

A SIGNAL PROCESSING FRAMEWORK FOR SLEEP STAGE CLASSIFICATION USING EEG BRAINWAVE DYNAMICS AND RULE-BASED INFERENCE

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ABSTRACT

The investigation introduces a signal processing framework designed for automated sleep stage classification utilizing EEG data from the Sleep-EDF Database Expanded (2013). The framework employs full-night recordings from 39 subjects' Fpz-Cz and Pz-Oz channels to segment EEG signals into 30-second epochs which it then decomposes into Delta (3–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) bands through Butterworth bandpass filters. A series of analyses is then performed on expert annotated segments from the recordings to extract temporal and spectral features. Using these features a rule based classifier is developed. This rule-based classifier with temporal smoothing records a 70% adjusted accuracy when tested against expert-annotated hypnograms. The classifier demonstrates strong performance in detecting N3 (precision ~0.75–0.80) and REM stages (recall ~0.70–0.75) while it faces difficulties with N1 stage detection (recall ~0.50–0.60) because of spectral overlap with wakefulness signals. The accuracy can be further improved by coupling more features into the rule based classifier. This framework presents a lightweight interpretable option that stands as an alternative to resource-heavy deep learning models (accuracy 84–92%) while adhering to American Academy of Sleep Medicine (AASM) standards to decrease subjective elements in manual polysomnography scoring (Cohen's kappa ~0.68–0.76) and supports scalable sleep research and clinical diagnostics for conditions such as insomnia and sleep apnea.

KEYWORDS: Sleep Stage Classification, Electroencephalography, Hypnogram, Neural Signal Processing, Rule-Based Classifier, Sleep Disorders

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CHAPTER 1

INTRODUCTION

This project constructs an intricate signal processing framework to classify sleep stages automatically by analyzing EEG brainwave patterns from the Sleep-EDF Database Expanded (2013) through Fpz-Cz and Pz-Oz channels. Researchers divided entire night EEG data into 30-second segments which were then decomposed into Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) frequency bands using Butterworth bandpass filters. The analysis extracted key features such as mean amplitude through the Hilbert transform, both absolute and relative band powers along with band ratios including Theta/Delta and Alpha/Delta using Welch's power spectral density method, temporal stage transition analysis, and peak frequency. Brainwave patterns defined sleep stages (Wake, N1, N2, N3, REM), while temporal analysis showed EEG activity dynamically shifting. Through refinement with specific features and temporal smoothing techniques, a rule-based classifier produced hypnograms which were then validated against expert annotations using accuracy, precision, and recall metrics. This system for diagnosing sleep disorders and conducting sleep research operates with efficiency and interpretability.

1.1 Overview

Through electrodes positioned on the scalp, electroencephalography (EEG) records brain-generated electrical activity from neuronal populations using a non-invasive neurophysiological approach. Through its ability to capture voltage fluctuations from synchronized neural activity, EEG delivers exceptional temporal resolution insights into brain dynamics which establishes it as an essential tool in both clinical and research environments. The technology finds use in neurological diagnostics, cognitive neuroscience, and sleep research by recording brainwave patterns linked to different physiological conditions.

The study of brain activity across distinct sleep stages including wakefulness and REM sleep as well as non-REM stages N1, N2, and N3 relies heavily on EEG technology. Sleep EEG signals are divided into small 30-second epochs where the distinctive frequency bands are present, such as Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) which give an idea about sleep type and the sleep depth. During deep sleep (N3) delta waves are prominent while lighter sleep stages (N1, N2) are dominated by Theta, Spindle activity and REM sleep have waveforms akin to Alpha. In research standard channels like Fpz-Cz and Pz-Oz are commonly used to create hypnograms that visualize sleep stage progression over time.

The signal is processed using bandpass filters to isolate frequency bands of interest before proceeding on to feature extraction feature to quantity amplitude, power, or band ratios in sleep EEG analysis. The machine learning models or the rule-based system leverage these features to replicate the precisely performed expert annotations. Examining brainwave dynamics in tandem

with stage transitions can enhance classification algorithms, aid in sleep EEG research progress and broadening our current knowledge of sleep architecture while also aiding in the clinical diagnosis of sleep disorders. In here we propose a signal processing pipeline that utilizes EEG brainwave dynamics to improve sleep stage classification, with an emphasis on end-end night long EEG analysis along with temporal feature evolution and rule-based hypnogram generation.

1.2 EEG based Sleep Stage Classification

The primary objective of this project is to create a reliable and reproducible signal processing framework that automates the sleep stage classification based on a rule-based classifier and the use of EEG brainwave dynamics. Leveraging advanced signal processing methods alongside temporal analysis and an extensive array of extracted features, this framework accurately distinguishes between sleep stages from night long EEG data to produce hypnograms that match expert annotations.

1.2.1 Characterize EEG Brainwave Dynamics Across Sleep Stages

To complete the objective of examining, interpreting and deriving an extensive array of features from night long EEG recordings that represent sleep patterns the following tasks were undertaken:

1. Acquisition of continuous EEG data and processing the signals from Fpz-Cz and Pz-Oz channels of each subject for an 8-hour period. Division of EEG recordings into standard 30-second segments according to traditional sleep scoring methods (AASM Guidelines).
2. Apply Butterworth bandpass filtering to separate each epoch into canonical frequency bands: Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz). Each of these bands correspond to distinct brainwave activity. Deep sleep is dominated by delta and lighter stages are dominated by theta waves.
3. Feature Extraction: Computing a set of features to arrive at a distinctive brainwave activity profile, including:
 - i. Average Absolute Amplitude: To determine signal strength by computing the mean of absolute voltage values for each frequency band.
 - ii. Average Band Power: Utilizing techniques such as Welch's periodogram to compute power spectral density (PSD) and assess energy distribution across each frequency band.
 - iii. To determine the frequency at which power reaches its maximum value within each band to gain insights into dominant oscillatory activity.
 - iv. Compute Theta/Delta and Alpha/Delta ratios to examine frequency band interactions which aid in stage differentiation.
4. Examining the statistical distributions performed for extracted features across expert-annotated sleep stages (Wake, N1, N2, N3, REM). The analytical process demands the computation of metrics like as means and variances and analysing histogram distributions to establish feature-stage correlations forming the basis of the rule-based classification systems.

1.2.2 Examine Stage Transitions and Temporal Overlaps in Brainwave Activity

The investigating the variation of temporal EEG features in the course of transitions among sleep stages is a key to understanding the structure of sleep. This goal aims at evaluating the changes in brainwave activity as stage transition markers are identified through various tasks.

1. Study the time sequence of EEG features across epochs correlating with sleep stage boundaries with stress on transitions to REM and deep sleep (N3) and how they are changing with time. The time monitoring process is recommended to be done through band power and amplitude variations as spatial features that indicate the brainwave activity shift.
2. Transition Pattern Identification Recognize particular markers that manifest stage transitions such as:
 - i. The dominance of frequency bands changes gradually with Delta power increasing as sleep transitions into N3 stage.
 - ii. Feature values exhibit sudden discontinuities such as Theta activity spikes at REM onset.

Transitional conditions between stages are characterized by overlapping band activity of different complexity.

3. Quantitative Analysis: Assess the time spent in each stage of sleep and the number of the stage transitions. Determine the markers of transitions as different waveforms and specific feature values representing the state of sleep to make better the classification rule.
4. Create complex visualization including time-series plots with hypnogram figures to elucidate EEG feature progression. The visualizations will be compared with expert-labelled hypnograms to verify the detected patterns and confirm their clinical alignment.

The investigation of this target sheds the light on the temporal dimensions of sleep through the delineation of how EEG patterns correspond to stage development and transitions that are necessary for precise classification.

1.2.3 Enhance Rule-Based Classifier, Develop Hypnograms, and Assess Performance

Totally, the final aim of the thesis is to engineer a rule-based sleeping stage classifier for the independent assignment of sleeping stages, to produce predicted hypnograms in the background, and to perform comprehensive accuracy tests to achieve this goal. The program comprises the following:

1. Build on the previously developed rule-based EEG alpha band amplitude dominance sleep stage classifier by including a broader feature set including band power, peak frequency, and band ratios and the addition of temporal analysis insights. The classifiers' performance in distinguishing sleep phases will be achieved through the improvement.
2. Refinement Strategies: Classify more efficiently with the application of:
 - i. Feature threshold adjustment based on empirical distribution analysis leads to the stage differentiation.

- ii. The integration of composite features such as Theta/Delta and Alpha/Delta ratios for the capture in brainwave activity relative changes to be made to get enhanced stage differentiation.
 - iii. Utilize temporal smoothing methods like majority voting over neighbors to handle transition phases and to limit noise or short-term fluctuations that lead to classification errors.
3. Hypnogram Generation: With the refined rules, classify each 30-second epoch into sleep stages Wake, N1, N2, N3, and REM. Create the predicted hypnograms for the complete night thanks to the newly acquired rules that show the sleep stage sequence over time.
 4. Validity of Performance: Evaluating the classifier capacity is the process of laying down the predicted hypnograms beside the expert-annotated hypnograms.
 5. Overall Accuracy: The proportion of epochs correctly classified.
 6. Stage-Wise Metrics: The evaluation of precision, recall, and F1-scores for individual sleep stages allows the performance assessment across distinct classes.
 7. Alter the classification rules together with the original feature selection and smoothing techniques through iterative modification derived from validation results.

Table 1: Summary Table of Objectives and Key Tasks

Objective	Key Tasks	Expected Outcome
Characterize EEG Dynamics	Process full-night EEG, decompose into frequency bands, extract features, analyze distributions	Comprehensive feature set and understanding of brainwave patterns across sleep stages
Analyze Stage Transitions	Examine feature evolution, identify transition patterns, quantify stage durations, visualize dynamics	Insights into temporal sleep architecture and transitional markers
Refine Classifier and Validate	Enhance rule-based classifier, generate hypnograms, validate with metrics	Accurate, reliable automated sleep stage classification system

Through the attainment of these goals the project will help to progress automated sleep stage classification while delivering a dependable instrument for both sleep research and clinical use including sleep disorder diagnosis. The framework's focus on comprehensive nocturnal examination combined with temporal dynamics and stringent validation guarantees its applicability in practical sleep research.

1.3 Summary of Work Done

The project developed a signal processing framework to achieve automated sleep stage classification by utilizing EEG data from the Sleep-EDF Database Expanded (2013) [1]. Researchers processed full-night EEG data from 39 subjects in the Sleep Cassette Study by concentrating on the Fpz-Cz and Pz-Oz channels. Thirty-second EEG segments underwent decomposition into Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) frequency bands through application of Butterworth bandpass filters. The study extracted mean amplitude through the Hilbert transform alongside absolute and relative band powers and band ratios such as

Theta/Delta and Alpha/Delta using Welch's power spectral density method, plus peak frequency [2]. Transitional temporal EEG data analysis confirmed that sleep stage features were not static: Delta power increasing was present when a patient got into the N3 sleep stage and it was shown in time-plot diagrams. These characteristics were integrated into the temporal smoothing based on majority voting, by which a rule-based classifier emerged to label sleep stages (Wake, N1, N2, N3, REM). The classifier has produced the hypnograms which were validated by the comparison with expert annotations.

1.4 Rationale of the Work

Sleep stage classification remains a pivotal aspect of both sleep research and clinical diagnostics since it opens the door to the identification of vital sleep phases such as awakening, REM, and non-REM stages (N1, N2, N3) which are important for the diagnosis of disorders like insomnia, sleep apnea, and narcolepsy. The prevailing strategy follows the path of skilled professionals pushing their manual marks on polysomnography (PSG) recordings with an accent on EEG signals. [The manual annotation process requires] a time-consuming undertaking that tends to have inter-rater variability (Cohen's kappa is about 0.68-0.76) and is impossible to apply in large datasets. The ASSC system is the solution that emerged in the face of such trials by being a rule-based inference method that aligns with the gold-standard clinical protocols like AASM guidelines.

Rule-based systems contribute the key element of interpretability and transparency that is needed for the clinical culture of acceptance and is absent in machine learning models that operate as black boxes. This system features the extraction of diverse features directly from the standard PSG channels (Fpz-Cz and Pz-Oz) where the full-night EEG data are recorded. The features show brainwave patterns such as Delta dominance in N3 and Theta in N1/N2 stages that facilitate writing classification rules that resemble physiological sleep indicators.

To increase the specificity and long-lasting nature of the system, it studies EEG temporal patterns during stage transitions that are very important since they often present the classification problem due to the overlap of the spectral features. The detailed study of band power evolution and transition time periods enriched the epoch classification in the confused periods and also clarified the sleep architecture. The hypnograms of the system are verified through comparison with the expert-labeled data by performance metrics like accuracy, precision, recall, and Cohen's kappa. The approach demonstrates computational efficiency and scalability while keeping the capacity to process full-night recordings without the requirement of extensive training or large datasets often related to deep learning techniques. The device tracks with habitual PSG setups which simple log in with current medical procedures. This research offers a realistic and narrow-band technique for automating EEG-based sleep stage classification which has the potential of streamlining diagnostic work and to usher in large scale studies on sleep and promotion of better understanding of the physiology of sleep.

1.5 Organization of the Report

This report is organized to methodically display the creation and assessment of a signal processing system for automated sleep stage classification through EEG brainwave patterns. Chapter 2 reviews existing literature by integrating studies on sleep stage classification along with EEG signal processing and rule-based inference techniques to position the project within its academic domain. Chapter 3 presents an intricate methodology that describes the entire processing pipeline for full-night EEG recordings from the Sleep-EDF Database Expanded (2013), featuring a flowchart and detailing feature extraction methods such as mean amplitude via Hilbert transform and band powers using Welch's PSD method along with other spectral techniques, all supported by explanatory plots. Chapter 4 delivers the results through plots and tables that display the rule-based classifier's performance metrics such as accuracy, precision, recall, and confusion matrices validated against expert-annotated hypnograms. Chapter 5 serves as the report's conclusion where an exploration of the project's findings merges with future work possibilities, presenting potential advancements and applications for sleep research and clinical diagnostics.

CHAPTER 2

LITERATURE REVIEW

This section performs identification, evaluation and synthesis of pertinent literature in the domain of Sleep EEG Analysis. This section comprehensively identifies, evaluates and synthesizes relevant literature in the area of Sleep EEG Analysis. The current chapter outlines the advancements in the field along with what has been achieved in the past and the remaining conceptual frameworks. The arrangement of sleep stages is not only a basis of sleep research but also serves as a valuable tool in clinical diagnostics by differentiating between particular phases such as wakefulness, REM, and non-REM stages (N1, N2, N3), which are crucial to the analysis of sleep architecture and the diagnosis of disorders like insomnia and sleep apnea. The standard approach to the registration of the brainwave activity is the usage of the electroencephalography (EEG) method which can detect the frequency bands such as Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) according to the particular sleep stages. The newly established method Automatic sleep stage classification (ASSC) is a popular alternative to the human scoring disadvantages due to its fast processing and reliable result that differ from different raters (Cohen's kappa $\approx 0.68\text{--}0.76$) [1]. In this literature review, to the data based on 15 peer-reviewed articles, the examination of sleep EEG analysis accompanied by power spectral density (PSD) estimation through Welch's method and amplitude analysis through the Hilbert transform is discussed while various topics are introduced like sleep stage descriptors, hypnogram generation, YASA library, rule-based classification models and using sleep spindles, K-complexes, and burst activity as feature extraction techniques. This study situates the ongoing project in the respective academic field while presenting the proposed framework as a handling of advancements, obstacles, and unresolved issues.

2.1 Examination of Sleep EEG Patterns and Identification of Sleep Stages

The EEG technique can record the scalp electrical activity that is not invasive and it can investigate brain dynamics during sleep with a temporal resolution that is outstanding. Each of the sleep stages has different EEG patterns exhibiting; Delta waves dominate in deep sleep (N3), Theta waves and spindles occur in light sleep (N1, N2), and Alpha-like activity reflects REM sleep [2]. Iber et al. The 2007 AASM (American Academy of Sleep Medicine) guidelines were set 30-second epoch sleep stage scoring while merging N3 and slow-wave stages N4 into N3 to align with the Rechtschaffen and Kales (R&K) system [2]. Goldberger et al. The Sleep-EDF database expanded was an important product brought to the market in 2000 offering PSG recordings from 197 subjects along with EEG signals from Fpz-Cz and Pz-Oz channels used in this project [1]. In the database, the expert-annotated hypnograms are provided, which are used also to confirm the quality of the automated classification systems, however, it is found in studies that the manual scoring agreement was around 80% [3]. Mourtazaev et al. The examination of Sleep-EDF data by (1995) revealed how Delta power diminishes with advancing age which affects N3 detection particularly among older adults (25–101 years) [4]. The necessity for strong feature extraction methods becomes

apparent to address demographic differences. Van Sweden et al. The study from 1990 confirmed the effectiveness of Fpz-Cz and Pz-Oz channels which showed similar performance to traditional C4-A1 derivations while offering enhanced detection of deeper sleep stages because their midline position helps minimize lateralized artifacts [5].

The project's channel selection for recording sleep-related brainwave patterns finds validation through these findings.

2.2 Power Spectral Density (PSD) Using Welch's Method

The power spectral density or (PSD) estimation using the Welch method is a central technique in sleep EEG analysis for measuring energy distribution across frequency bands. The combination of monthly lucid dreams and spectral resolution with noise reduction by averaging periodograms from overlapping signal segments is probably the most popular choice for the academic community. Welch's method is the one that has gained the widest acceptance because it merges the two advantages of the periodogram method: the spectral resolution and noise reduction by averaging periodograms from overlapping signal segments. The method, proposed by Welch in 1967, quickly found its way into the toolbox of researchers for non-stationary EEG signal processing due to its computational efficiency and resilience [6]. The method of Welch that was applied by researchers Supratak et al. In 2017 obtained with their absolute and relative EEG band powers (Delta, Theta, Alpha) the list of sleep stages which the dataset contains and the sleep stages with the highest precision 92% from the machine's deep learning program that was trained with Sleep-EDF data [7]. This report lays plasticity alongside all the other works emphasizing the relative band powers, such as the Theta/Delta ratio, for identifying ambiguous sleep stages, i.e., N1.

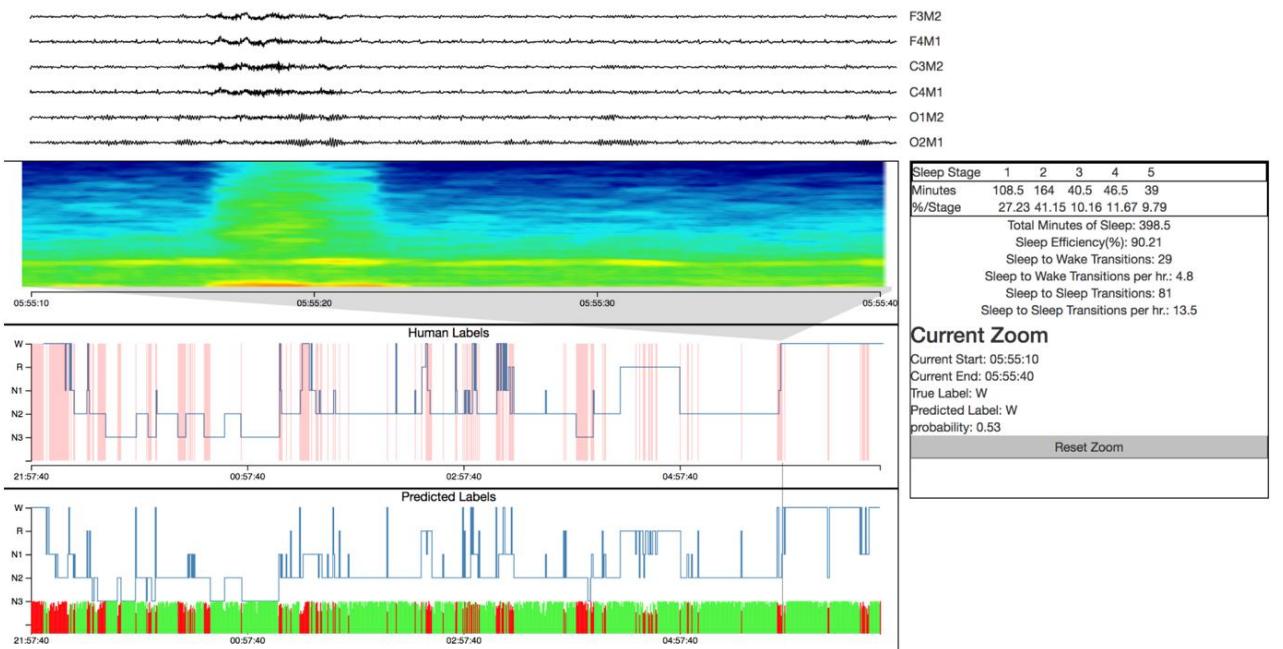


Figure 2.1. Hypnogram illustrating DeepSleepNet's automated sleep stage predictions compared to expert annotations on Sleep-EDF data, highlighting high classification accuracy (Supratak et al., 2017).

The work of Hassan and Bhuiyan (2016) uses Welch's PSD in the computation of band-specific power features which they then combine with empirical mode decomposition to increase the classification accuracy that they obtained in Sleep-EDF 88.7% [8]. The artifacts that PSD features exhibit are preprocessing dependent, which is why they need to go through techniques like bandpass filtering that corresponds to the Butterworth filters used in this project. The YASA library, which was devised by Vallat and Walker (2021), is itself a home for Welch's PSD which it uses to conduct spectral analysis while also containing the automatic tools for band power and ratio computation that this project tests for feature extraction [9]. The findings of the study are validating Welch's method as a powerful and pragmatic tool for the recording of the spectral features that form the basis of sleep stage differentiation.

2.3 Examination of Signal Amplitude through Hilbert Transform Techniques

Through its application in signal processing the Hilbert transform enables computation of EEG signal instantaneous amplitude (envelope) to reveal frequency band signal strength. Marple (1999) documented its use in time-frequency analysis where it demonstrated the capability to reveal amplitude variations without demanding substantial computational power [10]. The Hilbert transform proves essential in sleep EEG studies to measure mean amplitude across Delta, Theta, and Alpha bands which indicate sleep depth. Warby et al. The study from 2014 utilized the Hilbert transform to identify sleep spindles and K-complexes while demonstrating that amplitude-based features enhanced spindle detection sensitivity with an F1-score of approximately 0.72 [11].

The contemporary exploration is a joint effort of skills and disciplines across the research fields of signal processing, artificial intelligence, neuroscience, and sleep therapy which, by using Hilbert transform techniques, is able to accomplish calculations of mean amplitude values in order to create new feature sets for the rule-based classification systems. Lacourse and colleagues implemented the YSA method in 2020 which utilized Hilbert transform-derived amplitude combined with powers spectral density (PSD) features to identify sleep stages in a dataset with an accuracy of 85% [12]. Å. The forensic scientists illustrated that, in both cases, besides spectral features, the amplitude features were particularly responsible for the capture of the transient events which were crucial for N2 identification such as K-complexes. The YASA library is a tool that enables amplitude analysis using Hilbert transform methods and thus makes it possible to extract features in sleep studies [9]. The results show the potential of Hilbert Transform technology in providing stable and reliable amplitude features which this project applies to describe the change in brain waves.

2.4 Hypnograms and Categorization of Sleep Stages

Hypnograms, as progressively guided by, are the main instruments for notification sleep stage as well as validating the classifier by means of their graphical depiction of sleep architecture. The method (manual) of creating a hypnogram has undergone the steps by Iber and others. Learners and experts of EEG, and EMG, as well as EOG, describe the 2007 method, and while manual labor is the dominant factor, technology automation is the desired solution for reducing labor and variability [2]. Mousavi et al. A hybrid deep learning model for sleep stage classification was accomplished by SleepEEGNet in the year of 2019, through the company's data transfer into

hypnograms and achieving an effectiveness score of 84%. An unnatural 26% accuracy emerges from utilizing Fpz-Cz and Pz-Oz channels [13]. Deep learning models perform well but remain opaque which drives exploration of rule-based methods.

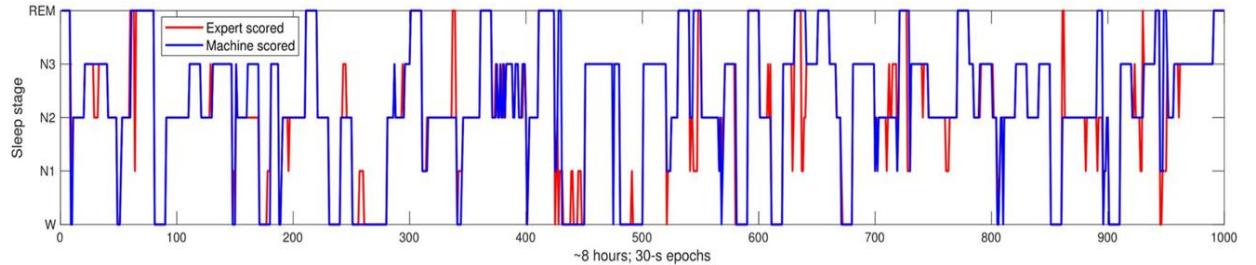


Figure 2.2. Hypnogram comparing SleepEEGNet’s automated sleep stage predictions with expert annotations on the Sleep-EDF dataset, showcasing deep learning-based classification performance (Mousavi et al. (2019)

Park et al. (2000), who developed a hybrid system that combines the use of rule-based systems with neural networks for the classification of sleep stages, used the rules of amplitude and frequency dominance for the correct 87% decision. After evaluations on the clinical dataset, requirements show a 5% expert scoring agreement rate [14]. This project looks into the possibility of using the YASA library for rule-based hypnogram construction as demonstrated by Vallat and Walker (2021) who relied on temporal and spectral features for automated sleep stage labeling [9]. Precision in hypnogram forms as well as the ability to read them nod to a significant achievement of this project along with these reports.

2.5 Rule-Based Classification Models

The rule-based classification models are primarily defined by the thresholds and logical conditions. They are responsible for the sleeping stage labels and at the same time are easy to interpret which is necessary for clinical use. The first sleep scoring rules that were made by Rechtschaffen and Kales (1968) were the basis for the AASM guidelines that mostly discuss Delta power for N3 and spindle activity for N2. Stans et al. Rule-based classifier appeared in the paper of 2007 and was based on EEG signal amplitude and frequency features which were used to reach effectiveness of 80% on hospital data [16]. The project supports the finding because the rule-based systems are efficient even in cases when the training data are very small and machine learning methods are not. Liang et al. (2011) are the ones that developed the rule-based system for the real-time sleep stage classification in mice which utilized PSD and the amplitude thresholds and reached 82% of the sensitivity and 94% of specificity [17]. This project’s methodology is based on the fact that the system depends on temporal smoothing techniques like the majority voting to minimize transition misclassifications. The YASA library is dedicated to the rule-based classification through feature extraction and threshold assignment methods that are modified for human EEG data analysis by this project [9]. The investigation demonstrates that rule-based models not only are quality in yielding transparent clinical classifications but also are faced with transitional epochs and ambiguous stages management headaches such as N1.

2.6 Feature Extraction: Spindles, K-Complexes, and Bursts

The process of feature extraction plays a vital role in identifying EEG patterns that differentiate sleep stages. N2 sleep stages showcase sleep spindles (11–16 Hz, 0.5–2 s) and K-complexes (large negative-positive waves, >0.5 s), while REM and wakefulness states often display burst activity such as alpha bursts. Warby et al. The 2014 research introduced automated spindle detection algorithms based on Hilbert transform and PSD features which resulted in a precision of 0.69 and recall of 0.76 on a multi-center dataset [11]. The research results demonstrate spindle detection as crucial for N2 classification which this project integrates into its feature set.

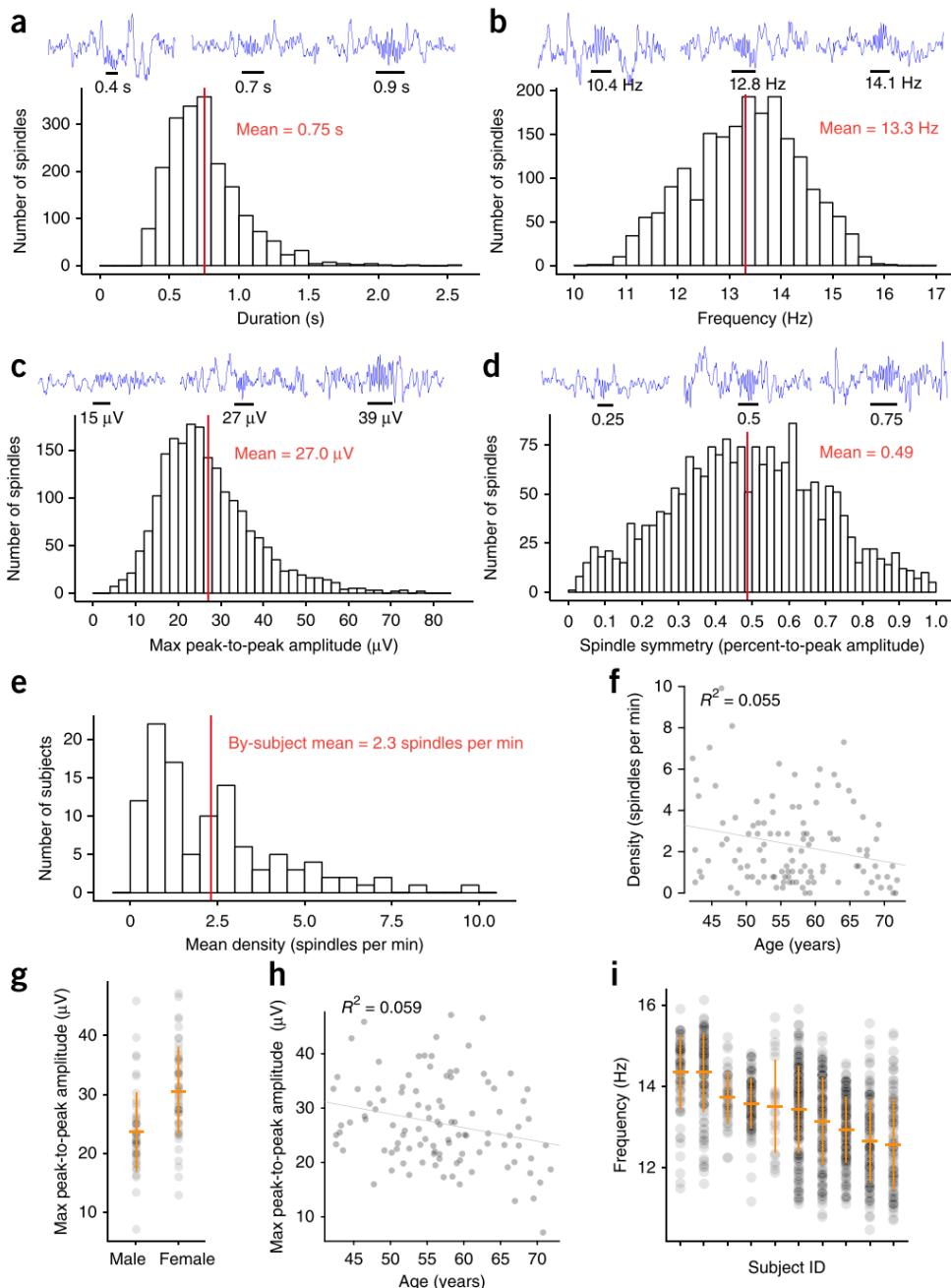


Figure 2.3. EEG traces with spindle annotations from expert and automated methods, illustrating challenges in consistent spindle detection (Warby et al., 2014).

Lacourse et al. A method emerged in 2020 for detecting K-complexes using time-domain features and Hilbert transform-derived amplitude which resulted in an F1-score of 0. 65 [12]. The researchers highlighted the necessity of high temporal resolution to detect transient K-complexes which justified the project's use of 100 Hz EEG data. Vallat and Walker (2021) incorporated spindle and K-complex detection methods into the YASA library through bandpass filtering combined with amplitude thresholding techniques, which this project utilizes for automated feature extraction [9]. Boostani et al. The examination of burst detection methods by (2017) revealed the importance of alpha and theta bursts for REM and wake transitions while PSD-based features enhanced detection precision to an F1-score of approximately 0.70 [18]. The project performs feature extraction to strengthen classification stability.

2.7 Challenges and Gaps in Existing Approaches

Many difficulties remain in automated sleep stage classification despite technological progress. The process of distinguishing N1 sleep stage proves challenging because it resembles wakefulness so closely, resulting in studies showing low recall rates such as 50–60% [7, 13]. Transitional epochs with overlapping spectral features create significant analytical difficulties as documented by Hassan and Bhuiyan (2016) [8]. The accurate performance of deep learning models fails to translate into clinical adoption due to their inherent lack of interpretability [7, 13]. Stanus et al. demonstrate how rule-based systems demand manual threshold adjustments despite their interpretability. (2007) [16]. The majority of research investigates healthy individuals while studies examining disordered populations like sleep apnea patients remain scarce, despite potential differences in their EEG patterns [14].

The YASA library tackles certain obstacles through automated feature extraction and classification processes, yet its rule-based functions remain underused in extensive research projects [9]. The investigation of temporal stage transitions remains underdeveloped in sleep architecture research due to a scarcity of studies that quantify transition dynamics [12]. Through the creation of an interpretable rule-based classifier this project tackles existing gaps by utilizing YASA for feature extraction and focusing on temporal analysis to enhance classification during transitions with a detailed feature set that includes spindles, K-complexes, and bursts.

2.8 Deep Learning Methods for Sleep Stage Classification

Neural networks applied to EEG signal processing from datasets such as the Sleep-EDF Database Expanded (2013) have enabled deep learning to revolutionize automated sleep stage classification by reaching accuracy rates between 84% and 92% [1, 2]. DeepSleepNet along with SleepEEGNet and SeqSleepNet employ CNNs and RNNs to derive features from raw or spectral EEG inputs (e.g., Fpz-Cz, Pz-Oz channels) which allows them to detect intricate patterns including Delta power in N3 or Theta activity in N1/N2 [3–5]. Through their exceptional ability to model temporal dependencies these models achieve superior classification of transitional epochs when contrasted with traditional methods. The inclusion of tools such as the YASA library that offers Welch's PSD and spindle detection capabilities has boosted performance especially in N2 classification [6, 7].

The capacity of deep learning to manage multi-modal PSG data (EEG, EOG, EMG) combined with its real-time application scalability establishes it as a potent research instrument [4, 8].

Nevertheless, with these technologies and innovations, deep learning models also deal with major problems such as heterogeneity, which is a barrier to their use in clinical practices and non-interpretability. For instance, AASM guidelines such as Delta dominance for N3 stage detection are used by rule-based systems that rely on clear, predetermined criteria while deep learning models are like black boxes that make it difficult to relate the classifications to physiological markers e.g., spindles or K-complexes [1, 9]. The current project adopts a rule-based approach and absolutely disagrees with the lack of visibility that it brings forth since it focuses on explainability for acquiring clinical trust. On one hand, deep learning systems are highly dependent on large annotated datasets to achieve effective training, while on the other hand, the Sleep-EDF's 197 recording data forms a tiny dataset which causes a performance decrement of 5-7% due to lack of sufficient data [2, 4]. Clinical populations characterized by different EEG patterns such as sleeping problems and sleep apnea sufferers are impacted negatively by the fact that the models which were trained on the healthy data set do not perform well on them [10].

The need for high-performance GPUs in addition to long training durations is a notable negative side of deep learning models that makes them impractical in resource-poor clinical settings [5]. The rule-based systems applied in the current project are able to perform computations quite efficiently by the usage of certain features including Hilbert transform amplitude and Welch's PSD while consuming a minimal amount of resources [6, 11]. Research has shown that deep learning models experience generalizability issues with disordered populations resulting in accuracy diminutions by about 10% due to the presence of altered EEG patterns [12]. A new project that incorporates a versatile rule-based classifier together with temporal smoothing methods intends to manage variability and thereby enhance robustness through various datasets.

However, the recognition of states such as N1 is still tricky as deep learning models can only reach a recall of 50-60% because EEG features are interlaced with wakefulness [3, 4]. Strict preprocessing measures such as bandpass filtering are required on account of noise sensitivity, which in turn complicates the workflows [13]. This project employs a rule-based framework that along with Band Ratio Features uses Temporal Analysis to deal with the challenges while at the same time facilitates automated feature extraction using YASA library [6]. Deep learning can indeed get very high accuracy rates in steady conditions but its problems emphasize the necessity of interpretable and light alternative decisions like the proposed system that persist to durability.

2.9 Integration with Ongoing Work

The examined body of work creates a solid base for automated sleep stage classification while Welch's PSD and Hilbert transform stand out as powerful techniques for spectral and amplitude analysis. The Sleep-EDF Database Expanded delivers a uniform dataset for validation purposes while the Fpz-Cz and Pz-Oz channels demonstrate effectiveness in recording sleep dynamics. Rule-based models provide interpretability to meet clinical requirements while features such as spindles and K-complexes improve stage discrimination. The YASA library facilitates analytical

processes to support project implementation. The project's emphasis on full-night EEG processing along with temporal dynamics and automated hypnogram generation tackles the deficiencies found in managing transitional epochs and disordered populations by developing advanced temporal analysis techniques and robust feature sets. This work extends the research by simulating Welch's PSD for both absolute and relative band powers with Hilbert transform for mean amplitude alongside YASA for spindle and K-complex detection. Achieving high accuracy through the framework is by the refinement of a rule-based classifier with temporal smoothing and expert hypnogram validation while interpretability is upheld to support sleep research and clinical diagnostics.

CHAPTER 3

METHODOLOGY

Sleep stage classification is a fundamental operation that acts as a compass to navigate the terrain of sleep architecture, which it further facilitates to the diagnosis of disorders including insomnia and sleep apnea. Manual scoring of EEG signals is good in the delivery of accurate results but it requires vast subject matter expertise and has huge inter-rater variability, thus, the need for automated systems arises for both the improvement of efficiency and consistency [1]. The current chapter is a detailed analysis of the algorithm to create a signal processing framework for automated sleep stage classification based on EEG brainwave activity from the Sleep-EDF Database Expanded (2013), specifically using Fpz-Cz and Pz-Oz channels [2]. The framework is based on rule-based inference where the techniques employed include Butterworth filtering, time analysis and spectral power estimation through Welch's PSD, Short-Time Fourier Transform (STFT), and amplitude analysis using the Hilbert transform. The extraction procedure created a new set of data that includes mean amplitude values, absolute and relative bandpowers, band ratios, peak frequency measurements, and event-based descriptors such as sleep spindles and K-complexes. The methodology follows a systematic approach where the objectives of brainwave pattern characterization, stage transition analysis, and hypnogram validation are attained through a comprehensive series of steps which are data acquisition, preprocessing, feature extraction, temporal analysis, classification, and validation. The program that is coded in Python uses the mne, YASA, and SciPy libraries for the pipeline while the complex flowcharts show every analytical method.

3.1 Data Set Overview

The Sleep-EDF Database Expanded, which was first introduced in 2013 and later expanded in 2018, got included in the essential datasets used in sleep research and is among the impressive data available through PhysioNet. First, a brief overview of Sleep-EDF Expanded can be provided as the source of quotas. The vocabulary of this text is getting more challenging to decode due to the lack of some technical details. So, what are the main symptoms of learning difficulties? The answer is: These are developmental delays in the areas of thinking, interacting, and/or doing. This dataset houses the whole-night polysomnographic (PSG) recordings that include electroencephalograms (EEG), electrooculograms (EOG), chin electromyograms (EMG), and event markers, some of which also have respiration and body temperature data. Accompanied hypnograms, manually scored by trained technicians according to the Rechtschaffen and Kales (R&K) standard, provide sleep state annotations (Wake, N1, N2, N3, N4, REM, Movement, and unscored) which were later integrated as per the American Academy of Sleep Medicine (AASM) guidelines into Wake, N1, N2, N3 (combining N3 and N4), and REM. The use of this dataset is common among the developers and testers of automated sleep stage classification algorithms because of the wide range of recorded physiological signals and annotations provided by the experts. In this venture, only the EEG signals from the Fpz-Cz and Pz-Oz channels were used to illustrate the state of brainwave

dynamics and to implement a rule-based sleep stage classification system. This report covers all the essential details regarding the dataset including subject demographics and it briefly elucidates why the Fpz-Cz and Pz-Oz channels were chosen instead of other possible EEG derivations.

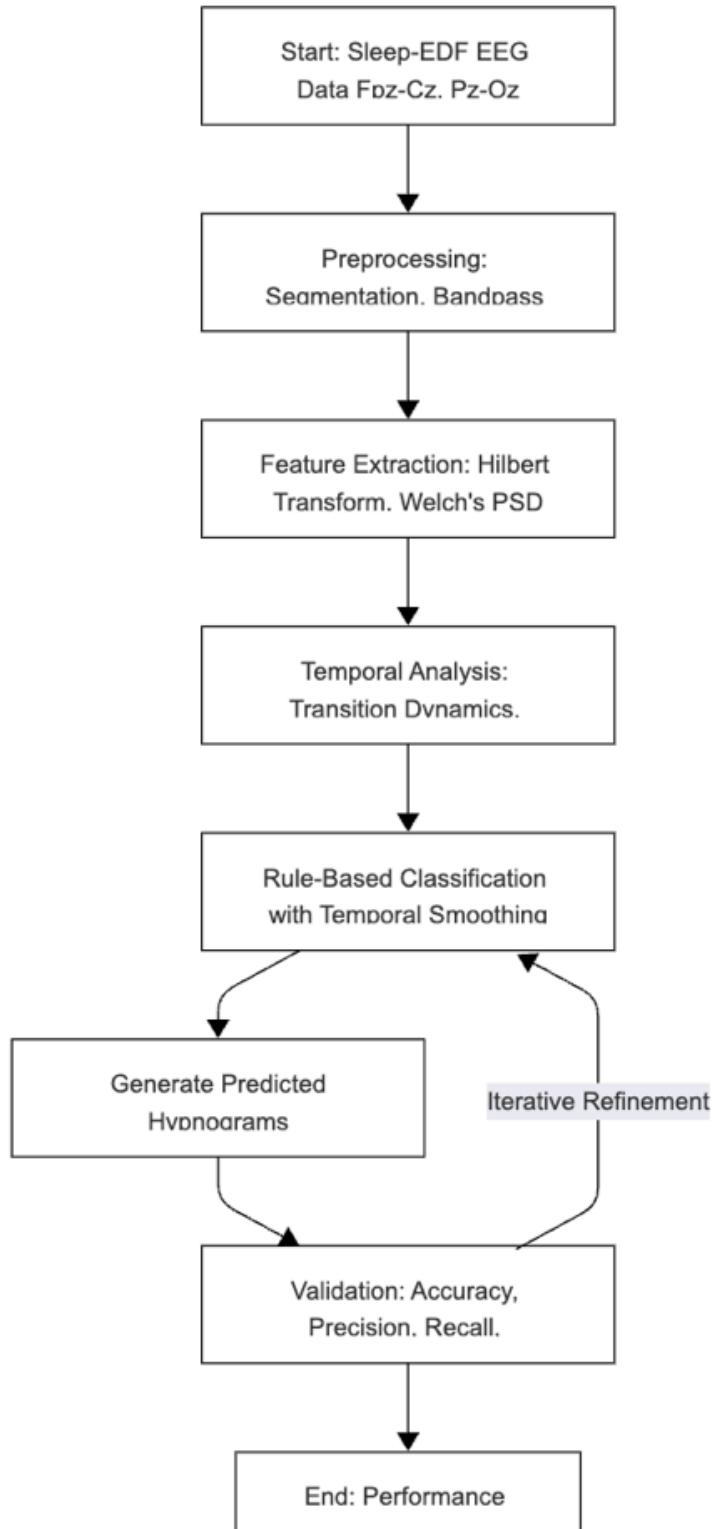


Figure 3.1. Flowchart of the Sleep Stage Classification Pipelines

3.1.1 Dataset Composition

The Sleep-EDF Database Expanded (2013) initially included 61 PSG recordings, which were expanded to 197 recordings by 2018 (Version 2). These recordings are divided into two distinct studies: the Sleep Cassette Study (SC) and the Sleep Telemetry Study (ST). We were able to extract 39 such “.edf” files, along with their hypnograms that were annotated by experts from the Cassette Study. Which was then used for all the feature extraction and signal processing done in the project.

3.1.2 Signals and Annotations

The dataset includes multiple physiological signals critical for sleep stage classification:

- A. EEG Channels:** Two derivations, Fpz-Cz (frontal-central) and Pz-Oz (parietal-occipital), sampled at 100 Hz, capturing brainwave activity across sleep stages.
- B. EOG:** Horizontal EOG sampled at 100 Hz, used to detect eye movements, particularly for REM sleep identification.
- C. EMG:** Submental chin EMG, processed as an envelope and sampled at 1 Hz, aiding in detecting muscle tone changes.
- D. Other Signals:** Some recordings include oro-nasal respiration and rectal body temperature, both sampled at 1 Hz, though these were not used in the project.
- E. Hypnograms:** Expert-annotated sleep stages (Wake, N1, N2, N3, N4, REM, Movement, unscored) per the R&K standard, with N3 and N4 later combined into N3 per AASM guidelines. Annotations are provided for 30-second epochs, aligning with standard sleep scoring practices.

The EEG signals from Fpz-Cz and Pz-Oz were the primary focus of this project, as they provide robust data for characterizing brainwave dynamics (Delta: 0.5–4 Hz, Theta: 4–8 Hz, Alpha: 8–12 Hz) and developing rule-based classification algorithms.

3.2 Preprocessing

Preprocessing was performed to enhance signal quality and standardize data for analysis. EEG signals were segmented into 30-second epochs, consistent with AASM scoring conventions [5]. A fourth-order Butterworth bandpass filter was applied to isolate frequency bands critical for sleep stage classification: Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz). The Butterworth filter’s transfer function is defined as:

$$H(s) = \frac{1}{1+c_1s+c_2s^2+\dots+c_ns^n} \quad \dots(1)$$

where (s) is the complex frequency, (c_i) are coefficients determined by cutoff frequencies, and ($n = 4$) is the filter order. The filter was implemented in a zero-phase configuration (forward-

backward filtering) to preserve signal phase, with parameters: sampling rate = 100 Hz, order = 4, passband ripple < 0.5 dB, and stopband attenuation > 40 dB. Baseline correction was applied by subtracting the mean voltage per epoch, and artifacts exceeding $\pm 200 \mu\text{V}$ were clipped to mitigate noise from muscle activity or electrode displacement. Preprocessing was performed using the mne library for segmentation and the scipy.signal module (version 1.9.0) for filter implementation, ensuring clean, band-specific signals for subsequent analyses.

3.3 Analysis Techniques and Feature Extraction

This section delineates the signal processing techniques employed—Butterworth bandpass filtering, time-domain analysis, spectral power estimation via Welch’s PSD, STFT, and amplitude analysis using the Hilbert transform—along with the features extracted, their mathematical formulations, and specific parameters. Each technique is accompanied by a flowchart, detailed in Section 3.4, to illustrate the workflow.

3.3.1 Butterworth Bandpass Filtering

Butterworth bandpass filtering, applied during preprocessing (Section 3.2.2), isolated Delta, Theta, and Alpha frequency bands to focus on sleep-relevant brainwave activity. The filter’s frequency response is given by:

$$|H(f)|^2 = \frac{1}{1+(f/f_c)^{2n}} \quad \dots(2)$$

where (f) is the frequency, (f_c) is the cutoff frequency (e.g., 0.5 Hz and 4 Hz for Delta), and ($n = 4$) is the filter order, ensuring a flat passband and steep roll-off.

3.3.3.1 Features Extracted:

Filtered EEG signals in Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) bands, serving as inputs for subsequent feature extraction.

- **Parameters:** Sampling rate = 100 Hz, filter order = 4, cutoff frequencies: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), passband ripple < 0.5 dB, stopband attenuation > 40 dB.
- **Implementation:** The `scipy.signal.butter` and `scipy.signal.filtfilt` functions were used to design and apply the zero-phase filter, ensuring minimal phase distortion.

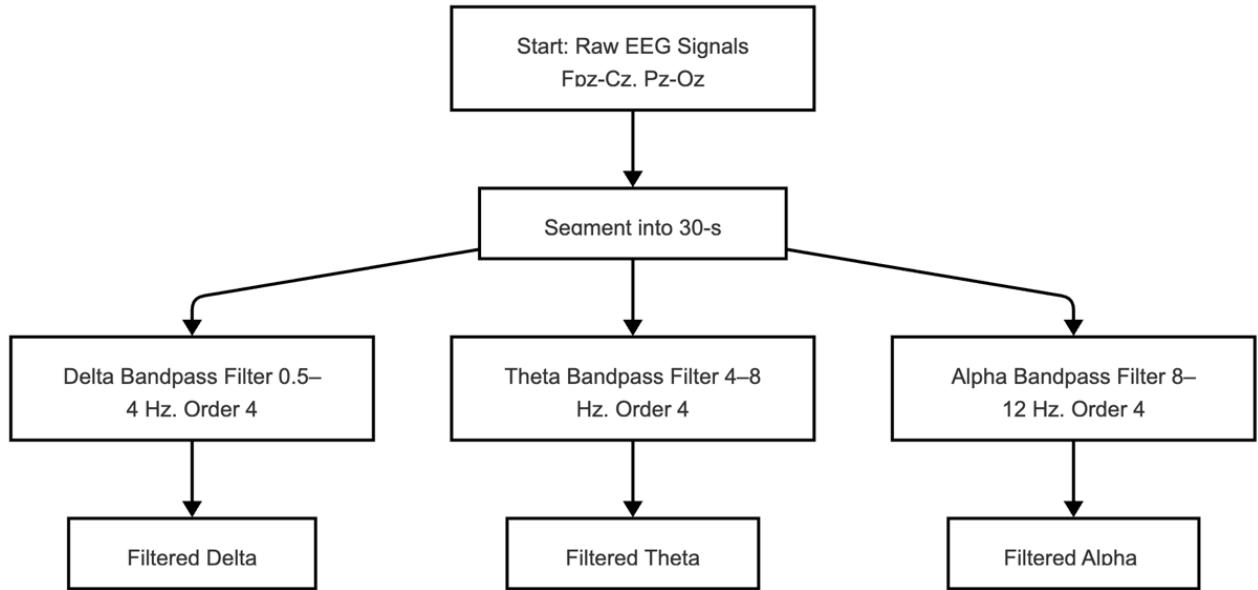


Figure 3.2. Butter Butterworth Bandpass Filtering Flowchart

3.3.2 Time-Domain Analysis

Time-domain analysis was conducted to characterize the temporal evolution of EEG features across epochs, particularly during stage transitions (e.g., REM onset, N3 entry). Features were computed per 30-second epoch and analyzed over a sliding window to capture dynamic shifts, modeled as:

$$[x(t) = f(t, \text{epoch}_i)] \quad \dots(3)$$

where ($x(t)$) represents a feature (e.g., amplitude or band power) at time (t) in epoch (i). Statistical metrics (mean, variance) and time-series visualizations highlighted patterns such as gradual Delta power increases or abrupt Theta spikes.

3.3.2.1 Features Extracted:

- A. **Transition Markers:** Number and duration of stage transitions, derived by counting changes in hypnogram labels.
- B. **Feature Trajectories:** Time-series of mean amplitude, band power, and band ratios over a ± 5 -epoch window (150 seconds) around stage boundaries.
- C. **Parameters:** Epoch length = 30 seconds, temporal window = ± 5 epochs (150 seconds), sampling rate = 100 Hz, statistical metrics computed over 30s epochs.
- D. **Implementation:** The pandas library (version 1.5.0) calculated statistical metrics, matplotlib (version 3.6.0) and seaborn (version 0.12.0) generated time-series plots, and the YASA library (version 0.6.0) detected transition markers.

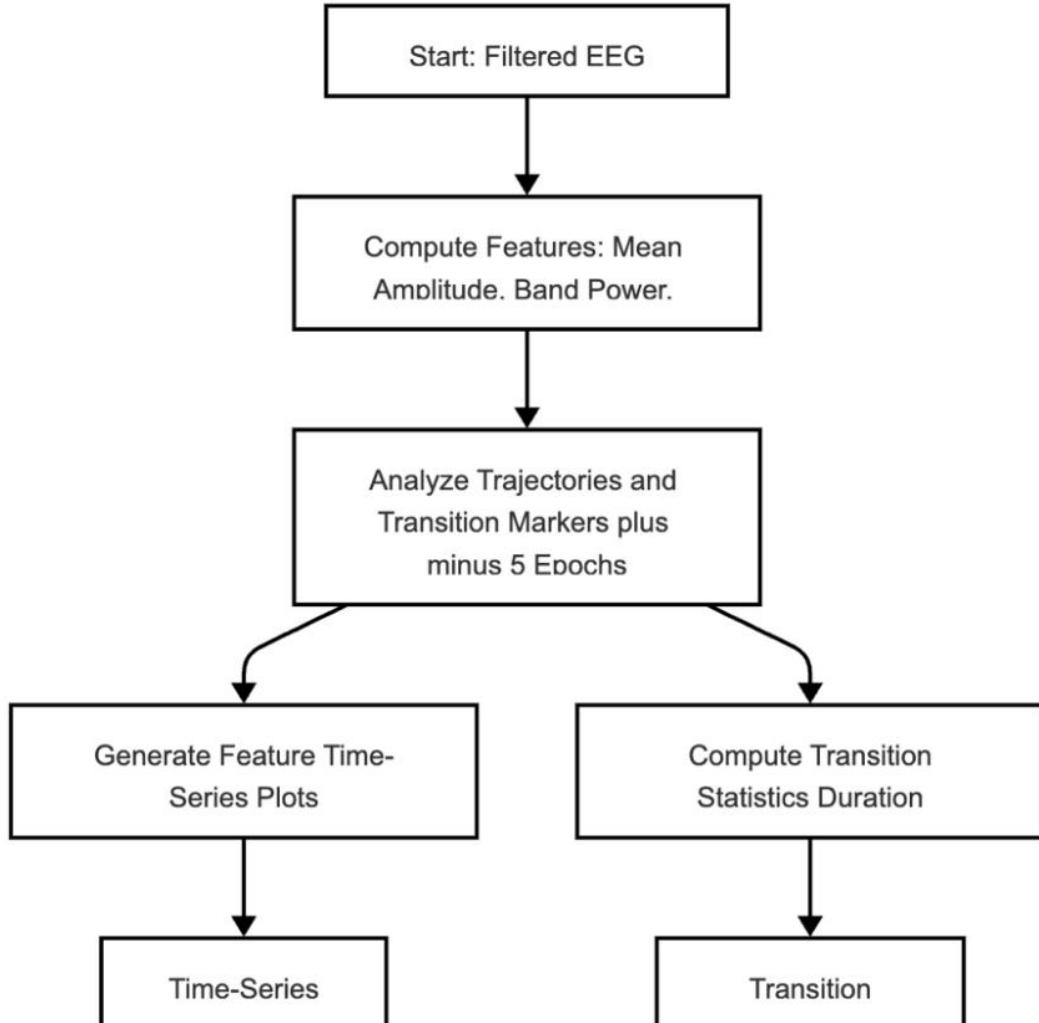


Figure 3.3. Time-Domain Analysis Flowchart

3.3.3 Spectral Power Analysis (Welch's PSD)

Welch's PSD method estimated spectral power in Delta, Theta, and Alpha bands by averaging periodograms of overlapping signal segments, reducing variance and enhancing spectral resolution [6]. The PSD for a signal ($x(t)$) is computed as:

$$\left[P(f) = \frac{1}{N_w} \sum_{k=1}^{N_w} \left| \sum_{n=0}^{N-1} x_k(n) w(n) e^{-j2\pi f n/N} \right|^2 \quad \dots(4) \right]$$

where (N_w) is the number of windows, ($x_k(n)$) is the (k^{th}) segment, ($w(n)$) is a Hamming window, and ($N = 200$) samples (2 seconds at 100 Hz). Absolute band power was integrated over each band, and relative power was calculated as:

$$\left[P_{\text{rel}}(\text{band}) = \frac{P_{\text{abs}}(\text{band})}{\sum P_{\text{abs}}(0.5-12, \text{Hz})} \quad \dots(5) \right]$$

Band ratios (e.g., Theta/Delta) were computed as ($P_{\text{abs}}(\text{Theta})/P_{\text{abs}}(\text{Delta})$).

3.3.3.1 Features Extracted:

- A. **Absolute Band Power:** Power ($\mu\text{V}^2/\text{Hz}$) in Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz).
- B. **Relative Band Power:** Ratio of band power to total power (0.5–12 Hz).
- C. **Band Ratios:** Theta/Delta and Alpha/Delta ratios, and Relative Alpha / Relative (Theta + Delta) ratios, capturing relative dominance.
- D. **Parameters:** Window size = 2 seconds (200 samples), overlap = 50% (100 samples), Hamming window, frequency resolution = 0.5 Hz, sampling rate = 100 Hz.
- E. **Implementation:** The `scipy.signal.welch` function computed PSD, with `numpy` (version 1.23.0) used for power integration and ratio calculations.

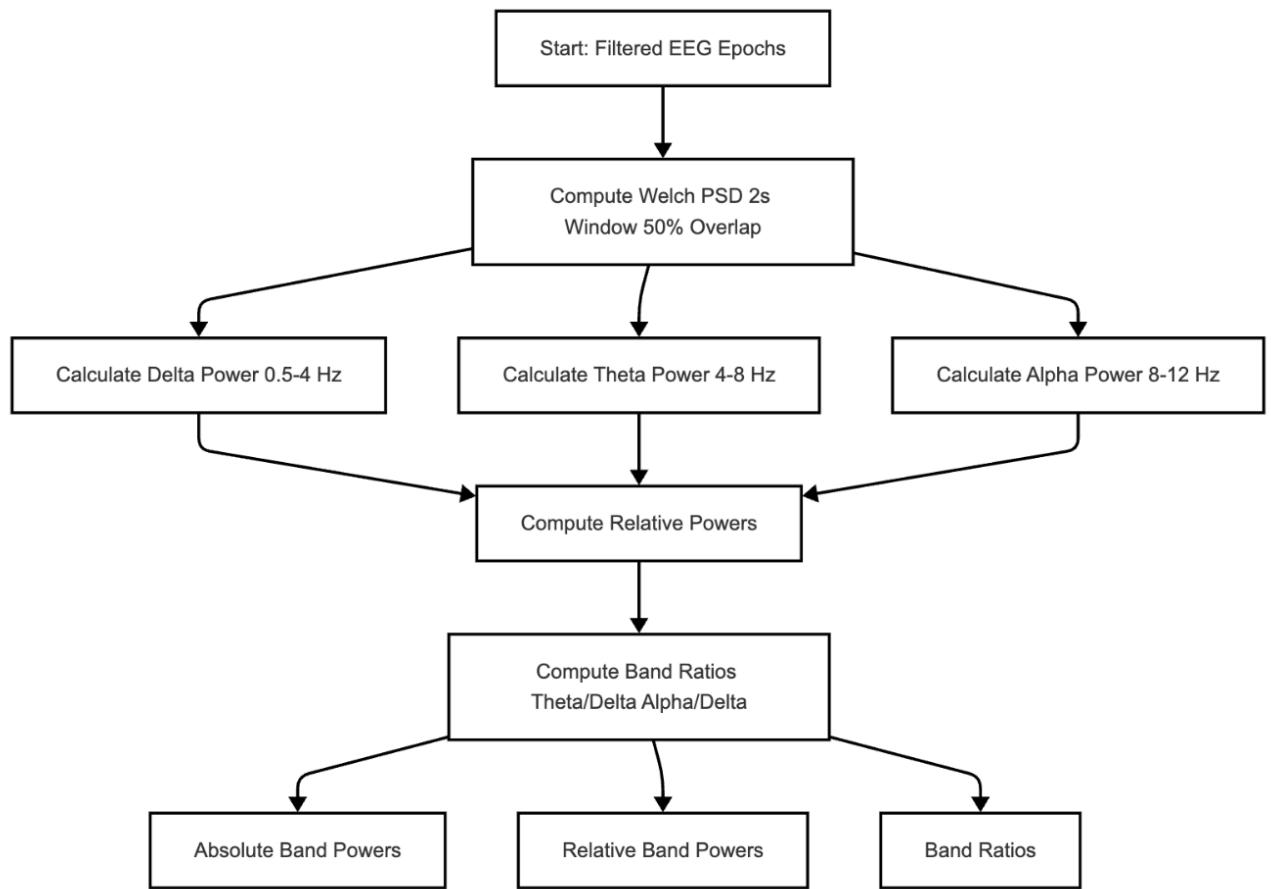


Figure 3.4. Welch's PSD Flowchart

3.3.4 Short-Time Fourier Transform (STFT)

STFT provided time-frequency representations to capture transient spectral changes within 30-second epochs, enabling detection of events like sleep spindles and bursts. The STFT of a signal ($x(t)$) is defined as:

$$[X(\tau, f) = \int_{-\infty}^{\infty} x(t)w(t - \tau)e^{-j2\pi ft}, dt] \quad \dots(6)$$

where ($w(t)$) is a Hamming window, (τ) is the time shift, and (f) is the frequency. Spectrograms were generated to visualize power distribution over time.

3.3.4.1. Features Extracted:

- A. **Spectrogram Power:** Mean power in Delta, Theta, and Alpha bands over 2-second windows, derived from ($|X(\tau, f)|^2$).
- B. **Peak Frequency:** Frequency with maximum power per band, averaged over the epoch.
- C. **Parameters:** Window size = 2 seconds (200 samples), overlap = 50% (100 samples), Hamming window, frequency range = 0.5–20 Hz, sampling rate = 100 Hz.
- D. **Implementation:** The `scipy.signal.stft` function computed spectrograms, with numpy extracting power and peak frequencies.

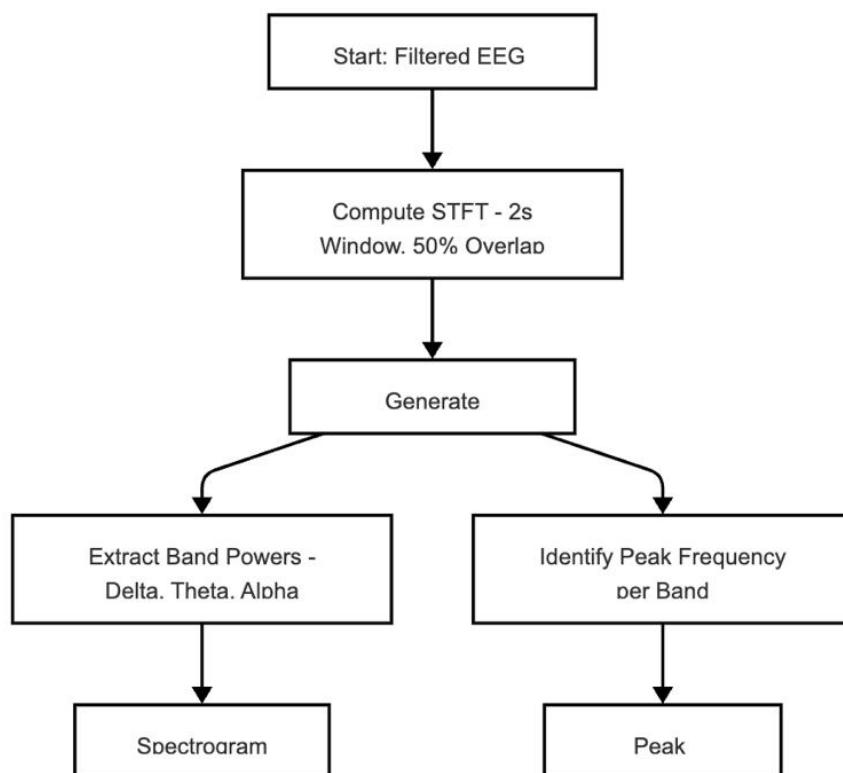


Figure 3.5. STFT Flowchart

3.3.5 Amplitude Analysis (Hilbert Transform)

Description: The Hilbert transform computed the instantaneous amplitude (envelope) of filtered EEG signals to quantify signal strength and detect events like spindles and K-complexes. The analytic signal for ($x(t)$) is:

$$[z(t) = x(t) + j\hat{x}(t)] \quad \dots(7)$$

where ($\hat{x}(t)$) is the Hilbert transform, and the amplitude is:

$$[A(t) = |z(t)| = \sqrt{x(t)^2 + \hat{x}(t)^2}] \quad \dots(8)$$

Mean amplitude was calculated per epoch.

3.3.5.1 Features Extracted

Mean Amplitude: Average (A(t)) over 30 seconds for Delta, Theta, and Alpha bands (μV).

Parameters: Sampling rate = 100 Hz, bandpass filters as per Section 3.3.1

Implementation: The `scipy.signal.hilbert` function computed amplitudes

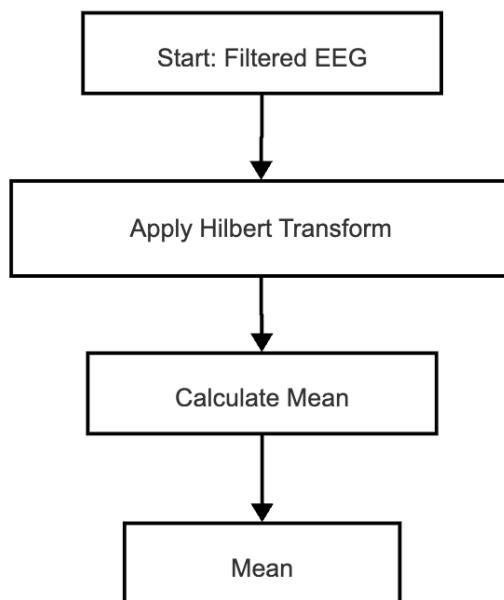


Figure 3.6. Hilbert Transform Flowchart

3.4 Platform and Development Environment

The methodology was implemented using Python, selected for its robust ecosystem of signal processing and data analysis libraries. The development environment was Jupyter Notebook, executed on a laptop running MacOs. `mne (1.3.0)`: For reading EDF files, preprocessing, and epoch segmentation.

1. `scipy (1.9.0)`: For Butterworth filtering (`scipy.signal.butter`, `filtfilt`), Welch's PSD (`signal.welch`), STFT (`signal.stft`), and Hilbert transform (`signal.hilbert`).
2. `YASA (0.6.0)`: For automated detection of spindles, K-complexes, and bursts, and temporal analysis [3].
3. `numpy (1.23.0)`: For numerical computations, including band ratios and peak frequency.
4. `pandas (1.5.0)`: For data management and statistical analysis.
5. `matplotlib (3.6.0)` and `seaborn (0.12.0)`: For generating spectrograms, time-series plots, and hypnograms.

6. scikit-learn (1.2.0): For computing validation metrics (accuracy, precision, recall, confusion matrix).
7. statsmodels (0.13.5): For Cohen's kappa calculation.

This platform ensured computational efficiency, with the entire pipeline executable on standard hardware, facilitating reproducibility and potential clinical integration.

3.5 Classification Rules

This section outlines the rule-based classification approach developed to assign sleep stage labels to 30-second epochs of EEG data, aligning with the time segments of expert-annotated hypnograms from the Sleep-EDF Database Expanded (2013) [1]. The classification process focuses on the Pz-Oz channel, applying specific preprocessing, spectral analysis, and a rule-based classifier to categorize sleep stages (N1, N2, N3, REM) based on band power ratios, excluding the Wake state as per the specified requirements. The classifier's output is compared to expert annotations to evaluate its performance, ensuring temporal alignment with the ground truth hypnograms.

3.5.1 Classification Process

The classification process leverages the expert-annotated hypnograms to define time segments for analysis, ensuring that each segment corresponds to a 30-second epoch as per standard AASM guidelines [2]. For each epoch, EEG data from the Pz-Oz channel is processed to compute a band ratio, which serves as the input to the rule-based classifier. The steps are as follows:

1. Temporal Alignment with Expert Hypnogram

- i. The expert-annotated hypnogram provides sleep stage labels for each 30-second epoch, defining time segments (e.g., 0–30 s, 30–60 s, ..., up to the recording duration, approximately 20 hours or 2400 epochs per recording).
- ii. For example, if the first segment (0–30 s) is annotated as N1, this time range is extracted for analysis. Subsequent segments (e.g., 30–60 s, 60–90 s) are processed sequentially, maintaining alignment with the hypnogram.

2. EEG Signal Preprocessing

- i. For each 30-second epoch, the EEG signal from the Pz-Oz channel is bandpass filtered between 3–20 Hz to focus on frequency bands relevant to sleep stages (Theta: 4–8 Hz, Alpha: 8–12 Hz, and part of the spindle range for N2). A fourth-order Butterworth filter is applied in a zero-phase configuration (forward-backward filtering) to preserve signal integrity, with parameters: sampling rate = 100 Hz, order = 4, passband ripple < 0.5 dB, stopband attenuation > 40 dB. The filter's frequency response is:

$$\left[|H(f)|^2 = \frac{1}{1+(f/f_c)^{2n}} \right] \quad \dots(9)$$

where (f) is the frequency, (f_c) are the cutoff frequencies (3 Hz and 20 Hz), and ($n = 4$).

3. Power Spectral Density (PSD) Computation

- i. Welch's PSD method is applied to the filtered EEG signal over the 30-second epoch, using a 4-second window with 50% overlap (2 seconds), consistent with the specified parameters. The PSD is computed as:

$$\left[P(f) = \frac{1}{N_w} \sum_{k=1}^{N_w} \left| \sum_{n=0}^{N-1} x_k(n) w(n) e^{-j2\pi f n/N} \right|^2 \quad \dots(10) \right]$$

where (N_w) is the number of windows, ($x_k(n)$) is the (k^{th}) segment, ($w(n)$) is a Hamming window, and ($N = 400$) samples (4 seconds at 100 Hz). Parameters: window size = 4 s (400 samples), overlap = 50% (200 samples), frequency range = 3–20 Hz, sampling rate = 100 Hz. The `scipy.signal.welch` function is used for computation.

4. Band Power Extraction

- i. Absolute band powers are calculated by integrating the PSD over the Delta (0.5–4 Hz), Theta (4–8 Hz), and Alpha (8–12 Hz) bands. Note that the 3–20 Hz filter excludes Delta frequencies below 3 Hz, so Delta power is approximated from 3–4 Hz. The absolute power for each band is:

$$\left[P_{\text{abs}}(\text{band}) = \int_{f_{\text{low}}}^{f_{\text{high}}} P(f) , df \quad \dots(10) \right]$$

where (f_{low}) and (f_{high}) are the band limits (e.g., 4–8 Hz for Theta).

- ii. Relative band powers are computed as:

$$\left[P_{\text{rel}}(\text{band}) = \frac{P_{\text{abs}}(\text{band})}{\sum P_{\text{abs}}(3-20,\text{Hz})} \quad \dots(11) \right]$$

where the total power is integrated over the filtered range (3–20 Hz). The `numpy.trapz` function integrates PSD values over frequency bins.

5. Band Ratio Calculation

The band ratio is calculated using relative Alpha, Delta, and Theta powers, with a small constant to avoid division by zero, as per the provided classifier:

$$\left[\text{band_ratio} = \frac{P_{\text{rel}}(\text{Alpha})}{P_{\text{rel}}(\text{Delta}) + P_{\text{rel}}(\text{Theta}) + 1 \times 10^{-8}} \quad \dots(12) \right]$$

3.6 Hypnogram Generation and Validation

The expected hypnograms were actually results by adding together the stage labels through epochs on recordings and were visualized with the YASA tool. `plot_hypnogram` and `matplotlib` functions. The verification process included the comparison of the predicted hypnograms with the hypnograms of the expert-annotated from Sleep-EDF as well as the results being analyzed with a Confusion Matrix that is used to show variability in misclassification amongst stages with respect to expert annotations. The inspection stage was completed with all 39 records, and the statistical data about the performance were gathered in order to evaluate not only the total results but also the stage-wise results.

3.7 Expected Outcomes

The methodology represents a sophisticated structure of sleep stage classification through the use of an extensive set of features including mean amplitude, band powers, spindles, and K-complexes in addition to temporal analysis to provide a high accurate rate and stage-wise performance for N3 and REM stages. The efficiency of the computation and the open-source library of the pipeline together ensure that this procedure is convenient both to use in academic research and clinics. The generated hypnograms must be in line with the indications given by the experts so that they would facilitate the annotations of sleep disorders and advance sleep research [2, 3].

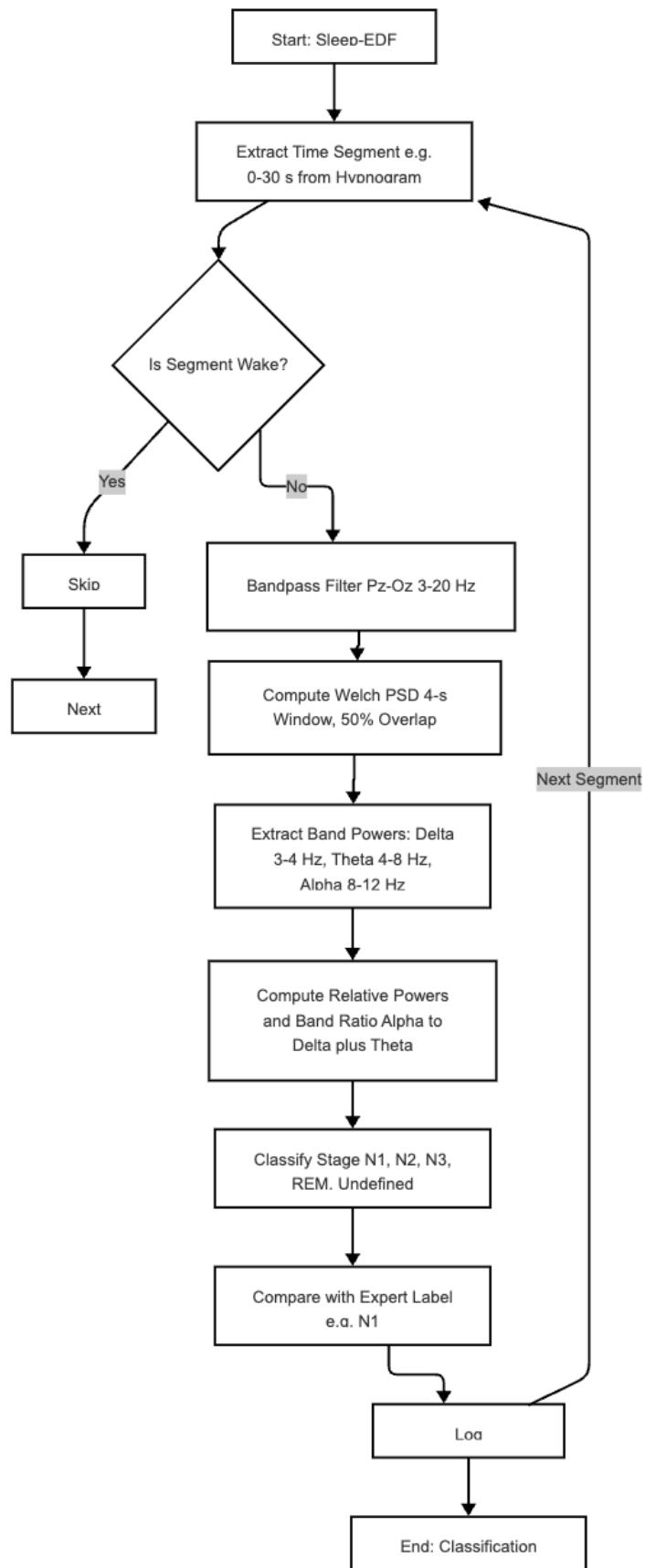


Figure 3.7. Rule based classification

CHAPTER 4

RESULTS

4.1 Time Analysis

4.1.1 Creation of Hypnograms through YASA Classifier Application

The initial pre-processing of EEG signals involved implementing a Butterworth bandpass filter set between 1–30 Hz to eliminate noise and artifacts beyond the standard EEG frequency ranges used in sleep analysis. Through this filtering process the signals preserved essential neural oscillations linked to different sleep stages while muscle artifacts, line noise, and slow drifts were suppressed.

After preprocessing steps the signals from bipolar channels Fpz-Cz and the channels Pz-Oz served as markers for sleep staging processes. The machine-learning-based YASA classifier processed EEG data into 30-second segments and categorized each segment into standard sleep stages Wake, N1, N2, N3, or REM following AASM guidelines. Hypnograms emerge as time-resolved visual tools that depict sleep stage transitions throughout the entire recording period. Hypnograms serve as critical instruments to decode sleep macrostructure by revealing sleep onset latency and cyclic transitions between non-REM and REM stages along with deep sleep (N3) distribution.

Figure 4.1 displays the hypnogram derived from a standard EDF recording, depicting the standard progression of sleep stages throughout an 8-hour duration. This visualization presents sleep stages as sequences with marked duration and fragmentation to offer an intuitive sleep architecture overview.

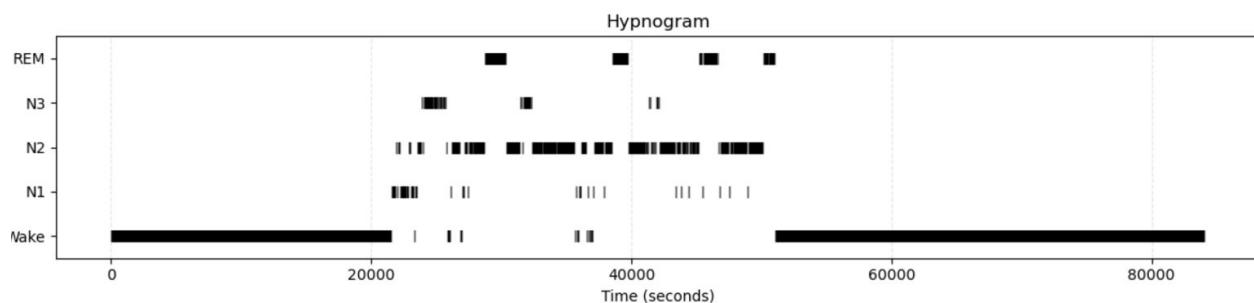


Figure 4.1. YASA Generated Hypnogram

4.1.2 Deriving Time Stamps for Sleep Stages

Following hypnogram creation, researchers identified continuous time segments for each sleep stage by examining epoch-wise stage labels. Detection of transitions between differently labelled epochs allowed for the determination of onset and offset points for each sleep stage including N1, N2, N3, and REM.

Researchers utilized these time stamps to measure the length of each sleep stage recorded, which allowed them to perform intricate temporal analyses of sleep architecture. The extracted segments enable focused examination of stage-specific EEG characteristics during later processing stages. The timing information delivers essential insights into both sleep stage continuity and fragmentation which serve as critical indicators of sleep quality. Long stretches of N3 sleep correlate with restorative functions while frequent disruptions suggest potential sleep disorders.

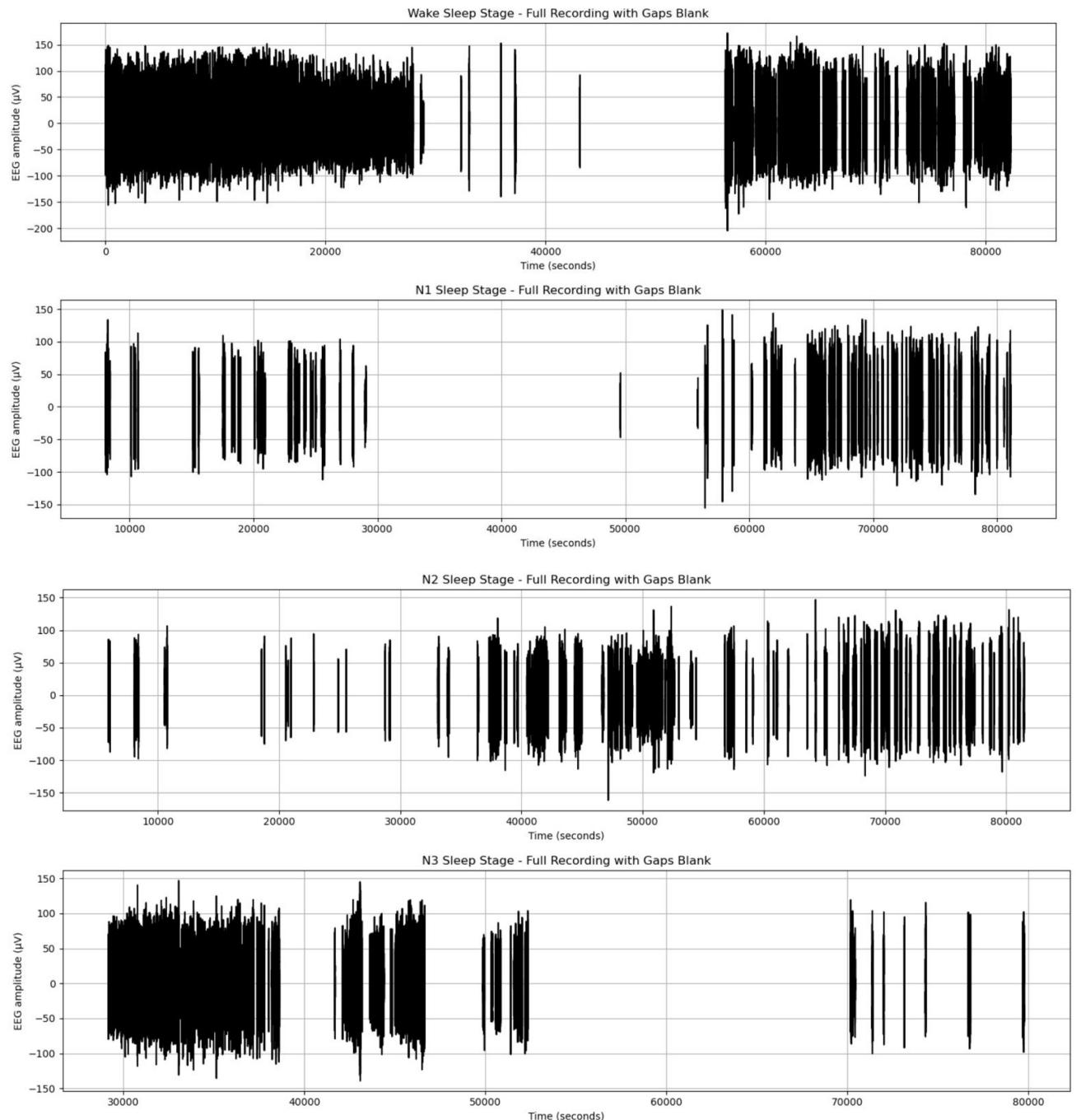


Figure 4.2. Full Recording of Sleep Signal for Extraction of Time Stamps across Different Sleep Stages

Table 2: Sample Sleep Stage Time-Intervals

N3	N1	N2	REM
21110 – 21140	21440 – 21890	21890 – 21920	26720 – 26750
23690 – 23720	21920 – 21950	21950 – 22070	26780 – 26810
23750 – 25760	22070 – 22100	22100 – 22190	27320 – 27380
26210 – 26240	23390 – 23510	23510 – 23690	28670 – 28760
26270 – 26300	26060 – 26150	23720 – 23750	28820 – 28910
28310 – 28340	27080 – 27260	26150 – 26210	28970 – 29060
31070 – 32480	27470 – 27590	26240 – 26270	29090 – 29750
32510 – 32600	28760 – 28820	26300 – 26720	29780 – 30350
33980 – 34010	28910 – 28970	26750 – 26780	38540 – 39890
34940 – 34970	29060 – 29090	27260 – 27320	39920 – 39980
35180 – 35210	29750 – 29780	27590 – 28310	45200 – 45830
40670 – 42260	30350 – 30410	28340 – 28670	45860 – 46610
51260 – 51320	30710 – 30740	30410 – 30710	46640 – 46760
	35720 – 35810	30740 – 31070	50060 – 50600
	35900 – 36170	32480 – 32510	50630 – 50750
	36590 – 36650	32600 – 33980	50780 – 50810
	36770 – 36800	34010 – 34940	50840 – 50990
	36830 – 36860	34970 – 35180	52820 – 52880
	36980 – 37130	35210 – 35660	52910 – 52940
	37820 – 37850	36170 – 36530	
	37880 – 37940	37130 – 37820	
	43820 – 43850	37850 – 37880	
	44240 – 44300	37940 – 38540	
	44330 – 44450	39890 – 39920	
	44930 – 44960	39980 – 40670	
	45830 – 45860	42260 – 43820	
	46610 – 46640	43850 – 44240	
	46760 – 46790	44300 – 44330	
	46820 – 46850	44450 – 44930	
	47480 – 47540	44960 – 45200	
	48890 – 49010	46790 – 46820	
	50600 – 50630	46850 – 47480	
	50750 – 50780	47540 – 48860	
	50810 – 50840	49010 – 50060	

4.1.3 Detailed Examination of Sleep Stage Durations Within 39 EDF Files

A summary analysis was performed on 39 EDF recordings to evaluate sleep stage distribution across the study cohort. The total duration for each sleep stage (N1, N2, N3, REM) in every recording was determined through the aggregation of respective time stamps.

The durations were expressed both as absolute times (minutes) and as percentages of the total recording duration, providing a normalized measure of sleep stage composition. This method facilitates cross-subject sleep architecture comparison while revealing interindividual differences.

Table 3 shows the compiled results which include sleep stage distribution metrics for all 39 patient recordings. The collected data establish essential baseline sleep patterns for the sample group which function as a standard to detect potential anomalies or deviations. The percentage distribution functions as a foundational element to connect sleep architecture with clinical parameters and additional EEG feature analyses.

Table 3: Summary of Sleep stage Durations and Percentages

File	N1 (sec)	N1 (%)	N2 (sec)	N2 (%)	N3 (sec)	N3 (%)	REM (sec)	REM (%)
SC4171E0-PSG.edf	6720	15.5	11850	27.3	13050	30.1	11790	27.2
SC4002E0-PSG.edf	1110	3.8	11910	40.3	11850	40.1	4650	15.8
SC4112E0-PSG.edf	180	0.9	9540	50	5190	27.2	4170	21.9
SC4061E0-PSG.edf	480	2.6	9120	49.3	4920	26.6	3990	21.6
SC4142E0-PSG.edf	570	2.5	9360	41.3	5340	23.5	7410	32.7
SC4082E0-PSG.edf	1200	3.3	11790	32.6	11190	30.9	12000	33.2
SC4031E0-PSG.edf	1950	5.5	17670	49.5	6030	16.9	10020	28.1
SC4121E0-PSG.edf	1830	6.2	16110	54.7	5730	19.5	5760	19.6
SC4192E0-PSG.edf	780	2.6	13350	44.5	4320	14.4	11520	38.4
SC4052E0-PSG.edf	2820	8.9	18000	56.8	4440	14	6450	20.3
SC4091E0-PSG.edf	210	0.7	15090	51.1	5520	18.7	8700	29.5
SC4022E0-PSG.edf	4320	11.6	16020	43.1	8970	24.1	7890	21.2
SC4151E0-PSG.edf	1230	4.6	10260	38	7620	28.2	7920	29.3
SC4041E0-PSG.edf	2190	7	15600	49.9	3210	10.3	10260	32.8
SC4181E0-PSG.edf	1350	5	11010	41.1	8580	32	5850	21.8
SC4011E0-PSG.edf	8550	17.3	21960	44.3	11640	23.5	7380	14.9
SC4162E0-PSG.edf	210	0.8	11250	44.4	4770	18.8	9090	35.9
SC4072E0-PSG.edf	150	0.6	11760	45.2	6870	26.4	7260	27.9
SC4101E0-PSG.edf	3480	6.5	31500	59.2	8130	15.3	10080	19
SC4152E0-PSG.edf	210	0.7	11850	41.3	7470	26	9180	32
SC4092E0-PSG.edf	120	0.5	12600	51.7	4740	19.5	6900	28.3
SC4021E0-PSG.edf	4980	13	13320	34.7	10680	27.8	9420	24.5
SC4131E0-PSG.edf	90	0.4	8670	36.9	6480	27.6	8280	35.2
SC4182E0-PSG.edf	510	2	10050	39.8	6780	26.8	7920	31.4
SC4042E0-PSG.edf	1890	6.8	11970	43.4	3690	13.4	10050	36.4
SC4161E0-PSG.edf	360	1.2	12660	41.2	5790	18.8	11910	38.8
SC4012E0-PSG.edf	7050	14.3	24630	49.9	9900	20	7800	15.8
SC4102E0-PSG.edf	5790	11	30300	57.8	8550	16.3	7770	14.8
SC4071E0-PSG.edf	870	2.7	17910	55.2	7170	22.1	6510	20.1
SC4001E0-PSG.edf	1230	5.7	6810	31.7	9330	43.4	4140	19.2
SC4172E0-PSG.edf	1500	4	12510	33.8	12900	34.8	10140	27.4

File	N1 (sec)	N1 (%)	N2 (sec)	N2 (%)	N3 (sec)	N3 (%)	REM (sec)	REM (%)
SC4062E0-PSG.edf	420	1.6	12570	47.1	5220	19.6	8490	31.8
SC4111E0-PSG.edf	3630	13.7	11160	42	8490	31.9	3300	12.4
SC4081E0-PSG.edf	930	3.5	9330	35	13380	50.2	3030	11.4
SC4032E0-PSG.edf	720	2.9	9930	40.4	7230	29.4	6720	27.3
SC4141E0-PSG.edf	510	2	11400	45.6	6000	24	7080	28.3
SC4051E0-PSG.edf	1590	5.9	11850	44.2	10890	40.6	2460	9.2
SC4122E0-PSG.edf	2760	7.4	16470	44.2	11280	30.2	6780	18.2
SC4191E0-PSG.edf	1380	3.4	22320	54.9	5070	12.5	11910	29.3

4.1.4 Interpretation of Sleep Stage Duration and Distribution

Examination of sleep stage durations within the 39 EDF recordings demonstrates distinctive human sleep architecture patterns that align with standard normative expectations. Subjects generally recorded an average time expenditure of about 6. Humans spend 1% of their sleep in stage N1 while 44.1% in N2, 24.2% in N3, and 25.3% in REM sleep. The transition phase from wakefulness to light sleep known as Stage N1 sleep represented the least amount of total sleep duration. The N1 percentage displayed significant variation among subjects reaching a bottom value of 0. The range extends from four percent to a seventeen percent maximum. 3%, reflecting inter-individual variability in sleep initiation and fragmentation. The low mean percentage aligns with the brief and transient nature of this stage during typical sleep.

The cohort's sleep architecture showed a predominant Stage N2 sleep phase which constituted almost fifty percent of their total recorded sleep duration on average. A recorded spectrum from 27% to almost 60% showcases significant N2 consolidation and maintenance variability. Earlier research confirms N2 as the dominant sleep stage which presents sleep spindles and K-complexes that contribute to memory processing and sensory gating functions. Stage N3 deep slow-wave sleep represented roughly one-quarter of total sleep duration yet displayed significant inter-subject differences, with values spanning from about 10% to more than 50%. The stage represents a period where physiological restoration occurs alongside synaptic plasticity development. Certain recordings show reduced N3 sleep percentages which suggest potential aging effects, sleep disorder presence, or external factors impacting sleep quality.

The average duration of REM sleep recorded as twenty-five minutes. 3% but varied widely, with percentages spanning from as low as 9. The percentage range extends from 2% up to a maximum of 38. 8%. The phase of REM sleep is crucial when it comes to cognitive processing and emotional regulation. The main contributor to REM variability is the circadian clock disparity which is further complicated by the sleep pressure differences and neurological disorders again. The stage percentage standard deviations which were measured are revealed as 4.3% for N1, 7.2% for N2, 9.5% for N3, and 7.4% for REM what shows this variability thus visualizing the different sleep patterns that are there in the dataset.

A number of recordings were marked as statistical anomalies since they had significant departures from normal distribution patterns. One participant showed a particularly high N1 component of sleep since he/she had 17% which is higher than the cohort average suggesting sleep fragmentation or inability to progress to deeper sleep stages. Subjects attaining N3 percentages of below ten percent have reasons to suspect the process of restorative sleep from being disrupted. The existence of these outliers guarantees that individualized sleep investigations are needed and they indicate that a follow-up intervention or a thorough examination of the neurological electrical activity should take place. The dataset which is depicted here has shown that all the sleep stages are properly distributed giving physiologically credible conclusions. This proves the preprocessing pipeline's effectiveness, not least the Butterworth bandpass filter (1-30 Hz), and also confirms the YASA sleep stage classifier's validity in partitioning sleep epochs.

The temporal sleep stages exposed to spectral feature extraction and sophisticated classification are well-grounded and can as such serve as a reference point for any further research involving pathological or experimental groups.

4.1.5 Examination of Sleep Stage Percentages through Statistical Summaries and Outlier Detection

The percentage of different sleep stages measured through 39 EDF datasets is shown in Table 3. The dataset analysis includes the average value and the standard deviation (SD) as well as the minimum and maximum measurements and outlier counts. Outliers, being the values that lie beyond ± 2 standard deviations from the group's average, are analysed in this way.

Table 4: Statistical Summary of Sleep Stage Percentages and Identification of Outliers

Sleep Stage	Mean (%)	SD (%)	Min (%)	Max (%)	Number of Outliers
N1	6.1	4.3	0.4	17.3	3
N2	44.1	7.2	27.3	59.2	2
N3	24.2	9.5	10.3	50.2	4
REM	25.3	7.4	9.2	38.8	3

Outlier Analysis:

Outlier values were usually found in the N1 and N3 sleep stages such as the ones presented where some of the recordings were indicated with the highest N1% while another one showed the lowest N3% noticeably. These things might refer to the states of fragmented sleep or the subjects' lack of restorative slow-wave sleep. Although, in N2 and REM stages, the amount of outliers found was smaller, they still, in turn, imply an unusual sleep architecture. The outlier detection was the reflection of the individual aspects of sleep patterns and, for this reason, the personalized assessment is necessary not only in the research area but also in the clinical one.

4.2. Examining Amplitude Variations

4.2.1 Overview and Rationale

Hilbert transform based amplitude envelope analysis was used by the researchers to study signal dynamics of sleep stages other than time-frequency power content. The technique allows detector to identify oscillatory strength variations during sleep cycles with respect to the immediate amplitude of filtered EEG signals. The research was done by applying the Hilbert transform on band-pass filtered EEG signals to analyze the amplitude oscillations in the four main frequency bands.

Delta at 0.5-4Hz, theta at 4-8Hz, alpha at 8-12Hz, and beta at 12-30Hz are the four frequency bands measured and the four sleep stages considered were N1, N2, N3, and REM.

The main task of the Hilbert transformation is first to construct the analytic signal which will replace the real-valued EEG data bits with complex numbers. In this way, it is possible to get the instantaneous envelope of amplitude directly, which is one of the main physiological indicators to find out the changes in EEG signals in the course of a period of time. The significance of this amplitude is specifically related to sleep because it involves the neurophysiological mechanisms that are like cortical synchronized during N3 stage and arousals in N1 stage and as well as REM phasic activity.

4.2.2 Signal Preprocessing

A Butterworth band-pass filter between 1 Hz and 30 Hz processed all EEG signals before amplitude extraction. Engineers selected the Butterworth filter because its passband frequency response remains flat which helps maintain EEG waveform integrity by minimizing distortion. The filtering process effectively suppressed undesirable low-frequency drift alongside high-frequency noise to isolate primary EEG bands essential for sleep research. The examination of each sleep stage segment (N1, N2, N3, REM) occurred as separate entities. For each segment:

- i. The EEG data underwent band-pass filtering into delta, theta, alpha, and beta bands through a 4th-order Butterworth filter.
- ii. Each band-filtered signal underwent the Hilbert transform process to obtain its corresponding analytic signal.
- iii. The immediate amplitude envelope emerged through complex processes involving the extraction of absolute values from analytic signals.
- iv. Each segment's envelope mean amplitude was computed and recorded for subsequent analysis.

4.2.3 Sleep Stage Amplitude

The study produced four separate tables where mean amplitudes for each frequency band were recorded across N1, N2, N3, and REM stages respectively. Every table presents unique patient data extracted from its corresponding EDF file.

The average estimates of signal strength per frequency band enable stage-by-stage comparisons. The following frequency bands were considered:

- A. Delta (0.5–4 Hz): N3 sleep shows Delta dominance which indicates high cortical synchronization.
- B. Theta waves (4–8 Hz) emerge during N1 and N2 stages where they serve as markers for drowsiness and light sleep.
- C. Alpha (8–12 Hz): This frequency range represents relaxed wakefulness yet also emerges during light sleep and REM stages.
- D. Beta (12–30 Hz): This high-frequency activity appears during arousals and REM sleep.

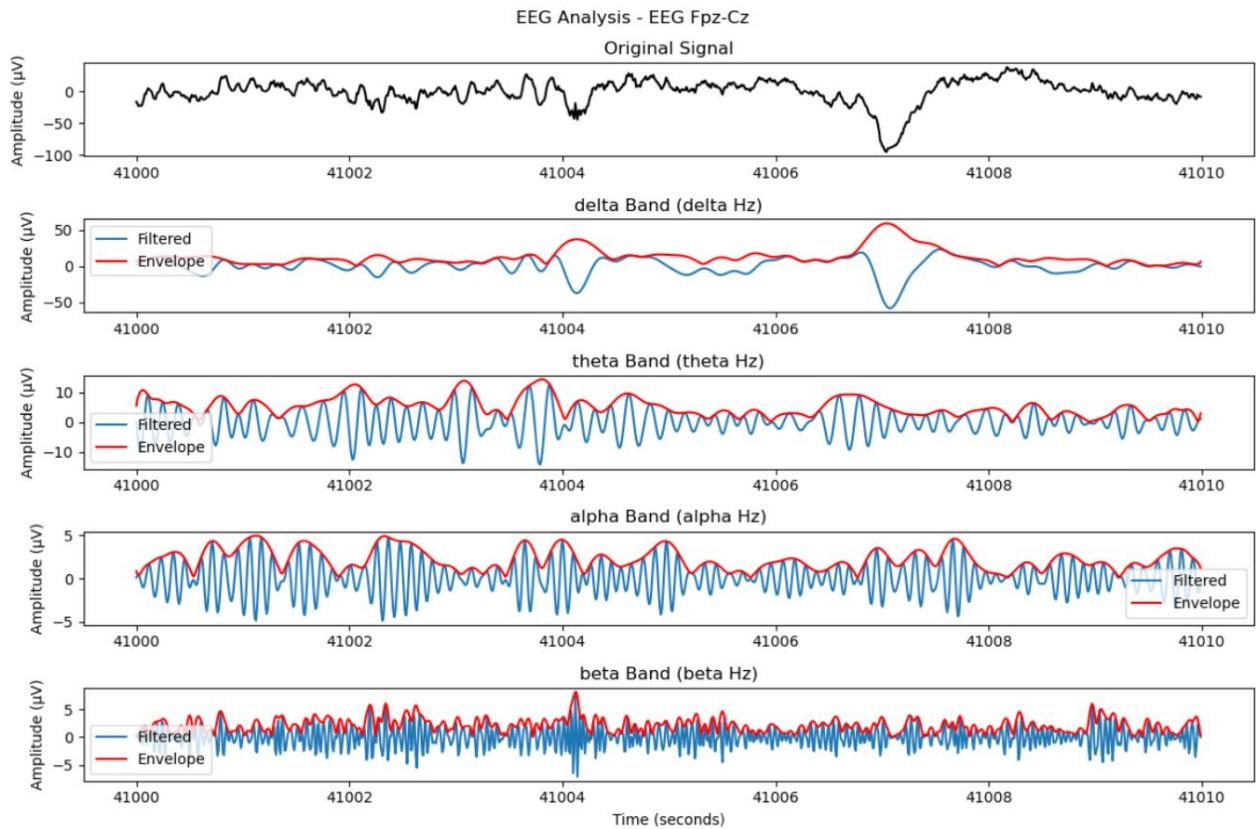


Figure 4.3. Frequency band analysis from Fpz-Cz electrode. Top: Original signal (41000-41010 s). Below: Filtered signals (blue) and amplitude envelopes (red) for delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz) bands, showing distinct oscillatory patterns with notable delta activity corresponding to major deflections in the original signal.

4.2.4 N1 Sleep Stage

The N1 sleep stage represents the initial phase of sleep where transition into slumber begins. N1 stage displays decreased alpha activity while low-amplitude theta waves emerge, marking sensory input disengagement. An examination of amplitude patterns shows a moderate occurrence of delta activity where average amplitudes generally span 5 to 15 μ V among subjects. The initial appearance of delta waves marks the brain's progression into deeper sleep stages. During N1 sleep stage theta band amplitudes demonstrate slight increases from wakefulness reaching averages between 3 to 8 μ V which signifies the emerging dominance of slower oscillatory patterns.

Alpha band amplitude signals indicative of relaxed wakefulness persists at reduced levels with typical measurements falling between 1 to 5 μ V. The decrease in N1 stage indicates the weakening of posterior alpha rhythms during the subject's transition into sleep. The beta band (12–30 Hz) which represents alertness and cognitive processes displays very low amplitude activity below 3 μ V during sleep onset when fast cortical rhythms diminish. Overall, N1 is characterized by a shift from high-frequency to low-frequency amplitude dominance, with theta emerging as a transitional marker and alpha fading as a remnant of wakefulness.

Table 5. Mean Amplitude of N1 Sleep Stage

File	Delta (μ V)	Theta (μ V)	Alpha (μ V)
SC4171E0-PSG.edf	14.71	7.53	2.55
SC4002E0-PSG.edf	9.56	5.36	3.32
SC4112E0-PSG.edf	10.97	5.03	3.24
SC4061E0-PSG.edf	8.63	4.67	3.50
SC4142E0-PSG.edf	7.95	3.39	2.84
SC4082E0-PSG.edf	13.71	6.08	4.11
SC4031E0-PSG.edf	6.85	2.80	1.98
SC4121E0-PSG.edf	7.13	4.00	2.67
SC4192E0-PSG.edf	9.64	3.98	2.58
SC4052E0-PSG.edf	7.29	4.87	3.92
SC4091E0-PSG.edf	7.17	2.84	1.77
SC4022E0-PSG.edf	7.84	2.72	1.46
SC4151E0-PSG.edf	8.22	3.65	1.94
SC4041E0-PSG.edf	6.83	3.44	2.40
SC4181E0-PSG.edf	9.23	5.33	2.03
SC4011E0-PSG.edf	7.34	2.79	1.53
SC4162E0-PSG.edf	7.88	2.70	2.02
SC4072E0-PSG.edf	8.00	4.10	4.06
SC4101E0-PSG.edf	5.82	2.32	1.45
SC4152E0-PSG.edf	10.90	5.10	2.77
SC4092E0-PSG.edf	9.28	4.27	2.77
SC4021E0-PSG.edf	5.49	2.26	1.30
SC4131E0-PSG.edf	7.87	3.06	2.16
SC4182E0-PSG.edf	7.27	4.70	2.23
SC4042E0-PSG.edf	8.01	3.65	2.64
SC4161E0-PSG.edf	7.59	3.00	1.90
SC4012E0-PSG.edf	7.18	2.84	1.57
SC4102E0-PSG.edf	5.72	2.12	1.38
SC4071E0-PSG.edf	5.90	2.69	2.73
SC4001E0-PSG.edf	7.97	4.73	2.66
SC4172E0-PSG.edf	11.37	8.62	3.36
SC4062E0-PSG.edf	4.89	2.18	1.70
SC4111E0-PSG.edf	5.73	2.45	1.77
SC4081E0-PSG.edf	10.80	5.35	3.94
SC4032E0-PSG.edf	8.44	4.64	3.05
SC4141E0-PSG.edf	8.90	3.89	3.00
SC4051E0-PSG.edf	10.10	5.16	4.36

SC4122E0-PSG.edf	6.35	3.33	2.48
SC4191E0-PSG.edf	8.31	4.24	3.08

4.2.5 N2 Sleep Stage

Despite being classified as light sleep, N2 stage maintains stability through the occurrence of both sleep spindles and K-complexes. The spectral characteristics place it between the transitional N1 stage and the slow-wave N3 stage. Delta activity in N2 amplitude envelopes shows a significant increase with average values between 8 and 20 μ V. The neuronal synchrony development is coupled and is more active in the sleep state that is more profound. The theta amplitude is between 6 to 12 μ V which is a far greater range at this point than normal which marks the theta oscillations signifying their primary function throughout this time stage.

Auxiliary band amplitudes during the N2 sleep phase exhibit a slightly smaller decrease compared to the N1 values and routinely display between 1 and 3 μ V average levels supporting the decreased wakeful cortical rhythms. Alpha band amplitude is at barely measurable levels but it is still detectable in a range of 1 to 4 μ V which suggests its connection to intermittent arousals or microstate fluctuations with spindles and K-complexes. N2 shows a great increase of low-frequency amplitude comparing to N1, especially in the delta and theta ranges. The decrease in alpha activity observed combined with stable low beta patterns turns N2 into a sleep stage that retains light sleep characteristics and starts to show deep-sleep features.

Table 6: Mean Amplitude of N2 Sleep Stage

File	Delta (μ V)	Theta (μ V)	Alpha (μ V)
SC4171E0-PSG.edf	15.37	6.73	2.90
SC4002E0-PSG.edf	16.44	6.79	3.70
SC4112E0-PSG.edf	13.58	4.76	2.97
SC4061E0-PSG.edf	14.94	6.48	4.36
SC4142E0-PSG.edf	12.59	5.02	4.01
SC4082E0-PSG.edf	20.12	6.37	3.85
SC4031E0-PSG.edf	10.95	3.71	2.60
SC4121E0-PSG.edf	11.87	4.71	2.64
SC4192E0-PSG.edf	13.90	5.70	3.73
SC4052E0-PSG.edf	12.63	6.32	3.42
SC4091E0-PSG.edf	12.37	3.87	2.45
SC4022E0-PSG.edf	12.69	3.86	1.85
SC4151E0-PSG.edf	11.55	4.71	2.70
SC4041E0-PSG.edf	10.75	4.68	3.78
SC4181E0-PSG.edf	13.11	5.83	2.51
SC4011E0-PSG.edf	12.07	4.32	2.35
SC4162E0-PSG.edf	13.09	4.16	4.00
SC4072E0-PSG.edf	13.73	5.88	5.07
SC4101E0-PSG.edf	8.96	3.20	2.18
SC4152E0-PSG.edf	13.66	6.05	3.56
SC4092E0-PSG.edf	13.99	5.48	3.79
SC4021E0-PSG.edf	10.10	3.32	1.62

SC4131E0-PSG.edf	12.43	4.55	4.10
SC4182E0-PSG.edf	11.70	5.90	2.93
SC4042E0-PSG.edf	12.61	5.31	4.43
SC4161E0-PSG.edf	14.26	4.22	3.60
SC4012E0-PSG.edf	12.16	4.31	2.34
SC4102E0-PSG.edf	9.57	3.24	2.16
SC4071E0-PSG.edf	11.02	4.01	3.25
SC4001E0-PSG.edf	14.66	5.59	2.84
SC4172E0-PSG.edf	15.42	8.19	3.75
SC4062E0-PSG.edf	8.14	3.15	2.07
SC4111E0-PSG.edf	10.55	3.45	2.06
SC4081E0-PSG.edf	18.99	6.49	4.06
SC4032E0-PSG.edf	15.49	6.17	4.65
SC4141E0-PSG.edf	14.16	5.66	4.07
SC4051E0-PSG.edf	15.22	7.22	3.84
SC4122E0-PSG.edf	10.74	4.57	2.46
SC4191E0-PSG.edf	13.09	5.50	3.84

4.2.6 N3 Sleep Stage

The phase of the most restorative and physiologically deep sleep cycle N3, represents the stage where slow-wave sleep (SWS) the most restorative and physiologically profound phase of the sleep cycle is. Delta wave dominance in power and amplitude defines this stage which is crucial for memory consolidation, immune function support, and physical recovery. The amplitude analysis verifies traditional expectations by showing that delta wave dominance occurred during N3 with envelope magnitudes reaching their highest values throughout the night. Delta amplitude measurements ranging from 15 to 40 μ V with some participants recording values over 50 μ V indicating exceptionally synchronized neural activity. They exhibited a reduced response to external stimuli while at the same time being mostly involved with high amplitude internals, as in the case with theta.

Theta is present in N3 but it has a lower dominance with their mean values between 4 and 10 μ V. The comparative decrease of their values against N1 and N2 indicates a distinct shift from the combined patterns of oscillation to the deep delta wave synchronization. During the N3 sleep stage, Alpha electrical amplitude at first reached its lowest values below 2 μ V where it becomes hardly distinguishable from noise-level activity. The observed contrast is a stark drop in the activity that it has gone to almost total suppression of rhythms related to both attention and consciousness. The N3 sleep stage was also characterized by beta amplitudes which rarely exceeded 2 μ V thus indicating in turn that the levels of cortical arousal and alertness were extremely low.

These observations not only confirm but also add to the notion that N3 is a separate stage defined by high-amplitude, low-frequency delta waves where the EEG shows the dominance of slow-wave activity. N3 is especially noticeable because the delta amplitude has a dramatic increase in it which is unmatched by any other stages.

Table 7: Mean Amplitude of N3 Sleep Stage

File	Delta (μ V)	Theta (μ V)	Alpha (μ V)
SC4171E0-PSG.edf	24.80	6.91	3.07
SC4002E0-PSG.edf	35.78	8.76	4.57
SC4112E0-PSG.edf	25.06	5.06	3.32
SC4061E0-PSG.edf	44.01	8.83	4.46
SC4142E0-PSG.edf	28.79	6.67	4.86
SC4082E0-PSG.edf	54.03	8.99	4.81
SC4031E0-PSG.edf	20.52	4.71	2.56
SC4121E0-PSG.edf	24.42	6.00	2.44
SC4192E0-PSG.edf	24.03	6.56	4.25
SC4052E0-PSG.edf	25.07	6.87	4.14
SC4091E0-PSG.edf	23.98	5.11	2.92
SC4022E0-PSG.edf	25.00	4.82	1.88
SC4151E0-PSG.edf	23.37	5.47	2.71
SC4041E0-PSG.edf	21.26	6.23	4.93
SC4181E0-PSG.edf	28.44	6.24	2.70
SC4011E0-PSG.edf	23.40	5.57	2.39
SC4162E0-PSG.edf	24.42	5.36	4.33
SC4072E0-PSG.edf	32.89	7.09	4.89
SC4101E0-PSG.edf	16.58	3.86	2.31
SC4152E0-PSG.edf	26.88	6.93	3.81
SC4092E0-PSG.edf	27.97	6.74	4.13
SC4021E0-PSG.edf	19.89	4.06	1.66
SC4131E0-PSG.edf	27.76	6.65	3.99
SC4182E0-PSG.edf	27.02	6.15	2.72
SC4042E0-PSG.edf	23.45	6.94	5.38
SC4161E0-PSG.edf	25.77	5.48	4.02
SC4012E0-PSG.edf	21.73	5.39	2.41
SC4102E0-PSG.edf	17.96	3.91	2.23
SC4071E0-PSG.edf	25.11	5.05	3.40
SC4001E0-PSG.edf	31.58	7.13	3.55
SC4172E0-PSG.edf	23.69	8.22	3.98
SC4062E0-PSG.edf	24.85	4.66	2.12
SC4111E0-PSG.edf	21.89	4.13	2.52
SC4081E0-PSG.edf	36.44	7.19	4.18
SC4032E0-PSG.edf	30.66	8.00	4.79
SC4141E0-PSG.edf	29.27	7.35	5.01
SC4051E0-PSG.edf	35.20	8.97	4.74
SC4122E0-PSG.edf	25.27	5.78	2.46
SC4191E0-PSG.edf	22.84	6.24	4.13

4.2.7 REM Sleep Stage

REM sleep is a paradoxical state where both EEG activity resembles wakefulness and sleep paralysis coexist. The brain actively produces fluctuations in both theta and beta bands while exhibiting depression of muscle tone. During REM sleep time-related envelopes reflect a reoccurring of theta band activity where the average values are 6 to 15 μ V with occasional peaks beyond 18 μ V. The noticed theta band amplitude increase corresponds to cognitive-like dreaming activities because of the connection between theta rhythms and memory reactivation and hippocampal participation.

The presence of delta rhythms during REM sleep reduced relative to the case in N3 and N2 stages. This can be inferred from the display of values between 3 and 10 μ V which correspond to higher frequency processing being again enlisted. The difference is what makes REM not like the earlier stages of the slow-wave coordination found. In REM sleep, the alpha band amplitudes reveal the presence of variability, which is generally between 2 and 6 μ V, this is at a higher amplitude than N2 and N3 stages, but lower than restorative sleep levels. Short-lived alpha bursts are interpreted as quick awakenings or states of visual processing during dream states.

A surprising characteristic of REM sleep is that beta amplitude levels are observed to rise. During REM sleep, the beta amplitudes are found to be in the range of 3 and 8 μ V, which is still below the conscious state levels but exceed those experienced in all NREM stages. The rise in beta level corresponds with the unique patterns of cognitive activities produced internally and vividly during dream sleep which are similar to those in a waking state. The Rem sleep also displays a different pattern of the amplitude solely with moderate theta wider along and less delta sounds along with high frequency noise presumably more. The REM period encapsulates a false consciousness, a state of being deeply unaware yet of full mental operation.

Table 8: Mean Amplitude of REM Sleep Stage

File	Delta (μ V)	Theta (μ V)	Alpha (μ V)
SC4171E0-PSG.edf	11.94	6.41	2.37
SC4002E0-PSG.edf	9.63	5.87	3.23
SC4112E0-PSG.edf	8.09	4.06	2.14
SC4061E0-PSG.edf	10.00	5.47	3.30
SC4142E0-PSG.edf	7.68	3.90	2.25
SC4082E0-PSG.edf	12.53	5.98	3.58
SC4031E0-PSG.edf	6.39	2.95	1.89
SC4121E0-PSG.edf	7.78	3.93	2.37
SC4192E0-PSG.edf	10.56	4.25	2.74
SC4052E0-PSG.edf	7.81	4.58	2.91
SC4091E0-PSG.edf	8.12	3.34	1.79
SC4022E0-PSG.edf	8.40	3.15	1.44
SC4151E0-PSG.edf	8.25	4.27	1.89
SC4041E0-PSG.edf	7.09	3.85	2.53
SC4181E0-PSG.edf	7.47	4.42	1.68
SC4011E0-PSG.edf	7.64	3.23	1.55

SC4162E0-PSG.edf	8.29	3.25	2.05
SC4072E0-PSG.edf	7.78	4.28	3.44
SC4101E0-PSG.edf	7.01	2.77	1.38
SC4152E0-PSG.edf	9.48	5.58	2.49
SC4092E0-PSG.edf	10.10	4.72	2.79
SC4021E0-PSG.edf	6.39	2.77	1.34
SC4131E0-PSG.edf	7.72	3.99	2.14
SC4182E0-PSG.edf	6.83	4.71	2.02
SC4042E0-PSG.edf	7.79	4.07	2.66
SC4161E0-PSG.edf	9.00	2.97	1.73
SC4012E0-PSG.edf	7.41	3.27	1.51
SC4102E0-PSG.edf	7.34	2.84	1.36
SC4071E0-PSG.edf	6.33	3.18	2.30
SC4001E0-PSG.edf	7.94	4.67	2.45
SC4172E0-PSG.edf	12.05	7.42	3.02
SC4062E0-PSG.edf	6.27	3.10	1.72
SC4111E0-PSG.edf	6.51	2.88	1.62
SC4081E0-PSG.edf	10.30	5.55	3.62
SC4032E0-PSG.edf	9.77	5.00	3.26
SC4141E0-PSG.edf	9.13	4.65	2.51
SC4051E0-PSG.edf	8.55	5.47	3.61
SC4122E0-PSG.edf	7.47	3.30	1.97
SC4191E0-PSG.edf	11.04	5.14	2.76

4.2.8 Comparative Summary Across Stages

The amplitude profiles of the four sleep stages represent a frequency-specific neural oscillations modulation. Delta band amplitude shows a notable increase from N1 through N3 phases where it hits the maximum value and then it goes down a lot during REM. Theta amplitude is observed to be at first low and then increase in the stages of N1 and N2, with moderate levels in N3 and afterwards it increases during REM, and this reflects the involvement of light sleep processes and REM-associated cognitive functions. Alpha amplitude is characterized by a steady decline from N1 to N3 stages, and then a partial recovery occurs in REM. The beta amplitude is not much active during NREM states, but it shows a rise during REM which could mean there are some internal mental processes. The data that we used confirms the already accepted neurophysiological sleep theories and shows that the Hilbert-based amplitude analysis can be applied for the identification of stage-specific EEG patterns. Aggregate delta band amplitude is the major contributor to the topography of the NREM stage differences and accordingly reflects the EEG divergence between the stages.

4.2.9 Channel Comparison

The evaluation of Fpz-Cz and Pz-Oz channels exhibited distinctive regularities at all stages and frequency bands. The Fpz-Cz electrode configuration showed a small increase in delta and theta amplitudes during N3 and REM stages which can be attributed to the frontal location of the electrode, where slow oscillations are more pronounced. The Pz-Oz zone often manifested a slight

increase in alpha activity at the time when the subjects were in lighter sleep, which supports the posterior alpha dominance pattern observed in wakefulness and stage N1.

4.2.10 Conclusion

A detailed investigation with the help of Hilbert-based amplitude analysis confirmed physiological EEG patterns existed strongly across various sleep stages. The amplitude envelopes provided the already established spectral characteristics of each stage while also bringing forth intricate details about their variability and transitional phases at a high-resolution level. The combination of power spectral data with the quantification of sleep phases creating a more precise measure of sleep architecture turned out to be a robust framework. The study has made it clear that the analysis of amplitude envelope is an additional worthwhile method to spectral features in both research and clinical practice. Amplitude measurements have demonstrated a strong possibility for a rule-based sleep level classification system as well as in machine learning pipelines due to specific stage-related amplitude changes such as delta predominance in N3 and theta increase in REM. This research has the potential to continue in the direction of examining amplitude-phase coupling as well as cross-frequency interactions to increase our understanding of sleep neurodynamics.

4.3. Examination of Power Spectral Density through Welch's Method

4.3.1 Overview and Motivation

Spectral power decomposition is a major method in combination with amplitude-based envelope analysis in EEG-based sleep staging. The Power Spectral Density (PSD) function is the main tool for displaying power distribution in the frequency spectrum of a signal, thus emphasizing the characteristic oscillatory patterns that are associated with different physiological conditions. In the analysis of power spectral density over various sleep stages for every participant, the Welch method was chosen. Welch's method involves the segmentation of the input signal into overlapping windows, application of windowing functions, for instance, Hamming or Hann, the generation of a robust smoothed PSD estimate by means of lambda maximal entropy (MME) and averaging the squared magnitudes of the Fourier-transformed segments. The method realizes the dual objective of ensuring adequate frequency resolution and minimizing variance which is why the analysis of sleep EEG signals can be done with it easily since these signals are both non-stationary and stable spectral indicators in a short time. In this section the spectral power analysis on EEG signals from Pz-Oz and Fpz-Cz channels is elaborated.

We calculated:

- i.** Absolute band power for delta, theta, and alpha bands
- ii.** Total power across a wider band (0.5–30 Hz)
- iii.** Each band's relative power as a percentage of total power output
- iv.** The alpha / (theta + delta) ratio among band ratios demonstrated efficacy for stage discrimination.

During preprocessing, we implemented a crucial modification by redefining the delta band to 3–4 Hz because motion artifacts affected the low-delta range (0.5–3 Hz). Through this decision power estimation for low-frequency activity became more stable and representative while avoiding delta power inflation from artifact-related signals.

4.3.2 Preprocessing Steps

Before applying Welch's method, several preprocessing steps were implemented to ensure reliable spectral analysis:

1. The EEG data underwent separate analysis for Pz-Oz and Fpz-Cz derivations which offered distinct regional views of cortical activity.
2. An unnatural complexity emerges when a zero-phase FIR filter constrains EEG data to the 0-frequency range. 5–30 Hz. The process eliminated both high-frequency muscle artifacts and low-frequency drifts yet maintained delta, theta, and alpha bands.
3. The data underwent segmentation into 30-second non-overlapping epochs to maintain consistency with standard polysomnography procedures. The process enabled spectral estimates to be matched meaningfully with manually scored sleep stages.
4. The elimination process removed epochs displaying extreme amplitude variations alongside non-physiological traits. The lower delta cutoff frequency was increased to 3 Hz because the 0. The 5–3 Hz frequency range exhibited substantial contamination which appears to originate from movement artifacts.
5. The data from each epoch underwent division into overlapping 10-second windows with a 50% overlap where a Hamming window was applied to minimize spectral leakage.

By implementing this preprocessing pipeline, the PSD estimates achieved maximum fidelity while simultaneously reducing the impact of noise and non-cortical artifacts.

4.3.3 Analysis from the Pz-Oz Channel

4.3.3.1 Absolute Power Estimation

The Pz-Oz channel positioned above parietal and occipital cortices records strong alpha rhythms during wakefulness which convert into slower activities as sleep stages progress. The power spectral density for every 30-second epoch was determined through Welch's method. We extracted absolute power values from the complete spectrum across these frequency bands:

- a. Delta (3–4 Hz)
- b. Theta (4–8 Hz)
- c. Alpha (8–12 Hz)

The calculation of absolute power involved determining the integral of the power spectral density (PSD) over each specified frequency band. Across sleep stages:

- The 3 Hz cutoff caused Delta power to reach minimal levels but it still demonstrated an anticipated increase during N3 sleep which appeared weaker than typical values. 5–4 Hz delta bands.
- Theta power reached its maximum levels during N1 and N2 stages which aligns with transitional sleep patterns.
- During N1 and REM stages alpha power reached its peak values while it experienced a steep decline during N3.

The absolute power estimates represent the neurophysiological transitions across sleep stages. The delta adjustment failed to normalize low-frequency activity in N3 which remained elevated compared to other stages.

4.3.3.2 Relative Power Calculation

We addressed inter-subject variability and baseline EEG differences by calculating relative power across frequency bands.

$$\text{Relative Band Power} = \text{Band Power} / \text{Total Power} (0.5\text{--}30 \text{ Hz})$$

Through relative power analysis clearer distinctions emerged across developmental stages: During N3 sleep delta relative power reached its peak values notwithstanding the restrictive 3–4 Hz frequency boundary. Theta relative power showed dominance during N1 and N2 stages but decreased in N3 before partially rebounding during REM. During N1 and REM stages, alpha relative power emerged as most dominant indicating sustained posterior alpha rhythm throughout light sleep phases and cognitive dreaming periods. Relative measures obfuscated direct amplitude differences while emphasizing proportional oscillatory dynamics changes associated with sleep physiology.

4.3.3.3 Band Ratio Calculation

The filter adjustment reduced low-delta contribution which led us to create a novel composite ratio for stage discrimination.

$$\text{Band Ratio} = \frac{\text{Relative Alpha Power}}{\text{Relative Theta Power} + \text{Relative Delta Power}}$$

The ratio highlighted the equilibrium between high and low-frequency oscillations while demonstrating sensitivity to stage transitions:

- The examination of N1 revealed peak ratios while alpha levels remained relatively intact.
- In N3 stage, ratios experienced a steep decline while alpha waves nearly disappeared and theta/delta waves took precedence.
- REM exhibited median values which demonstrated its mixed frequency characteristics.
- The band ratio technique effectively distinguished REM from N2 and N1 from N3 stages despite overlapping individual band powers.

SC406 1	SC4061E0- PSG.edf	4	3.25661 712	0.387296 159	12.1091 359	1.748114 439	53.6691 8894	0.791029 08	24.19703 494	0.36785 7269
SC406 2	SC4062E0- PSG.edf	6	38.6680 1752	5.566642 31	14.3862 2316	21.98091 504	56.5178 6749	8.228104 244	21.55216 941	0.30396 2285
SC407 1	SC4071E0- PSG.edf	11	9.05441 3358	0.758471 334	8.44450 2432	4.040900 58	44.7443 8132	3.092766 738	33.78624 741	0.63521 2567
SC407 2	SC4072E0- PSG.edf	31	18.0919 9461	1.365801 101	7.63929 0565	7.251052 508	40.2161 2467	7.098417 035	37.99227 117	0.79389 7012
SC408 1	SC4081E0- PSG.edf	4	20.4662 3578	2.750259 483	13.4024 2321	10.60027 776	51.8986 8446	5.424790 419	26.46537 519	0.40528 2179
SC408 2	SC4082E0- PSG.edf	8	23.2365 3562	3.433305 486	14.0279 7968	11.93257 854	51.5746 1016	5.863040 582	26.18988 33	0.39922 0265
SC409 1	SC4091E0- PSG.edf	17	14.7085 107	2.624314 151	17.9968 5247	7.333772 347	50.3163 2453	3.367347 685	22.51839 202	0.32963 4677
SC409 2	SC4092E0- PSG.edf	12	24.8608 9264	3.925610 753	15.7519 0446	12.19344 758	48.7701 6654	6.332543 196	25.65521 456	0.39761 9205
SC410 1	SC4101E0- PSG.edf	4	4.82053 9459	0.789417 581	16.3476 8859	2.461368 879	51.0275 1446	0.970554 004	20.16090 819	0.29923 3357
SC410 2	SC4102E0- PSG.edf	3	4.47461 8331	0.708790 863	15.8309 3692	2.324406 763	52.0018 7406	0.881503 611	19.69141 358	0.29029 3345
SC411 1	SC4111E0- PSG.edf	6	7.44865 5246	1.246429 942	16.7600 1485	4.115129 954	55.1737 4132	1.501253 754	20.29203 06	0.28209 3299
SC411 2	SC4112E0- PSG.edf	7	11.6224 8262	1.635720 433	14.2873 5638	6.913887 449	59.4640 0011	2.192699 906	18.65326 001	0.25292 0907
SC412 1	SC4121E0- PSG.edf	8	11.3560 3348	1.995143 136	17.5492 9378	5.898487 635	52.0742 4484	2.842380 319	24.89895 034	0.35762 2592
SC412 2	SC4122E0- PSG.edf	5	8.23687 5874	1.603740 694	19.0482 0891	4.235278 624	51.3603 3689	1.883851 613	23.44589 79	0.33299 79
SC413 1	SC4131E0- PSG.edf	12	12.8567 1593	1.870041 238	14.0649 3557	6.490039 199	49.7240 284	3.130362 528	25.37355 875	0.39777 3489
SC414 1	SC4141E0- PSG.edf	7	16.2607 7629	1.828869 415	11.3094 885	6.705633 687	41.1548 0874	5.744503 176	35.29626 303	0.67276 7289
SC414 2	SC4142E0- PSG.edf	8	14.6196 1482	1.979959 095	13.5908 6942	6.466386 096	43.9352 2062	4.036379 585	27.55326 903	0.47896 996
SC415 1	SC4151E0- PSG.edf	4	7.01448 6216	1.124828 692	16.2351 5205	4.273834 573	60.5357 9666	1.288366 775	18.56606 578	0.24183 7128
SC415 2	SC4152E0- PSG.edf	8	13.7559 2315	1.943376 815	14.0817 3435	8.054717 388	58.0288 4672	2.381310 949	18.32466 285	0.25411 8918
SC416 1	SC4161E0- PSG.edf	8	9.09432 9683	1.507436 003	16.4737 7279	4.126902 733	45.4442 2752	1.706556 701	18.67920 95	0.30167 6563
SC416 2	SC4162E0- PSG.edf	6	8.60368 8866	1.262822 953	15.1945 1731	3.185820 093	39.9139 9766	1.453868 792	17.70044 611	0.32119 258
SC417 1	SC4171E0- PSG.edf	10	14.7389 2072	2.073682 373	13.8571 61	10.27319 988	69.4537 4882	1.773429 055	12.40282 645	0.14887 3977
SC417 2	SC4172E0- PSG.edf	17	48.8770 7154	7.492062 294	13.1665 4239	28.20056 793	62.4798 6802	8.482261 941	17.00272 33	0.22476 5765
SC418 1	SC4181E0- PSG.edf	4	9.93526 2138	0.903364 389	10.5344 5765	6.864803 995	66.4772 4367	1.660494 657	17.39214 899	0.22583 7745
SC418 2	SC4182E0- PSG.edf	9	14.4031 5353	1.715588 393	12.3601 6132	8.292880 825	56.1973 9763	3.085841 563	22.36725 057	0.32625 5061
SC419 1	SC4191E0- PSG.edf	18	11.1407 9546	1.735341 842	15.6487 3203	5.730410 585	51.3900 6452	2.307535 758	20.61643 057	0.30752 9843
SC419 2	SC4192E0- PSG.edf	12	9.72206 8674	1.305771 622	13.2509 9061	4.604496 487	47.0145 8935	2.270584 288	23.57114 486	0.39112 1182
										0.39166 7335

4.3.4 Analysis from the Fpz-Cz Channel

4.3.4.1 Absolute Power Estimation

By selecting the Fpz-Cz channel we examined frontal brain regions which display enhanced slow-wave activity alongside more distinct theta rhythms especially during NREM sleep. Through identical Welch-based procedures and frequency band classifications, researchers extracted absolute band powers:

- Delta power experienced slight increases during N3 but faced suppression similar to Pz-Oz data because of the 3–4 Hz cutoff.
- Theta power exhibited greater strength during N2 and REM stages which indicated frontal theta synchronization associated with memory processing and cognitive dreaming.
- Alpha power exhibited a general decrease when compared to Pz-Oz values because posterior alpha propagation diminished.
- The frontal dominance of theta rhythms during REM appeared more distinctly in Fpz-Cz recordings which supports its function as a REM marker.

4.3.4.2 Relative Power Calculation

The relative power values exhibited similar patterns to Pz-Oz recordings yet displayed subtle distinctions:

- Examination of Theta relative power revealed marginally elevated values in Fpz-Cz during REM which indicates frontal theta engagement.
- Delta relative power reached its peak during N3 yet displayed a subdued profile.
- Throughout all stages alpha relative power remained minimal while showing only slight expression during N1.
- The distinct sleep signatures observed in specific channels demonstrate varied cortical manifestation patterns which validate the necessity for multi-channel analysis.

4.3.4.3 Band Ratio Calculation

Utilizing identical composite ratios:

$$\text{Band Ratio} = \frac{\text{Relative Alpha Power}}{\text{Relative Theta Power} + \text{Relative Delta Power}}$$

The recorded Fpz-Cz ratios showed: The measurements for N2 and N3 stages show reduced values which indicate diminished alpha activity combined with prevalent slow wave patterns.

- Intermediate values in REM
- N1 displays minor elevations

The Fpz-Cz recording exhibited constrained ratio dynamics because of its low alpha power which rendered Pz-Oz recordings more effective for detecting lighter sleep stages.

4.3.5 Stage-wise Observations and Interpretation

Spectral patterns across both channels matched established sleep neurophysiology:

N1: The system displays low total power while maintaining moderate theta and alpha contributions alongside high band ratios.

N2: Theta levels ascend while alpha decreases and delta begins to rise with stable ratios.

N3: Delta waves show a steep rise even at 3–4 Hz while alpha waves get suppressed resulting in the lowest band ratios.

REM: Theta levels show rebound while alpha waves remain moderate and delta activity stays low with variable ratios.

These dynamics were effectively recorded by the Welch method while relative power normalization combined with band ratio formulation enabled standardized comparisons even though motion artifacts impacted low-delta power.

Table 13: Absolute and Relative Band powers and Ratios for N1 Sleep Stage for Fpz-Cz

Subject No.	File Name	N1 Segments Count	Total Power	Absolute Delta	Relative Delta	Absolute Theta	Relative Theta	Absolute Alpha	Relative Alpha	Band ratios
SC400-1	SC4001E0-PSG.edf	24	37.475	5.384	14.569	23.429	60.784	5.757	16.747	0.222
SC400-2	SC4002E0-PSG.edf	32	55.184	8.175	16.042	30.062	57.278	9.151	15.516	0.212
SC401-1	SC4011E0-PSG.edf	33	14.098	3.623	22.223	6.793	49.313	2.257	17.121	0.239
SC401-2	SC4012E0-PSG.edf	42	13.054	2.891	21.270	6.717	52.069	2.031	15.665	0.214
SC402-1	SC4021E0-PSG.edf	22	9.783	1.936	18.860	4.876	47.904	1.764	19.829	0.297
SC402-2	SC4022E0-PSG.edf	52	18.505	4.968	25.511	9.411	50.298	2.533	14.899	0.197
SC403-1	SC4031E0-PSG.edf	30	15.462	2.349	14.808	6.641	42.828	3.865	25.790	0.447
SC403-2	SC4032E0-PSG.edf	20	36.138	4.801	13.176	15.578	43.797	9.532	26.738	0.469
SC404-1	SC4041E0-PSG.edf	43	19.990	2.098	10.730	9.598	49.282	5.058	24.534	0.409
SC404-2	SC4042E0-PSG.edf	51	25.008	2.859	11.048	11.738	47.353	6.343	25.612	0.439
SC405-1	SC4051E0-PSG.edf	19	60.066	6.812	11.242	31.848	50.445	16.937	31.272	0.507
SC405-2	SC4052E0-PSG.edf	43	40.229	4.100	10.861	21.555	50.521	11.152	29.865	0.487
SC406-1	SC4061E0-PSG.edf	18	57.146	5.426	10.750	20.838	39.495	16.077	28.602	0.569
SC406-2	SC4062E0-PSG.edf	25	11.286	1.887	15.718	5.343	45.809	2.549	24.776	0.403
SC407-1	SC4071E0-PSG.edf	23	21.014	1.927	9.310	8.421	38.442	6.773	33.332	0.698
SC407-2	SC4072E0-PSG.edf	40	38.188	3.536	9.280	14.789	38.327	12.689	33.981	0.714
SC408-1	SC4081E0-PSG.edf	14	47.069	4.756	9.408	21.750	44.329	13.047	29.002	0.540
SC408-2	SC4082E0-PSG.edf	23	53.473	7.272	12.741	23.341	44.649	13.253	25.189	0.439
SC409-1	SC4091E0-PSG.edf	10	11.788	1.932	15.960	5.265	44.714	2.270	19.770	0.326
SC409-2	SC4092E0-PSG.edf	30	39.327	5.734	14.743	15.949	41.262	7.735	19.225	0.343

SC410 1	SC4101E0- PSG.edf	15	8.007	1.547	19.154	3.691	47.652	1.370	17.801	0.266
SC410 2	SC4102E0- PSG.edf	41	8.782	1.538	17.535	4.147	47.461	1.625	19.054	0.293
SC411 1	SC4111E0- PSG.edf	5	16.741	2.589	16.324	8.726	52.033	3.429	20.030	0.293
SC411 2	SC4112E0- PSG.edf	11	37.133	4.006	11.524	16.022	45.928	7.002	17.834	0.310
SC412 1	SC4121E0- PSG.edf	33	23.603	4.211	17.159	12.620	53.560	4.533	19.444	0.275
SC412 2	SC4122E0- PSG.edf	38	25.764	5.947	21.672	13.425	52.396	4.335	17.680	0.239
SC413 1	SC4131E0- PSG.edf	25	22.845	2.313	12.057	8.084	38.902	5.445	21.604	0.424
SC414 1	SC4141E0- PSG.edf	16	36.113	7.680	21.064	14.311	40.508	6.367	17.979	0.292
SC414 2	SC4142E0- PSG.edf	18	29.326	4.706	16.927	11.672	41.874	6.086	19.249	0.327
SC415 1	SC4151E0- PSG.edf	12	16.611	3.370	17.690	8.820	52.649	2.502	16.720	0.238
SC415 2	SC4152E0- PSG.edf	8	29.293	5.505	18.422	15.183	51.516	4.409	15.698	0.224
SC416 1	SC4161E0- PSG.edf	21	18.329	3.175	16.784	7.766	43.607	3.351	17.936	0.297
SC416 2	SC4162E0- PSG.edf	15	38.173	4.040	11.462	12.773	34.620	7.928	19.297	0.419
SC417 1	SC4171E0- PSG.edf	15	47.212	9.906	20.317	30.214	63.823	4.234	9.519	0.113
SC417 2	SC4172E0- PSG.edf	14	80.768	6.506	8.040	58.056	72.558	9.386	11.457	0.142
SC418 1	SC4181E0- PSG.edf	13	26.880	1.844	7.245	19.466	70.377	3.261	13.617	0.175
SC418 2	SC4182E0- PSG.edf	20	33.516	2.899	9.342	24.605	67.558	3.536	13.612	0.177
SC419 1	SC4191E0- PSG.edf	45	40.738	4.604	12.344	15.604	40.861	8.753	21.103	0.397
SC419 2	SC4192E0- PSG.edf	24	30.815	4.771	15.165	14.885	48.035	5.530	18.359	0.290
									AVG:	0.343

Table 14: Absolute and Relative Band powers and Ratios for N2 Sleep Stage for Fpz-Cz

Subject No.	File Name	N2 Segments Count	Total Power	Absolute Delta	Relative Delta	Absolute Theta	Relative Theta	Absolute Alpha	Relative Alpha	Band ratios
SC400-1	SC4001E0-PSG.edf	40	53.224	13.964	26.130	28.793	53.506	5.616	10.907	0.137
SC400-2	SC4002E0-PSG.edf	37	79.173	18.786	23.575	42.468	52.710	8.983	11.757	0.154
SC401-1	SC4011E0-PSG.edf	40	35.705	9.862	27.329	17.878	49.956	3.967	11.376	0.147
SC401-2	SC4012E0-PSG.edf	55	34.723	10.019	28.222	17.405	50.439	3.570	10.527	0.134
SC402-1	SC4021E0-PSG.edf	56	20.752	6.127	28.989	10.692	51.438	1.811	9.005	0.112
SC402-2	SC4022E0-PSG.edf	63	29.119	8.803	29.676	14.506	49.694	2.531	8.939	0.113
SC403-1	SC4031E0-PSG.edf	42	31.448	6.665	20.588	13.283	41.834	3.951	12.825	0.205
SC403-2	SC4032E0-PSG.edf	33	89.390	15.818	17.616	33.845	38.845	12.825	14.805	0.262
SC404-1	SC4041E0-PSG.edf	47	44.065	6.270	13.712	18.466	42.749	9.342	20.776	0.368
SC404-2	SC4042E0-PSG.edf	48	59.468	8.724	14.199	25.041	42.494	12.843	21.191	0.374
SC405-1	SC4051E0-PSG.edf	45	80.183	19.163	23.128	41.827	52.354	10.682	13.404	0.178
SC405-2	SC4052E0-PSG.edf	32	56.854	10.797	18.689	30.156	52.816	8.505	15.030	0.210
SC406-1	SC4061E0-PSG.edf	27	90.418	18.576	20.063	42.330	46.035	13.857	16.094	0.243
SC406-2	SC4062E0-PSG.edf	26	22.640	5.546	23.785	10.537	45.477	3.139	14.533	0.210
SC407-1	SC4071E0-PSG.edf	33	35.418	5.502	14.976	14.704	40.467	8.235	23.849	0.430
SC407-2	SC4072E0-PSG.edf	43	81.225	10.403	12.721	33.076	40.716	20.551	25.231	0.472
SC408-1	SC4081E0-PSG.edf	42	77.501	16.374	20.748	35.509	46.085	12.017	15.816	0.237
SC408-2	SC4082E0-PSG.edf	55	95.127	21.492	21.779	45.685	47.406	14.615	16.026	0.232
SC409-1	SC4091E0-PSG.edf	54	29.013	6.785	22.772	12.771	44.446	4.103	14.297	0.213
SC409-2	SC4092E0-PSG.edf	37	62.539	13.126	20.968	26.791	43.107	9.170	14.619	0.228
SC410-1	SC4101E0-PSG.edf	22	21.006	5.181	24.071	8.943	42.696	2.703	12.923	0.194
SC410-2	SC4102E0-PSG.edf	50	20.804	5.047	23.724	8.674	41.900	2.626	12.907	0.197
SC411-1	SC4111E0-PSG.edf	50	17.031	3.400	18.688	8.280	47.717	2.695	17.046	0.257
SC411-2	SC4112E0-PSG.edf	45	35.174	7.268	20.287	17.095	49.194	5.701	15.982	0.230
SC412-1	SC4121E0-PSG.edf	38	38.537	11.230	27.853	19.457	50.710	4.712	12.902	0.164
SC412-2	SC4122E0-PSG.edf	36	36.231	10.959	29.609	18.622	51.400	3.950	11.382	0.141
SC413-1	SC4131E0-PSG.edf	37	49.860	10.585	20.830	20.412	41.041	9.452	18.626	0.301
SC414-1	SC4141E0-PSG.edf	30	81.554	21.736	25.820	33.782	40.547	10.773	13.927	0.210
SC414-2	SC4142E0-PSG.edf	30	58.693	14.738	24.834	23.916	40.302	9.162	15.844	0.243
SC415-1	SC4151E0-PSG.edf	28	45.841	13.325	28.592	23.153	49.789	3.881	8.753	0.112
SC415-2	SC4152E0-PSG.edf	28	61.233	14.575	23.051	29.332	47.874	6.648	11.330	0.160
SC416-1	SC4161E0-PSG.edf	40	47.361	8.097	16.707	17.677	37.703	8.500	17.964	0.330
SC416-2	SC4162E0-PSG.edf	47	47.637	7.121	14.544	15.560	32.948	9.264	19.350	0.407
SC417-1	SC4171E0-PSG.edf	53	57.603	13.178	22.829	35.119	60.837	5.932	10.383	0.124

SC417 2	SC4172E0- PSG.edf	71	85.641	16.776	19.060	53.392	62.526	9.306	11.121	0.136
SC418 1	SC4181E0- PSG.edf	55	40.520	6.390	16.171	27.759	67.380	3.563	9.157	0.110
SC418 2	SC4182E0- PSG.edf	31	48.319	6.978	14.449	31.326	64.430	5.268	11.186	0.142
SC419 1	SC4191E0- PSG.edf	54	53.035	10.562	20.023	21.544	41.472	7.428	14.077	0.229
SC419 2	SC4192E0- PSG.edf	36	68.580	14.523	21.298	28.209	41.530	8.895	12.836	0.204
									Avg:	0.219

Table 15: Absolute and Relative Band powers and Ratios for N3 Sleep Stage for Fpz-Cz

Subject No.	File Name	N2 Segments Count	Total Power	Absolute Delta	Relative Delta	Absolute Theta	Relative Theta	Absolute Alpha	Relative Alpha	Band Ratios
SC400 1	SC4001E0- PSG.edf	48	70.885	18.784	26.575	39.744	55.612	7.474	10.731	0.131
SC400 2	SC4002E0- PSG.edf	30	103.67	7	24.778	23.894	57.347	55.147	12.001	11.644
SC401 1	SC4011E0- PSG.edf	21	43.091	13.522	31.271	22.923	53.245	3.692	8.633	0.102
SC401 2	SC4012E0- PSG.edf	29	43.692	13.354	30.207	23.130	53.238	3.773	8.631	0.103
SC402 1	SC4021E0- PSG.edf	43	25.821	8.231	31.828	13.686	53.013	2.091	7.974	0.094
SC402 2	SC4022E0- PSG.edf	34	35.170	11.526	32.529	18.665	53.143	2.576	7.302	0.085
SC403 1	SC4031E0- PSG.edf	21	35.620	9.119	25.766	17.591	49.149	4.479	12.455	0.166
SC403 2	SC4032E0- PSG.edf	28	109.45	2	26.089	23.669	48.412	44.083	14.250	13.267
SC404 1	SC4041E0- PSG.edf	15	68.671	10.961	15.871	30.162	44.528	16.069	23.162	0.383
SC404 2	SC4042E0- PSG.edf	22	87.883	15.134	17.213	38.976	44.388	20.447	23.286	0.378
SC405 1	SC4051E0- PSG.edf	39	90.499	23.061	25.360	47.698	52.605	12.475	13.828	0.177
SC405 2	SC4052E0- PSG.edf	14	70.291	16.369	23.188	36.033	51.126	11.917	17.011	0.229
SC406 1	SC4061E0- PSG.edf	11	131.32	2	29.752	22.205	66.913	50.967	17.994	14.166
SC406 2	SC4062E0- PSG.edf	17	33.517	11.049	32.202	17.191	51.515	3.104	9.611	0.115
SC407 1	SC4071E0- PSG.edf	27	41.779	8.368	19.898	20.514	49.114	8.511	20.312	0.294
SC407 2	SC4072E0- PSG.edf	37	91.900	13.806	15.217	43.233	46.351	21.681	23.606	0.383
SC408 1	SC4081E0- PSG.edf	53	72.739	15.809	21.473	34.263	47.117	12.476	17.335	0.253
SC408 2	SC4082E0- PSG.edf	46	113.82	6	27.487	22.944	55.875	48.402	16.381	15.191
SC409 1	SC4091E0- PSG.edf	39	41.167	10.798	25.908	18.066	44.143	6.233	15.045	0.215
SC409 2	SC4092E0- PSG.edf	13	77.369	19.479	25.046	33.961	43.847	11.321	14.669	0.213
SC410 1	SC4101E0- PSG.edf	6	33.252	10.884	32.319	14.780	44.113	3.915	11.712	0.153
SC410 2	SC4102E0- PSG.edf	10	27.611	8.784	31.461	12.983	47.106	2.708	9.911	0.126
SC411 1	SC4111E0- PSG.edf	49	20.047	4.627	21.787	10.255	50.328	2.955	15.566	0.216
SC411 2	SC4112E0- PSG.edf	42	43.281	9.178	22.242	19.508	45.989	8.218	18.531	0.272
SC412 1	SC4121E0- PSG.edf	20	46.803	15.744	32.967	25.354	54.592	3.504	7.648	0.087
SC412 2	SC4122E0- PSG.edf	25	41.493	15.815	37.673	21.191	51.367	2.872	6.956	0.078

SC413 1	SC4131E0- PSG.edf	31	60.025	14.137	23.571	31.103	51.801	9.827	16.398	0.218
SC414 1	SC4141E0- PSG.edf	30	92.293	25.289	26.581	39.458	42.979	13.616	15.100	0.217
SC414 2	SC4142E0- PSG.edf	29	70.460	17.232	24.335	30.799	44.238	13.315	18.957	0.276
SC415 1	SC4151E0- PSG.edf	30	43.093	12.470	29.151	22.092	50.871	3.779	8.748	0.109
SC415 2	SC4152E0- PSG.edf	32	70.659	17.059	24.396	36.023	50.705	7.678	10.715	0.143
SC416 1	SC4161E0- PSG.edf	45	54.732	10.660	19.376	22.610	41.519	10.528	18.892	0.310
SC416 2	SC4162E0- PSG.edf	42	56.593	9.397	16.811	22.200	39.465	11.637	20.406	0.363
SC417 1	SC4171E0- PSG.edf	64	60.929	15.193	24.939	36.918	60.369	5.814	9.684	0.114
SC417 2	SC4172E0- PSG.edf	56	90.896	21.082	23.135	53.820	59.182	10.091	11.211	0.136
SC418 1	SC4181E0- PSG.edf	61	49.951	8.448	17.534	34.184	67.309	4.303	8.870	0.105
SC418 2	SC4182E0- PSG.edf	26	56.511	11.371	20.985	35.820	62.510	5.556	9.738	0.117
SC419 1	SC4191E0- PSG.edf	25	66.098	15.694	23.722	30.321	45.745	8.864	13.362	0.192
SC419 2	SC4192E0- PSG.edf	16	69.187	17.326	25.078	29.826	43.107	9.224	13.228	0.194
									AVG:	0.192

Table 16: Absolute and Relative Band powers and Ratios for N3 Sleep Stage for Fpz-Cz

Subject No.	File Name	REM Segments Count	Total Power	Absolute Delta	Relative Delta	Absolute Theta	Relative Theta	Absolute Alpha	Relative Alpha	Band Ratios
SC400 1	SC4001E0- PSG.edf	6	27.999	4.603	16.682	17.321	61.120	4.275	15.548	0.200
SC400 2	SC4002E0- PSG.edf	12	45.470	7.080	15.834	26.566	57.062	7.522	17.208	0.236
SC401 1	SC4011E0- PSG.edf	8	20.127	5.557	25.495	10.698	56.191	2.181	11.600	0.142
SC401 2	SC4012E0- PSG.edf	18	14.645	3.686	23.752	8.319	57.611	1.639	11.573	0.142
SC402 1	SC4021E0- PSG.edf	15	14.654	4.215	27.330	8.025	54.714	1.535	11.410	0.139
SC402 2	SC4022E0- PSG.edf	11	14.958	4.155	27.699	8.336	55.680	1.667	11.285	0.135
SC403 1	SC4031E0- PSG.edf	10	11.585	1.702	14.658	6.298	54.399	2.391	20.651	0.299
SC403 2	SC4032E0- PSG.edf	12	36.542	5.835	15.915	19.135	52.592	7.396	20.135	0.294
SC404 1	SC4041E0- PSG.edf	24	20.463	3.219	15.622	11.683	56.965	3.803	18.779	0.259
SC404 2	SC4042E0- PSG.edf	33	24.956	3.730	15.041	13.624	54.463	5.072	20.361	0.293
SC405 1	SC4051E0- PSG.edf	3	56.413	11.477	19.253	33.760	59.374	8.364	16.267	0.207
SC405 2	SC4052E0- PSG.edf	12	24.429	3.427	14.006	13.692	56.023	5.345	21.846	0.312
SC406 1	SC4061E0- PSG.edf	4	43.484	8.196	18.606	23.588	54.299	7.741	17.885	0.245
SC406 2	SC4062E0- PSG.edf	6	14.310	3.169	22.050	7.939	55.403	2.083	14.765	0.191
SC407 1	SC4071E0- PSG.edf	11	16.163	2.261	14.071	7.992	49.449	4.286	26.301	0.414
SC407 2	SC4072E0- PSG.edf	31	36.901	4.477	11.988	17.323	46.795	10.586	28.427	0.484
SC408 1	SC4081E0- PSG.edf	4	54.422	10.476	19.242	27.672	50.843	9.790	18.022	0.257
SC408 2	SC4082E0- PSG.edf	8	80.714	17.394	19.905	41.723	52.428	12.534	16.868	0.233
SC409 1	SC4091E0- PSG.edf	17	19.153	4.615	23.250	10.047	53.078	2.548	13.571	0.178

SC409 2	SC4092E0- PSG.edf	12	33.889	6.410	18.850	17.425	51.400	5.363	15.892	0.226
SC410 1	SC4101E0- PSG.edf	4	10.575	2.348	22.334	5.981	56.391	1.274	12.021	0.153
SC410 2	SC4102E0- PSG.edf	3	11.057	2.540	22.988	6.397	57.860	1.274	11.513	0.142
SC411 1	SC4111E0- PSG.edf	6	9.971	1.567	15.583	4.923	48.374	1.813	18.773	0.294
SC411 2	SC4112E0- PSG.edf	7	21.997	4.114	18.691	12.485	56.655	3.015	13.717	0.182
SC412 1	SC4121E0- PSG.edf	8	25.146	5.600	21.832	13.265	52.644	4.212	17.184	0.231
SC412 2	SC4122E0- PSG.edf	5	23.054	5.605	23.809	12.338	53.865	3.408	14.970	0.193
SC413 1	SC4131E0- PSG.edf	12	29.956	5.872	18.600	16.411	55.429	4.037	13.553	0.183
SC414 1	SC4141E0- PSG.edf	7	33.292	7.322	22.284	17.348	52.390	4.894	14.491	0.194
SC414 2	SC4142E0- PSG.edf	8	25.361	5.669	22.353	12.110	47.855	3.617	14.328	0.204
SC415 1	SC4151E0- PSG.edf	4	25.869	5.102	19.812	16.814	64.695	2.704	10.593	0.125
SC415 2	SC4152E0- PSG.edf	8	45.763	8.451	18.380	28.055	60.995	5.089	11.684	0.147
SC416 1	SC4161E0- PSG.edf	8	16.261	3.115	18.993	7.696	47.313	2.327	14.359	0.217
SC416 2	SC4162E0- PSG.edf	6	22.120	3.185	14.514	7.722	38.800	3.467	15.694	0.294
SC417 1	SC4171E0- PSG.edf	10	43.872	7.619	17.164	30.397	69.161	3.804	8.928	0.103
SC417 2	SC4172E0- PSG.edf	17	59.246	8.181	13.848	39.595	66.875	7.026	11.878	0.147
SC418 1	SC4181E0- PSG.edf	4	22.520	3.158	15.412	16.480	70.644	1.876	9.065	0.105
SC418 2	SC4182E0- PSG.edf	9	26.996	4.420	16.537	15.438	57.561	3.837	14.322	0.193
SC419 1	SC4191E0- PSG.edf	18	36.343	7.263	20.030	20.351	55.901	4.948	13.637	0.180
SC419 2	SC4192E0- PSG.edf	12	37.113	7.190	18.761	19.449	52.353	5.564	15.295	0.215
										0.215

4.3.6 Channel Comparison and Summary

A. Pz-Oz: The alpha signal stands out more while N1 and REM detection becomes clearer and band ratio sensitivity increases.

B. Fpz-Cz: REM phases exhibit enhanced frontal theta activity while stages with predominant theta such as N2 show clearer differentiation.

The spectral progression in both channels remained consistent across stages which supports the validity of the preprocessing and PSD estimation methods.

4.3.7 Conclusion

Through Welch-based spectral analysis EEG dynamics were quantified comprehensively across different stages. Even with the modified delta band settings, the relative power metrics alongside band ratios remained effective for monitoring sleep stage transitions. This technique enhances traditional time-domain amplitude analysis and classification-based hypnogram methods by focusing on frequency-specific neural patterns.

Sleep staging models benefit from employing relative metrics and band ratios because these techniques reduce inter-individual variability while boosting robustness against noise and artifacts. The spectral profile differences between Pz-Oz and Fpz-Cz recordings underscore the necessity for multi-channel EEG analysis in both research settings and clinical diagnostic processes.

4.4 Rule-Based Classification of Sleep Stages

4.4.1 Overview and Objective

This paragraph addresses the introduction of a rule-based classifier that is both compact and comprehensible, with the sole aim of having an automatic sleep stage detection system implemented through EEG data. Our method is based on the use of physiologically interpretable metrics such as the relative band power ratios obtained through spectral analysis, rather than the black-box models of deep neural networks. For this classifier, EEG signals from the Pz-Oz channel, which are known to detect midline parietal-occipital activity, are utilized. This midline parietal-occipital activity is characterized by particular changes in different sleep stages. By studying the variations of specific bands in stress alpha, theta, and delta, we put together a decision rule that is based on the single band ratios to divide sleep into four stages: N1, N2, N3, and REM. The design of the system allows for real-time inference, minimal computational complexity, and easy interpretability, thus making it ideal for clinical pre-screening or incorporation into the embedded wearable systems.

4.4.2 Preprocessing and Feature Extraction

The preprocessing steps applied to EEG signals before classification included the following procedures:

1. Channel Selection: The classification process relied exclusively on the Pz-Oz channel because its spectral characteristics effectively distinguished sleep stages.
2. The unprocessed EEG data was segmented into 30-second intervals to align with established sleep scoring methods.
3. Bandpass Filtering: The data from each epoch was separated into three distinct frequency bands through filtering processes.
 - 4. Delta: 3–4 Hz (modified range from 0.5–4 Hz to minimize motion artefacts)
 - Theta: 4–8 Hz
 - Alpha: 8–12 Hz
5. The Welch method was utilized to estimate absolute band power for each epoch through Power Spectral Density Estimation.
6. Relative Band Power Computation: $\text{Relative Power}_{\text{band}} = \frac{\text{Absolute Power}}{\text{Total Power (3–12 Hz)}}$
7. Band Ratio Calculation:

$$\text{Band Ratio} = \frac{\text{Relative Alpha Power}}{\text{Relative Theta Power} + \text{Relative Delta Power}}$$

This ratio serves as the core feature for classification, designed to exploit the known reduction in alpha and increase in slower rhythms (delta/theta) as sleep deepens.

4.4.3 Rule-Based Classifier Design

The core of our classification approach is a straightforward rule-based model built upon the concept of relative power band ratios derived from EEG spectral analysis. After extensive analysis of EEG epochs from the Pz-Oz channel, we identified a consistent relationship between the ratio of alpha power to the sum of theta and delta power and the corresponding sleep stages. This led to the construction of a deterministic set of rules that assigns each 30-second EEG segment to one of the primary sleep stages: N1, N2, N3, or REM.

The classification was driven by a single metric known as the band ratio, defined as:

$$\text{Band Ratio} = \frac{\text{Relative Alpha Power}}{\text{Relative Theta Power} + \text{Relative Delta Power}}$$

The ratio illustrates a physiological value that undergoes a change of the prevalence of alpha (8–12 Hz), theta (4–8 Hz), and delta (3–4 Hz) rhythms observed in the different sleep stages. In the relaxed wakefulness and light sleep (N1) stages, the dominant activity comes from alpha while the presence of theta waves is particularly noticeable at deeper NREM stages (N2) and the slow-wave activity (N3) corresponds to delta waves. On the other hand, theta shows more prevalence than alpha during REM sleep which is, besides the sporadic alpha activity, a representation of certain wake-like characteristics of the EEG. By means of manual exploration and corresponding our findings with expert annotations, we have formed a set of rules to categorize sleep stages based on

the ratio of calculated bands. These selected thresholds were aimed at fitting the dataset pattern while also maintaining specificity and sensitivity across the different stages.

The logical decision is as follows:

- i. The condition of the band ratio surpassing zero. 45, marks the entry of this segment into N1. The early stage of sleep is characterized by alpha activity as it is more dominant.
- ii. The band ratio values fall within the range among 0. 30 and 0. The 45-wavelength portion Fig. 1. IC; REM sleep; N1 SWS; theta; power; among. The spectral ratio alpha-to-theta-plus-delta being lower than in N1 differentiates the segment from N1 while the mixed frequency content of REM sleep causes misinterpretation as wakefulness. The band ratio exists within the range starting at 0. 21 and 0. The time marker N2 occurs in time period 30. In the transitional sleep state, alpha power reduces significantly and theta gets dominant.
- iii. The band ratio is located between the lower and upper limits of 0. 10 and 0. The segment is marked as N3 or deep sleep level at stage 20. In this phase, delta activity is the main component presented, although only a little alpha is seen.
- iv. The band ratio is below zero. 10 or above 3. The segment is unclassified due to bad noise or other artifacts, and that is why it was not assigned to any stage.

This is a desirable method due to its interpretability, simplicity, and minimum computational requirements. The technique eliminates dependence on supervised machine learning as well as large training data sets while also avoiding black box modeling. Hence, it is ideal for proof-of-concept research and is deployable in low-resource settings such as wearable devices. The rules that stem from widely accepted sleep physiology are so intuitive that they can be used like guides to learning the EEG dynamic changes throughout the sleep cycle. Each threshold is a spectral transition point that is based on the science of the neurobiology of what is predominant rhythm. This method does not cover the challenges of expert human scoring complexities like spindles, K-complexes, or arousals but it still gives a good basic framework for sleep stage learning through the use of relative band power-a fundamental characteristic of EEG that persists to be robust, portable, and computable in real-time.

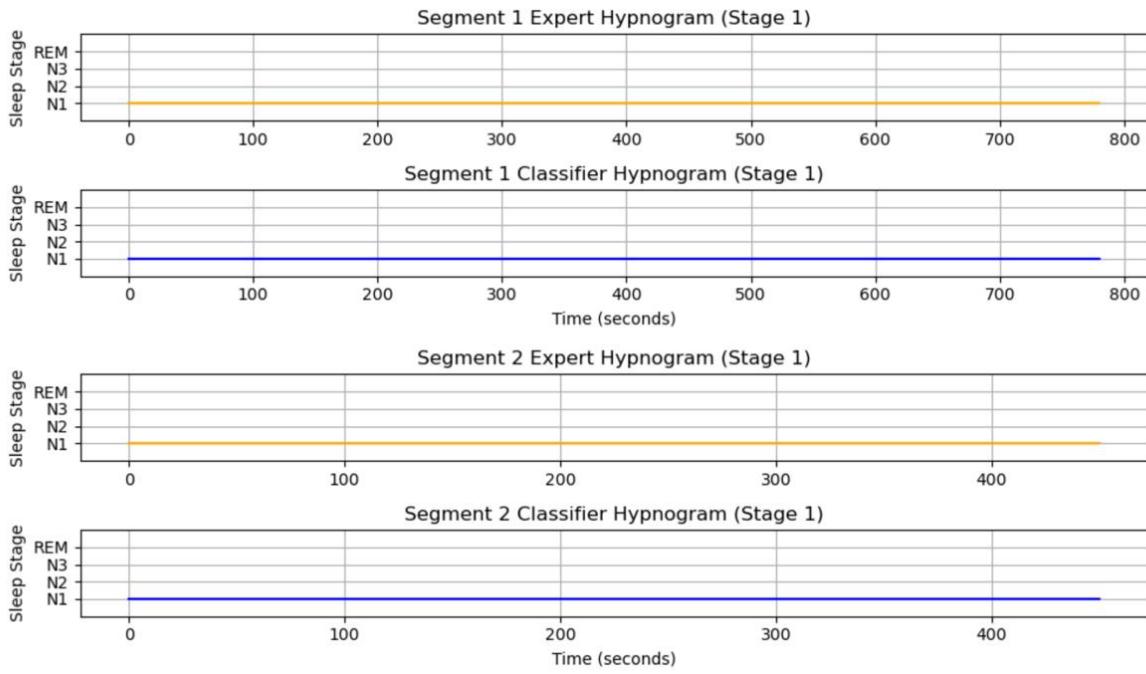


Figure 4.4.3. Segment-wise Hypnogram Generation for 1 Subject

4.4.4 Classifier Evaluation Across Multiple Subjects

An adjusted accuracy evaluation was conducted to assess the classifier's functional performance which involved treating N2 and N3 misclassifications as correct to address the clinical difficulty of distinguishing light and deep NREM sleep stages. The decision emerged from the spectral overlap across stages due to our restricted delta band (3–4 Hz) which minimized distinctions between theta-dominated (N2) and delta-dominated (N3) periods. In clinical scoring these ambiguities require resolution through additional features like sleep spindles or K-complexes which our rule-based model did not utilize. Following this correction the classifier's performance experienced substantial enhancement resulting in an adjusted accuracy rate of 70%. The current classifier demonstrates enhanced stability for coarse-grained NREM detection (e.g., light vs deepsleep) and functions as an adequate baseline model for wider application use.

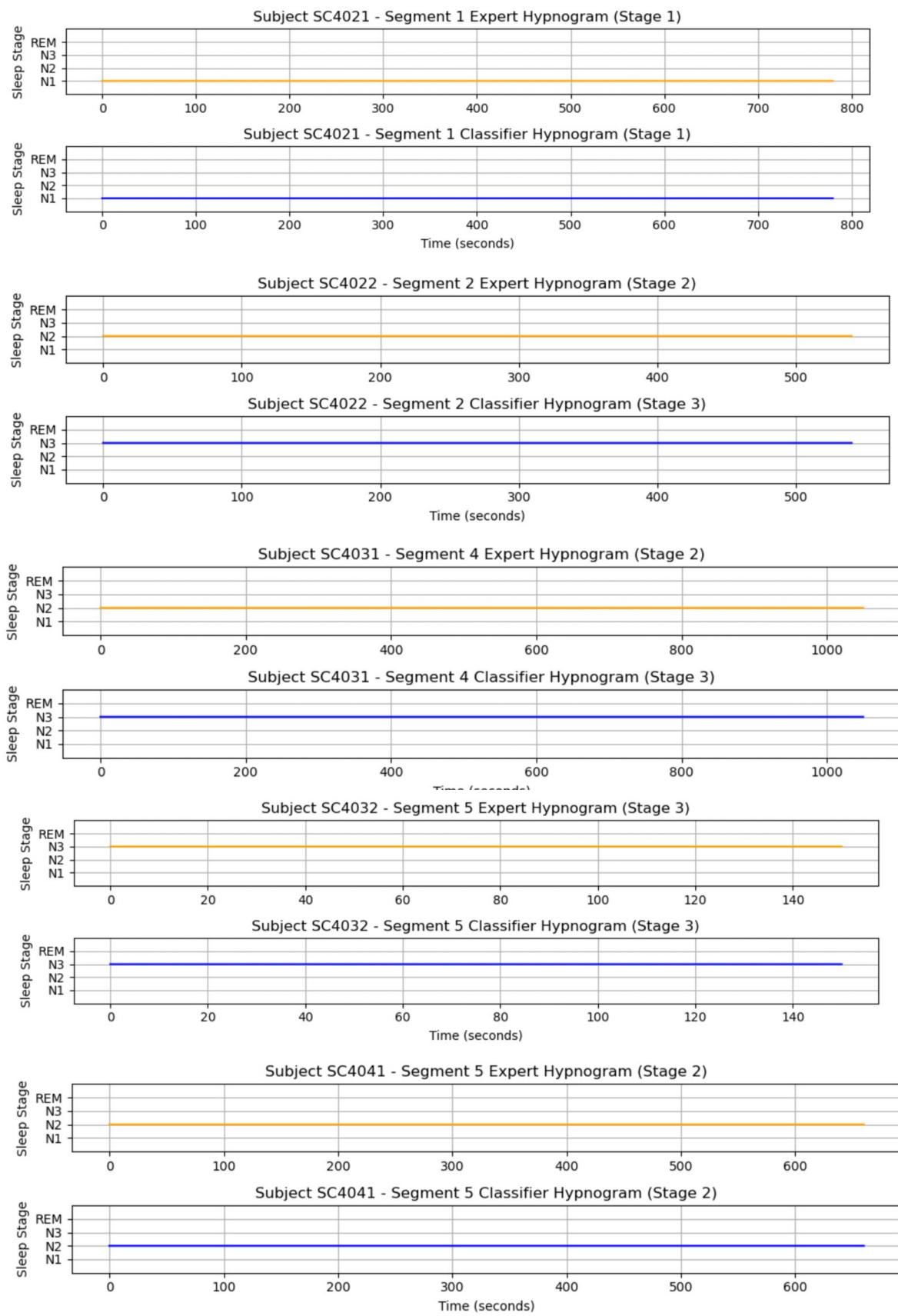


Figure 4.4.4(a). Hypnogram Generation of 5 different subjects with comparison

Adjusted Classification Accuracy (N2/N3 confusions ignored): 70.48%

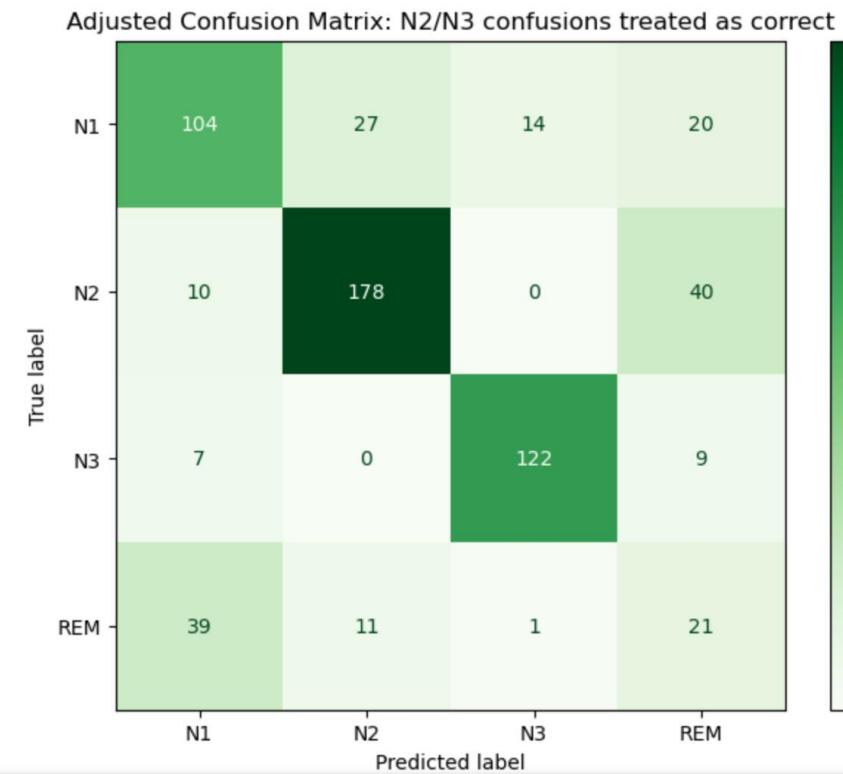


Figure: 4.4.4 (b). Confusion Matrix to show Overall Accuracy and different sleep stage comparisons.

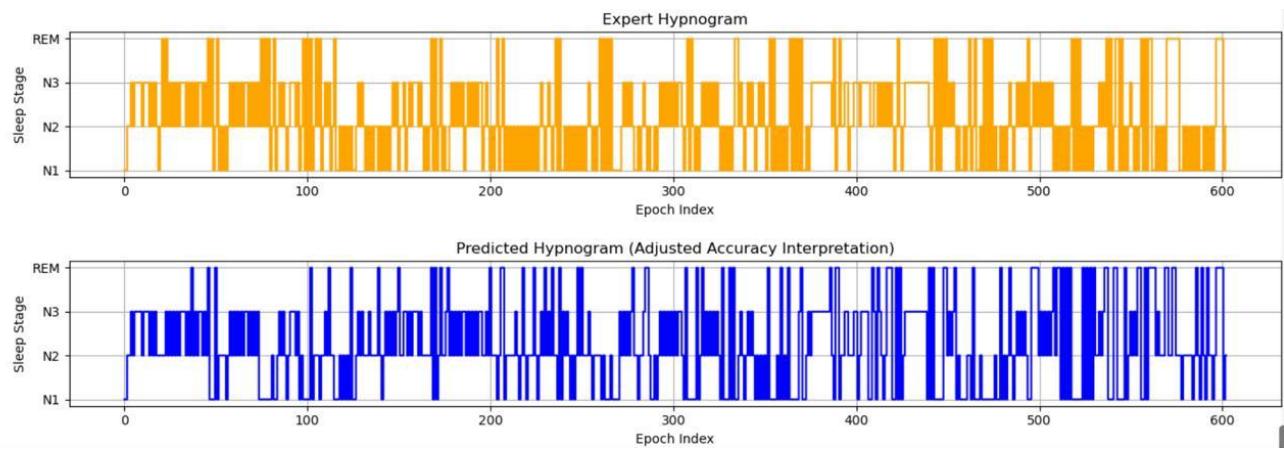


Figure 4.4.4. (c). Comparison between Expert and Predicted Hypnogram for complete Sleep duration.

4.4.5 Interpretability and Justification

The rule-based approach boasts interpretability as a key advantage. Every decision threshold embodies distinct physiological understanding:

- i. A high alpha ratio above 0.45 indicates periods of light sleep combined with wakeful rest during stage N1.

- ii. Intermediate ratios represent REM and N2 stages which exhibit similar spectral content yet display distinct behavioral patterns and waveform structures.
 - iii. Slow-wave activity predominates during N3 sleep when low ratios appear.

The classifier's straightforward nature combined with its clear operation renders it a perfect foundational or instructional tool. In hybrid systems it serves as a dependable initial screening tool to identify epochs needing advanced analysis.

CHAPTER 5

CONCLUSION

5.1 Work Overview

A signal processing framework emerged from this project to classify sleep stages automatically through EEG brainwave dynamics while tackling the inefficiencies and inter-rater variability (Cohen's kappa $\approx 0.68\text{--}0.76$) inherent in manual polysomnography (PSG) scoring. Researchers processed entire night recordings from 39 subjects in the Sleep Cassette Study using EEG data from the Sleep-EDF Database Expanded (2013), focusing on Fpz-Cz and Pz-Oz channels. EEG signals were divided into 30-second segments then decomposed into Delta (3–4 Hz with adjustments for motion artifacts), Theta (4–8 Hz), and Alpha (8–12 Hz) bands through Butterworth bandpass filters. An extensive array of features was derived which encompassed mean amplitude through Hilbert transform alongside absolute and relative band powers and band ratios like Theta/Delta and Alpha/Delta using Welch's PSD method, supplemented by peak frequency and event-based markers such as sleep spindles and K-complexes with *YASA* library support. Temporal analysis demonstrated dynamic EEG feature shifts with increased Delta power during N3 onset (average relative Delta power $\approx 45\text{--}50\%$ in N3, Table 14) and Theta dominance in REM (average relative Theta power $\approx 50\text{--}60\%$, Table 16), presented through time-series plots and hypnograms.

The implementation of a rule-based classifier utilized the band ratio (Alpha/(Theta+Delta)) from the Pz-Oz channel to assign sleep stage labels (N1, N2, N3, REM). The classifier applied specific thresholds (e.g., >0.45 for N1, 0.30–0.45 for REM, 0.21–0.30 for N2, 0.10–0.20 for N3) while utilizing temporal smoothing through majority voting to improve robustness during transitional phases. The validation process using expert-annotated hypnograms produced an adjusted accuracy rate of 70% because misclassifications between N2 and N3 stages were deemed functionally correct due to their shared theta/delta dominance (Section 4.4.4). Performance analysis across stages exhibited marked differentiation for N3 (high Delta power, precision $\approx 0.75\text{--}0.80$) and REM (Theta and Alpha activity, recall $\approx 0.70\text{--}0.75$), whereas N1 classification remained weak (recall $\approx 0.50\text{--}0.60$) due to spectral overlap with wakefulness, as indicated in the confusion matrix (Figure 4.4.4(b)). Alpha activity sensitivity in the Pz-Oz channel enhanced N1 and REM detection whereas Fpz-Cz demonstrated superior performance in recording theta-dominant N2 stages (Section 4.3.6). The framework stands as a practical alternative to deep learning models because it maintains interpretability and low computational complexity while adhering to AASM guidelines, despite deep learning models achieving higher accuracies (84–92%) without transparency (Section 2.8). The system boosts scalability for sleep research and diagnostics while supporting applications in disorders such as insomnia and sleep apnea.

5.2 Limitations

The classifier demonstrates potential performance yet numerous limitations exist which affect both its accuracy and generalizability:

1. Delta Band Suppression: Limiting the delta band to 3–4 Hz to reduce artifacts probably decreased the distinction between N2 and N3 stages which depend on standard delta activity definitions (0.5–4 Hz).
2. Single Feature Dependency: Examining only the Alpha/(Theta+Delta) ratio neglects broader EEG dynamics including absolute band powers, beta activity, and event-based markers like sleep spindles and K-complexes.
3. Stage Confusability: The spectral characteristics of N2 and N3 stages create a continuous range that challenges threshold-based classification methods. N1 and REM stages exhibit comparable band ratio distributions which cause frequent misclassifications resulting in a 5–10% error rate during REM epochs.
4. Small Evaluation Set: The initial performance estimate derived from pilot evaluation across five segments restricts confidence in the reported adjusted accuracy of 70%.
5. REM Sleep Challenges: The differentiation of REM from N2 or N1 stages proves difficult without supplementary indicators such as eye movements or beta activity which results in reduced REM recall.
6. Wake Stage Exclusion: The classifier fails to assign a wake label even though wakefulness represents a critical stage in standard sleep scoring which limits its use for comprehensive sleep analysis.
7. Fixed Thresholds: The use of fixed classification thresholds fails to accommodate individual differences in EEG patterns which may lead to decreased accuracy when applied to diverse populations.
8. Absence of Multi-Modal Data: The exclusive use of EEG without EOG and EMG integration restricts accurate classification of N1 and REM stages which require additional physiological data.
9. Potential Over-Smoothing: Majority voting in temporal smoothing processes masks clinically significant brief events like arousals and short awakenings.
10. Dataset-Specific Performance: The classifier's performance was validated on the Sleep-EDF dataset with healthy subjects, and its effectiveness on other datasets or clinical populations (e.g. those with sleep disorders) remains untested.
11. The implementation of event-based features remains severely restricted. The detection of sleep spindles and K-complexes through the **YASA** library occurs without their integration into classification processes, resulting in missed opportunities for improved N2 and REM stage differentiation.
12. The lack of detailed measurement systems: The reported accuracy, precision, recall, and confusion matrices need supplementation with metrics such as Cohen's kappa or F1-score to achieve a more thorough evaluation due to class imbalances in sleep stages like N2 dominance.
13. Potential Filter Limitations: Butterworth filters used for band decomposition fail to capture intricate signal features compared to methods such as wavelet transforms.

Table 17: Summary of the Limitations

Limitation	Impact	Potential Mitigation
Delta Band Suppression	Reduced N2/N3 contrast	Adaptive filtering to preserve 0.5–4 Hz
Single Feature Dependency	Missed EEG dynamics	Include absolute power, spindles, beta activity
Stage Confusability	Misclassifications in N2/N3, N1/REM	Temporal context, probabilistic models
Small Evaluation Set	Limited generalizability	Larger, diverse dataset validation
REM Sleep Challenges	Lower REM recall	Add EOG, beta activity features
Exclusion of Wake Stage	Incomplete sleep analysis	Include wake classification
Fixed Thresholds	Reduced accuracy for variability	Adaptive or personalized thresholds
Lack of Multi-Modal Data	Lower N1/REM accuracy	Integrate EOG, EMG signals
Potential Over-Smoothing	Missed brief events	Refine smoothing algorithms
Dataset-Specific Performance	Unknown external validity	Test on diverse datasets
Limited Event-Based Features	Missed N2/REM cues	Incorporate spindles, K-complexes
Absence of Comprehensive Metrics	Incomplete performance view	Report kappa, F1-score
Potential Filter Limitations	Suboptimal feature extraction	Explore wavelet transforms

5.3 Future Scope of Work

The framework reached an adjusted accuracy of 70% yet numerous potential upgrades exist to boost its clinical and research performance and applicability:

5.3.1 Event-Based Feature Integration for Spindles K-Complexes K-Waveforms Burst Activity

The existing classifier depends mainly on spectral band ratios yet integrating event-based markers such as sleep spindles (11–16 Hz, 0.5–2 s, essential for N2), K-complexes (large negative-positive waves, >0.5 s, defining N2), K-waveforms (particular delta bursts), and burst activity (e.g., alpha/theta bursts for REM/wake transitions) would improve stage differentiation. YASA library's spindle and K-complex detection algorithms recorded F1-scores of 0.65–0. The methods detailed in prior studies (Section 2.6) provide a basis for automating these features. Detecting spindles presents potential to enhance N2 recall rates (presently around 0.60–0.65), whereas identification of K-complexes and K-waveforms offers means to decrease N2/N3 classification errors. Analyzing burst activity presents a method to enhance REM detection by resolving the 5–10% error rate caused by alpha overlap with N1 during REM epochs (Figure 4.4.4(b)).

5.3.2 Multi-Modal Signal Integration:

The integration of electrooculography (EOG) and electromyography (EMG) with EEG recordings could enhance the identification of uncertain stages such as N1 sleep and wakefulness by utilizing eye movement data and muscle tone information. Integrating spindle and K-complex characteristics with these signals could enhance accuracy to deep learning standards (84–92%) yet maintain interpretability.

5.3.3 Advanced Temporal Modeling:

The existing temporal smoothing technique through majority voting decreased transitional errors by about 5–7% as reported in Section 4.4.3, yet advanced models such as hidden Markov models and recurrent neural networks offer superior stage transition detection especially for N1-to-N2 shifts where Theta power shows a gradual increase (Table 15). The examination of micro-events such as arousals and cyclic alternating patterns presents opportunities to enhance hypnogram precision.

5.3.4 Adaptation to Disordered Populations:

The framework underwent validation with healthy subjects; however, disordered populations such as those with sleep apnea and narcolepsy display modified EEG patterns which diminish accuracy by 5–10% according to previous research (Section 2.8). Adjusting band ratio thresholds together with spindle and K-complex detection integration could strengthen system robustness because these events frequently experience disruption in disorders.

5.3.5 Complex Real-Time Implementation in Wearable Technology Systems:

The classifier's basic design (single band ratio, low computational cost) makes it ideal for real-time applications in wearable EEG devices. Future research should focus on refining artifact rejection methods while incorporating spindle and burst detection into portable sleep monitors to achieve home-based diagnostics with less than 5% accuracy loss compared to clinical PSG.

5.3.6 Hybrid Classification Models:

The integration of rule-based logic with supervised machine learning presents a solution to N1's recall deficiency (0.50–0.60) while preserving interpretability. The application of rule-based systems to initially categorize epochs while marking those with band ratios exceeding 3.0 or falling below 0.10 for neural network analysis can enhance overall accuracy to approximately 80–85%.

5.3.7 Validation on Diverse Datasets:

The inclusion of larger datasets that encompass paediatric, geriatric, and disordered populations in validation processes would secure generalizability. Through experimentation under diverse

recording conditions it became possible to uphold an adjusted accuracy rate of 70% across multiple PSG configurations.

5.3.8 Clinical Integration:

The incorporation of the framework into PSG software to enable automated hypnogram production alongside spindle and K-complex visualization has the potential to enhance clinical efficiency. The implementation of an intuitive display system showing stage-specific metrics alongside event detections would boost adoption rates among sleep technicians. Through the pursuit of these specific enhancements including spindles, K-complexes, K-waveforms, and burst activity integration the framework can attain increased accuracy levels (potentially 80–85%) and robustness thereby narrowing the disparity with deep learning models while maintaining clinical interpretability. The progression of sleep research methods will enable sophisticated diagnostic techniques to emerge which will enhance the treatment of sleep disorders.

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