An In-depth Analysis of Automatic Sleep Stage Categorization

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Abstract
Sleep stage scoring is frequently done manually by sleep analysts who examine polysomnographic (PSG) data collected in sleep labs. The inspection procedure, on the other hand, is time-consuming and complex. Because of these limits, an ASSC system is more important than ever. As previously stated, the ASSC, which is the identification of discrete phases of sleep, is widely used to diagnose and treat numerous sleep disorders. The evolution and problems of multiple existing approaches for sleep stage categorization based on Electroencephalogram (EEG) data are examined in this research. The ASSC largely depends on numerous signal processing modification techniques to extract characteristics from EEG data. Previous feature extraction techniques may be classified into four categories based on their domain: time-domain, frequency-domain, time-frequency domain, and nonlinear features. We cover the benefits and downsides of various techniques in each section. We also learnt about the fundamentals of electroencephalography (EEG), the many forms of sleep disorders, and the standard EEG databases used to evaluate investigations.

Keywords: *Sleep stage scoring, Electroencephalogram, time-frequency features, machine learning, sleep disorders.*

1. Introduction

Sleep is an essential human requirement that is vital for their health. Sleep substantially influences the brain and plays an essential part in a person's performance, physical activity, and learning ability [1-3]. Sleep is thought to be a reversible state in which the eyelids close and many neural systems become dormant. Thus, sleep can render an individual fully or partially unconscious, resulting in reduced brain activity. A human spends about one-third of their life sleeping. In general, the amount of sleep required varies according to age. The National Sleep Foundation (NSF) recommends that most individuals get seven to nine hours of healthy sleep each night. The NSF changed their recommendations in 2015 based on rigorous literature, and they are displayed in Table 1.

Table.1 Sleep Recommendations

Name	Age	Required hours of sleep
Infant	4 - 11 months	12 – 15 hours
Toddler	1 – 2 Years	11 – 14 hours
Pre-schooling	3 – 5 years	10 – 13 hours
School-age child	6 – 13 years	9 – 11 hours
Teen	14 - 17 years	8 – 10 hours
Young Adult	18 – 25 years	7 – 9 hours
Adult	26 – 64 years	7 – 9 hours
Older adult	65+ years	7 – 8 hours

Sufficient sleep is essential due to the presence of a direct relationship between sleep quality and an individual's mental and physical function. Sleep problems are on the rise in the modern world as a result of a stressful and mechanical lifestyle. Furthermore, several studies have found that certain neurological and physiological conditions can interfere with regular sleep patterns [8].According to a report [4, 5], roughly 50–70 million people in the United States suffer from sleep disturbances. Furthermore, sleep disturbances are responsible for more than 90% of depressive disorders [6].Only around 30% of adults receive fewer than six hours of sleep every night, whereas only about 30% of high school kids get at least eight hours [15]. Furthermore, sleep difficulties can lead to a variety of issues, including melancholy, tiredness, and even mortality. According to a survey conducted by the National Highway Traffic Safety Administration in the United States, sleeping while driving was responsible for at least 100,000 automobile accidents [7]. In Germany, one out of every four accidents is caused by sleep problems, while in Australia, more than a billion dollars has been spent on deaths caused by tiredness. Based on these findings, sleep may be viewed as a severe issue that must be addressed by humans. Furthermore, it is necessary to create automatic sleep analysis technologies that can identify sleep-related

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illnesses such as sleep apnea, insomnia, narcolepsy, sleepiness, exhaustion, and so on.

There are 84 different categories of sleep disorders based on the international classification of sleep disorders (ICSD-II) criteria [9].Sleep issues not only have an influence on physical activity throughout the day, but they also have a long-term impact on cognitive processes such as learning, attention, and memory. Excessive daytime sleepiness, neurocognitive impairments, and cardiovascular illness are some of the possible consequences of Obstructive Sleep Apnea Syndrome (OSAS) [10]. Accurate sleep-scoring prediction based on numerous biological records is essential to safeguard people from these calamities. The primary goal of sleep stage scoring is to identify sleep phases that are important in the diagnosis and treatment of sleep disorders. In general, sleep stage grading is performed using polysomnographic (PSG) recordings obtained from patients during their nightly sleep at the hospital [11]. Electromyogram (EMG), Electrocardiogram (ECG), Electrooculogram (EOG), and Electroencephalogram (EEG) are the greatest examples of PSG data (EEG). Visual scoring approaches, in which diverse signals are subjected to visual interpretation, have achieved extensive use to date [12]. However, visual scoring systems have various drawbacks, such as the expert's experience, which might result in different results from different experts [13, 14]. Furthermore, the visual examination is a time-consuming process in which the expert must identify the EEG all night. As a result, automated scoring entered the picture, which was an efficient way of sleep stage scoring.

Several academics have recently presented several strategies for automated sleep stage scoring processing. To generate an appropriate sleeping stage score for a patient based on biological inputs, several signal processing approaches and machine learning methods have been developed [16]. All of these approaches are roughly classified into two types: single-channel and multi-channel processing methods. Only EEG is employed in the first technique to analyze sleep problems. EEG provides the most important information about brain activity, which is employed not only in brain research but also in the study of neurological illnesses [17]. Sleep neurology is an active issue in contemporary biological research, in which EEG data are utilized to investigate and assess the functionality of the brain during sleep, as well as to diagnose various types of sleep disorders. There are several ways for classifying sleep phases that involve single channels [18-20]. Multi-channel approaches, on the other hand, use several biological signals for sleep stage categorization, such as EMG [21] and EOG. Although multi-channel approaches [22, 23] are more successful than single-channel methods, they impose an exorbitant expense on patients, particularly in the sleep test at home. Furthermore, the increased number of wires attached to the patient causes sleep disruption [24]. This research examines numerous cutting-edge automated sleep staging approaches, as well as their benefits and drawbacks. The whole evaluation is divided into four sections based on the characteristics gathered from EEG signals: time-domain features; frequency domain features; time-frequency features; and nonlinear features. We addressed the advantages and disadvantages of each of these feature models. Furthermore, we investigated the specifics of typical visual examination methods used in the past for sleep stage categorization. Along with the cutting-edge methodologies, we addressed the specifics of various typical datasets. The remainder of the study is organized as follows: Section II examines preliminary EEG studies in depth, such as fundamental EEG features, different forms of sleep disorders, and different datasets utilized in previous research. Section III delves into the specifics of cutting-edge procedures and was completed in four sub-phases. The final part addresses the analysis and concludes with observations made during this survey.

2. Preliminaries

In this section, we go over preliminary elements including EEG acquisition, EEG frequency bands, and the many categories of sleep disorders recognized by conventional researchers.

2.1 Electroencephalogram

In general, the human brain is seen as a dynamic network made of millions of neurons linked together by dendrites and axons. The primary function of neurons is to enable adequate communication from and to the brain. According to [25], the entire brain may be split into three primary structures: the stem, cerebellum, and cerebrum. The cerebrum is the largest of these three structures and is separated into two hemispheres that each have an outer surface known as the cerebral cortex. Again, this cortex is divided into four lobes: occipital, temporal, parietal, and frontal [26]. To evaluate brain activity, many forms of biological signals are produced, including Positron Emission Tomography (PET) [28], functional Near-Infrared Spectroscopy (fNIRS) [29], functional Magnetic Resonance Imaging (f-MRI), Magnetoencephalography (MEG), and EEG. Among these signals, EEG is proven to be the most effective and powerful signal, carrying the most relevant information and having the greatest practical recommendations in clinical neurology. EEG is a non-invasive technique for measuring the electrical activity of the cerebral cortex. EEG is recorded by putting many electrodes in different places on the scalp of the head. PSG data are typically collected in one night by monitoring the patient's sleep EEG, chin and leg surface EMGs, EOG signals, blood oxygen level, respiratory rate, and airflow through the mouth and nose [30]. The visual evaluation of complete night PSG data is done using two standard procedures: Rechtschaffen and Kales [31] and the American Academy of Sleep Medicine (AASM) [32]. According to the R&K and AASM standards, the EEG signal is a more informative bio-signal than other signals. EEG signal experts first divide the signal into tiny epochs depending on certain intervals. Then they graphically mark each era depending on the rhythm of its standards (frequency bands) [33]. The four standard EEG rhythms are Beta, Alpha, Theta, and Delta (shown in Table.2). Furthermore, two additional rhythms that occur mostly during the second sleep period are called K-complexes and spindles. Figure 1 depicts examples of EEG signals from various frequency bands.

Table.2 Rhythms (Frequency bands) of EEG

Name of Band (Rhythm)	Frequency range (Hz)
Delta	0.5 – 4
Theta	4 – 8
Alpha	8 – 13
Beta	13 – 30
Spindles	12- 1 4
K-Complexes	0.5 – 1.5

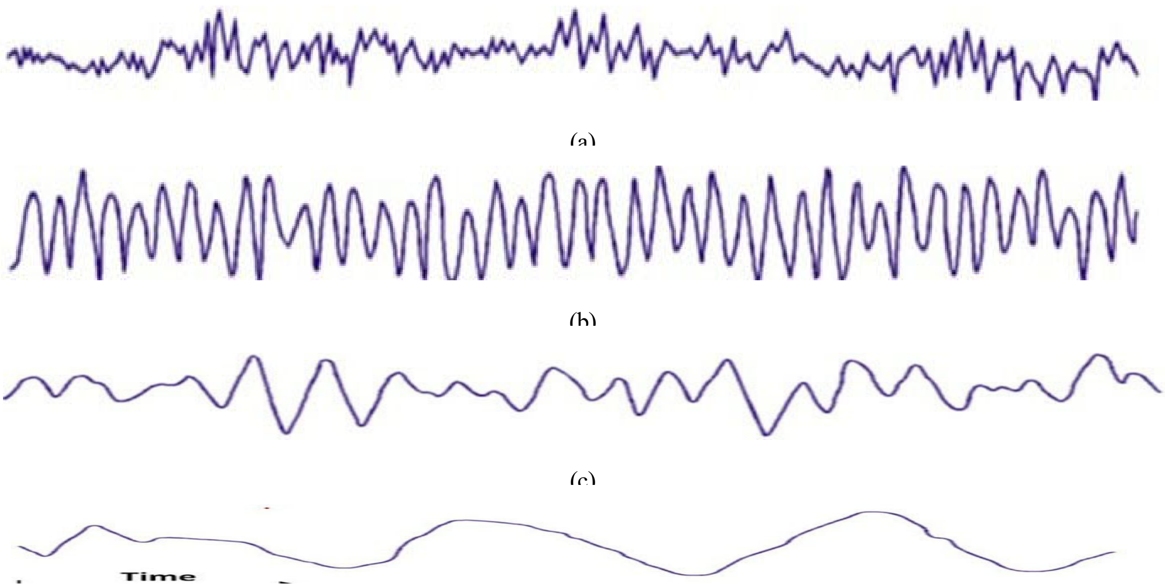

Fig.1 samples of EEG signals at different frequency bands. (a) Beta (12-30), (b) Alpha (8-12), (c) Theta (4-8) and (d) Delta (0.5-4)

2.2 Types of Sleep disorders

For about three decades, the R&K sleep categorization paradigm controlled sleep stage research, and it is now a generally acknowledged standard for determining human sleep problems [34]. The sleep study is divided into seven phases, according to R&K standards: Movement Time (MT), Rapid Eye Movement (REM), Non-rapid Eye Movement (NREM) includes stages 1, 2, 3, and 4, and Wakefulness (W). Even if the R&K standardized sleep via seven phases, there are still several concerns to be handled [35]. A minimum of three electrodes must be put on the occipital, central, and frontal head regions, according to the most recent AASM model. This scenario focuses on REM sleep, slow-wave sleep, microarousal, K-complexes, sleep spindles, sleep phases, and sleep and waking transition. In contrast to the R&K standard, the MT stage is retraced in AASM, and sstages 3 and 4 are integrated into N3. The new AASM trend eliminates the R&K norm and has little influence on the REM phases, Sleep Efficiency, and Total Sleep Time. It does, however, have a significant effect on sleep latency measurement, NREM sleep distribution phases, and Wakes After Sleep Onset (WASO). These consequences have a substantial influence on both scientific and clinical investigations. There are five sleep phases, as described by AASM standards, and they are listed in Table 3.

Table.3 Different types of sleep disorders according to AASM

Stage	Description
Wake (W)	This stage is rendered through the help of alpha or faster frequency bands that occupy more than 50% of the epoch, larger EMG tone, and frequent eye movements.
REM	This stage is characterized if any saw-tooth wave is observed in the epoch along with rapid eye movements and a lower EMG signal.
N1	This stage is characterized by the alpha that occupies more than 50% epoch during theta activity, evidenced by vertex waves and slow rolling eye movements.
N2	This stage is characterized by when the epoch is observed to have K-complexes (less than three minutes) and sleep spindles.
N3	This stage is characterized by the detection of delta activity over 20% of epoch length.

2.3 Databases used in research

Several databases are created by past researchers for the stud and analysis of sleep disorders in human beings. Some of them are briefly outlined here.

2.3.1 Sleep-EDF database

The Sleep EDF database [36] has a total of 197 PSG recordings from a single night. This database contains several biological signals such as chin EMG, EOG, EEG, and Event markers. Some of the records additionally include body temperature and breathing. The sleep patterns are manually graded by well-trained professionals using the R&K standard visual assessment procedure. These patterns (Hypnograms) are not rated and consist of sleep phases W, R, 1, 2, 3, 4, M.

2.3.2 St. Vincent's University Hospital EEG

This dataset [37] contains 25 PSG recordings collected over the course of a single night using a three-channel HolterEEG. Adults are submitted to suspected sleep problem breathing for the purpose of creating this database. Subjects are chosen at random throughout a six-month period beginning in September 2002 and ending in February 2003. Patients referred to the sleep disorders clinic at St. Vincent's University Hospital in Dublin for a probable diagnosis of primary snoring, central sleep apnea, and obstructive sleep apnea were used to identify the participants. All of the patients are over the age of 18, and none of them has heart illness or autonomic dysfunction and is not taking medication. Twenty-five people (4 females and 21 men) were chosen for PSG recordings. A well-trained technician assessed the sleep phases according to R&K standards and labelled each epoch with eight annotations: Wake, REM, Stage 1, 2, 3, 4, Artifact, and Indeterminate.

2.3.3 Cyclic Alternating Pattern EEG database

The CAP sleep database [38, 39] contains a total of 108 PSG recordings obtained at the Ospedale Maggiore of Parma, Italy's centre for sleep disorders. The EEG waveforms include three EEG channels (C3 or C4, F3 or F4, and O1 or O2, also known as A1 or A2), two EOG channels, EMG signals from the submentalis muscles, bilateral anterior tibial EMG, respiration signals (SaO2, thoracic effort, abdominal, and airflow), and an EKG. A total of 16 health subjects are used, all of whom are free of medicines that influence the central nervous system and do not suffer from any neurological problems. Among the 108 recordings, 92 are abnormal recordings (2-bruxism, 4-SBD, 5-narcoleptic, 9-insomnia, 10-PLM 22-RBD, and 40 NFLE). The scoring is supplied by experienced neurologists in accordance with the R&K regulations. Each epoch is denoted by the letters W, S1-S4, R, and MT. EEG signals are captured at 512 Hz, and pre-filtering such as LP (30 Hz), HP (0.3 Hz), and Notch Filter are used (50 Hz).

2.3.4 HMC Sleep Staging database

The sleep staging database at Haaglanden Medisch Centrum (HMC) [40] comprises of 154 PSG recordings obtained in a whole night with the assistance of 154 individuals (66 Female and 88 Male) in the year 2018. This database contains ECG, Chin EMG, EOG, and EEG data. Annotations that proclaim the grading of sleep patterns (hypnograms) are also accessible and are annotated with the assistance of a well-trained specialist at HMC. All epochs are assigned to one of five sleep disorders: W, N1-N4, and R.

3. Literature Survey

The conventional approach for sleep stage classification consists of three stages: pre-processing, feature extraction, and classification. Figure 2 depicts the total sleep stage classification approach. The input EEG data is pre-processed in the first phase, which removes external artefacts and disturbances. Following that, the feature extraction phase entails extracting a collection of features from the EEG. Finally, the final phase uses machine learning techniques to classify the input EEG based on the extracted characteristics by comparing them to pre-trained features. We concentrated on feature extraction in this part because each technique uses a machine learning algorithm for classification. There are four types of comprehensive feature extraction methods: time-domain features, frequency domain features, time-frequency domain features, and nonlinear features.

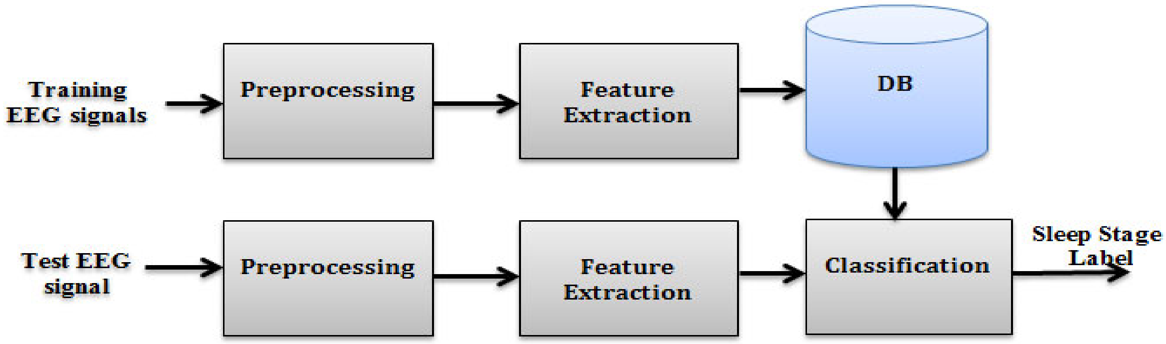

Fig.2 General Schematic of Automatic sleep stage classification system

3.1 Time domain features

Time-domain characteristics may be immediately retrieved from the EEG data and are easy to understand and use. Due to their straightforward interceptive nature, they are easily suitable for real-time application and may depict the signal's morphological characteristics. For the PSG records of 20 healthy patients, K. Susmakova and A. Krakovska [41] assessed time-domain variables such as distribution characteristics and linear spectra measurements. They divided each epoch into five stages, such as waking and four stages of sleep, after analyzing 818 measurements. In the instance of a one-dimensional signal, they used the Fisher Quadratic classifier for classification. For the characterization of the sleep stage, B. Weiss et al. [42] performed a spatio-temporal analysis of the multifractal and monofractal properties of EEG data. The range of fractal spectra (dD) and approximated Hurst exponent (H) in 10 healthy participants was measured. At all electrodes, they saw higher levels of H for NREM stage 4 compared to tREM stage 2 and REM. The dD measure, however, reveals the opposing contribution. They only archived a substantial performance in the categorization of REM and NREM stage 2 as a result of this contentious resolution. Using the EOG, EMG, and EEG recordings of five healthy people, S. Ozsen [43] proposed a novel approach for classifying sleep stages. They extracted the characteristics from EEG epochs using a modified sequential feature selection technique. They utilized five distinct designs of an artificial neural network (ANN) for classification, each of which made use of various features and network parameters. In order to categorize sleep into six phases, M. Diykh et al. [44] collected statistical data in the temporal domain and used the structural graph similarity and the K-means method (SGSKM). Every EEG signal is originally divided into numerous segments since they are thought of as single-channel signals. The next step is to extract statistical characteristics from each segment and feed them to SGSKM for classification of sleep phases. The categorization of EEG data is then performed by O.K. Fasil and R. Rajesh [45] using an exponential energy characteristic. The upper and lower bounds of the time domain exponential energy, which are better suited for low and high amplitude data, were used to represent each EEG epoch.

The Hjorth feature component was created by B. Hjorth [46] and was based on the statistical motions of the EEG power spectrum. It has been discovered that this novel feature is less complicated than traditional time-domain and frequency-domain features. Complexity, Mobility, and Activity are Hjorth characteristics that, respectively, quantify the variance of time series, the fraction of standard deviation of the power spectrum, and the variation in frequency. Three specific feature groups were constructed by B. L. Su et al. [47]. The EEG signal's waveform pattern is intercepted by the first group. The next two groups were made to deal with problems caused by differences in EEG signals between people.

3.2 Features of the Frequency Domain

When measuring frequency domain characteristics, the appropriate features are assessed after the EEG signals are converted to the frequency domain. Higher-order spectra and spectral characteristics are the two types of frequency features (HOS). The EEG signal is first converted into the frequency domain using the Fourier transform in order to extract spectral characteristics (FT). Following the computation of the autocorrelation across the frequency domain signal, an estimation of power spectral density is made. PSD can be estimated using non-parametric or parametric approaches, respectively.

Non-parametric techniques derive the PSD values from the signal samples in a specified time range. The Welch and Periodogram non-parametric techniques are the two most used. In their technique for sleep staging based on rules, S. F. Liang et al. [48] investigated analyzing twelve characteristics. They collected spectral and temporal information from EMG, EOG, and EEG data. They created a hierarchical decision tree with fourteen rules for categorization. The K-Means Clustering-Based Feature Weighting (KMCFW) mechanism is a mix of the K-NN (k-nearest Neighbor) method and decision tree classifiers, as suggested by S. Gunes et al. [49]. Each EEG signal is represented by 129 characteristics according to the feature extraction method they used, Welch spectral analysis [50]. Additionally, they calculated the mean, standard deviation, maximum, and lowest values for 129 characteristics in order to lower the feature count. Although the fundamental benefit of FT is its ease of implementation, they have also benefited from low-frequency resolution at shorter length signals.

On the other hand, model-based approaches are used in parametric methods to estimate the PSD. Moving Average (MA), Autoregressive (AR), and Autoregressive Moving Average are examples of model-based methods (ARMA). Using EEG data, T. Kayikcioglu et al. [51] suggested a quick approach for classifying sleep stages. By monitoring the changes in the frequency spectrum, they assessed the frequency domain characteristics. They used the AR approach to extract coefficients for each 5-s epoch. Partial Least Squares (PLS) was used to categorize three features for classification purposes, with an optimal beta determined using k-fold cross-validation. In order to monitor the poles of a second-order time-varying AR model fitted over an EEG signal, M. Rahbar et al. [52] constructed a reliable model based on Kalman filtering. By segmenting the broad frequency bands into several subbands depending on the brain's rhythms, they were able to increase the frequency resolution. Only when the length is large and the SNR is low do the parametric approaches work. Since it is necessary for the other two models, the decision of the AR order has a greater influence.

Another frequency domain feature extraction technique used in several biological applications is HOS [53, 55]. The frequency content of higher-order statistics of signals is represented by HOS. Because the signal in HOS has a second-order spectrum, phase information is lost during the power spectrum computation. The capacity of HOS to examine the non-linearity and non-Gaussian properties of the EEG signal is by far its greatest benefit. The HOS are particularly helpful in the analysis of sleep EEG signals since the EEG signal is a complicated type signal that requires nonlinear interaction of frequency components. HOS was utilized by U. Acharya et al. [54] to extract secret data from EEG sleep signals. For various stages of sleep, they suggested bi-coherence and bi-spectrum plots that may be utilized as visual motifs in a variety of diagnostic applications. These plots are used to extract a variety of HOS characteristics from NREM stages 1-4, REM, and W sleep phases. The Gaussian Mixture Model (GMM) is then given the information to automatically identify the various phases of sleep.

3.3 Time-Frequency Domain Features

Since the EEG signal is non-stationary, or has changing properties over time, many time-frequency approaches are used to analyze it. A time-domain EEG signal may be converted into a time-frequency signal in a general sense using modelling, energy distribution, and decomposition. Applications involving sleep often employ the final two techniques [56, 57]. There are primarily two techniques for signal decomposition: the Short Time Fourier Transform and the Wavelet Transform. The STFT breaks down the EEG signal into a number of fundamental operations. The technique of time-frequency analysis is both easy and efficient. The signal is initially evenly windowed in STFT, and then each window is put through a frequency domain transformation using FT. The most common decomposition technique is WT, which uses several types of filters to break down a signal into dyadic frequency scales. The mother wavelet function is where all of the various filters have their roots. Both the continuous and discrete varieties of WT can be used for the investigation of sleep stages. WT is an effective instrument since it provides many frequency resolutions for the signal description. After decomposition, the signals are orthogonal to the mother wavelet function. Furthermore, the complete wavelet characteristics cannot be invaded by coloured noise at different scales.

As a result, several writers created various time-frequency feature-based sleep stage categorization techniques. For the categorization of sleep stages, T. H. Sanders et al. [58] introduced the cross-coupling system (CFC). To increase classification accuracy, they also integrated average power with CFC. A wide range of feature extraction techniques, including those in the frequency, temporal, and time-frequency domains, were used by S. Khaligi et al. [59]. They sought to identify the ideal signal combination by taking into account three signals, including EEG, EOG, and EMG. For the extraction of time-frequency features, they used a shift-invariant transform known as the Maximum Overlap Wavelet Transform (MODWT). They then used a support vector machine (SVM) for classification after using histogram analysis for feature selection. et al. [60] extracted characteristics from an ECG to identify tiredness using the Discrete Wavelet Transform (DWT). They first applied a bandpass filter with cut-off frequencies of 0.5 Hz and 100 Hz to the original ECG recordings to extract the noise from them in order to remove the muscle movements. Then, using a 3rd order Debauchies' wavelet filter with five stages of decomposition, the filtered signal is submitted to DWT. The bands are then classified using K-means clustering by computing various statistical parameters, such as the mean, standard deviation, variance, and median for each band.

With the use of three time-frequency-based techniques, including the Hilbert Huang Transform (HHT), Continuous Wavelet Transform (CWT), and Choi-Williams Distribution, Fraiwan L et al. [61] adopted single-channel EEG-based sleep staging (CWD). They calculated Renyi's entropy for the retrieved characteristics and then fed them to classification using a random forest approach. A two-stage sleep categorization approach was suggested by T. Sousa et al. in [62]. Each epoch was initially classified into various nodes of a decision tree using SVM.The misclassified epochs are identified and a new classification is proposed in the next phase. Through the use of the wavelet transform, spectral analysis, and fuzzy c-means algorithm (FCM), M. Obayya et al. [63] sought to categorize six phases of sleep. Every 30 epochs, a total of 12 health recordings are examined. For the purpose of detecting sleepiness, Khushaba, R.N. et al. [64] employed three signals, including the ECG, EEG, and EOG. For feature extraction, they created the effective fuzzy mutual information-based wavelet packet transform (FMIWPT). Fuzzy memberships that accurately reflect the content are used to calculate the MI. To extract useful features from EEG, EMG, and EOG for apnea-hypopnea detection, Schlüter, T., and S. Conrad [65] employed FT in conjunction with wavelet transform and Dyadic Dynamic Time Warping (DDTW) in conjunction with waveform recognition. They were classified using a decision tree algorithm and adhered to R&K sleep phases. Jain V. P. et al. [66] used wavelet transformations and ANN to classify sleep stages using EEG information. Time-frequency analysis for feature extraction was used by Tsinalis, O. et al. [67] to identify different phases of sleep in accordance with the AASM guidelines. For classification, they applied an ensemble learning technique using a group of stacked sparse autoencoders. Transfer SVM (TSVM), a modified form of SVM created by Wu and Wen [68], is used to classify different phases of sleep using an ECG. Additionally, they used DWT to extract features. They divided the EEG into four subbands by raising the frequency of each band by four, assuming that the majority of sleep material is present in the ECG at 0–30 Hz. After DWT, four approximate and four precise bands are obtained.

An Optimized Flexible Analytic Wavelet Transform (OFAWT) was created by Sachin Taran et al. [69] for the categorization of sleep phases using EEG data. By resolving the inequality constraint, they used a genetic algorithm to optimize the parameters of OFAWT. The time domain measurements are used as EEG features, and OFAWT decomposes the signal on a band-limited basis. The classification is then carried out sub-band-wise using a variety of techniques, including decision trees, ensemble classifiers, k-NN, and discriminant analysis. By combining Dual State-Space Models (DSSMs) and Local Energy (LE), H. Shen et al. [70] suggested improved model-based essence features (IMBEFs) for the categorization of sleep phases. Initially, they used Wavelet Packet Decomposition to break down the EEG data into specifics and approximations (WPD). The LE is then estimated using specifics, while DSSMs are measured using approximations. After that, the sleep is categorized in accordance with R&K principles, using the collected IMBEFs as input to the proper classifier. Two recurrent neural network (RNN) models were used by F. Moradi et al. [71] to categorize the different phases of sleep. To determine the connection between EEG signals and musical tones, they used DWT and WPD. CWT was used to extract EEG characteristics while playing musical rhythms. Then, music is produced using the pre-trained RRNs.

The EEG was divided into six subbands using five layers of wavelet decomposition by Sharma M. et al. [72]. They modified it for a time-frequency two-band energy localization filter. They then construct discriminating characteristics from the decomposed coefficients, such as log energy and fuzzy entropy, and feed them to various supervised machine learning algorithms for classification. Empirical Mode Decomposition (EMD) [74] was used by Hasan A. R. et al. [73] to segment the baseline ECG data before computing characteristics based on statistical movements. Then, for classification purposes, they used adaptive boosting algorithms and decision trees. As soon as possible, Hasan A. R. et al. [75] enhanced their approach by using the EMD instead of the Ensemble EMD (EEMD). The calculated statistical movements are sent to the newly created classifier known as Random Under Sampling Boosting for each segment (RUSBoost).

Additionally, other writers used time-frequency characteristics to achieve the categorization of sleep phases using deep learning methods like Convolutional Neural Network (CNN). The Hilbert-Hubert Transform (HHT) was first applied to the EEG data by Zhang et al. [76] before the generated features were sent to orthogonal CNN (OCNN) for classification. Similar to this, XU et al. [77] classified sleep stages using several CNN architectures on multi-channel EEG recordings. The EEG input was directly fed by Mousavi [78] to a deep CNN that has nine convolutional layers and two fully linked layers. They used no feature extraction or feature selection techniques; hence, they saw very low accuracy followed by increased complexity. They created a classifier that could interpret both the EEG data and the pictures using an LSTM-based RNN. With a single-channel EEG, Korkalainen et al. [79] employed a CNN and

LSTM neural network combination to analyze public datasets. For the categorization of sleep phases using single-channel EEG recordings, Michielli et al. [80] used a cascaded RNN architecture based on LSTM. The classifications of classes two and four were tested by the writers.

3.4 Nonlinear Features

Some writers employed the nonlinear feature extraction approach to categorize the various stages of sleep since the EEG data includes nonlinear features and complicated dynamics [81, 84]. The goal of F. Karimzadeh et al. [83] was to identify and analyze cyclic alternative patterns (CAP), a crucial component of ECG signals. To distinguish CAPs from non-CAPs, they used SVM, k-NN, and LDA to assess a family of entropy characteristics. T. Nakamura et al[87] .'s goal was to use fuzzy entropy and permutation entropy to automatically classify sleep stages from EEGs. Multi-scale entropy analysis starts with these two entropies as its kernels. They took into account a sleep transition signal that comes before epoch data by 30 seconds. They used SVM for categorization as well. To describe EEG recordings, J. L. R. Sotleo et al. [88] extract entropy characteristics from them. The Q-alpha technique is then used to optimize them for relevance. The last sleep step is obtained by feeding the generated characteristics to a clustering method [89]. An entropy-based strategy for the categorization of sleep phases using multi-channel EEG recordings was put out by R. K. Tripathy et al. [90]. They first used a novel Multivariate projection-based fixed boundary empirical wavelet transform to divide signals into subbands (MPFBEWT). Then, using the multi-channel data, they calculate entropy characteristics like dispersion and bubble entropies. Finally, a mixed learning algorithm is employed to categorize the various stages of sleep. This approach employs sparse representation and distances from nearest neighbours and is based on class-specific residuals.

Table.4: Literature survey comparison on the Automatic sleep stage classification

Author Name	Year	Method	Features	Drawback
K. Susmakova, A. Krakovska [41]	2008	1. Time-domain features 2. Fisher Quadratic classifier	1. Distribution characteristics and 2. linear spectra measures	1.Time-domain features lost the frequency information and are hence not robust for similar sleep stages 2. Sensitive to additive noises
B. Weiss et al. [42]	2009	1. Time-domain features	1. Multifractal and Monofractal features 2. Hurst Exponent and Range	
Ozsen [43]	2013	1. Time-domain features 2. ANN	modified sequential features	
S. Gunes et al. [49]	2010	1. Frequency domain features (non-parametric) 2. k-NN	1. Welch spectral features 2.Mean, standard deviation, maximum and minimum	Temporal information is lost which shows a great impact on the people of different ages
T. Kayikcioglu et al. [51]	2018	1. Frequency domain features (parametric) 2. PLS	Spectrum changes in the frequency domain through AR	
M. Rahbar et al. [52]	2020	1. Frequency domain features (parametric) 2. Kalman filtering	1. track poles through 2nd order AR model	
U. Acharya et al. [54]	2010	1. Frequency domain features (HOS) 2. GMM	bi-coherence and bi-spectrum plots	
S. Khaligi et al. [59]	2014	1. Time-frequency features 2. SVM	1. MODWT features 2. Histograms	1. Much advantageous compared to time and frequency domain features 2. Complexity is high for a system with minimal configurations 3. Wavelet transform is not shifting invariant
Gurudath N et al. [60]	2014	1. Time-frequency features 2. K-means clustering	1. Five levels DWT features with 3rd order Db wavelet 2.mean, standard deviation, variance, and median	
Fraiwan L et al. [61]	2012	1. Time-frequency features 2. Random Forest	1. HHT, CWT, and CWD features 2. Renyi's entropy	
M. Obayya et al. [63]	2014	1. Time-frequency features 2. FCM	1. Wavelet and spectral features	
Khushaba, R.N et al. [64]	2011	1. Time-frequency features 2.Three signals such as EEG, ECG, and EOG 3. FCM	1. WPT features 2. Mutual information features	
Schlüter, T.; Conrad, S [65]	2010	1. Time-frequency features 2. Decision Tree 3.Used three signals EEG, EOG, and EMG	1. Fourier transform features 2. DDTW features	
Jain V. P et al. [66]	2012	1. Time-frequency features 2. ANN	1. Wavelet features	
Wu wen [68]	2021	1. Time-frequency features 2. TSVM	1. DWT features	
Sachin Taran et al. [69]	2020	1. Time-frequency features 2. Ensemble classifier 3. genetic algorithm	1. OFAWT features 2.k-NN, decision tree, and discriminant analysis	
H. Shen et al. [70]	2020	1. Time-frequency features 2. Ensemble classifier	1. WPD features 2. Local energy 3. Dual state-space models	
Sharma M. et al. [72]	2020	1. Time-frequency features 2.Multiple machine learning algorithms	1. Wavelet features 2. Log energy 3. Fuzzy entropy	
Hasan A. R. et al. [73], [75]	2017	1. Time-frequency features 2. RUSBoost	1. EMD features 2. EEMD features 3. statistical movement features	
Zhang et al. [76]	2020	1. Time-frequency features 2. Deep learning	1. HHT features 2. OCNN	
T. Nakamura et al. [87]	2017	1. Nonlinear features 2. multi-scale entropy analysis 2. SVM	1. fuzzy entropy and permutation entropy	Less robust for real-time applications due to the loss of time and frequency characteristics
J. L. R Sotleo et al. [88]	2014	1. Nonlinear features 2. clustering process [89] 3. Q-alpha algorithm	1. entropy features	
R. K. Tripathy et al. [90]	2020	1. Nonlinear and rime-frequency features 2. hybrid learning algorithm	1. MPFBEWT features 2. Entropy features	Huge complexity due to the multiple features extraction

4. Discussion and Conclusion

The primary goal of this work is to present a clear and extensive analysis of several automated approaches to classifying different stages of sleep. Clinical applications of sleep staging to evaluate brain function are numerous. Furthermore, the success of a visual inspection strategy relies heavily on the analyst's level of experience and training. In addition, there should be no more than an 83% similarity between two experts' assessments on the same sleep signal [91]. However, the age of the expert also has a substantial influence on accuracy since the eyes and brain weariness varies greatly amongst experts.

4.1 Discussion on features

The results of the study show that four main categories of variables are used for EEG sleep stage categorization. Features can be classified as either time-based, frequency-based, time-frequency-combination, or nonlinear. The survey's observations on these four classes of traits are addressed in detail below.

4.1.1 Time features

According to the cited study, time domain characteristics were the first to be applied to the automated stage categorization of sleep. Therefore, measures of central tendency and dispersion including mean, variance, skewness, kurtosis, and so on are recommended for sleep research. AR [92] is widely utilized for EEG analysis and has shown promising results in sleep stage discrimination [93]. As a result, the AR coefficients are widely regarded as a useful tool in a variety of contexts. However, time-domain characteristics suffer greatly from being too sensitive to additive disturbances.

4.1.2 Frequency features

Each sleep stage is given its own set of frequencies in the context of frequency characteristics aided sleep stage categorization. Various strategies, including HOS, parametric, and non-parametric, are used to depict various spectral bands under this heading. Research shows that the characteristics derived from the Welch approach are superior than those derived from any other method. This is because non-parametric approaches are more successful than parametric ones since they are less sensitive to noise and more resistant to motion artefacts and disturbances. Since the calculation of a single autocorrelation function is all that is required by the non-parametric approaches. The HOS characteristics, on the other hand, probe the frequency behaviour of the relevant cumulant and offer phase coupling within the signal. When compared to other frequency-domain characteristics, the HOS of a signal provides unique information and allows for the extraction of many features since it reflects the surface qualities in bi-frequency space. On the other hand, the HOS capabilities place a significant computational strain due to the many signal multiplications with its shifted counterparts. The limited frequency range of EEG is the biggest drawback of using HOS.

4.1.3 Time-Frequency features

The time and frequency information of the signal are both readily available, which is the major benefit of time-frequency characteristics. These characteristics may be broken down into two broad classes: linear and nonlinear. Spectrogram and Choi-Williams are used to extract linear characteristics from the EEG data, whereas Wavelet and STFT are used to obtain nonlinear features. The wavelet properties are effective in identifying the sleep stage transition because the onset of sleep is related to both amplitude fluctuations and frequency band shifts. In contrast to frequency features, which often need proper auto-correlation function computations, wavelet features have this step eliminated. The wavelet features are robust over long time periods because they are insensitive to the non-stationary nature of EEG signals. In summary, the wavelet transform offers greater benefits in EEG analysis than the alternative time-frequency domain characteristics. In this specific context, the CWT outperforms the DWT with regard to frequency resolution inside the sub-band. For classifying sleep phases, CWT gives more stable and elicited characteristics, and the features are more redundant than those given by DWT [94].

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