Springfield, Australia; Rajendra.Acharya@usq.edu.au

June 2023

Abstract. *Background*: Insomnia is a common sleep disorder in which a person has difficulty falling asleep or staying asleep, leading to disrupted sleep quality. Sleep makes up a significant portion of a person's life, and sufficient sleep is considered a crucial aspect of overall health. Poor sleep can lead to several physical and mental health problems, while getting enough sleep can boost the immune system and reduce the risk of major illnesses such as cancer and high blood sugar. With recent advancements in artificial intelligence (AI), machine learning (ML), and deep learning (DL), it is now possible to automate the analysis of sleep using various physiological signals. This has led to the development of multi-modal detectors and technologies that can assess physical exertion, sleep quality, and circadian measures, resulting in more accurate detection of various sleep disorders such as sleep apnea, narcolepsy, and schizophrenia. This paper aims to explore the algorithms and techniques described in the literature for the automatic detection of insomnia.

Methods: We have reviewed research papers published from 2015 to 2022 that focus on the automatic detection of insomnia, which is one of the most commonly occurring sleep disorders. Before 2016, traditional machine learning (ML) techniques were primarily used for this purpose. However, since 2017, deep learning (DL) technology has also been employed to identify sleep disorders. The studies we examined discussed a variety of ML and DL algorithms, including support vector machines (SVM), k-nearest neighbours (KNN), decision tree (DT), random forest (RF), linear discriminant analysis (LDA), convolutional neural network (CNN), and long short-term memory (LSTM) classifiers. These algorithms use different physiological signals to recognize insomnia.

Results: In our research, we have detailed a range of factors related to automated systems for detecting insomnia, including different algorithms, databases, features,

physiological signals, classifiers, and performance metrics, as well as the advantages and limitations of these systems. We have also noted that the continued development of DL algorithms will significantly impact future detection systems for insomnia. This is because DL algorithms require significantly more data for training and testing compared to traditional ML techniques. As a result, future systems may need to be designed with the ability to process large amounts of data effectively.
Conclusion: Based on our review of the studies included in this paper, we have identified a research gap in the current methods for identifying insomnia and opportunities for future advancements in the automation of insomnia detection. While the current techniques have shown promising results, there is still room for improvement in terms of accuracy and reliability. Future developments in technology and machine learning algorithms could help address these limitations and enable more effective and efficient identification of insomnia. For example, the integration of additional physiological signals and the use of more advanced deep learning models could lead to more accurate and comprehensive detection of insomnia.

Keywords: Insomnia, sleep disorder, automated detection, ML, DL

1. Introduction

Sleep is a vital physiological activity that the human body relies on to restore and rejuvenate itself, both mentally and physically [1]. Sleep is a crucial part of a person's daily routine and circadian rhythm, as it supports various functions that are essential for overall well-being. Adequate sleep is essential for the proper functioning of motor abilities, which include movements and actions controlled by the nervous system, such as walking, talking, and writing. In addition, sleep plays a critical role in cognitive capacity, which encompasses the mental processes involved in learning, thinking, and problem-solving. Adequate sleep also supports emotional and mental stability, as it helps to regulate mood and manage stress levels. [2]. In addition to supporting various bodily functions, sleep also plays a critical role in maintaining optimal physical health. For instance, adequate sleep can strengthen the immune system and carbohydrate metabolism, which helps lower the risk of developing serious illnesses, such as cancer and high blood sugar. Moreover, long-term sleep deprivation can increase the risk of developing alzheimer's disease because sleep is necessary for memory consolidation, retention and for reducing the buildup of the protein beta-amyloid, which can lead to dementia. Insufficient sleep has also been linked to an increased risk of coronary artery blockage and brittleness, which can raise the risk of heart disease, stroke, and congestive heart failure. Interestingly, the study of sleep disorders is not a recent phenomenon; as early as 1913, Henri Pieron, a French scientist, was already exploring sleep disorders [3]. There are numerous experimental research studies currently available that offer indisputable evidence of the importance of sleep for both humans and animals. Russian physician Marie de Manacéine studied sleep-deprived puppies that were kept in a continual state of activity. She asserted that being sleep-deprived for a few days was lethal. Italian physiologists Lamberto Daddi and Giulio Tarozzi conducted comparable studies in 1898 [4]. They kept the dogs awake by walking them; the animals perished after 9–17 days, and their survival was unrelated to food consumption. Similar to animals, insufficient sleep can be fatal to humans as well. For instance, when a person is driving while under the influence of insufficient sleep, which impairs their cognitive functioning and puts their own life as well as the lives of those around them in danger [5]. For another instance, in a rare hereditary illness termed fatal familial insomnia (FFI), the patient's sleeplessness became worse over time and no known medication appears to be able to induce sleep [6]. Eventually, the patient dies as a result of his physical and mental health decline.Even though it is obvious that getting enough sleep is crucial for maintaining a healthy lifestyle, many people struggle to get an appropriate night of sleep. In comparison to 32.7% of adults in two-parent homes and 31% of adults without children, 42.6% of single parents sleep less than seven hours every night [7].Struggling with sleep can be caused by a variety of factors, such as high levels of stress and anxiety, medical conditions like sleep apnea, poor sleep habits like consuming caffeine or alcohol too close to bedtime, psychological factors like depression, trauma or grief, and certain medications like antidepressants or stimulants [8, 9, 10, 11] etc. Losing the natural sleep rhythm can occur for a variety of reasons, including excessive caffeine consumption, jet lag, varying working shifts, etc. Sleep problems are diverse and require specific treatments targeted at the underlying cause. Accurately identifying the root cause is essential to effectively address sleep difficulties. [12, 13]. It is difficult to quantify the amount of sleep required because our sleep requirements vary according to age and other factors that are unique to each individual. Figure (1) depicts the average quantity of sleep people get at various stages of life [14].

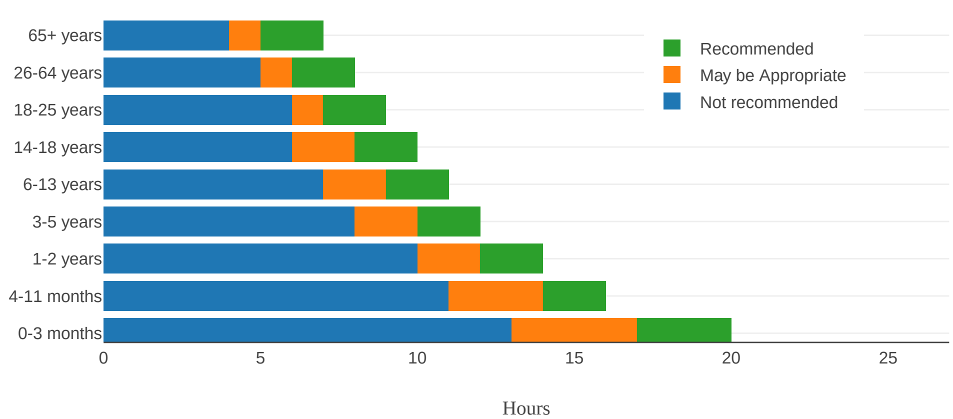


Figure 1: Graphical representation of age-wise sleep durations

Insomnia is a widespread sleep issue that impacts millions of individuals worldwide. It can have a detrimental impact on health and raise the risk of conditions like depression, anxiety, and heart disease. Over the years, as the importance of sleep was understood by researchers and the increasing rate of insomnia among the public was observed, several measures were devised for proper diagnosis of insomnia as reported in Figure (2). Conventional method use to diagnose insomnia such as questionnaire and sleep diaries are predominantly subjective and reliant on human recall, leading to significant biases [15]. The insomnia symptom questionnaire is a 13-item self-report tool used to diagnose insomnia.It is structured in three steps [16]: (a) determining the presence of difficulties beginning or maintaining sleep, or feeling that the sleep was non-restorative or didn't refresh the body. (b) determining the frequency of complaints and duration of these symptoms. (c) assessing the severity of daytime correlates of the sleep complaint. The sleep quality index is a self-reported questionnaire that evaluates

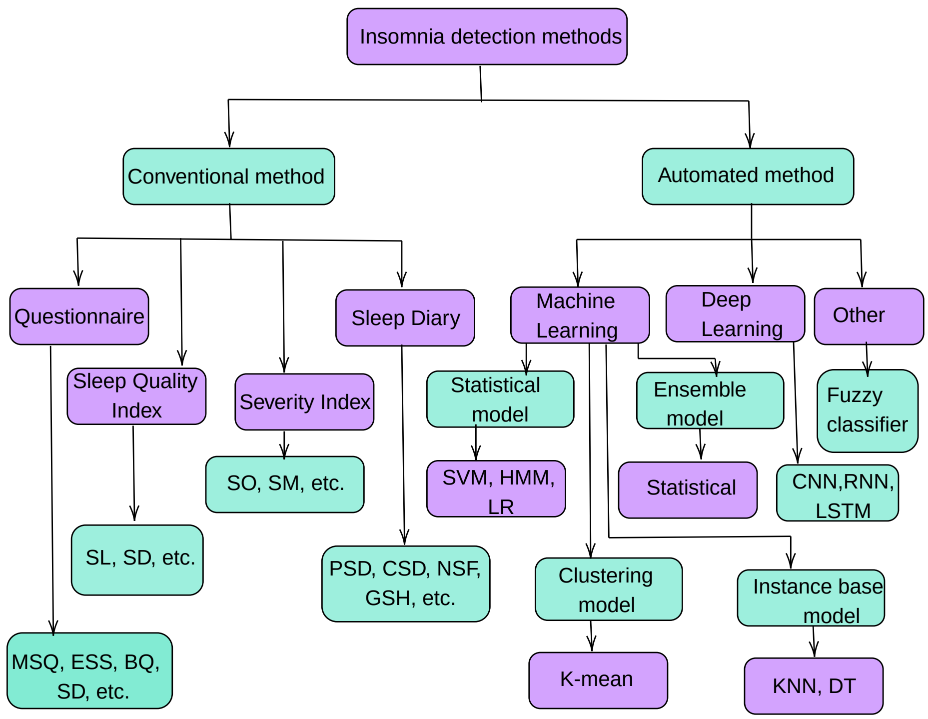


Figure 2: Illustration of various AI techniques employed for automated insomnia detection.

sleep quality and disruptions over a one-month period. Subjective sleep quality, sleep la- tency, sleep length, habitual sleep efficiency, sleep disruptions, usage of sleeping medicine, and daytime dysfunction are the parameters included to identify patient's sleep difficulties. The severity index is a seven-item self-assessment questionnaire that evaluates the nature, severity, and impact of insomnia. The dimensions assessed are: severity of sleep onset, sleep maintenance, and early morning awakening problems, sleep dissatisfaction, interference of sleep difficulties with daytime functioning, notice-ability of sleep problems by others, and distress caused by sleep difficulties. Sleep diaries can be used to identify and monitor insomnia, in which, patients proactively self-monitor or record their sleep on a night-by-night basis, which is an effective strategy for assessing and tracking therapy results. The consistent challenge in all the conventional approaches is that they all rely heavily on human input for accurate diagnosis. Thus, researches have started working on automatic detection techniques which uses physiological signals for the detection of insomnia. In this paper, we have seen ML based approaches to detect insomnia. Signals such as polysomnography (PSG), electroencephalography (EEG), actigraphy etc. are acquired using sleep monitoring of patients, these signals are then processed using different filters and transformation techniques so that it is ready for feature extraction.

Traditional methods of diagnosing insomnia often rely on subjective reports from patients, which may be biased or inaccurate. Automated detection methods, on the other hand, can analyze objective data such as EEG, ECG, or HRV to identify patterns that may indicate a sleep disorder, and can do so in a more efficient and standardized manner. Also, automated detection of insomnia has the potential to improve the accuracy and efficiency of identifying sleep disorders, allowing for earlier interventions and better outcomes for patients. Additionally, it can also be used in research to identify study participants with sleep disturbances, allowing for more accurate analysis and interpretation of study results. It can be integrated into consumer technology, providing users with personalized insights and recommendations for improving their sleep habits. Overall, the motivation for a review of automated detection of insomnia is to assess the current state of the field, identify areas of strengths and weaknesses, and highlight opportunities for future research and development. By improving our ability to accurately and efficiently detect insomnia, we can improve the lives and health outcomes of millions of people worldwide.

In this paper, we present a systematic assessment of studies by various research groups in the field of automatic detection of insomnia using physiological data, through various signals and also highlight the most cutting-edge ML and DL algorithms for application in certain domains. Figure (3) illustrates a graphical representation of the uniqueness of our study. This can serve as a foundation for future research and provide a sense of context for assessing recent discoveries. This review highlights:

- A detailed analysis of a broad set of algorithms from 31 research papers.
- An exploration of the possibility of automating sleep problem diagnosis using digital technologies and AI.
- We draw attention to the shortcomings of the current automated methods for detecting insomnia and make suggestions for improvements. Future directions for automated detection research have also been discussed.

The remainder of the article is structured as follows: The architecture of sleep is explained in section II. The environment for automated insomnia detection is discussed in section III. The technique used to compile the research papers is outlined in section IV. Section V represents the data analysis used for the study. Section VI describes different types of algorithms and classifiers related to the reviewed studies. Sections VII and VIII deal with discussion and conclusion, respectively.

Figure 3: Comparison of our study with other review papers related to insomnia detection.

2. The Anatomy of Sleep

Sleep architecture, refers to the basic structural organization of normal sleep. As per the Rechtschaffen and Kale's guidelines, the six stages of sleep are [17]: wakefulness (W), non-rapid eye movement (NREM)-S1, S2, S3, S4 and rapid eye movement (REM) are shown in Figure (4). Due to their similarities, the American Academy of Sleep Medicine (AASM) [18, 19] later designated S1 as N1, S2 as N2, S3 and S4 as slow wave sleep (SWS) or N3. Moreover, these phases are distinguished by the existence of different rhythms, as described:

- Wakefulness: This stage of sleep might be referred to as "wakefulness" based on the EEG patterns and different physiological changes. During this phase, the brain is at its most active. High-frequency alpha and beta rhythms are predominant during this period [20]

Table 1: List of abbreviations and acronyms used

Abbrevation	Definition	Abbrevation	Definition
AASM	American Academy of Sleep Medicine	MRI	Magnetic Resonance Imaging
ABWFB	Anti-symmetric biorthogonal wavelet filter bank	MSE	Multiscale Entropy
AI	Artificial Intelligence	MSQ	Mini Sleep Questionnaire
BQ	Berlin Questionnaire	MSV	Mean Square Value
CAP	Cyclic Alternating Pattern	NREM	Non-Rapid Eye Movement
CART	Classification And Regression Tree	PAC	Phase Amplitude Coupling
CCM	Complex Correlation Measure	PCA	Principal Component Analysis
CSD	Consensus Sleep Diary	PI	Primary Insomnia
DFA	Detrended Fluctuation Analysis	PRISMA	Preferred Reporting Items for Systematic Reviews and Meta Analysis
DL	Deep Learning	PSD	Pittsburgh Sleep Diary
DNN	Deep Neural Network	PSG	Polysomnography
DT	Decision Tree	PSQI	The Pittsburgh Sleep Quality Index
EBooT	Ensemble Boosted Trees	RCME	Refined Composite Multi-scale Entropy
EBDT	Embedded Bitmap Data Table	rDNA	Recombinant Deoxyribonucleic Acid
EBT	Ensemble Bagged Trees	ReHo	Regional Homogeneity
EBTC	Example-based text categorization	REM	Rapid Eye Movement
ECG	Electrocardiogram	RF	Random Forest
EEG	Electroencephalogram	ROC	Receiver Operating Characteristic
EMG	Electromyography	rsFC	Resting-state Functional brain Connectivity
EOG	Electrooculogram	RVR	Relevance Vector Regression
ESS	Epworth Sleepiness Scale	SampEn	Sample Entropy
FCS	Functional connectivity	SD	Standard Diary
GSH	Get Self Help Sleep Diary	SL	Sleep Latency
HMM	Hidden Markov Model	SM	Sleep Maintenance
JBDT	Joint Duration Bandwidth	SO	Sleep Onset
KNN	K-Nearest Neighbor	SQ	STOP Questionnaire
LDA	Linear Discriminant Analysis	SSA	Singular Spectrum Analysis
LLE	Largest Lyapunov Exponent	SVM	Support Vector Machine
LR	Logistic Regression	SWR	Sleep-Wake Ratio
LSTM	Long Short Term Memory	TAP	Thermometry, Actimetry, body Position
MASS	Massachusetts-Universities	TST	Total Sleep Time
ML	Machine Learning	VMHC	Voxel-mirrored homo topic

- N1: In this stage, low-frequency theta rhythms begin to replace the alpha rhythms. This is the lightest stage of sleep, and the sleeper could be awakened by noise, lights, or tremors outside [21]. The muscles begin to relax as the respiration and heart rates begin to calm down.
- N2: In this stage, EEG reveals very low-voltage, mixed-frequency activity in the brain that is characterized by the existence of sleep spindles, and k-complexes which are crucial for memory consolidation [22]. Memory and new tasks are stored during

this stage, and many sleep spindles are observed in those who learn or do something new before sleeping.

- Slow wave sleep (SWS) or N3: It comprises stages S3 and S4. Low-frequency delta waves are most prevalent in stages S3 and S4. They first show up in S3 and predominate in S4. The respiration and heart rate are the slowest at this point.
- REM: It is preceded by the NREM sleep stage. Theta rhythms, flat EEG waves, Sawtooth waves, and low muscle tones in EMG characterize it. The breathing becomes erratic, and the heart rate rises throughout this phase. In this stage, dreams are present, and the muscles constrict to inhibit movement because of dreams [23].

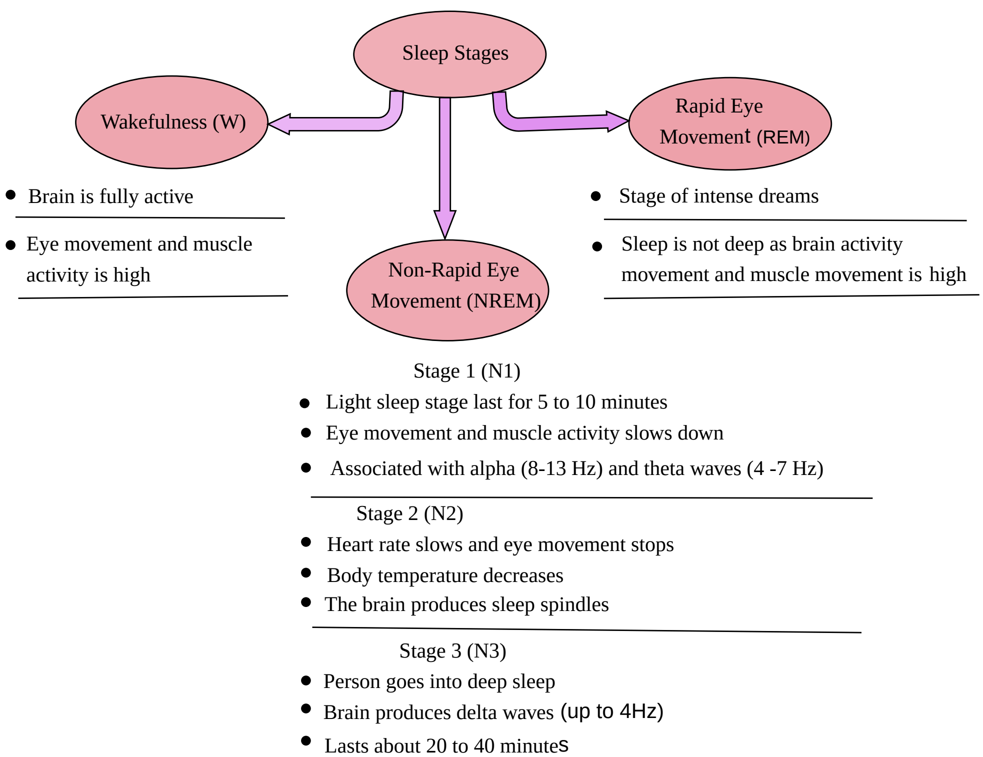


Figure 4: Details of various sleep stages.

At some point in our lives, almost everyone has a transitory sleep impairment. For up to 40% of the population, these disturbances persist and develop into chronic conditions. The most typical condition is insomnia [24, 25]. A person has insomnia when they are unable to get enough or good quality sleep, or when they find it difficult to get to sleep or to stay asleep. Acute and chronic insomnia can be categorized into two groups [26, 27]. A change in the sleep environment, stress at work, self-medication, and other circumstances can cause acute insomnia, which typically lasts for one to two weeks. The reason for chronic insomnia, however, is more complicated and calls for a more strategic approach because it may be either physical (caused by certain medications or a long-term medical condition like asthma) or psychological (for example, if a person experiences insomnia due to stress but even after the stress goes away the patient continues to experience insomnia) [28, 29]. Insomnia that lasts more than a month or at least three nights per week is often referred to as chronic insomnia [30, 31], which is further classified as primary or secondary. Insomnia with a psychological cause is referred to as primary insomnia (PI), also known as psychophysiological insomnia. Subclinical mood disorders and conditioned arousal to the bedroom are two causes of PI. As an alternative, a medical or psychological condition results in secondary insomnia (SI). Medical conditions including cancer, lung illness, hypertension, etc. can all contribute to SI. Secondary insomnia can also be brought on by mood and worry [32].

Traditionally, in physical examination, a review of the patient's sleeping patterns, or a sleep study, is used to diagnose insomnia [33]. The majority of approaches developed to diagnose insomnia are primarily reliant on patient responses. Despite providing adequate prediction accuracy, traditional approaches can lead to incorrect diagnoses for patients. This occurs because patients frequently provide erroneous or inaccurate information on sleep surveys, either on purpose or unintentionally, which results in poor prediction [34]. Similarly to this, the issue of misleading reporting in sleep diaries is persistent. Additionally, patients frequently find it tedious to describe their sleep each day, which hinders diagnosis [35]. The issue with conventional methods is that, to provide an accurate diagnosis, they all significantly rely on human input. As a result, scientists have begun to develop automatic detection methods for insomnia that rely on physiological cues, yet there is currently no definite test to identify insomnia [36].

AI and ML have recently been used to develop automated methods for the identification of insomnia. AI refers to the ability of a computer or a robot to develop human-like intelligence, this is made attainable by learning algorithms that try to simulate, how the human brain learns [37]. AI has been able to advance medical sciences by employing ML algorithms to mimic human cognition in the analysis of complex or large data sets to identify and treat diseases or disorders. ML is the process of using trained learning algorithms to automate the tracking of changes in data patterns. The data can be divided into two sets: a training and a test set, a specific algorithm is then trained using the training set which includes particular features, that do not provide any discrimination and are then deleted to reduce the computation time. This process is then repeated to fine-tune the learning model for increasing the prediction accuracy [38]. Features are extracted from any biomedical signal data (for example, polysomnography for insomnia), and then they are collected as data to be used for training and testing [39]. After the data is processed and run through the machine learning model, the model's performance is defined by key performance factors such as precision, sensitivity and F1 score [40].

3. Background for automated detection of insomnia

Automated identification of insomnia is the process of spotting possible cases of insomnia or other sleep disorders using technology and algorithms.It can be used in many settings, including healthcare, research, and consumer technology. Automated insomnia detection in healthcare can assist in identifying patients who might benefit from additional sleep problem testing or therapy. It can be used in research to identify study participants who have insomnia or other sleep problems, enabling more precise analysis and interpretation of study findings. It can be incorporated into smartphone apps or wearable technologies to give consumers individualized information and suggestions for bettering their sleeping patterns.In this paper, we have seen ML and DL based approaches to detect insomnia, which is explained with the help of Figure (5). Signals such as PSG, MRI, CT, PET, actigraphy etc. are acquired using sleep monitoring of patients, these signals are then processed using different filters and transformation techniques so that it is ready for feature extraction. Because of the noise, stochastic nature of the signals, and significant variability both within and between individuals, characterization of biological signals is difficult. A feature is a quantifiable quantity derived from the signal's patterns. The process of feature extraction is very important as it reduces the size of the data used for computation or analysis significantly. The extracted features can be represented in various forms such as frequency-based features obtained using Fourier analysis, time-frequency features obtained using the short-time Fourier transform and the wavelet transform, statistical features by using moments and correlation analysis.

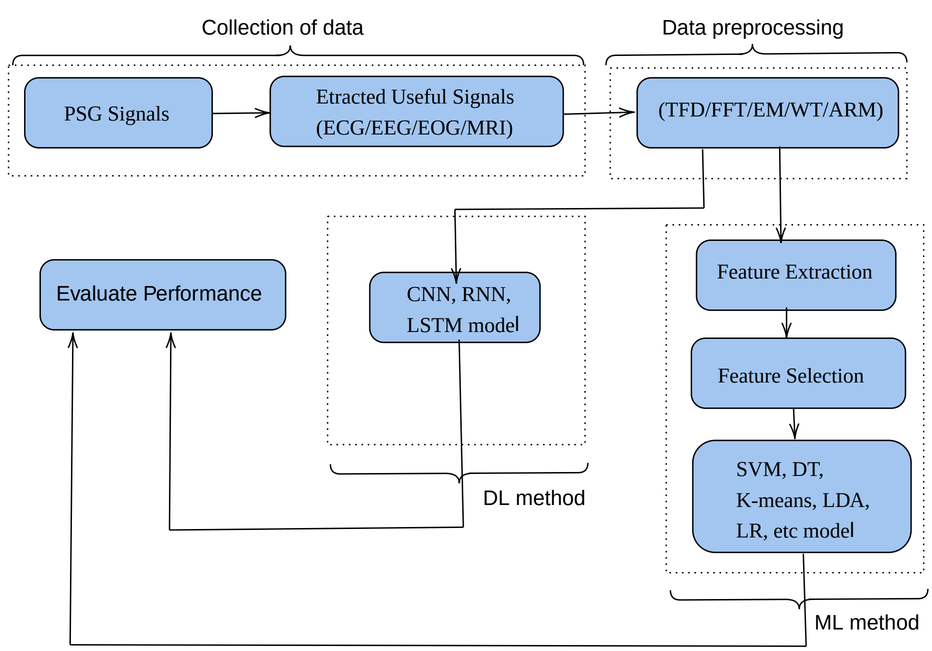


Figure 5: General framework used for automatic detection of insomnia.

3.1. Signals used in the studies

Several physiological signals are being researched for their applications in the automated detection of insomnia. Some of the most commonly studied signals include:

3.1.1. CT (Computed Tomography) CT is an imaging modality that uses X-rays to produce detailed images of the body. It can be used to detect abnormalities in the brain or other parts of the body that may be causing sleep disturbances, such as tumors or structural abnormalities. Also, it can be used to detect sinus or nasal abnormalities that may be causing breathing problems during sleep. However, CT does have some limitations when it comes to studying sleep disorders like insomnia [41]. One of the main limitations is that CT uses ionizing radiation, which can be harmful if used excessively. Also, the changes found on CT scanning would account for a tiny proportion of the causes of insomnia, as the majority are not due to a structural abnormality.

3.1.2. PSG (Polysomnography) A sleep study, commonly known as polysomnography, is a comprehensive examination used to diagnose sleep disorders. During the study, polysomnography records your brain waves, blood oxygen levels, heart rate, and respiration, as well as eye and leg movements. PSG recordings includes multichannel signals from electroencephalogram (EEG), electrocardiogram (ECG), electromyography (EMG), and electrooculography (EOG) [42].

- EEG (Electroencephalography): EEG measures the electrical activity of the brain and is commonly used to study sleep patterns. Studies have shown that changes in EEG patterns during sleep can be indicative of insomnia.
- ECG (Electrocardiography): ECG measures the electrical activity of the heart and can be used to study heart rate variability (HRV). HRV is associated with sleep quality, and studies have shown that changes in HRV patterns can be indicative of insomnia.
- EOG (Electrooculography) is a technique for determining the corneal-retinal standing potential, which exists between the front and back of the human eye. The electrooculogram is the name given to the signal that arises as a result of this process
- Actigraphy: Actigraphy is a non-invasive method of monitoring movement and activity levels using a small wearable device. It is often used to study sleep patterns and can be used to detect disruptions in sleep caused by insomnia.
- Respiratory signals: Respiratory signals, such as respiration rate and airflow, can also be indicative of insomnia. Sleep-disordered breathing, which includes conditions such as sleep apnea, is a common cause of secondary insomnia.

3.1.3. MRI (Magnetic Resonance Imaging) MRI is a non-invasive imaging modality that uses strong magnetic fields and radio waves to produce detailed images of the brain.

While MRI is not commonly used as a primary tool for the diagnosis of insomnia, it can be used to study brain anatomy and function in individuals with insomnia and other sleep disorders. Some studies have used MRI to investigate structural changes in the brains of individuals with insomnia. For example, one study found that individuals with chronic insomnia had reduced gray matter volume in certain regions of the brain, including the frontal cortex, compared to healthy controls [43]. MRI can also be used to study brain function in individuals with insomnia. For example, functional MRI can be used to measure changes in blood flow and oxygenation in the brain, which are indicative of changes in neural activity. Overall, while other imaging modalities such as MRI, CT, and PET have their own strengths and are useful for studying different aspects of the brain, EEG is often preferred for the detection and study of sleep disorders such as insomnia due to its high temporal resolution, non-invasiveness, portability, and ability to directly measure neural activity.

3.1.4. Various DL methods Deep learning has become increasingly popular in scientific computing, and its algorithms are widely utilized by various industries to solve complex problems. Different types of neural networks shown in Figure 6 are used by deep learning algorithms to perform specific tasks [44, 45].

Convolutional Neural Nets (CNNs): The primary objective of a CNN is to extract

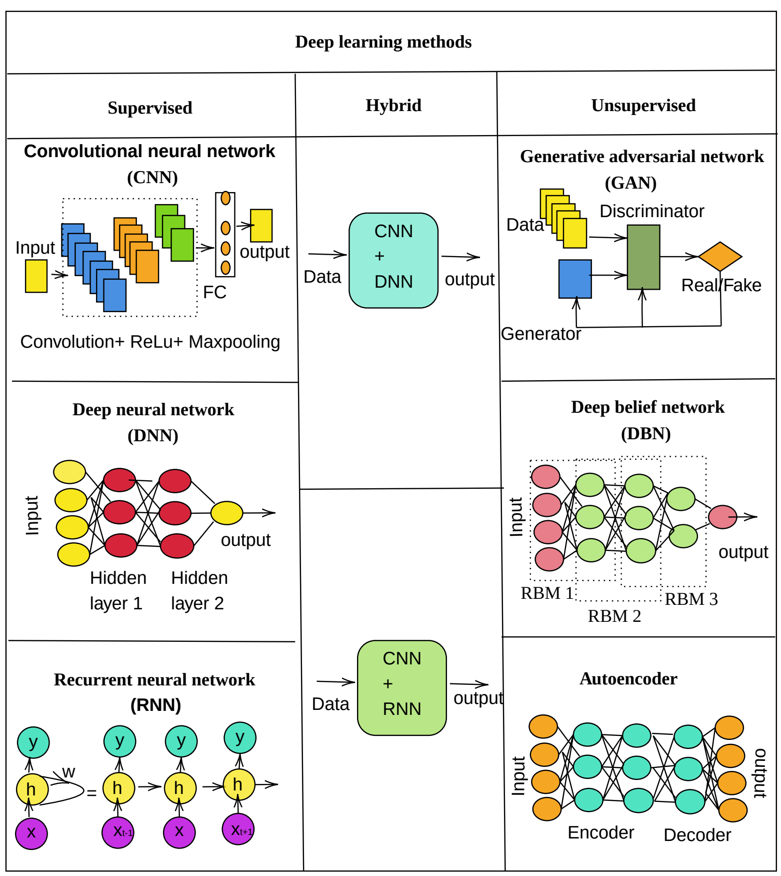


Figure 6: Various DL architectures used for automated insomnia detection.

higher-level features in the input data using convolutional operations. This capability has made CNNs highly effective in image recognition tasks, which has helped to establish the power of deep learning. In a CNN, the input data is processed through connected layers, ultimately producing a set of class scores in the output layer. Each neuron in a given layer is connected to a small patch of the output from the previous layer, enabling the network to identify and extract relevant features from the input data.
Deep Neural Networks (DNNs): commonly implemented as feed forward networks (FFNNs), where the input data moves forward through the layers towards the output layer without any backward flow. The connections between the layers are one-way, in the forward direction, and the nodes are not revisited.

Recurrent Neural Networks (RNNs): They are designed with connections that form directed cycles. These cycles enable the output of the long short-term memory (LSTM) to be utilized as an input for the current phase. This allows RNNs to have a memory component, which can retain information from previous inputs.The internal memory of LSTM enables it to remember previous inputs, which makes it especially useful for tasks that require the analysis of sequential data.
Generative Adversarial Networks (GANs): It is a type of deep learning algorithm that can create new data instances similar to the ones found in the training data. GANs consist of two components: a generator that learns to produce synthetic data and a discriminator that learns to differentiate between real and fake data. GANs have been used to generate realistic images and cartoons, create lifelike photographs of human faces, and render 3D objects.
Deep Belief Networks (DBNs): These models that involve multiple layers of stochastic, latent variables and are used for generative purposes. The latent variables, also called hidden units, have binary values and are organized into multiple layers of Restricted Boltzmann Machines (RBMs) that communicate with each other. DBNs are utilized in image and video recognition, as well as motion-capture data.
Autoencoders: These are a kind of feedforward neural network where the input and output layers are identical. Autoencoders work by training neural networks to replicate data from the input layer to the output layer. They are useful for various purposes, such as pharmaceutical discovery, predicting popularity, and processing images.

4. Review method

This systematic review was conducted according to PRISMA guidelines, which is a widely used framework for reporting systematic reviews and meta-analyses in the health and medical sciences.

4.1. Inclusive and exclusive criteria

In the inclusive criteria, Google Scholar, IEEE, Science Direct and PubMed were used to search the articles that had terms such as “Insomnia Detection”, “Automated

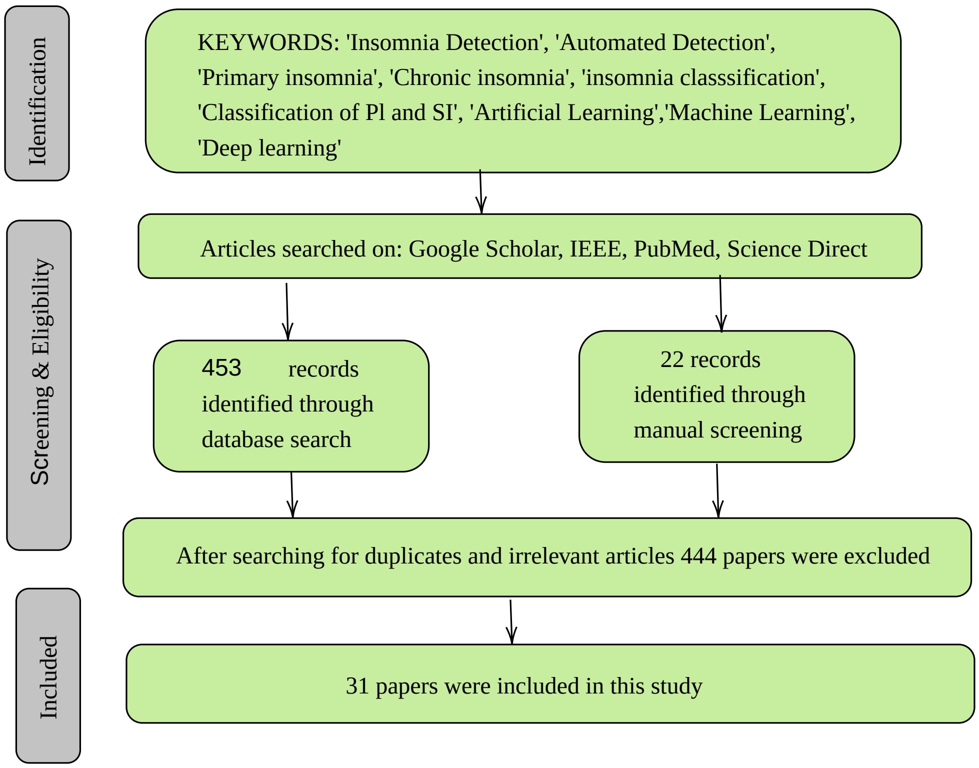


Figure 7: PRISMA guidelines employed for the selection of papers for automat detection of insomnia

Detection", "Primary Insomnia", "Chronic Insomnia", "Insomnia classification", "PI and SI classification", "Artificial Learning", "Machine Learning", "Deep learning" regardless of the publication year. In addition, related papers found in the reference of other papers were also included. Evaluated publications that have researched the automated detection of insomnia, to distinguish between primary and secondary insomnia, were eligible for inclusion. In the exclusive criteria papers whose study subjects were insomnia, or their classification, but there was no automated process involved for its identification or classification were discarded. Papers whose objective was not to detect insomnia, but focused on its treatment, were also excluded. Papers whose aim was to advance AI and ML in medical sciences, but insomnia was not part of the study, were excluded. The database search results are explained in further detail in the table (2).

4.2. Screening of papers

The search yielded a total of 475 publications across the databases. After excluding 372 duplicate articles, the remaining 103 articles were manually screened based on the relevance of their titles and abstracts to the review topic. For manual screening, the criteria were decided based on the applicability and experimental setup used in the individual study, which comprises whether the proposed method is tested on untrained /

Table 2: Database search results.

Sr. No.	Database	No. of results	Keywords
1	IEEE	36	“insomnia detection”, “automated detection”,
2	Google Scholar	252	“primary and secondary insomnia”, “chronic
3	PubMed	7	insomnia”, “insomnia classsification”, “artificial
4	Science Direct	180	learning”, “ML”, “DL”

test data or implemented on real hardware, which supports its efficacy in the detection of insomnia at home. This criterion helped us to segregate 62 irrelevant articles from the batch of 103. Full-text versions were retrieved for the remaining 41 articles and analyzed thoroughly. 10 of them were excluded after reading, as the studies had not been specifically designed for the detection of insomnia. Thus, 31 articles chosen for this review satisfy the condition of presenting novel studies for the detection of insomnia. Additionally, these studies also sustain against their methodologies for detecting insomnia using EEG, ECG, EOG, EMG, MRI, PSG, and actigraphy signals, which include either ML or DL algorithms, for classification between insomniac patients and normal subjects only [46, 47]. Figure (7) shows the flow chart of the search strategy, with ‘n’ being the number of articles. As the majority of the articles (31 articles) were published after 2014, figure (8) describes the timeline chosen for this review is roughly the last ten years. This highlights how important this topic is and how important it is for a review to consolidate the various approaches that have been taken and identify new research lines.

5. Database

Most of the studies were based on private databases, which are acquired at the respective hospitals and not publicly available, For example, Morilla et al. [48] use one of the largest privately available databases of 262 subjects from the Chronobiology Laboratory located at the University of Murcia. The rest of the studies were based on one or two of the following open-access datasets that are available on Physio Net: CAP [49], and Mendeley Dataset [50]. The details of these public databases, which are available for study on Physio net and others, are provided in Figure (9). Many sleep researchers have used this well-liked open-access dataset [36, 51, 52, 53], which comprises overnight PSG recordings.

5.1. Feature Extraction

For feature extraction, the physiological signal can be analyzed in different domains.The physiological signal can be examined in the time and frequency domains for feature extraction. The different time domain features are mean absolute value (MAV), zero

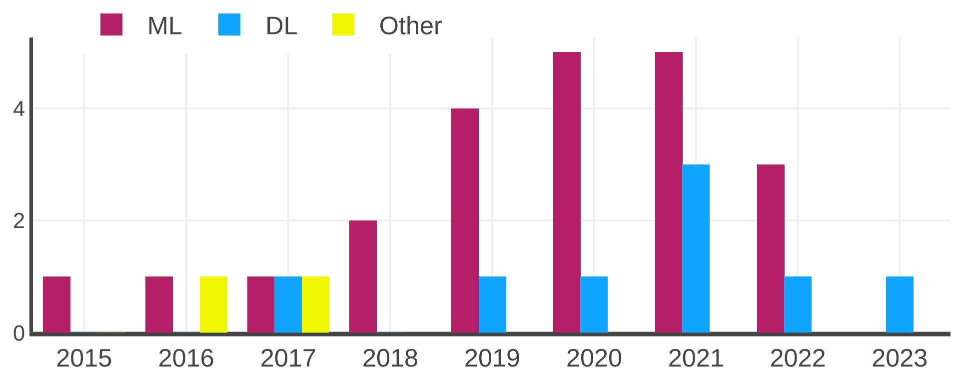


Figure 8: Number of insomnia studies conducted every year from 2015 to 2022.

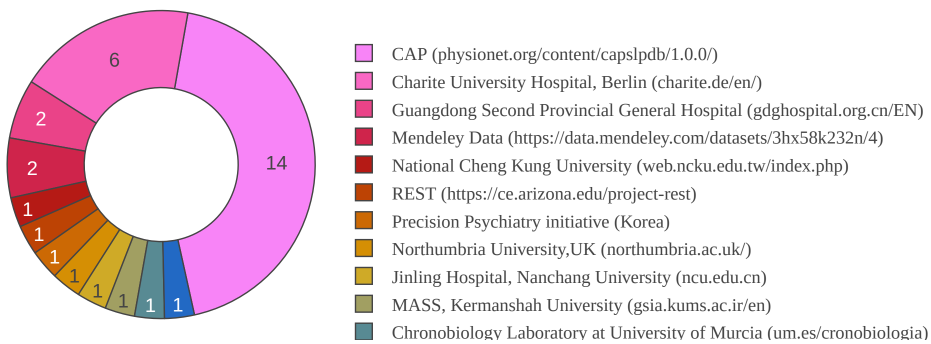


Figure 9: Data set used for Insomnia

crossings (ZC), slope sign changes (slope sign), waveform length (wavelet), and Willison amplitude (wAmp) [54, 55]. In addition to this, the study reviewed included standard deviation, zero crossing rate, Hjorth parameters (mobility and complexity), peak-to-peak amplitude, root-mean-square (RMS). Frequency domain features can be extracted widely by fast Fourier transform (FFT) and power spectral density (PSD). Physiological signal feature extraction also uses wavelet transform (WT), fast Fourier transform (FFT), short time Fourier transform (STFT), and Fourier transform (FT).

6. Comparative Analysis

The bulk of articles was carried out as a result of current advancements in AI. The study includes 22 (ML) and 7 (DL) research articles in total. We evaluated 31 papers on insomnia detection based on author, year of publication, data set, Number of subjects, features, classifier, signals, sensitivity, specificity, and accuracy included in Table (3).

Table 3: Summary of papers, considered for this study.

Authors	Year	Dataset	No. of subjects	Features/ Techniques	Classifier	Signals	Sen. (%)	Spc. (%)	Acc. (%)
Sharma et al. [56]	2022	CAP	108 (66 insomnia)	Wavelet transform, maximally flat bi-orthogonal filter bank, 8 sub-bands for EMG, 5 sub-bands for EOG Hjorth parameters Features: 42 (24 EMG, 18 EOG)	EBTC	EOG, EMG	-	-	94.3
Tripathi et al. [57]	2022	CAP	14 (8 insomnia)	PSD Features: Heart rate variability (HRV)	RF, DT, LDA	ECG	96	94	96
Murarka et al. [58]	2022	CAP	75 (6-insomnia)	1-D CNN	CNN	EEG	56.5	86.41	70.88
Tiwari et al. [59]	2022	-	-	FFT	KNN, ANN, SVM	EEG	83, 94, 98	85, 92, 97	88, 92, 99
Urtnasan et al. [60]	2021	CAP	35 (7 insomnia)	1D-DL	CNN	ECG	-	-	97
Sharma et al. [36]	2021	CAP	13 (7 insomnia)	ABWFB, JDBL, Features: 6 Features (L-1,2,3,4 and infinity norm and p- norm)	SVM, KNN	ECG	99.34	98.72	97, 87
Kusmakar et al. [61]	2021	project REST [62]	80 subjects (40 insomnia)	N-fold cross-validation, Intensity filters (wake limits =0, 20, 40, 80) Features: 12 features (mean, SD, Poincare Map, Ratio, CCM, SampEn, TST, SL, WASO, SWR, SE	RF, SVM	Actigraphy	76	82	80,75
Sharma et al. [63]	2021	CAP	13 (7 insomnia)	Biorthogonal filter bank, wavelet-based norm features, six sub-bands from 1-D wavelet decomposition (A, D1, D2, D3. D4, D5) Features: L1, L2, L-infinity features for each sub-band	SVM, KNN, EBT, EBooT	EEG	-	-	71.2, 77.2, 90.7, 61.2
Malik et al. [64]	2021	CAP	108 (92 insomnia)	Empirical mode decomposition Features: Statistical, time, frequency, time-frequency domain, chaotic 6 ECG, 6 EMG	KNN, LR	ECG, EMG	-	-	-
Wei Qu et al. [65]	2021	MASS, Kermanshah University Institute of Medical Research (Woolcock), Australia	32 (41 insomnia)	Domain classifier, Activation map visualization Features: Encoders, decoders	LSTM	EEG, EOG, EMG, ECG	-	-	90.9
Dimitriadis et al. [66]	2021	CAP	9 (insomnia)	PSD, PAC	RF	EEG	-	-	74
Miracle et al. [67]	2021	CAP	44 (8 insomnia)	DL	CNN	ECG	-	-	89

Authors	Year	Dataset	No. of subjects	Features/ Techniques	Classifier	Signals	Sen. (%)	Spc. (%)	Acc. (%)
Kuo et al. [52]	2020	National Cheng Kung University	32 (16 insomnia)	Method: RCMSE, MSE	SVM	EOG	96.63	82	89.31
Angelova et al. [51]	2020	Northumbria University, UK	45 (21 insomnia)	N-fold cross-validation (N = 45) Features: 10 features (mean, SD, Poincare Map, ratio, CCM, SampEn, TST, WASO, SWR)	RF, SVM	Nocturnal Actigraphy	76	92	84, 73
Dai et al. [68]	2020	Jinling Hospital and Hospital of Nanchang University	96 (48 insomnia)	VMHC, seed-based connectivity, 5-fold cross validation	SVM, ROC curve	MRI	81.3	87.5	88
Ma et al. [69]	2020	Guangdong Second Provincial General Hospital	76 (30 acute insomnia)	PSQI, whole brain nodal rsFc	RVR	MRI	-	-	-
Yang et al. [70]	2020	CAP	18 (9-normal,9-insomnia)	SSA, Hjorth, PSD	CNN	EEG	-	-	99.16
Heyat et al. [71]	2020	CAP	14 (8-insomnia)	PSD, Welch method	KNN, NN	ECG	99.9, 73.3	99.9, 58.3	99.9, 73.3
Park et al. [52]	2019	Precision Psychiatry initiative (Korea Advanced Institute of Science and Technology)	42 patients (ISI Score greater-than 15)	Butterworth filter, 5-fold cross-validation Features: 40 features (HYP-m), 57 features (EEG-m)	SVM	EEG, HYP-M	96.63	82	89.31
Li et al. [72]	2019	Guangdong Second Provincial General Hospital	82 (38 insomnia)	Voxel wise FCS large scale FC, ReHo Features: 3 types of FC features	SVM	MRI	84.9	79.1	81.5
Morilla et al. [48]	2019	Chronobiology Laboratory at University of Murcia	262 (184 insomnia)	–	DT	wrist temperature, body position, motor activity	88.5	71.4	88.4
Liu et al. [73]	2019	First Affiliated Hospital of Jinan University in Guangzhou, China	20 (insomnia)	Monte Carlo permutation, Student's t-test	RF, ANN	rDNA	-	-	-
Mendonça et al. [74]	2019	CAP	34 (19-insomnia)	-	LSTM	EEG	75	77	76
Abdullah et al. [75]	2018	Private (collected at Charité University)	20 (10 insomnia)	LLE, DFA, SampEn Features: 3 Non-linear EEG features	SVM	EEG	85	80	83
Mostafa et al. [76]	2018	Charité University Hospital, Berlin	115 (54-insomnia)	Statistical, Hjorth parameter, amplitude	LDA, CART, SVM	EEG	65, 53, 65	71, 97, 81	71, 73, 74

Authors	Year	Dataset	No. of subjects	Domain/Features	Classifier	Signals	Sen. (%)	Spc. (%)	Acc. (%)
Mulaffer et al. [77]	2017	Private (collected at Charité University)	124 (54 insomnia)	Butterworth filter, 5-fold cross-validation Features: 40 features(HYP-m), 57 features(EEG-m)	SVM	EEG, HYP-M	-	-	76
M. Rezaei et al. [78]	2017	Mendeley Data	22 (11 insomnia)	Power spectrum analysis independent component analysis (ICA) Features: frequency domain, 14 EEG,6 EOG, 3 EMG	Poincare's map	EEG, EOG, EMG	-	-	-
Shahin et al. [79]	2017	Charite University Hospital, Berlin	83 (42 insomnia)	DNN	DNN-HMM	EEG	-	-	92
Siddiqui et al. [80]	2016	CAP (Physio Net)	25 (9 insomnia)	Method: PSD Features: 3 types of FC features	-	EEG	-	-	-
Hamida et al. [81]	2016	Charite University Hospital, Berlin	35 (19 insomnia)	Hjorth parameters, Power and ratios of relative power Features: 24	PCA	EEG	99.2	89.9	91
Hamida et al. [82]	2015	Charite University Hospital, Berlin	36 (18 insomnia)	Hjorth parameters	K-means clustering	EEG	89	91.8	-

6.1. Performance metrics

Studies use various performance metrics to evaluate and show the results of their work. It is possible to evaluate the performance of the categorization using a variety of measures. Calculated by taking into account the true positive (T_P), true negative (T_N), false positive (F_P), false negative (F_N) and (P_e) as Relative observed agreement among raters and (P_o) Hypothetical probability of chance agreement values are the parameters that are most often shared throughout all the works. These parameters may be represented by Baratloo et al.[81]. The accuracy (A_{CC}), specificity (S_{PC}), precision (or positive predictive value P_{PV}), and recall (or sensitivity), may be defined as follows

$$S_{PC} = \frac{T_N}{T_P + F_P} \tag{1}$$

$$S_{EN} = \frac{T_P}{T_P + F_N} \tag{2}$$

$$P_{PV} = \frac{T_P}{T_P + F_P} \tag{3}$$

$$A_{CC} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{4}$$

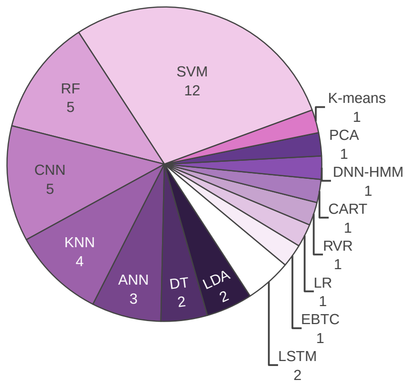
$$K = \frac{P_o - P_e}{1 - P_e} \tag{5}$$

In some research, receiver operating characteristic evaluations were also carried out to evaluate the discriminating effectiveness of various constructed models. For this review, only S_{EN}, S_{PC}, Kappa and A_{CC} results were compared across the selected studies. The performance of the 31 studies in this review is summarized in Table 3.

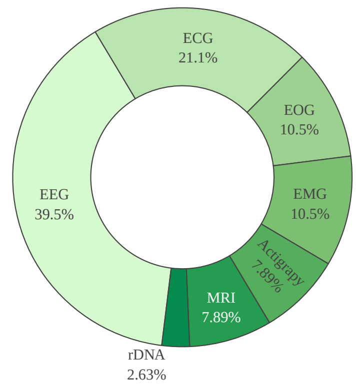
6.2. Detailed analysis of insomnia detection using ML

Various physiological signals are being researched for their applications in the automated detection of insomnia. We have observed that EEG and PSG were the most often employed physiological signals for detection. [81, 75, 77, 76, 35]. According to Hamida et al., [81], utilizing Hjorth parameters features derived in the time-frequency domain, a k means classifier was employed to accurately predict insomnia. The technique was modified since each person's EEG signals have specific patterns that are impacted by different physiological processes (e.g., arousal, onset, hypnosis, etc.). The time-frequency domains of the signal are affected by these events. The Interdisciplinary Sleep Center at Charité University Hospital in Berlin collected the data on a total of 36 individuals (18 with primary insomnia and 18 controls). The approach produced the greatest kappa= 0.83 and sensitivity of 91.6% of any model created using EEG inputs. In contrast to previous research, the data set taken into consideration for this was quite limited. The study with the largest data set that used EEG/PSG signal is performed by Mullafer et al. [77]. In this study, an SVM classifier was used to assess two distinct methods for identifying insomnia. Participants for this study were recruited at the Interdisciplinary Sleep Center of Charité University Hospital in Berlin, Germany, a total of 124 individuals participated of which 54 were suffering from insomnia, and the remaining were Normal Patients. using SVM Classifier, EEG-m achieved an accuracy of 81% while another method, HYP-m achieved an accuracy of 71.3%. For the EEG-m, 57 features (statistical measures, Hjorth parameters, amplitude measures, spectral measures etc.) per channel were extracted. They found 40 additional features: 5 stage ratio features that assessed the number of epochs per stage over the overall number of epochs, 15 transition ratio features that measured the number of transitions between every two stages, and 20 stage pair ratio features which measured the number of epochs per stage over the number of epochs of a different stage. Other notable work by Abdullah et al. [75]included high accuracy levels. The study aimed to classify non-linear EEG features using an SVM classifier. At Charité University (Berlin, Germany), PSG data were gathered from 10 healthy people and 10 patients with primary insomnia. N1, N2, and N3 are the stages of sleep. A 30-second epoch was used to score REM and NREM. The EEG channel C3–A2 with a sampling frequency of 100 Hz was studied. The nonlinear measurements were extracted at a frequency of 200 Hz. The study by Shahin et al. [76], proposed a method in which each epoch is assigned to one of the sleep phases (W, N1, N2, N3, or REM) by an automatic sleep stage scoring classifier, and an epoch-level control/insomnia classifier distinguishes epochs from insomnia and control participants. Both classifiers are DNN based and fed 114 characteristics extracted from the EEG channels C3 and C4. When an RBF SVM classifier was trained using a mixture of the two feature sets, the system attained an F1 score of 83%.

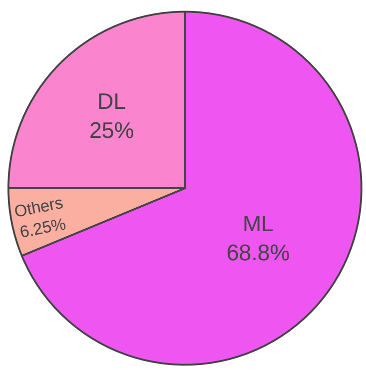
There is a unique study that has utilized ECG signals for feature extraction [35]. In this study, an optimal antisymmetric bi-orthogonal wavelet filter bank (ABWFB) has



(a) Distribution of classifiers for insomnia



(b) Distribution of signals for insomnia



(c) Distribution of automated method for insomnia detection

Figure 10: Results obtained for automated insomnia detection using various classifiers, physiological signals and AI techniques

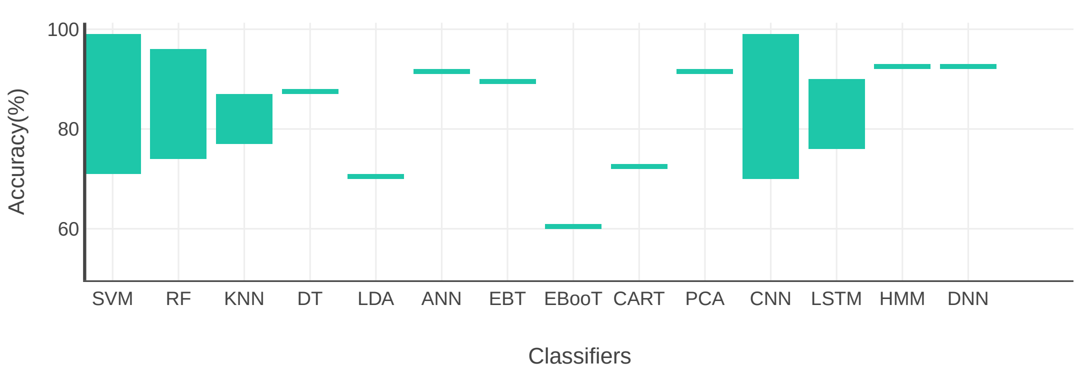


Figure 11: Bar graph representation of accuracy obtained by various AI methods for automated insomnia detection.

been used. The L-1 norm features are extracted using ECG signals, this is a unique approach to the extraction of features. The study utilized the CAP sleep database which is an open-source database, a total of 13 patients were included in the study, out of which 7 were insomniac patients and 6 were healthy. With the ten-fold cross-validation approach and ECG signals corresponding to the REM sleep stage, the study attained the greatest classification accuracy of 97.87 %, F1-score of 97.39%, and Cohen's kappa value of 0.9559 for K-nearest neighbor (KNN). With tenfold cross-validation matching to the REM sleep stage, the support vector machine (SVM) produced the highest value of 0.99 for the area under the curve. Another study [83] has used the EOG signal of PSG for insomnia identification. Firstly, the EOG signal was filtered using a band-pass signal then features were extracted using RCMSE values with a scale factor of 1 to 8 using 30s epochs. After that, the RCMSE values with a scale factor of 1 to 9 within the first 27.5 minutes were used to compute the mean as an input to the classifier.

Since the monitoring of PSG signals requires the visitation to sleep centres, a few researchers have come up with theories to detect insomnia using actigraphy data from wearable devices such as Fitbit [84, 85]. Angelova et al. [51] and Kusmakar et al. [61] have also used actigraphy signals as data for the classifiers. Identification using actigraphy signals is beneficial as monitoring can be conducted in a more natural environment and can be made more accessible. The highest accuracy using actigraphy signals was achieved by Morilla et al. [48] with an accuracy of 88.4%, a specificity of 88.5, a sensitivity of 71.4, and 0.90 as the area under the curve (AUC). They also have the largest data set with a total of 262 patients out of which 184 were insomnia subjects. Using actigraphy sensors an integrated variable called TAP (thermometry, actimetry, and body position) was initialized, it showed higher accuracy when these three parameters were considered individually. To initialize TAP, all three signals were normalized between 0 and 1, then sleep probability was determined using a dynamically defined threshold. Four indexes were calculated by non-parametric analysis, they included a sleep phase marker (TAP-L5h), a wakefulness phase marker (TAP-M10h), a global index of circadian rhythms' robustness (sleep CFI), and TAP-RA gives information on sleep depth and diurnal activation. Using these indexes, a decision tree was built that discriminated subjects as insomniacs, delayed sleep phase syndrome, and healthy. Another notable study is proposed by Angelova et al.[51], in which nocturnal actigraphy data from seven nights was taken for people with acute insomnia. The main source for feature extraction is the actigraphy time series data, whose collection was approved by the University of Glasgow Ethics Committee. A total of 10 linear and non-linear features were selected using statistical operations and 3 features total sleep time (TST), wake after sleep onset (WASO), and sleep-wake ratio (SWR)) obtained directly from the actigraphy signal. Using 4 different filters on these features, 40 were extracted, and then RF and SVM classifiers were used for classification. RF showed better performance (accuracy- 84%) than SVM (73%) in classifying individuals with insomnia from healthy sleepers. Meanwhile, Kusmakar et al. [61] analyzed nocturnal awakenings in individuals with chronic insomnia (CI) and their cohabiting spouses using actigraphy signals from 40 couples. The performance of the RF classifier (accuracy: 80%) was superior to that of the SVM (75% accuracy). They were able to classify CI patients and their healthy bed companions with an accuracy of 80% (sensitivity: 76%, specificity: 82%).

Studies have also used MRI signals for the identification of insomnia [72, 68, 69]. Out of all these studies, Dai et al. [53] have the biggest data set containing 96 patients out of which 48 are insomniacs and 48 are used as control subjects. From the MRI signal, data from the central part of the brain and global signal average across the whole brain were used to remove any spurious variables using linear regression. The signal was further linearly de-trended using a band-pass filter. Finally, a Gaussian kernel was used to smoothen the images and was subjected to study specific symmetric MNI templates then using these images inter-hemispheric connections were observed using VMHC and seed-based connectivity. These were then classified using SVM and ROC curves to identify intra and inter-hemispheric dysfunctions, which gave us the power to discriminate between good sleepers and Primary insomniacs. Another study that came close to these results was of Li et al. [38]. In this study, Whole-brain voxel-wise FCS, as well as large-scale FC and ReHo analysis, were performed for each participant. For all three metrics, multivariate classification analysis was performed and then cross-validated using 5-folds. This method obtained an accuracy of 81.4%, a sensitivity of 84.9%, and a specificity of 79.1%. The accuracy levels of studies that employed MRI for the identification of insomnia were quite low compared to that of PSG/EEG and actigraphy. Thus, we can say that the best signal for the accurate detection of insomnia is EEG. Followed by actigraphy signals, which offer a more non-invasive method for insomnia detection.

6.3. Deep learning models for insomnia detection

Due to the enormous success of deep learning techniques, several deep learning-based solutions for automatically and objectively detecting insomnia have recently been developed [86]. A deep learning model trained on a dataset containing some insomnia individuals, however, may damage the model's ability to generalize due to the dearth of publicly available insomnia data, thus limiting the efficacy of insomnia detection. Unlike ML, just two DL models (CNN, LSTM) were employed to identify insomnia in our study. Seven DL articles were included in our investigation. Wei Qu [87] created an adaptation-based model by utilizing stage annotations from the source domain to more effectively extract aspects of the target domain that are associated with insomnia. Two pairs of the common encoder and private encoder are initially trained for each domain to separate sleep-related characteristics from sleep-irrelevant information. A domain classifier is introduced to further distinguish between the source domain and the target domain. The LSTM network and the common encoder of the target domain are then combined to identify sleeplessness with an accuracy of 90.9%. To aid medical practitioners in monitoring sleep and examining a person's mental stability, Murarka [88] developed a 1-dimensional CNN for distinguishing CAP phases. Single-channel standard electroencephalogram (EEG) recordings are used in the proposed model. The created model has a 76% percent automatic categorization accuracy rate. As ECG also plays an important role in insomnia detection, Urtnasan [60] used the single-lead ECG signal which was extracted from the 35 subjects with the control and the four sleep disorder groups in the CAP sleep database. In order to interface with electronic devices, a graphical user interface (GUI) is used by Miracle [56]. He used CNN to develop a GUI for the classification of the disorder.

7. Discussion

The work presented illustrates contemporary technologies that may be used to diagnose insomnia [89, 90]. Researchers are investigating an automated accurate insomnia diagnosis using ML and DL to overcome the limitations of the current methods. The creation of portable tools for diagnosing insomnia was another major impetus for the researcher to work in this approach. The method used by Hamida et al. [81] utilizing power and ratio of relative power as a feature using the Hjorth parameter showed attractive results. PSG, ECG, EEG and MRI are used by researchers for the detection of insomnia [91, 88, 92] as shown in Figure 10b. Only a few authors used other signals like actigraphy used by [61], wrist temperature, and body position by [48]. The SVM was the first preference as a classifier in many studies for automated insomnia detection. 11 out of 23 studies have used an SVM classifier used for classification between insomniac and normal patients [75].

An asymptomatic study utilizing natural language processing of electrical medical records (EMR) and a phenotyping study using clustering of time series data derived from wearable devices were both conducted [52, 61, 93] In addition, studies on intervention utilizing smartphone applications that reflect the COVID-19 isolation era were conducted [35, 94, 95, 96].

The popularity of DL has increased significantly since 2018 as it can handle huge data and yield high performances [97]. In comparison to ML techniques, which rely on deft human engagement during feature creation and selection, DL is considerably more process-centric [98, 99, 100]. Another consequence of being process-centric is the inter-changeability of algorithms. Still, there are more ML studies than DL in terms of approach, and most of the studies utilized smaller datasets. Due to this, external clinical validation utilizing outside data that was not observed during training conducted, and the internal validation research using cross-validation holds the majority of the stakes. The goal of the ML model is to find the best model which considers the trade between bias and variance. The bias is the difference between the hypothesized model and the unidentified true model, and the variance is how much the model changes when the training data is altered. To solve this problem it is necessary to deal with the overfitting issue, and for this training and testing datasets should be separated. The training set is used for training the model and evaluation is performed using the testing dataset. Overall, DL models are well-suited for the automated detection of insomnia using EEG signals due to their ability to learn complex patterns, handle large datasets, and flexibility in data representation [101, 102]. However, the performance of DL models depends on the quality and size of the training data, as well as the selection and tuning of model hyperparameters.

Automation in the field of insomnia detection comes with several advantages it not only saves lives but also has several advantages which are given below:

- Increased accessibility: Automated insomnia detection methods, such as actigraphy and heart rate variability, can be performed using non-invasive and inexpensive techniques, making them more accessible to researchers and patients [103, 104].
- Improved diagnosis: It can provide objective and quantitative measures of sleep quality, which can help to improve the accuracy and consistency of insomnia diagnosis [105, 106].
- Monitoring of treatment effectiveness: It can be used to monitor the effectiveness of treatment over time, proposing novel DL architectures.
- Identification of co-morbidities: Automated methods can help to identify comorbid conditions, such as sleep apnea, that may contribute to insomnia symptoms. Novel artificial intelligence models can detect such comorbid conditions.
- Cost-effective: These methods are relatively inexpensive and less time-consuming than traditional methods, making them a cost-effective solution for detecting insomnia.
- Large-scale data collection: It enables the collection of large-scale data, which can be used to identify patterns and trends in insomnia, which can be useful for research and public health purposes.

The diagnosis, treatment, and understanding of insomnia could all be considerably improved by automated methods, making them more broadly available and efficient. Automating the classification of insomnia presents challenges, including the difficulty of achieving high accuracy. Certain co-morbidities, such as sleep apnea, may be difficult to identify using some automated insomnia detection techniques, such as actigraphy, which can provide false positive or false negative results. Automated approaches for detecting insomnia, such as heart rate variability, may be influenced by outside variables like stress and drug use, which results in unreliable data and a lack of consistency. Automated insomnia detection methods are currently not standardized, which can result in inconsistent results, making it difficult to compare studies. Automated insomnia detection techniques frequently rely on the use of wearable technology and the gathering of personal information, which might present issues with security and privacy [107, 108, 109, 110].

Additionally, there is other future research that can benefit from the creation of standardized protocols and standards for the application of automated insomnia detection techniques in a variety of contexts. Future researchers can also look into the advantages of combining other modalities to identify insomnia more accurately, using actigraphy, heart rate variability, and polysomnography signals [111, 112, 113, 114, 115]. Automated insomnia detection methods generate a lot of data, which can be analyzed with machine learning and AI to find patterns and trends. This could aid with diagnosis and lead to more specialized treatment approaches. Furthermore, developing automated insomnia detection systems that can easily integrate with existing healthcare systems can improve the accessibility and scalability of insomnia detection and treatment. Overall, there are many opportunities for future research in automated insomnia detection, which can help to improve the accuracy, accessibility, and effectiveness of insomnia diagnosis and treatment.

7.1. Challenges

Automated detection of insomnia using physiological signals such as EEG poses several challenges. Here are some of the main challenges:

- Lack of Standardization: There is no standard method for collecting and analyzing EEG data, which can make it difficult to compare results across studies. This lack of standardization can also lead to inconsistencies in the performance of automated detection algorithms.
- Complexity of Sleep: Sleep is a complex process that involves multiple stages and is influenced by various factors such as age, sex, and health status. This complexity makes it challenging to accurately classify sleep stages and diagnose sleep disorders such as insomnia.
- Variability in Sleep Patterns: Sleep patterns can vary significantly between individuals, and even within individuals over time. This variability can make it difficult to develop automated detection algorithms that are accurate and reliable across diverse populations.
- Limited Data Availability: There is a limited amount of high-quality data available for training and testing automated detection algorithms for insomnia. This can make it challenging to develop algorithms that generalize well to new data and diverse populations.
- Interpreting Results: Automated detection algorithms may be able to accurately classify EEG signals as normal or abnormal, but interpreting these results in a clinical context can be challenging. It is important to consider other factors such as the patient's medical history and symptoms when making a diagnosis of insomnia.

Despite these challenges, advances in DL models and data acquisition techniques are helping to improve automated detection of insomnia. Ongoing research is needed to overcome these challenges and develop accurate and reliable automated detection algorithms for this common sleep disorder.

7.2. Future direction

In order to create a model for detecting insomnia at home using PSG signals, more research needs to be conducted. Patients often experience discomfort when sleeping in a laboratory setting in order to produce accurate data, so gathering sleep information from a patient's home would likely result in more reliable data. The potential workflow for such a device is depicted in Figure 12, and it is believed that using this configuration would lead to higher-quality recordings. Also, future research can be carried out by focusing on multi-night sleep monitoring and observing sleep patterns in a more natural environment to improve the accuracy of automated detection techniques for insomnia [116]. The use of EOG signals, which are used to research eye movements and create assistive devices, could be a good alternative for monitoring sleep in a more comfortable environment for the study subject to reduce false detection.

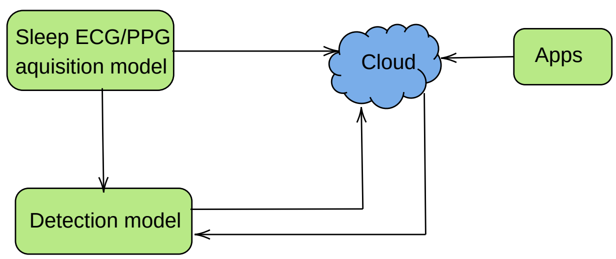


Figure 12: Block diagram of a cloud-based system that can be used for insomnia detection.

The lack of trust and interpretability associated with AI models has been a significant barrier to their adoption, particularly in critical domains like healthcare. Explainable artificial intelligence (XAI) has emerged as a valuable technique to address this challenge by providing explanations for the predictions or decisions made by AI models [117, 118]. XAI aims to provide transparency and interpretability to machine learning models and algorithms. It involves techniques and methods that allow humans to understand and interpret the decisions or predictions made by AI systems. Thus, XAI techniques should be used in conjunction with domain knowledge and clinical expertise to validate and interpret the model's predictions accurately.

8. Conclusion

The review highlights the potential of automated detection techniques for resolving insomnia, which is the most common sleep disorder and can lead to various health problems. The study reviewed the use of 15 different classifiers to examine 7 distinct signals for the automated detection of insomnia. The study found that combining EEG or PSG data with an SVM classifier was one of the most preferred strategies for detecting insomnia, while surprisingly not much research has been conducted on the use of ECG signals for detection despite its high accuracy levels and accessibility. Overall, the report emphasizes the need for continued research in the field of automated detection of insomnia to improve diagnosis and personalized treatment for this common sleep disorder. However, signals such as photoplethysmography (PPG)and heart rate variability (HRV) [119] can be used to identify insomnia. When compared to ECG, this leads to a substantially reduced data rate. These signals are therefore simpler to transmit and comprehend. This may be more cost-effective for healthcare providers. HRV and PPG signals are considered more patient-friendly than ECG because they require less equipment and are non-invasive. The patient's cooperation may benefit from this. According to the data compiled, DL is substantially less frequently utilized in the identification of insomnia. There is a need for research studies to use open-source databases for the classification of insomnia. The real-time, realistic system deployment at the moment is generating a great deal of interest. Additionally, by developing an automated method, the scope of data can be expanded so that patients can identify how their sleep condition conflicts with insomnia.

9. References

[1] M. Sharma, V. Patel, and U. R. Acharya, "Automated identification of insomnia using optimal bi-orthogonal wavelet transform technique with single-channel eeg signals," *Knowledge-Based Systems*, vol. 224, p. 107078, 2021.

[2] M. Walker, *Why we sleep: Unlocking the power of sleep and dreams*. Simon and Schuster, 2017.

[3] H. Piéron, "Ii. recherches sur les lois de variation des temps de latence sensorielle en fonction des intensités excitatrices," *L'année psychologique*, vol. 20, no. 1, pp. 17–96, 1913.

[4] M. Bentivoglio and G. Grassi-Zucconi, "The pioneering experimental studies on sleep deprivation," *Sleep*, vol. 20, no. 7, pp. 570–576, 1997.

[5] Q. Zhang, L. Xu, Y. Yan, G. Li, D. Qiao, and J. Tian, "Distracted driving behavior in patients with insomnia," *Accident Analysis & Prevention*, vol. 183, p. 106971, 2023.

[6] M. Chu, K. Xie, J. Zhang, Z. Chen, I. Ghorayeb, S. Rupprecht, A. T. Reder, A. Garay, H. Honda, M. Nagayama *et al.*, "Proposal of new diagnostic criteria for fatal familial insomnia," *Journal of neurology*, vol. 269, no. 9, pp. 4909–4919, 2022.

[7] S. Qi, C. Cao, G. Chen, T. Chan, Z. Wei, B. Zhang, H. Jun, and X. P. Dong, "Clinical and familial characteristics of ten chinese patients with fatal family insomnia," *Biomedical and Environmental Sciences*, vol. 25, no. 4, pp. 471–475, 2012.

[8] G. Lavigne and J. Montplaisir, "Restless legs syndrome and sleep bruxism: prevalence and association among canadians," *Sleep*, vol. 17, no. 8, pp. 739–743, 1994.

[9] C. Gaig, A. Iranzo, M. Pujol, H. Perez, and J. Santamaria, "Periodic limb movements during sleep mimicking rem sleep behavior disorder: a new form of periodic limb movement disorder," *Sleep*, vol. 40, no. 3, 2017.

[10] A. Iranzo, J. L. Molinuevo, J. Santamaría, M. Serradell, M. J. Martí, F. Valldeoriola, and E. Tolosa, "Rapid-eye-movement sleep behaviour disorder as an early marker for a neurodegenerative disorder: a descriptive study," *The Lancet Neurology*, vol. 5, no. 7, pp. 572–577, 2006.

[11] S. Miano and R. Peraita-Adrados, "Nocturnal frontal lobe epilepsy is often misdiagnosed as sleep disorders in children: a case series," *Rev Neurol*, vol. 56, no. 5, pp. 257–267, 2013.

[12] S. A. Bello and U. Alqasemi, "Computer aided detection of obstructive sleep apnea from eeg signals," *Available at SSRN 3890660*, 2021.

[13] A. Ramachandran and A. Karuppiah, "A survey on recent advances in machine learning based sleep apnea detection systems," in *Healthcare*, vol. 9. MDPI, 2021, p. 914.

[14] S. Chokroverty, "Overview of sleep & sleep disorders," *Indian Journal of Medical Research*, vol. 131, no. 2, pp. 126–140, 2010.

[15] V. Ibáñez, J. Silva, and O. Cauli, "A survey on sleep assessment methods," *PeerJ*, vol. 6, p. e4849, 2018.

[16] M. L. Okun, H. M. Kravitz, M. F. Sowers, D. E. Moul, D. J. Buysse, and M. Hall, "Psychometric evaluation of the insomnia symptom questionnaire: a self-report measure to identify chronic insomnia," *Journal of Clinical Sleep Medicine*, vol. 5, no. 1, pp. 41–51, 2009.

[17] S. C. C. of the Japanese Society of Sleep Research Society (JSSR):, T. Hori, Y. Sugita, E. Koga, S. Shirakawa, K. Inoue, S. Uchida, H. Kuwahara, M. Kousaka, T. Kobayashi *et al.*, "Proposed supplements and amendments to 'a manual of standardized terminology, techniques and scoring system for sleep stages of human subjects', the rechtschaffen & kales (1968) standard," *Psychiatry and clinical neurosciences*, vol. 55, no. 3, pp. 305–310, 2001.

[18] R. S. Rosenberg and S. Van Hout, "The american academy of sleep medicine inter-scorer reliability program: sleep stage scoring," *Journal of clinical sleep medicine*, vol. 9, no. 1, pp. 81–87, 2013.

[19] R. B. Berry, R. Budhiraja, D. J. Gottlieb, D. Gozal, C. Iber, V. K. Kapur, C. L. Marcus, R. Mehra, S. Parthasarathy, S. F. Quan *et al.*, "Rules for scoring respiratory events in sleep: update of the 2007 aasm manual for the scoring of sleep and associated events: deliberations of the sleep apnea definitions task force of the american academy of sleep medicine," *Journal of clinical sleep medicine*, vol. 8, no. 5, pp. 597–619, 2012.

[20] D. W. Carley and S. S. Farabi, "Physiology of sleep," *Diabetes spectrum: a publication of the American Diabetes Association*, vol. 29, no. 1, p. 5, 2016.

[21] H. R. Colten and B. M. Altevogt, Eds., *Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem*. Washington, DC: The National Academies Press, 2006.

[22] S. Gais, M. Mölle, K. Helms, and J. Born, "Learning-dependent increases in sleep spindle density," *Journal of Neuroscience*, vol. 22, no. 15, pp. 6830–6834, 2002.

[23] M. Takahara, S. Kanayama, H. Nittono, and T. Hori, "Rem sleep eeg pattern: examination by a new eeg scoring system for rem sleep period," *Sleep and Biological Rhythms*, vol. 4, pp. 105–110, 2006.

[24] C. M. Morin, G. Belleville, L. Bélanger, and H. Ivers, "The insomnia severity index: psychometric indicators to detect insomnia cases and evaluate treatment response," *Sleep*, vol. 34, no. 5, pp. 601–608, 2011.

[25] M. B. Bin Heyat, F. Akhtar, M. Ansari, A. Khan, F. Alkahtani, H. Khan, and D. Lai, "Progress in detection of insomnia sleep disorder: a comprehensive review," *Current Drug Targets*, vol. 22, no. 6, pp. 672–684, 2021.

[26] P. P. Doghramji, "Detection of insomnia in primary care," *Journal of Clinical Psychiatry*, vol. 62, pp. 18–26, 2001.

[27] M. M. Rahman, M. I. H. Bhuiyan, and A. R. Hassan, "Sleep stage classification using single-channel eog," *Computers in biology and medicine*, vol. 102, pp. 211–220, 2018.

[28] T. Roth, "Insomnia: definition, prevalence, etiology, and consequences," *Journal of clinical sleep medicine*, vol. 3, no. 5 suppl, pp. S7–S10, 2007.

[29] W. Qu, C.-H. Kao, H. Hong, Z. Chi, R. Grunstein, C. Gordon, and Z. Wang, "Single-channel eeg based insomnia detection with domain adaptation," *Computers in biology and medicine*, vol. 139, p. 104989, 2021.

[30] S. Passarella and M.-T. Duong, "Diagnosis and treatment of insomnia," *American Journal of Health-System Pharmacy*, vol. 65, no. 10, pp. 927–934, 2008.

[31] L. M. Ritterband, F. P. Thorndike, C. M. Morin, R. Gerwien, N. M. Enman, R. Xiong, H. F. Luderer, S. Edington, S. Braun, and Y. A. Maricich, "Real-world evidence from users of a behavioral digital therapeutic for chronic insomnia," *Behaviour Research and Therapy*, vol. 153, p. 104084, 2022.

[32] K. L. Lichstein, H. H. Durrence, B. W. Riedel, and U. J. Bayen, "Primary versus secondary insomnia in older adults: subjective sleep and daytime functioning." *Psychology and aging*, vol. 16, no. 2, p. 264, 2001.

[33] A. R. Schwartz, M. Cohen-Zion, L. V. Pham, A. Gal, M. Sowho, F. P. Sgambati, T. Klopfer, M. A. Guzman, E. M. Hawks, T. Etzioni *et al.*, "Brief digital sleep questionnaire powered by machine learning prediction models identifies common sleep disorders," *Sleep Medicine*, vol. 71, pp. 66–76, 2020.

[34] S. L. Halson, "Sleep monitoring in athletes: motivation, methods, miscalculations and why it matters," *Sports medicine*, vol. 49, no. 10, pp. 1487–1497, 2019.

[35] P. Philip, L. Dupuy, C. M. Morin, E. de Sevin, S. Bioulac, J. Taillard, F. Serre, M. Auriacombe, and J.-A. Micoulaud-Franchi, "Smartphone-based virtual agents to help individuals with sleep concerns during covid-19 confinement: feasibility study," *Journal of medical Internet research*, vol. 22, no. 12, p. e24268, 2020.

[36] M. Sharma, H. S. Dhiman, and U. R. Acharya, "Automatic identification of insomnia using optimal antisymmetric biorthogonal wavelet filter bank with ecg signals," *Computers in Biology and Medicine*, vol. 131, p. 104246, 2021.

[37] S. Das, A. Dey, A. Pal, and N. Roy, "Applications of artificial intelligence in machine learning: review and prospect," *International Journal of Computer Applications*, vol. 115, no. 9, 2015.

[38] J. W. Lai, C. K. E. Ang, U. R. Acharya, and K. H. Cheong, "Schizophrenia: a survey of artificial intelligence techniques applied to detection and classification," *International journal of environmental research and public health*, vol. 18, no. 11, p. 6099, 2021.

[39] B. Rajoub, "Characterization of biomedical signals: Feature engineering and extraction," in *Biomedical signal processing and artificial intelligence in healthcare.* Elsevier, 2020, pp. 29–50.

[40] M. M. Islam, A. K. M. Masum, S. Abujar, and S. A. Hossain, "Prediction of chronic insomnia using machine learning techniques," in *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT).* IEEE, 2020, pp. 1–7.

[41] K. Chousangsuntorn, T. Bhongmakapat, N. Apirakkittikul, W. Sungkarat, N. Supakul, and J. Laothamatas, "Computed tomography characterization and comparison with polysomnography for obstructive sleep apnea evaluation," *Journal of Oral and Maxillofacial Surgery*, vol. 76, no. 4, pp. 854–872, 2018.

[42] M. Engstrøm, E. Rugland, and M. S. Heier, "Polysomnography (psg) for studying sleep disorders," *Tidsskrift for den Norske laegeforening: tidsskrift for praktisk medicin, ny raekke*, vol. 133, no. 1, pp. 58–62, 2013.

[43] D. Riemann, U. Voderholzer, K. Spiegelhalder, M. Hornyak, D. J. Buysse, C. Nissen, J. Hennig, M. L. Perlis, L. T. van Elst, and B. Feige, "Chronic insomnia and mri-measured hippocampal volumes: a pilot study," *Sleep*, vol. 30, no. 8, pp. 955–958, 2007.

[44] A. Mathew, P. Amudha, and S. Sivakumari, "Deep learning techniques: an overview," *Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2020*, pp. 599–608, 2021.

[45] D. Buongiorno, G. D. Cascarano, I. De Feudis, A. Brunetti, L. Carnimeo, G. Dimauro, and V. Bevilacqua, "Deep learning for processing electromyographic signals: A taxonomy-based survey," *Neurocomputing*, vol. 452, pp. 549–565, 2021.

[46] R. Boostani, F. Karimzadeh, and M. Nami, "A comparative review on sleep stage classification methods in patients and healthy individuals," *Computer methods and programs in biomedicine*, vol. 140, pp. 77–91, 2017.

[47] S. T.-B. Hamida, B. Ahmed, D. Cvetkovic, E. Jovanov, G. Kennedy, and T. Penzel, "A new era in sleep monitoring: The application of mobile technologies in insomnia diagnosis," *Mobile Health: A Technology Road Map*, pp. 101–127, 2015.

[48] B. Rodriguez-Morilla, E. Estivill, C. Estivill-Domènech, J. Albares, F. Segarra, A. Correa, M. Campos, M. A. Rol, and J. A. Madrid, "Application of machine learning methods to

ambulatory circadian monitoring (acm) for discriminating sleep and circadian disorders," *Frontiers in neuroscience*, vol. 13, p. 1318, 2019.

[49] M. G. Terzano, L. Parrino, A. Sherieri, R. Chervin, S. Chokroverty, C. Guilleminault, M. Hirshkowitz, M. Mahowald, H. Moldofsky, A. Rosa *et al.*, "Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (cap) in human sleep," *Sleep medicine*, vol. 2, no. 6, pp. 537–554, 2001.

[50] A. Baratloo, M. Hosseini, A. Negida, and G. El Ashal, "Part 1: Simple definition and calculation of accuracy, sensitivity and specificity," *Emerg (Tehran)*, vol. 3, no. 2, pp. 48–49, 2015.

[51] M. Angelova, C. Karmakar, Y. Zhu, S. P. Drummond, and J. Ellis, "Automated method for detecting acute insomnia using multi-night actigraphy data," *IEEE Access*, vol. 8, pp. 74 413–74 422, 2020.

[52] S. Park, S. W. Lee, S. Han, M. Cha *et al.*, "Clustering insomnia patterns by data from wearable devices: algorithm development and validation study," *JMIR mHealth and uHealth*, vol. 7, no. 12, p. e14473, 2019.

[53] L. J. Monroe, "Psychological and physiological differences between good and poor sleepers." *Journal of abnormal psychology*, vol. 72, no. 3, p. 255, 1967.

[54] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *Journal of neuroengineering and rehabilitation*, vol. 7, no. 1, pp. 1–13, 2010.

[55] S. S. Kim, "Recent trends of artificial intelligence and machine learning for insomnia research," *Chronobiology in Medicine*, vol. 3, no. 1, pp. 16–19, 2021.

[56] M. Sharma, J. Darji, M. Thakrar, and U. R. Acharya, "Automated identification of sleep disorders using wavelet-based features extracted from electrooculogram and electromyogram signals," *Computers in Biology and Medicine*, vol. 143, p. 105224, 2022.

[57] P. Tripathi, M. Ansari, T. K. Gandhi, R. Mehrotra, M. B. B. Heyat, F. Akhtar, C. C. Ukwuoma, A. Y. Muaad, Y. M. Kadah, M. A. Al-Antari *et al.*, "Ensemble computational intelligent for insomnia sleep stage detection via the sleep ecg signal," *IEEE Access*, vol. 10, pp. 108 710–108 721, 2022.

[58] S. Murarka, A. Wadichar, A. Bhurane, M. Sharma, and U. R. Acharya, "Automated classification of cyclic alternating pattern sleep phases in healthy and sleep-disordered subjects using convolutional neural network," *Computers in Biology and Medicine*, vol. 146, p. 105594, 2022.

[59] S. Tiwari, D. Arora, and V. Nagar, "Detection of insomnia using advanced complexity and entropy features of sleep stage data of eeg recordings," *Measurement: Sensors*, vol. 24, p. 100498, 2022.

[60] E. Urtnasan, E. Y. Joo, and K. H. Lee, "Ai-enabled algorithm for automatic classification of sleep disorders based on single-lead electrocardiogram," *Diagnostics*, vol. 11, no. 11, p. 2054, 2021.

[61] S. Kusmakar, C. Karmakar, Y. Zhu, S. Shelyag, S. Drummond, J. Ellis, and M. Angelova, "A machine learning model for multi-night actigraphic detection of chronic insomnia: development and validation of a pre-screening tool," *Royal Society open science*, vol. 8, no. 6, p. 202264, 2021.

[62] L. M. Askie, "Australian new zealand clinical trials registry: history and growth," *Journal of Evidence-Based Medicine*, vol. 4, no. 3, pp. 185–187, 2011.

[63] M. Sharma, J. Tiwari, V. Patel, and U. R. Acharya, "Automated identification of sleep disorder types using triplet half-band filter and ensemble machine learning techniques with eeg signals," *Electronics*, vol. 10, no. 13, p. 1531, 2021.

[64] A. Malik, S. Z. H. Naqvi, S. Aziz, M. U. Khan, T. Hussain, and F. Hasan, "Detection of insomnia using electrocardiography and electromyography," in *2021 International Conference on Artificial Intelligence (ICAI)*. IEEE, 2021, pp. 234–239.

[65] W. Qu, C.-H. Kao, H. Hong, Z. Chi, R. Grunstein, C. Gordon, and Z. Wang, "Single-channel eeg based insomnia detection with domain adaptation," *Computers in biology and medicine*, vol. 139, p. 104989, 2021.

[66] S. I. Dimitriadis, C. I. Salis, and D. Liparas, "An automatic sleep disorder detection based on eeg

cross-frequency coupling and random forest model," *Journal of Neural Engineering*, vol. 18, no. 4, p. 046064, 2021.

[67] A. Atianashie Miracle, E. Armah, and N. Mohammed, "A portable gui based sleep disorder system classification based on convolution neural networks (cnn) in raspberry pi," *J. Eng. Appl Sci. Humanities*, vol. 6, pp. 13–23, 2021.

[68] X.-J. Dai, B.-X. Liu, S. Ai, X. Nie, Q. Xu, J. Hu, Q. Zhang, Y. Xu, Z. Zhang, and G. Lu, "Altered inter-hemispheric communication of default-mode and visual networks underlie etiology of primary insomnia: altered inter-hemispheric communication underlie etiology of insomnia," *Brain Imaging and Behavior*, vol. 14, pp. 1430–1444, 2020.

[69] X. Ma, D. Wu, Y. Mai, G. Xu, J. Tian, and G. Jiang, "Functional connectome fingerprint of sleep quality in insomnia patients: Individualized out-of-sample prediction using machine learning," *NeuroImage: Clinical*, vol. 28, p. 102439, 2020.

[70] L. Yang, Z. Yu, Y. Xu, W. Liu, L. Liu, and H. Mao, "Mental status of patients with chronic insomnia in china during covid-19 epidemic," *International Journal of Social Psychiatry*, vol. 66, no. 8, pp. 821–826, 2020.

[71] M. B. B. Heyat, *Insomnia: Medical sleep disorder & diagnosis.* Anchor Academic Publishing, 2020.

[72] C. Li, Y. Mai, M. Dong, Y. Yin, K. Hua, S. Fu, Y. Wu, and G. Jiang, "Multivariate pattern classification of primary insomnia using three types of functional connectivity features," *Frontiers in Neurology*, vol. 10, p. 1037, 2019.

[73] B. Liu, W. Lin, S. Chen, T. Xiang, Y. Yang, Y. Yin, G. Xu, Z. Liu, s. L. Liu, J. Pan *et al.*, "Gut microbiota as an objective measurement for auxiliary diagnosis of insomnia disorder," *Frontiers in Microbiology*, vol. 10, p. 1770, 2019.

[74] F. Mendonça, S. S. Mostafa, F. Morgado-Dias, and A. G. Ravelo-García, "A portable wireless device for cyclic alternating pattern estimation from an eeg monopolar derivation," *Entropy*, vol. 21, no. 12, p. 1203, 2019.

[75] H. Abdullah, C. R. Patti, C. Dissanyaka, T. Penzel, and D. Cvetkovic, "Support vector machine classification of eeg nonlinear features for primary insomnia," in *2nd International Conference for Innovation in Biomedical Engineering and Life Sciences: ICIBEL 2017 (in conjunction with APCMBE 2017), 10-13 December 2017, Penang, Malaysia.* Springer, 2018, pp. 161–164.

[76] M. Shahin, L. Mulaffer, T. Penzel, and B. Ahmed, "A two stage approach for the automatic detection of insomnia," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* IEEE, 2018, pp. 466–469.

[77] L. Mulaffer, M. Shahin, M. Glos, T. Penzel, and B. Ahmed, "Comparing two insomnia detection models of clinical diagnosis techniques," in *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* IEEE, 2017, pp. 3749–3752.

[78] M. Rezaei, H. Mohammadi, and H. Khazaie, "Eeg/eog/emg data from a cross sectional study on psychophysiological insomnia and normal sleep subjects," *Data in brief*, vol. 15, pp. 314–319, 2017.

[79] M. M. Siddiqui, G. Srivastava, and S. H. Saeed, "Diagnosis of insomnia sleep disorder using short time-frequency analysis of psd approach applied on eeg signal using channel roc-loc," *Sleep Science*, vol. 9, no. 3, pp. 186–191, 2016.

[80] M. Shahin, B. Ahmed, S. T.-B. Hamida, F. L. Mulaffer, M. Glos, and T. Penzel, "Deep learning and insomnia: assisting clinicians with their diagnosis," *IEEE journal of biomedical and health informatics*, vol. 21, no. 6, pp. 1546–1553, 2017.

[81] S. T.-B. Hamida, M. Glos, T. Penzel, and B. Ahmed, "How many sleep stages do we need for an efficient automatic insomnia diagnosis?" in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* IEEE, 2016, pp. 2431–2434.

[82] S. T.-B. Hamida, B. Ahmed, and T. Penzel, "A novel insomnia identification method based on hjorth parameters," in *2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT).* IEEE, 2015, pp. 548–552.

[83] C.-E. Kuo and G.-T. Chen, "A short-time insomnia detection system based on sleep eog with rcmse analysis," *IEEE Access*, vol. 8, pp. 69 763–69 773, 2020.

[84] J. Behar, A. Roebuck, M. Shahid, J. Daly, A. Hallack, N. Palmius, J. Stradling, and G. D. Clifford, "Sleepap: an automated obstructive sleep apnoea screening application for smartphones," *IEEE journal of biomedical and health informatics*, vol. 19, no. 1, pp. 325–331, 2014.

[85] J. Ramesh, N. Keeran, A. Sagahyroon, and F. Aloul, "Towards validating the effectiveness of obstructive sleep apnea classification from electronic health records using machine learning," in *Healthcare*, vol. 9. MDPI, 2021, p. 1450.

[86] S. S. Mostafa, F. Mendonça, A. G. Ravelo-García, and F. Morgado-Dias, "A systematic review of detecting sleep apnea using deep learning," *Sensors*, vol. 19, no. 22, p. 4934, 2019.

[87] J. Intha, P. Pramokchon, P. Khoenkaw, and K. Osathanunkul, "Analysis of effective sleep through logistic regression," in *2020 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON)*. IEEE, 2020, pp. 145–148.

[88] J. Hampton, *The ECG in practice*. Elsevier Health Sciences, 2013.

[89] C. E. Carney, D. J. Buysse, S. Ancoli-Israel, J. D. Edinger, A. D. Krystal, K. L. Lichstein, and C. M. Morin, "The consensus sleep diary: standardizing prospective sleep self-monitoring," *Sleep*, vol. 35, no. 2, pp. 287–302, 2012.

[90] J. You, Y. Ma, and Y. Wang, "Gtransu-cap: Automatic labeling for cyclic alternating patterns in sleep eeg using gated transformer-based u-net framework," *Computers in Biology and Medicine*, vol. 147, p. 105804, 2022.

[91] W. Zhao, E. J. Van Someren, C. Li, X. Chen, W. Gui, Y. Tian, Y. Liu, and X. Lei, "Eeg spectral analysis in insomnia disorder: A systematic review and meta-analysis," *Sleep Medicine Reviews*, vol. 59, p. 101457, 2021.

[92] M. Sharma, J. Tiwari, V. Patel, and U. R. Acharya, "Automated identification of sleep disorder types using triplet half-band filter and ensemble machine learning techniques with eeg signals," *Electronics*, vol. 10, no. 13, p. 1531, 2021.

[93] F. Hu, L. Li, X. Huang, X. Yan, P. Huang *et al.*, "Symptom distribution regularity of insomnia: Network and spectral clustering analysis," *JMIR Medical Informatics*, vol. 8, no. 4, p. e16749, 2020.

[94] P. Philip, L. Dupuy, C. M. Morin, E. de Sevin, S. Bioulac, J. Taillard, F. Serre, M. Auriacombe, and J.-A. Micoulaud-Franchi, "Smartphone-based virtual agents to help individuals with sleep concerns during covid-19 confinement: feasibility study," *Journal of medical Internet research*, vol. 22, no. 12, p. e24268, 2020.

[95] ——, "Smartphone-based virtual agents to help individuals with sleep concerns during covid-19 confinement: feasibility study," *Journal of medical Internet research*, vol. 22, no. 12, p. e24268, 2020.

[96] F. Ge, D. Zhang, L. Wu, and H. Mu, "Predicting psychological state among chinese undergraduate students in the covid-19 epidemic: a longitudinal study using a machine learning," *Neuropsychiatric disease and treatment*, pp. 2111–2118, 2020.

[97] R. Tripathy, "Application of intrinsic band function technique for automated detection of sleep apnea using hrv and edr signals," *Biocybernetics and Biomedical Engineering*, vol. 38, no. 1, pp. 136–144, 2018.

[98] M. Bruyneel and V. Ninane, "Unattended home-based polysomnography for sleep disordered breathing: current concepts and perspectives," *Sleep medicine reviews*, vol. 18, no. 4, pp. 341–347, 2014.

[99] O. Faust, Y. Hagiwara, T. J. Hong, O. S. Lih, and U. R. Acharya, "Deep learning for healthcare applications based on physiological signals: A review," *Computer methods and programs in biomedicine*, vol. 161, pp. 1–13, 2018.

[100] N. Cooray, F. Andreotti, C. Lo, M. Symmonds, M. T. Hu, and M. De Vos, "Detection of rem sleep behaviour disorder by automated polysomnography analysis," *Clinical Neurophysiology*,

vol. 130, no. 4, pp. 505–514, 2019.

[101] Y. Cha, "Practical artificial intelligence for physicians," *Paju: Koonja*, 2017.

[102] G. Hinton, "Deep learning—a technology with the potential to transform health care," *Jama*, vol. 320, no. 11, pp. 1101–1102, 2018.

[103] O. Faust, W. Hong, H. W. Loh, S. Xu, R.-S. Tan, S. Chakraborty, P. D. Barua, F. Molinari, and U. R. Acharya, "Heart rate variability for medical decision support systems: A review," *Computers in Biology and Medicine*, p. 105407, 2022.

[104] N. Isakadze and S. S. Martin, "How useful is the smartwatch ecg?" *Trends in cardiovascular medicine*, vol. 30, no. 7, pp. 442–448, 2020.

[105] L. Cai, R. Datta, J. Huang, S. Dong, and M. Du, "Sleep disorder data stream classification based on classifiers ensemble and active learning," in *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2019, pp. 1432–1435.

[106] N. I. Tapia and P. A. Estévez, "Red: Deep recurrent neural networks for sleep eeg event detection," in *2020 international joint conference on neural networks (IJCNN)*. IEEE, 2020, pp. 1–8.

[107] S. Xu, O. Faust, S. Silvia, S. Chakraborty, P. D. Barua, H. W. Loh, H. Elphick, F. Molinari, and U. R. Acharya, "A review of automated sleep disorder detection," *Computers in Biology and Medicine*, p. 106100, 2022.

[108] S. Kye, J. Moon, T. Lee, S. Lee, K. Lee, S.-c. Shin, and Y. S. Lee, "Detecting periodic limb movements in sleep using motion sensor embedded wearable band," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2017, pp. 1087–1092.

[109] M. Sharma, H. Lodhi, R. Yadav, N. Sampathila, K. Swathi, and U. R. Acharya, "Automated explainable detection of cyclic alternating pattern (cap) phases and sub-phases using wavelet-based single-channel eeg signals," *IEEE Access*, 2023.

[110] M. Sharma, H. Lodhi, R. Yadav, H. Elphick, and U. R. Acharya, "Computerized detection of cyclic alternating patterns of sleep: A new paradigm, future scope and challenges," *Computer Methods and Programs in Biomedicine*, p. 107471, 2023.

[111] M. Reite, D. Buysse, C. Reynolds, and W. Mendelson, "The use of polysomnography in the evaluation of insomnia," *Sleep*, vol. 18, no. 1, pp. 58–70, 1995.

[112] C. Armon, "Polysomnography: overview, parameters monitored, staging of sleep," *Medscape*, 2020.

[113] M. Sharma, P. Makwana, R. S. Chad, and U. R. Acharya, "A novel automated robust dual-channel eeg-based sleep scoring system using optimal half-band pair linear-phase biorthogonal wavelet filter bank," *Applied Intelligence*, pp. 1–19, 2023.

[114] M. Sharma, R. K. Patel, A. Garg, R.-S. Tan, and U. R. Acharya, "Automated detection of schizophrenia using deep learning: a review for the last decade," *Physiological Measurement*, 2023.

[115] M. Sharma, K. Kumar, P. Kumar, R.-S. Tan, and U. R. Acharya, "Pulse oximetry spo 2 signal for automated identification of sleep apnea: a review and future trends," *Physiological Measurement*, 2022.

[116] O. Faust, W. Hong, H. W. Loh, S. Xu, R.-S. Tan, S. Chakraborty, P. D. Barua, F. Molinari, and U. R. Acharya, "Heart rate variability for medical decision support systems: A review," *Computers in Biology and Medicine*, p. 105407, 2022.

[117] H. W. Loh, C. P. Ooi, S. Seoni, P. D. Barua, F. Molinari, and U. R. Acharya, "Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011–2022)," *Computer Methods and Programs in Biomedicine*, p. 107161, 2022.

[118] P. Linardatos, V. Papastefanopoulos, and S. Kotsiantis, "Explainable ai: A review of machine learning interpretability methods," *Entropy*, vol. 23, no. 1, p. 18, 2020.

[119] M. Sharma, M. Arif, and K. Asthana, "Automated iot-based detection of periodic leg movement using optimal wavelet-based entropy features," in *Internet of Things in Biomedical Sciences*, ser. 2053-2563. IOP Publishing, 2023, pp. 14–1 to 14–15. [Online]. Available: https://dx.doi.org/10.1088/978-0-7503-5311-3ch14