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Review Article

Signal Pre-Processing and Classification Algorithms for the Automatic Identification of Insomnia: A Short Review

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Abstract - *Insomnia is a sleep disorder when untreated, develops physiological, psychological, or psychiatric conditions like cardiovascular diseases, diabetes, stress, anxiety, memory loss, etc., for all age groups, mainly adults and older people. Identifying insomnia is cumbersome and demands human effort at the time of diagnosis. Enormous automated techniques were leveraged that can be viewed from the literature. The paper reviews various signal-processing methods that are helpful for artefact-free input and classification algorithms to identify the disorder automatically. This article looks into six signal-processing methods, three feature extraction, and seven classification algorithms, focusing on their advantages, disadvantages, and limitations. The presented paper concentrates on delivering a detailed review of the methods used in the detection process and can help choose an appropriate model. The work can perform a guideline for identifying insomnia using physiological signals.*

Keywords - *Sleep disorder, Machine Learning, EEG processing, Feature extraction, Deep Learning.*

1. Introduction

Sleep, an unbounded relation with human health, reflects in good and bad ways. A night of good sleep can take many lifestyle diseases away. Stress, anxiety, work habits, alcohol intake, caffeine consumption, or some drug intake may affect the sleep behaviour of a person, resulting in sleep disorders including insomnia [1], sleep apnoea [2], restless leg syndrome [3], narcolepsy [4], etc.

Insomnia is a sleep disorder that prevents you from restful sleep without any wakefulness in between for a minimum of 7-8 hours per night, according to the American Academy of Sleep Medicine (AASM) and the Sleep Research Society (SRS) [5]. Insomnia is found to be most common in all age groups and results from a person having difficulty falling asleep or staying asleep. It is present in adults and infants, too. Insomnia can be defined as a biological disorder suffered due to sleep fragmentation (inability to maintain sleep continuity), sleep deprivation (failure to obtain the necessary amount or quality of sleep), etc. [6]. A human rest undergoes various phases that can be depicted in Figure 1. The presence of sleep disorder depends on the number of occurrences of different phases while sleeping. The guidelines were designed by the American Academy of Sleep Medicine (AASM) for evaluating and diagnosing insomnia. With the rapid evolution of technology in disease detection, signal processing plays an essential role in the identification of insomnia. Insomnia can be identified from either Electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), and Electromyogram (EMG) signals. Brain activities during sleep can be measured using different physiological signals and help in its classification by leveraging Artificial Intelligence (AI). The approach of physiological signals in the development of an insomnia detection model includes signal recording, pre-processing, feature extraction, and classification, as shown in Figure 2.

EEG is the most relevant signal required for insomnia identification compared to ECG, EOG, and EMG. Hence, we can go for EEG signal processing methods. Since EEG is a nonstationary signal, special care should be taken in artefact suppression. EEG is the signal generated by the brain due to different neuronal activity and is found to be utilized for the identification of ineffective functioning of brain activities. The analysis of EEG signals during sleep can show the variations present in the pattern of sleep. At the same time, in EEG signal acquisition, the application of conductive gel on each electrode and filter design built into the acquisition device limits the mixing of noise with the signal to an extent. Still, the acquired signal can be affected by artefacts such as surrounding noise, line artefacts, baseline drift, etc., which has led to the development of digital signal processing techniques. The study of EEG signals for the diagnosis of sleep disorders is a challenging task due to its non-stationarity and dynamic nature. Also, the EEG signals will be present in microvolts that are very small in size, enhancing the inability to analyze the signal perfectly. The lower magnitude EEG signal varies due to background noises, presumably very much a challenging task without affecting its characteristics. Artefact-free input results in high dimensional performance parameters when implementing a classification algorithm for automated detection. Signal pre-processing can be considered the most relevant step in the development of a computerised model. EEG consists of different frequency bands as shown in Table 1 [7]:

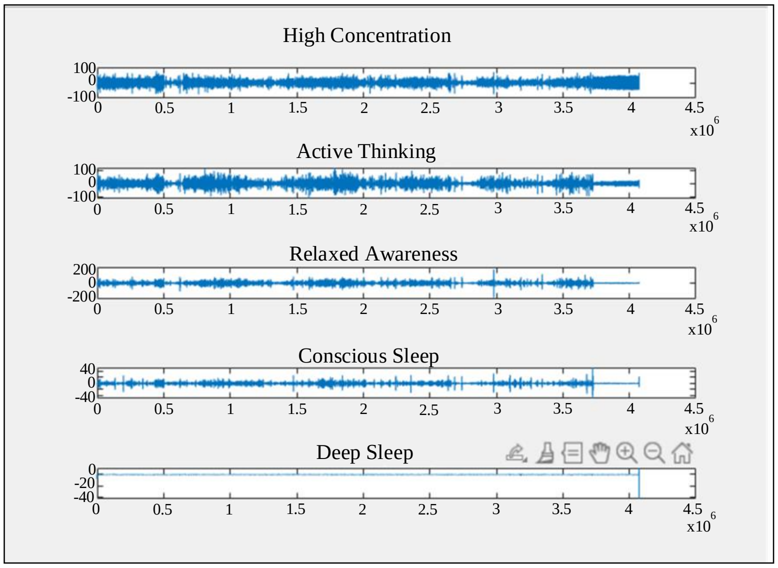

Fig. 1 Different phases of sleep

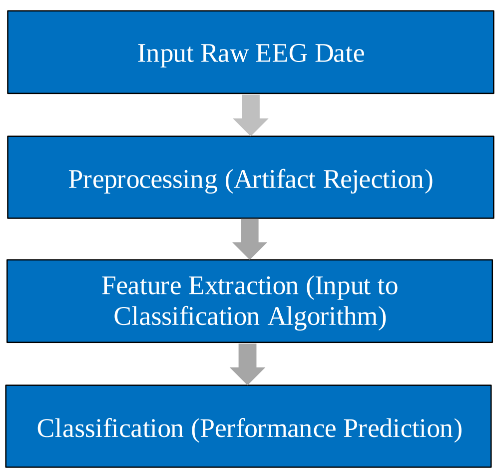

Fig. 2 Overview of EEG signal processing

Table 1. EEG frequency bands

EEG Frequency Bands	Frequency Range	Description
Delta Waves	0.5-4Hz	Associated with Deep Sleep
Theta Waves	4-7.5Hz	Associated with Consciousness Sleep
Alpha Waves	8-13Hz	Associated with Relaxed Awareness
Beta Waves	14-26Hz	Associated with Active Thinking and Attention
Gamma Waves	above 30Hz	The Fastest Wave of the Brain, Associated with Alertness and High Concentration

Sleep signals are associated with noise and other artefacts, which will not allow us to make a better identification model by deriving EEG frequency bands adequately for analysis. So, pre-processing has been done to remove those artefacts and make the sleep signals free from irrelevant data, which makes the detection model accurate.

A detailed description of the EEG processing techniques is depicted in Figure 2. The presented work focuses on reviewing all the steps in building a detection model. The result gives a clear idea of the various methods used in pre-processing, different ways of feature extraction, and available classification algorithms. Depending on the application, the selection of the methods will be varied. The summary work highlights the advantages, limitations, and applications of existing pre-processing and classification algorithms, which help in acquiring a better understanding of the available methods and can be leveraged as a guideline for building an efficient insomnia detection model.

1.1. EEG Acquisition

EEG can be recorded from the scalp of the brain as a physiological signal that represents brain activities, and observing the signal during sleep can show signal variations in various sleep stages. EEG acquisition device records brain actions using different electrodes with a conductive gel on the predefined locations called channels on the scalp that follow a 10-20 electrode system. Nowadays, EEG can be recorded non-invasively using wearable headbands. The electrode positions were indicated in [8] as:

- Vertex – midway between preauricular points.
- T3, T4- 10% of the coronal distance from respective preauricular points.
- Horizontal measurements- 10% of total circumference.

The 10-20 electrode placement protocol is a standardized protocol that designates 21 electrodes on the predefined reference points on the scalp. For placing the electrodes, the head is divided into several positions in which each electrode is indicated with an alphabet showing Frontal, Central, Posterior, Temporal, and Occipital (F, C, P, T, and O). The number defines the cerebral hemisphere where each letter is, for example, C3 and C4 [9].

1.2. EEG Artifacts

The presence of unwanted signals or noise that can contaminate a raw signal by reducing its quality and performance is identified as an artefact. The presence of an artefact is unavoidable during EEG recording and shows its significance in performing classification, and artefact-free input gives a better performance metric. Artefacts can occur due to the presence of surrounding noise while recording; distortion occurs due to slight body movements, for example, eye movements, limb movements, heart rate variability, etc., and can also occur due to power fluctuations and connection issues during EEG acquisition. Interference of signals such as ECG, EOG, and EMG can also be treated as artefacts in EEG recording. Cardiac, ocular, and muscle artefacts are considered intrinsic artefacts and show their significance in EEG, whereas external artefacts are also present by the completion of recording. The presence of these artefacts, whether intrinsic or extrinsic, is unavoidable and can be eliminated by performing pre-processing techniques suitable for the application.

2. EEG Pre-Processing

EEG is a type of physiological signal that reflects all the changes in brain activity while sleeping. EEG is susceptible to noise due to external interference like blinking the eyes, device interruption while recording, surrounding noise, etc. These are termed the artefacts present in the signal. The presence of artefacts in the signal while processing degrades the performance of the model as the artefacts have a significant impact on it. It is essential to remove unnecessary data without losing necessary information that is relevant for designing the model. A few methods are elaborated on in the paper for removing the artefact of the EEG signal.

2.1. Amplitude Comparison and Chi-Square Fit Tests

The amplitude of the EEG signal generally varies from 2-100μν in which the alpha frequency band is visible in 2-100μν, theta band in 10μν, beta in the range of 5-10μν, and delta in the range of 20-100μν. The amplitude outside the range can be considered as an artefact. For example, an EMG signal is available in the range of 0-10mν, which can be regarded as an artefact. At the beginning of the sleep study, pre-processing started with two tests for the identification of artefacts, say, amplitude comparison and chi-square fit tests [10] to a Gaussian distribution in which those epochs that are not identified in the amplitude check will be caught in 2nd test which helps in data reduction.

Sample data points are compared with a threshold level of ±90V amplitude level at the output, and any change in the threshold due to a signal with high amplitude at the input could be detected. The missing epochs in the amplitude comparison were sent for the chi-square fit test, which checks whether the epochs fall in the non-Gaussian distribution. The chi-square fit test is a statistical test employed to find the specific variable that could fall into a specified distribution. It could also verify that the particular data can be a representation of the complete distribution. This method could not detect slow wave artefacts present in the delta band as its amplitude could not exceed the threshold mentioned by the technique.

2.2. Self-Organized Maps (SOM)

Self-Organizing Maps can be considered as a learning algorithm for dimensionality reduction that can be mapped between input and processing elements of the map. The mapping might be topologically ordered, which means the location of the most active processing elements with similar characteristics will be closer to each other while preserving the basic structure of input space.

In 1997, a study suggested Self-Organized Maps (SOM) with Kohonen nets employing Fast Fourier Transforms (FFT) along with Differential Power Spectrum (DPS) using signal processing techniques, which resulted in pinpointing the stages correctly [11]. By indulging the method of FFT, it sounds easy to compute the frequency spectrum that corresponds to the brain signal. Kohonen net was utilized in the method to evaluate the associative fields for signals with the same feature relationship that was coded in EEG. FFT and power spectrum evaluate sleep stages by computing the cluster for the Differential Power Spectrum (DPS) algorithm, which can be fed as input to a Kohonen map. It is mainly used to identify sleep stages prominently.

2.3. EEG Pre-Processing Pipeline (PREP Pipeline)

Generally, a pipeline is a set of processing elements incorporated in a sequence. A pipeline consists of numerous methods in a sequence that can be executed one by one in an order. Pipelining encompasses various methods in a single window. PREP pipeline and HAPPE are such pipelines that include multiple techniques of signal pre-processing in the same stretch. PREP pipeline is an early-stage pre-processing that allows determining whether a dataset has issues by performing automated noise removal (without any filtering mechanism), bad channel detection, and referencing that helps to change raw EEG data into standardized ones. The PREP pipeline uses EEGLAB for channel interpolation [12], which is employed for large-scale analysis. It will remove line noise without using any filtering techniques, as filtering causes an impact on causality and its related computations.

Instead, the multi-taper decomposition approach with a clean-line plugin by EEGLAB removes only deterministic line components, preserving background spectral energy. Replacing the ordinary average reference with a robust average reference algorithm to evaluate the actual average in the absence of wrong channels. Harvard Automated Pre-Processing Pipeline for EEG (HAPPE) is an automated pre-processing technique designed for artefact removal; it has the advantage of a semi-automated setting along with being fully automated, which ensures to adjust user input, if required, before the completion of a fully automated pipeline that makes it more efficient [13]. It can be considered an extended version of the PREP pipeline.

2.4. Independent Component Analysis (ICA) & Principal Component Analysis (PCA)

Independent Component Analysis is a technique used for statistical analysis by separating multivariate signals into its components. The process of separating signals into independent sources is called blind source separation. ICA, which separates artefacts as independent components, can be considered an efficient tool for blind source separation, feature extraction, and detection [14]. In the ICA algorithm, even though it decomposes mixed signals, some components of brain activity will be removed if they are considered noise. Hence, there might be a chance of losing some vital information.

Moreover, ICA considers that the acquired signal is non-gaussian as well as linear in nature; in contrast, this can make ICA ineffective. ICA also suffers from convergence problems in which it cannot always find a solution for the requirement. Huang H says that, before data pre-processing, we should delete some data that is of less importance in the sleep staging and should take on Common Average Reference (CAR) to minimize noise, followed by Independent Component Analysis (ICA) to adjust the plugin in EEGLAB before bandpass filtering [15]. Another useful signal processing method is Principal Component Analysis, which reduces the dimensionality of features while protecting their statistical information.

PCA is a type of dimensionality reduction technique that enhances interpretability while minimizing information loss and can be mainly used for large datasets that are difficult to interpret [16]. The machine learning algorithm requires a more significant amount of data to perform the classification task. PCA applied to machine learning can improve the performance of the classifier for such high-dimensional data [17]. Maximum variance can develop a better model in machine learning that can be easily achieved with the involvement of PCA in the detection model. As the name implies, PCA deals with principal components, whereas ICA focuses on independent members.

2.5. Filtering

Several other EEG pre-processing methods in machine learning include regression methods, blind source separation methods, wavelet transforms, and filtering methods (frequency filtering, adaptive filtering, and Wiener filtering) [18]. Apart from all these methods, we can say that the most straightforward filtering technique for any signal processing is the Infinite Impulse Response (IIR) filter for an improved noise cut-off [19, 20].

Athar A. Ein Shoka also used filtering technology; the 6^{th}-order Butterworth filter has a 60 Hz cut-off frequency [21] for noise removal from EEG signals. In a comparison study, it is mentioned that IIR filters are preferred for low noise coverage and wavelet filters are selected for high noise coverage. However, wavelet filters are used for better noise reduction but are poor in preserving signal information [22] if not used with proper thresholding technique and wavelet transformation. As the sleep stages are included between 0.5-30 Hz, the combined use of High Pass Filter (HPF), Low

Pass Filter (LPF), and Independent Component Analysis (ICA) can provide the removal of low-frequency shift, high-frequency noise, and ocular artefacts present in overlapping frequency bands respectively [23].

2.6. Wavelet Transforms (WT)

Wavelet Transform is an extended version of the Fourier transform, which decomposes the given input into a set of wavelets. It is the most widely used signal-processing method in determining time-frequency characteristics in comparison with all other ways. It is mainly available in continuous wavelet transform and discrete wavelet transform. In contrast with the Fourier transform, the wavelet transform is applicable for analyzing the time-frequency domain as the Fourier transform will give an analysis of perfection in the frequency domain. Wavelet Transforms can be performed not only as a denoising method but also as a method for feature extraction. As EEG signals have different frequency bands, they can be used for extracting features from each frequency band in a simple manner.

Pre-processing can be performed using amplitude comparison, evaluating frequency spectrum, various filtering techniques, EEG pre-processing pipeline using EEGLAB plugin, independent component analysis, etc. The review found that EEG pre-processing works well while employing a filtering mechanism that can remove unnecessary data efficiently. Table 2 describes the advantages, disadvantages, and applications of signal processing methods described in the previous section.

Table 2. Analysis of various signal processing methods

Methods	Advantages	Disadvantages	Applications
Amplitude comparison and chi-square fit test	Efficient and automatic data reduction	Detection of artefacts with non-gaussian distribution of data	Power spectral analysis
Self-Organized Maps (SOM)	Assess associative fields of signals with the same feature relationship		Clustering
PREP pipeline	Fully automated and can be modified. Combines multiple artefact removal processes	Issues arise when the artefact removal steps are not performed uniformly across the dataset	Large-scale data analysis
HAPPE	Short-length sequences with high-level artefacts can be considered	Should run only resting state or event-related data. Files collected should have some channel associated	Good for large sample sizes with high-density channel layout
ICA	Dimensionality reduction and extraction of independent components from the original signal	The assumption of non-Gaussian sources may not be true	Source separation
PCA	Retains variance of the dataset	Cannot extract appropriate interferences if similarity exists in drift potentials and EEG data	Reduce feature dimensionality
Filtering			
Frequency filtering	Remove unnecessary frequency components	Performs inefficiency in the overlap of spectral distributions of EEG components and artefacts	Simple to implement
Adaptive filtering	Adaptable to the change of conditions in the input signal. Ability to adjust filter parameters to optimize performance for current input signal	Providing reference input requires more sensors. Not considering the correlation between the EEG signal and the artifacts present. Computational cost is higher	Time-varying noise
Weiner filtering	An additional reference signal is not required	A highly complicated computational process	Estimation of power spectral density
IIR filter	Work faster, requires a smaller number of coefficients to execute filtering	Non-linear phase response	Can be used where the linear phase is not required
Butterworth filter	Maintain the same shape frequency response for higher order. More linear phase response	Require higher order to implement a particular stop band specification	Noise reduction
Wavelet transform	High resolution in both time and frequency domain	Good noise reduction at high coverage	Nonstationary signal analysis

Amplitude comparison and chi-square fit test can be treated as an essential pre-processing step in signal processing in which the amplitude of sample data points may or may not be discarded after processing that cannot be investigated as an accurate method but instead can be observed as a preliminary step in processing.

The main disadvantage of the discussed method is that there can be a chance of missing slow-wave artefacts. Similarly, SOM with Kohonen net uses FFT for sleep stage evaluation and performs better on stationary signals. The non-stationarity behaviour of the EEG signal will have more or less an impact on its outcome.

However, PREP and HAPPE provide a single-line approach of all methods inculcated into it, which increases the complexity of the model and is likely to be expensive for a minimal dataset. Even though it can be utilized as a perfect companion for beginners in the research field of signal processing. The most common algorithms used in developing EEG-based detection models are ICA, PCA, WT, and frequency filtering.

Among all these, many studies have used frequency filtering in the initial step, followed by WT in developing machine learning-based classification models. Especially in insomnia detection, frequency filtering prevents unwanted frequencies from being removed, and the remaining frequencies can be decomposed using WT [24], producing an accuracy of 95.6 % in performing classification. PCA is known to be suited for enormous datasets and can be well done for combining them with deep learning networks for variety. In [25], PCA was utilized to extract the final one-dimensional feature as input to the convolution network by using its dimensionality reduction property. And achieved a classification with a maximum accuracy of $99.16 \pm 0.39\%$.

3. Feature Extraction Methods

The raw EEG signal becomes clear after noise removal, and to handle large amounts of EEG data, it is necessary to deduct data dimensions. The main aim of feature extraction is to refrain from the characteristics of a signal from the original data to accomplish exact classification using specific classification algorithms. Proper feature extraction and classification provide the chance of getting a correct classification result for our model.

In other words, we can say that feature extraction reveals the hidden characteristics of a signal. It makes us realize the most distinct features present in a signal. We could clean brain signals from noise and other artefacts using different filtering as well as noise removal methods and further proceed with the signal to extract its features. We can divide feature extraction into different categories: the time domain, some non-linear features, and the frequency domain.

3.1. Time Domain Features

The time domain analysis of a signal gives information about how the signal varies over time. Time domain features include statistical measures (such as mean, variance, skewness, kurtosis, median, and standard deviation), zero crossing widely used for signal processing, which expresses the noise rate present in the signal, and amplitude measures (peak-peak amplitude, RMS amplitude, Peak- RMS, Maximum and mean of 1^{st} and 2^{nd} deviate) [26].

3.2. Non-Linear Features

Non-linear methods have the potential to capture chaotic conduct and sudden changes in EEG signals. Since EEG signals are complex, non-linear, and nonstationary, nonlinear-based features give information on the presence of anti-static signals observed in sleep. Hjorth parameters (such as activity, mobility, complexity), identification of activity, and energy values with an elevated activity, whereas entropy features provide irregularity in complex signals [27-29]. Non-linear features include approximate entropy, sample entropy [30], fuzzy entropy [31], and permutation entropy [32], which play an efficient weapon in the analysis of the complexity of brain signals. Entropy features measure the uncertainty in the EEG signal.

3.3. Frequency Domain Features

Frequency domain analysis speaks about the variation of a signal for frequency change. The frequency domain features are efficiently extracted using wavelet analysis and power spectral density. Evaluation of spectral power also plays an essential role in identifying the presence of insomnia in a person with sleeplessness.

In contrast, increased beta power was observed in insomniacs compared to ordinary people if we did a sleep frequency analysis [33]. An important factor that exists in sleep is the K complex, which is a high voltage negative slow wave succeeding positive wave. Forget D [34] suggests that analysis of evoked k complex and evaluation of power spectral analysis promotes a valuable feature for a sleep study. Wavelet analysis performs well in both the time and frequency domain. At low frequencies, wavelet transformation gives good frequency information, and at high frequencies, wavelet transformation provides excellent time information.

Features including time domain, frequency domain, and amplitude measures are well suited for automatic insomnia identification. As EEG signals have different frequency bands and sleep stages can be well defined in those bands associated with it, frequency domain features will talk about sleep quality. Variations in the frequency bands during sleep give an exact idea about the sleep quality obtained for the person under test. Measurement of amplitude variations will provide a picture of ensuring the presence of any unwanted signals present in it.

4. Classification of Algorithms

EEG signals are classified according to the characteristics of the signals in the time or frequency domain. The extracted features will be fed into any classification algorithms to separate them into groups by realizing and predicting the EEG signal to a positive class or negative class. Many classification algorithms are available, which include machine learning, deep learning, etc.

Machine learning algorithms exclude the extraction of features and design of the model for classification, whereas feature extraction is done by itself in deep learning. Some of the commonly used machine learning, and deep learning algorithms, and their features are narrated.

4.1. Machine Learning Algorithms

Machine learning algorithms are Artificial Intelligence (AI) learning methods that predict output on the given input. It is mainly used for prediction and classification, specifically in disease detection. Both small and large datasets work with machine learning algorithms. However, there are chances of overfitting or underfitting the model if the model is not framed in a well-structured manner.

4.1.1. Support Vector Machine

Support Vector Machine (SVM) is the most commonly used and well-popularized machine learning algorithm for signal processing, which operates using an optimal hyperplane and separates data based on classes [35]. Once the SVM model is developed, it can be employed for classifying individual instances within the test data by identifying the best hyperplane, which is the “maximum margin hyperplane” that comes under the optimization technique [36].

SVM classification provides minimum classification error and is advantageous in obtaining a small data set of support vectors during the learning phase, which represents a given classification task [37]. Sleep staging can also be done by employing multiple SVMs in a decision tree framework called a dendrogram SVM, carried out at all repetitions of training-testing where the overall data is divided into training and test set, performs as a spinal cord for multiclass classification with definite binary SVM allocated to each node [38].

4.1.2. Decision Tree

Another supervised learning algorithm employed for solving regression and classification problems is called a decision tree that builds a model for training, used to predict class or target value variables through learning decision rules [39]. Although the main advantage of decision tree classification algorithms is that they can be used for online diagnostic services by using pre-trained classifiers, they prohibit online service due to the high expense of maintaining devices and services [40]. A decision tree is simple and easy to understand but is highly reliable for overfitting. Hyperparameter tuning is required to prevent overfitting.

A bagging classifier with a decision tree is treated as a machine-learning algorithm that fits a small number of hyperparameters [41]. Sleep classification in infants can be done using Decision Tree-based Neural Networks (DT-NN), which help in studying Sudden Infant Death Syndrome (SIDS), a significant reason for death in early infancy [42].

4.1.3. Random Forest Classifier

A Random Forest classifier is a tree-like structure that consists of many individual uncorrelated decision trees, but overfitting of trees may lead to the generation of limiting value of generalization error [43]. Random forest works on the principle that each decision tree present will make predictions, and the final prediction will be the most voted one, which proves improvement in predictive accuracy, reduction in variance, and it has control overfitting rather than using a single decision tree [44].

Sarica A in [45] reviewed random forest and mentioned that it is a set of classification and regression trees- CART on a similar size data set trained named bootstraps, which are created from a random resampling on bootstrap. Random forest would better perform at identifying wakefulness [46].

4.1.4. KNN

A supervised machine learning algorithm that uses nearest neighbours for the predictive performance is nothing but a KNN (K Nearest Neighbours) algorithm. The k value was chosen in such a way by calculating the distance between all instances in the training set and the classified instances [47]. The most desired value for k is 1; instead, selecting a different value results in the classification of the cases into class by a more significant vote of k’s nearest neighbours.

4.2. Deep Learning Algorithms

Deep learning, a division of Machine learning algorithms, uses multiple layers of neural networks for data processing. As in machine learning algorithms, deep understanding can also be divided into supervised and unsupervised learning. Convolutional Neural Networks and Artificial Neural Networks are some of them.

4.2.1. Convolutional Neural Network

A typical deep learning model architecture Convolutional Neural Network (CNN) is used for sleep stage classification that contains a neural network layer named a fully connected layer that performs the primary step of our motive – the classification task [48].

Multi-task CNN SoftMax layer can be used for performing joint classification, and prediction performs one -

to many mappings, should experiment with the varying sized convolutional kernel to understand features at varied resolutions, and is also suitable for capturing shift invariance property [49]. A new deep learning-based method called EEGSNet consolidates CNN with a multi-layer convolution kernel used to extract features that use only EEG spectrogram, yielding better accuracy with fixed input size [50].

4.2.2. Artificial Neural Network

Another method of the deep learning-based classification algorithm is an Artificial Neural Network (ANN), which solves non-linear problems, is easy to implement, and is highly effective in resolving classification problems that consist of elementary units called neurons [51]. Artificial Neural Networks are data processing mechanisms highly applicable in pattern recognition and decision-making that discover fuzzy rules used to accomplish connections between various sets of data that do not follow any particular rules to process the data [52].

C. Robert et al. elaborated on the application of artificial neural networks in sleep research, in which he reviewed various sleep analysis systems [53]. Table 3 shows the comparison of different AI algorithms, highlighting advantages, disadvantages, and applications.

Table 3. Analysis of different classification algorithms

Algorithm	Advantage	Disadvantage	Application
Support Vector Machine	i) Utilized for linearly and non-linearly separable data by selecting the appropriate kernel function. ii) Better generalization capacity	i) Not suitable for large datasets. ii) Not suitable for datasets with noise	Utilized for binary classification
Decision Tree	i) Capable of handling large datasets. ii) Easy to understand and implement. iii) No limit on the number of trees iv) Faster	i) Increase calculation complexity for a more significant amount of training data. ii) Not flexible in modelling the parameters.	Applicable to categorical and numerical problems
Bagging	i) Prevents overfitting ii) A smaller number of hyperparameters require tuning iii) Predictive accuracy is good	i) Computationally expensive ii) High bias if not adequately modelled.	Can be used for large datasets with high dimension
Random Forest	i) Reduced variance ii) Reduced overfitting iii) Better predictive accuracy.	i) Computational power is more ii) Computation time is more with a large number of trees iii) Even though training does not require more time, prediction is slow iv) More complex	Can be utilized in applications where computational power and time are not a concern
K Nearest Neighbors	Faster and easy to implement	i) Selection of the *k* value is difficult. ii) Does not work well with a large dataset	Can be utilized for lower-dimension datasets
Convolutional Neural Network	i) Feature extraction included in the algorithm. ii) High accuracy	Overfit with a small dataset	Suitable for large datasets
Artificial Neural Network	Easy to implement and fully automated	Larger processing time	Solves non-linear problems and can perform pattern recognition

5. Conclusion

The article focuses on describing EEG signal processing methods, feature extraction, and classification algorithms that can be used for the identification of insomnia and highlights the advantages, disadvantages, and applications. Raw EEG signal with noise present in it affects the accuracy of the classification and hence processes the signal with an efficient algorithm followed by feature extraction exhibiting a performance enhancement. Therefore, the choice of pre-processing and efficient classification algorithm suitable for the work is a prominent task in developing an automated insomnia detection model.

Abbreviations

EEG-Electroencephalogram, ECG-Electrocardiogram, EOG-Electrooculogram, EMG-Electromyogram, AASM-American Academy of Sleep Medicine, SRS-Sleep Research Society, ICA-Independent Component Analysis.

Author Contributions

SPM contributed to the design of the review till the completion of the manuscript. TV contributed to the interpretation of the study and the development of the manuscript. All authors have read and approved the manuscript.

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