Sleep Stage Classification From Polysomnography (PSG) Data

Authors

Ssewankambo Asuman (180041144)

Yahya Bello (180041147)

Faissal Hamadou (180041148)

Supervisor

Dr. Md. Azam Hossain

Assistant Professor

Department of Computer Science and Engineering (CSE)

Islamic University of Technology (IUT)

A thesis submitted to the Department of CSE in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering (CSE)

Department of Computer Science and Engineering (CSE)

Islamic University of Technology (IUT)

Organization of Islamic Cooperation (OIC)

Dhaka, Bangladesh

May 2023

Declaration:

This is to certify that the work presented in this thesis is the outcome of the analysis and the experiments carried out by Yahya Bello, Faissal Hamadou and Ssewankambo Asuman under the supervision of Dr. Md. Azam Hossain,Assistant Professor and Dr. Iqram Hussain. It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma, or other qualifications. Information derived from the published or unpublished work of others has been acknowledged in the text and a list of references is given.

Authors:

Ssewankambo Asuman
A National of Uganda
Student ID: 180041144
IUT-Dhaka

Yahya Bello
A National of Cameroon
Student ID: 180041147
IUT-Dhaka

Faissal Hamadou
A National of Cameroon
Student ID: 180041148
IUT-Dhaka

Supervisor:

20/05/2023

Dr. Md. Azam Hossain
Assistant Professor
Department of Computer Science and Engineering (CSE)
Islamic University of Technology (IUT)

Abstract

Sleep staging is an essential aspect of sleep assessment and disease diagnosis. Polysomnography(PSG) is commonly used to record electroencephalography(EEG) signals, which produce distinct patterns during different sleep stages. Automatic identification of these stages is crucial in diagnosing and treating sleep related disorders. This study focuses on the classification of sleep stages using polysomnography (PSG) data. The main objectives are to predict five-class sleep stages (Wake, N1, N2, N3, and REM) using EEG data from the Haaglanden Medisch Centrum (HMC) dataset, comparison Of light, deep, and wake sleep stages, and examine the predictive power of subject data from the Sleep Physionet dataset in predicting the sleep stages of other subjects. The dataset contains EEG sleep recordings of 154 subjects of which only 50 were investigated by using two machine learning models which are: Random Forest Classifier and XG Boost. The results and findings of this research indicate that the Random Forest Classifier algorithm achieved an accuracy of 82.62%, outperforming the XG Boost algorithm in sleep stage classification using the given dataset. The findings suggest that the Random Forest Classifier is a more effective model for sleep stage classification using PSG data. The study demonstrates the potential of using machine learning techniques for accurate sleep stage prediction. Further research can explore the generalizability of the model across different datasets and investigate the impact of additional features on classification accuracy. Our research makes contribution by investigating the application of Event-Related Potentials (ERP) in effectively categorizing sleep stages based on PSG data. ERP, which measures neural activity in response to specific stimuli, offers valuable insights into the underlying cognitive processes during sleep. By integrating ERP analysis into our classification approach, we aimed at enhancement of precision and interpretability of sleep stage identification. Our findings highlight the significance of incorporating ERP analysis as a supplementary technique alongside traditional EEG features, thereby advancing the understanding and diagnosis of sleep-related disorders.

Acknowledgements

As we reach this significant milestone of submitting our thesis work, marking the culmination of our Bachelor of Science study, we would like to express our sincere gratitude to the Divine. We are immensely thankful to Almighty Allah for His blessings and guidance, which have enabled us to successfully complete this research. It is through His mercy and grace that we have reached this point, and we attribute all thanks ad praises to Allah.

We would like to express our deepest gratitude to our supervisors, Dr. Iqram Hussain and Dr. Md. Azam Hossain, Assistant Professor for their invaluable guidance, support, and expertise throughout the entire duration of our research. Their dedication, patience, and unwavering commitment to our academic and personal growth have been instrumental in shaping this thesis.

Dr. Md. Azam Hossain has been an exceptional mentor, providing us with insightful feedback, challenging our ideas, and pushing us to strive for excellence. We are grateful for the countless hours spent discussing research methodologies, refining our arguments, and helping us navigate the complexities of our study. Their depth of knowledge and passion for the subject has inspired us to explore new avenues of inquiry.

We are equally indebted to Dr. Iqram Hussain for his continuous encouragement and guidance. His expertise in bioinformatics has been invaluable in shaping the theoretical framework and methodology of our research. His keen eye for detail and constructive criticism has significantly improved the quality of our work, and we are truly grateful for his mentorship.

We would also like to extend our appreciation to the entire Department of Computer Science and Engineering (CSE) community for providing a stimulating academic environment, resources, and research opportunities that have enriched our learning journey.

Finally, we would like to acknowledge the unwavering support and love from our respective teams and friends, whose collaboration, encouragement, and belief in our abilities have been a constant source of motivation. Thank you all for being integral parts of our academic journey. Your guidance, support, and encouragement have played a pivotal role in the successful completion of this thesis.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Sleep is a vital biological process that affects our physical and mental health and influences overall quality of life. It is divided into different stages.Sleep deprivation can lead to various mental illnesses and accidents. Polysomnography(PSG) is a commonly used technique to monitor sleep quality and diagnose sleep disorders, but it is time-consuming and requires a human expert to analyze the data. To address these challenges, researchers are exploring wearable health monitoring systems that use EEG and EOG electrodes to automate sleep staging and provide a simpler and more reliable approach to sleep monitoring. EEG signals are particularly helpful for tracking brain activity during sleep and differentiating between different sleep patterns.
Sleep stages refer to the progression from initial sleep onset to transitioning from light sleep to deep sleep. Sleep staging, a crucial task in the clinical analysis of polysomnographic sleep recordings(PSGs), plays a significant role in diagnosing various sleep disorders. PSGs record important biomedical signals during sleep medicine studies, serving as a fundamental diagnostic tool. In accordance with current standard recommendations for sleep scoring, the neurophysiological activity of individuals is divided into 30-second epochs. Each epoch can be classified into five states: wakefulness, stages N1, N2, N3, and R(REM sleep). Sleep staging involves monitoring multiple traces of neurophysiological activity, including electroencephalography(EEG), electromyography(EMG), and electrooculography(EOG). A typical PSG examination entails continuous signal recording via electroencephalogram(EEG) for a duration of 8 hours. Therefore, considering a subset of subjects from the dataset, our aim is to assess the predictability of sleep stages in one group of subjects based on the data of other subjects. Our method consists of data collection, preprocessing, data splitting, and finally fit the data into the respective models Random forest and XG Boost classifier as shown in the figure 1.1 below.

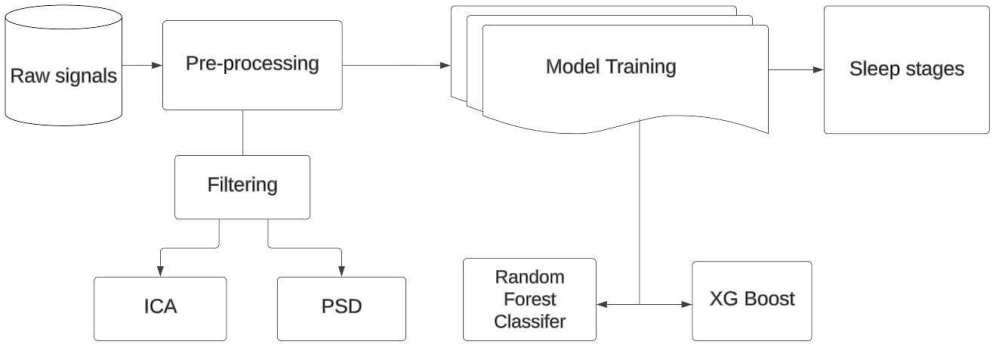


Figure 1.1: Workflow

1.1 Background Study

1.1.1 Sleep stages

Sleep is a vital physiological process that plays a crucial role in maintaining overall health and well-being. During sleep, the body undergoes various stages characterized by distinct patterns of brain activity, eye movement, and muscle tone.These stages include wakefulness, non-rapid eye movement(NREM) sleep, and rapid eye movement(REM) sleep.
NREM sleep is further divided into three stages: N1, N2, and N3. N1 represents the transition from wakefulness to sleep, while N2 is a deeper stage of sleep where the brain waves become slower and sleep spindles and K-complexes occur. N3, also known as slow-wave sleep(SWS), is the deepest stage of sleep characterized by the presence of slow delta waves.
REM sleep is characterized by rapid eye movements, vivid dreaming, and a highly active brain. During this stage, the muscles become relaxed and temporarily paralyzed to prevent acting out dreams.
A normal sleep pattern consists of cycling through these stages multiple times throughout the night in approximately 90-minute cycles. Each stage serves specific functions, including memory consolidation, restoration of energy, regulation of mood, and overall physiological and cognitive processes.

1.1.2 Recording process of EEG

An internationally accepted technique for standardizing the placement of electroencephalography(EEG) electrodes uses anatomical landmarks and is known as the "10-20 system" in the worldwide federation. All areas of the brain are covered by the system, which is based on the correlation between electrode position and the cerebral cortex's underlying region. The distances between neighboring electrodes, which are either 10% or 20% of the total distance(front-back or right-left) of the skull, are denoted by the numbers "10" and "20".

Each point in the figure 2,B below denotes a potential electrode position. Frontal, temporal, central, parietal, and occipital are represented by the letters F, T, C, P, and O. Odd numbers(1,3,5,7) refer to the left hemisphere, while even numbers (2,4,6,8) refer to the right. The z designates an electrode positioned in the middle.

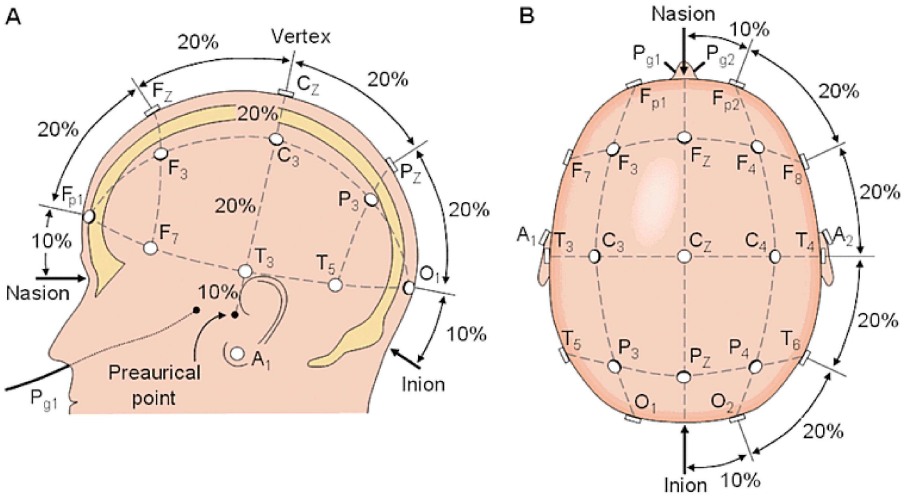


Figure 1.2: Electrode positioning

Step 1: Utilize the centimeter side of a measuring tape for taking measurements. Measure the length from the Nasion (nasal bridge) to the Inion (occipital pretuberance) over the scalp's midline (Figure 1.3).

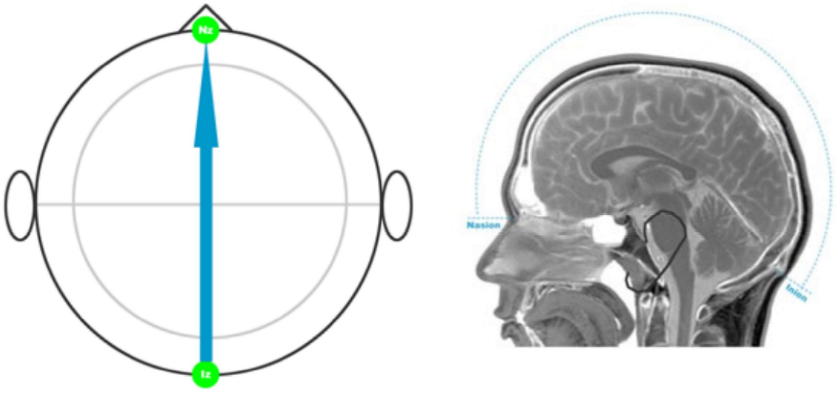


Figure 1.3: Measuring Nz and Iz

Step 2: Mark your preliminary Cz position by measuring and marking 50% of the total distance (Figure 1.4).

Step 3: To establish reference points, measure and mark a position 10% away from the Nasion and another position 10% above the Inion (Figure 1.4).

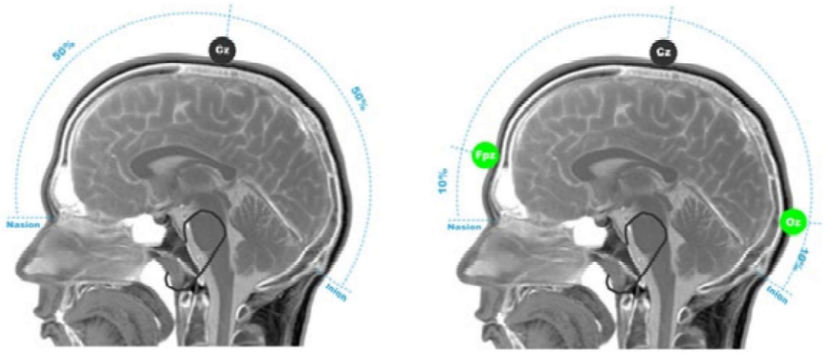


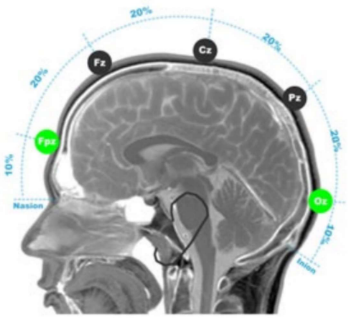
Figure 1.4: Measuring FPz,Oz, and Cz

Step 4: Create preliminary marks for Fz and Pz by measuring and marking a position 20% away from Cz (Figure 1.5a).

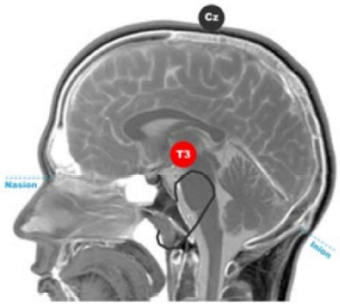
Step 5: Measure the distance between the preauricular points by lightly running your finger up and down just in front of the ear. The indentation above the zygomatic notch can be easily identified, especially when the mouth is slightly opened. Take note of the total length (Figure 1.5a).

Step 6: Find your true Cz mark by measuring and marking 50% of your total length and identifying the intersection with your previous 50% mark from the Nasion to the Inion (Figure 1.5b).

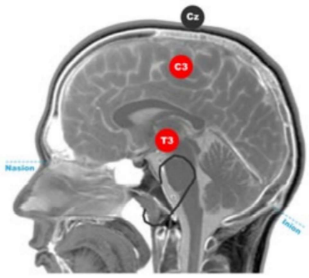
Step 7: Establish preliminary marks for T3 and T4 by measuring and marking a position 10% away from the preauricular points (Figure 1.5b).



(a) Measuring Fz, Pz



(b) Measuring T3 and T4

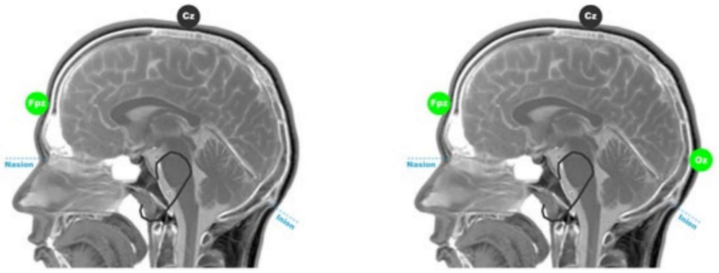


(c) Measuring C3 and C4

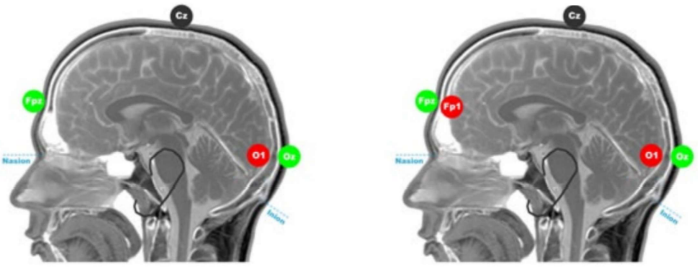
Figure 1.5: Measurement of central and reference electrodes

Step 8: Measure the distance from your initial T3 mark to Cz and record the total length. Similarly, measure the distance from your initial T4 mark to Cz and record the total length (Figure 1.5c).

Step 9: Determine preliminary marks for C3 and C4 by measuring and marking 50% of the total distance obtained in the previous step (Figure 1.5c).



(a) Measuring Fpz and Oz



(b) Measuring O1, O2,Fp1 and Fp2

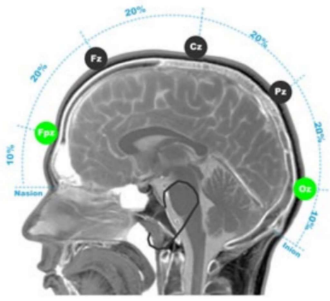
Figure 1.6: Measurement of front and back electrodes

Step 10: Draw a cross section mark on Fpz (Figure 1.6a).

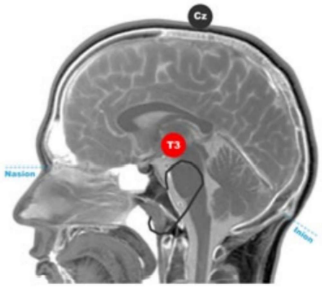
Step 11: Place the measuring tape around your head, encompassing your 10% Fpz mark and the 10% Oz mark located at the back of your head. Measure 50% of the circumference from Fpz to the back of your head. The true Oz mark can be identified at the intersection with your preliminary Oz mark (Figure 1.6a).

Step 12: Obtain the true marks for 01 and 02 by measuring and marking 5% of the total circumference to the left and right of Oz (Figure 1.6b).

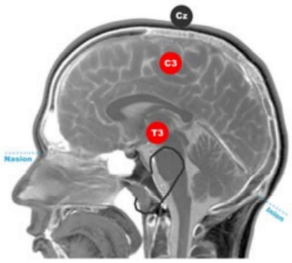
Step 13: Determine the true Fp1 and Fp2 marks by measuring and marking 5% of the total circumference to the left and right of Fpz (Figure 1.6b).



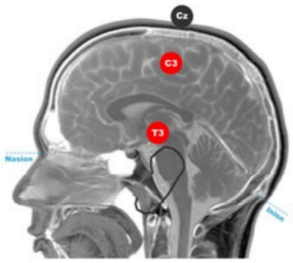
(a) Measuring O1, O2,Fp1 and Fp2



(b) Measuring Fz



(c) Measuring of F3 and F4



(d) Measuring of C3 and C4

Figure 1.7: Measurement of central and reference electrodes

Step 14: Establish marks for F7 and F8 by measuring and marking 10% below Fp1 and Fp2 (Figure 1.7a).

Step 15: Note the measurement from F7 to F8 (Figure 1.7a).

Step 16: Find the true mark for Fz by measuring and marking the midpoint between F7 and F8, and identifying the intersection with your preliminary Fz mark (Figure 1.7b).

Step 17: Note the measurement from F7 to Fz and repeat the same thing from F8 to Fz (Figure 1.7b).

Step 18: Obtain preliminary marks for F3 and F4 by measuring and marking half of the distance between F7-Fz and F8-Fz (Figure 1.7c).

Step 19: Find the true F3 mark by measuring and marking 20% of the Nasion-Inion distance from FP1 to F3. The intersection point will indicate the location of your true F3 mark.
Similarly, measure and mark 20% of the Nasion-Inion distance from FP2 to F4 to determine the true F4 mark. The intersection point will represent the true F4 mark (Figure 1.7c).

Step 20: Measure the distance from Fp1 to O1 to establish the preliminary mark for C3. Measure the distance from Fp2 to O2 to establish the preliminary mark for C4 (Figure 1.7d).

Step 21: Find the true C3 mark by measuring and marking half of the distance from FP1 to O1. The true C3 mark will be located at the intersection of your first and second markings. Similarly, measure and mark half of the distance from FP2 to O2 to identify your true C4 mark. The intersection of your first and second markings will indicate the location of the true C4 mark (Figure 1.7d).

Chapter 2

Literature Review

The literature review chapter in this thesis presents a thorough examination of research conducted in the field of sleep analysis and classification. It encompasses various significant studies, including investigations into the application of MEG/EEG technology for reliable group studies, the development of automated techniques for sleep stage classification using EEG signals, the utilization of machine learning methods to address imbalanced data in sleep stage classification, the introduction of a computationally efficient deep neural network model for sleep stage classification, and the exploration of how sleep deprivation and napping impact impulse inhibition. The primary objectives of this chapter are to establish a comprehensive knowledge base, identify gaps in existing research, and provide the necessary support for the subsequent analysis and findings presented within this thesis.

Paper Title: A Reproducible MEG/EEG Group Study With the MNE Software: Recommendations, Quality Assessments, and Good Practices[1]

Mainak Jas, Eric Larson, Denis A. Engemann, Jaakko Leppäkangas, Have published a work presents the results obtained by the reanalysis of an open dataset from Wakeman and Henson (2015) using the MNE software package.
Research Problem: Magnetoencephalography (MEG) and electroencephalography (EEG) are two neuroimaging techniques used to study the human brain.However, the acquisition, processing, and visualization of MEG/EEG data can be a complex and challenging process. The paper introduces MNE, a software that aims to simplify this process and make MEG/EEG data analysis more accessible to researchers.
Previous Research Findings: Previous research has shown that MEG/EEG data analysis requires extensive knowledge of signal processing, statistics, and programming. As a result, the use of these techniques has been limited to specialized research groups.Additionally, current MEG/EEG software

solutions have limitations in terms of data processing speed and functionality.
Analysis or Method Applied: The paper describes the development of MNE, a free and open-source software package that allows for the acquisition, processing, and visualization of MEG/EEG data.MNE is designed to be user-friendly and accessible to researchers without specialized technical expertise.The software includes features such as real-time visualization, signal processing, and statistical analysis.
Accuracy and Weaknesses of the Paper: The paper demonstrates the effectiveness of MNE through several case studies and comparisons with other MEG/EEG software packages. The authors demonstrate that MNE is faster and more accurate than other software packages, while also providing a wider range of functionality. However, the paper does not address some potential limitations of MNE, such as the need for high-quality data and hardware. Additionally, while the paper provides a detailed description of the software, it may be challenging for users without technical expertise to fully utilize its capabilities.
Overall, the paper provides a valuable contribution to the field of MEG/EEG research by introducing an accessible and powerful software package for data acquisition, processing, and visualization.

Paper Title: EEG-Based Automatic Sleep Stage Classification[2]

The paper "EEG-Based Automatic Sleep Stage Classification" presents a method for automatically classifying sleep stages using EEG signals. The authors propose a feature extraction method based on time-frequency analysis and statistical measures, and a classification algorithm based on a support vector machine (SVM). The method is evaluated using a dataset of EEG signals from 20 subjects, achieving an overall accuracy of 75.29%.
One weakness of the paper is that the dataset used for evaluation is relatively small, with only 118 subjects.Additionally, the study does not compare the proposed method with other state-of-the-art methods for sleep stage classification, which could provide a more comprehensive assessment of its performance.
Overall, the proposed method shows promise for automatic sleep stage classification using EEG signals, but further studies with larger datasets and comparisons with other methods are needed to validate its effectiveness.

Paper Title: Sleep Stage Classification For Medical Purposes: Machine Learning Evaluation For Imbalanced Data[3]

The paper "Sleep Stage Classification For Medical Purposes:Machine Learning Evaluation For Imbalanced Data" presents a machine learning ap-

proach for sleep stage classification using imbalanced datasets. The authors compare the performance of five different classifiers (K-Nearest Neighbors, Naive Bayes, Decision Tree, Random Forest, and Gradient Boosting) using three different evaluation metrics (accuracy, precision, and recall) on a dataset of 1,235 sleep recordings.
The authors employ various feature extraction techniques, including wavelet decomposition and statistical measures, to extract relevant features from the EEG signals. They also use data augmentation to balance the imbalanced dataset, which has a majority of stage 2 sleep recordings.
One weakness of the paper is that it does not compare the proposed method with state-of-the-art methods for sleep stage classification. Additionally, the authors do not provide a detailed explanation of the specific hyperparameters used for each classifier, which could affect the results.
The proposed method achieved an accuracy of 79.9%, precision of 79.9%, and recall of 79.6% on the test set. The Gradient Boosting classifier performed the best among the five classifiers tested.
Overall, the study demonstrates the potential of using machine learning for sleep stage classification on imbalanced datasets, but further studies are needed to validate its effectiveness on larger datasets and to compare it with other state-of-the-art methods.

Paper Title: Computation-Efficient Multi-Model Deep Neural Network for Sleep Stage Classification[4]

The paper "EEG-Based Automatic Sleep Stage Classification" presents a method for automatically classifying sleep stages using EEG signals. The authors propose a feature extraction method based on time-frequency analysis, statistical measures, and a classification algorithm based on a support vector machine (SVM) and Random Forest. The method is evaluated using a dataset of EEG signals from 118 subjects, achieving an overall accuracy of 75.6%.
One weakness of the paper is that the dataset used for evaluation is relatively small, with only 118 subjects. Additionally, the study does not compare the proposed method with other state-of-the-art methods for sleep stage classification, which could provide a more comprehensive assessment of its performance.
Overall, the proposed method shows promise for automatic sleep stage classification using EEG signals, but further studies with larger datasets and comparisons with other methods are needed to validate its effectiveness.

Paper Title: A Visual ERP Study of Impulse Inhibition following a Zaleplon-Induced Nap after Sleep Deprivation[5]

Authors: Rui Zhang,Yanli Zhang,Ling Wei,Yongcong Shao,Guanghui Deng.
The paper was publsihed in the year 2016.
Dataset: The data for the study were collected from 24 healthy college students. The participants were randomly assigned to either a nap group or a control group. EEG data were collected during the Go/No-Go task.
Problem Addressed: The paper aimed to investigate the effects of a nap induced by the sleep aid drug zaleplon on cognitive performance, specifically impulse inhibition. The study sought to address the question of whether a nap can improve cognitive function following sleep deprivation.
Previous Research Findings: Previous research has shown that sleep deprivation can have negative effects on cognitive function, including impulse inhibition. It has also been suggested that napping can help to improve cognitive function, but the effects of a nap induced by zaleplon on cognitive function had not yet been studied.
Analysis or Method Applied: The study used a visual event-related potential (ERP) paradigm to measure neural activity associated with impulse inhibition. Participants were first sleep deprived for 24 hours, after which they were randomly assigned to either take a nap induced by zaleplon or stay awake. Participants then completed a Go/No-Go task while their neural activity was measured using electroencephalography (EEG). with the accuracy of 82%.
Dataset Sources and Collection Methods: The data for the study were collected from 24 healthy college students. The participants were randomly assigned to either a nap group or a control group. EEG data were collected during the Go/No-Go task.
Weakness of the Paper: The study had a small sample size. Additionally, the study only investigated the effects of a single nap, so it is unclear whether the effects observed in this study would generalize to other contexts or to repeated napping.

In Summary, The first paper introduces the MNE software package with the goal of simplifying the analysis of MEG/EEG data. While it demonstrates effectiveness, it lacks a comprehensive discussion of its limitations. The second paper presents a promising EEG-based method for classifying sleep stages but requires further evaluation and comparisons. The third paper focuses on using machine learning to classify sleep stages with imbalanced data, achieving positive outcomes but lacking comparisons with state-of-the-art methods. To address these limitations and advance the existing research, this study proposes the integration of ERP (Event-Related Potentials) and two machine learning models, namely Random Forest and XGBoost. By incorporating ERP and leveraging the strengths of these ma-

chine learning algorithms, this approach aims to overcome the challenges identified in previous studies. Its objective is to enhance the accuracy and reliability of sleep stage classification from EEG data, thereby making significant contributions to the field of sleep assessment and disease diagnosis.

Chapter 3

MNE and Time-Frequency

MNE and time-frequency analysis are crucial concepts within the fields of neuroimaging and signal processing. MNE involves the measurement and examination of the magnetic and electric fields generated by neural activity in the brain, enabling the non-invasive investigation of brain function and the underlying neural processes. Conversely, time-frequency analysis focuses on studying the dynamic changes in neural activity over time and across different frequency bands. This analysis provides valuable insights into the temporal characteristics and frequency composition of brain signals, aiding in the exploration of the intricate dynamics of brain activity. By combining these approaches, researchers gain a comprehensive understanding of brain function and uncover the complexities of neural processes.

3.1 MNE

MNE is an Open-source Python package for exploring, visualizing, and analyzing human neurophysiological data: MEG, EEG, sEEG, ECoG, NIRS, and more (Figure 3.1).

Statistic: parametric and non-parametric, permutation tests and clusteri
Machine learning: Advented decoding models, include time generalization
Source Estimation: Distributed , sparse,mixed-norm,beamformers,dipole fitting and more
Encoding model: receptive field estimation with optional smoothness priors **Data visualization:** Exploring data from multiple perspective
Connectivity: All to all spectral and effective connectivity measures

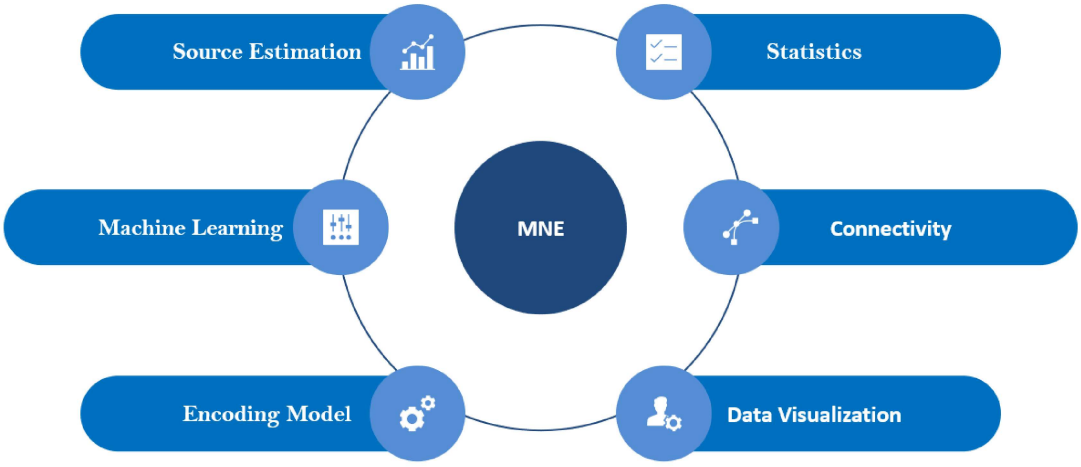


Figure 3.1: MNE Application

3.2 Time-Frequency

In your brain, there is a constant buzz of activity occurring. However, this activity is not as random and disorderly as it may initially appear. Rather, there is a sense of organization and rhythm to it. When specific regions of the brain engage in communication with one another, a synchronized signal emerges, akin to ripples spreading across the surface of a pond. These waves originate from various locations within the brain and exhibit different frequencies, each serving a distinct purpose.
While there is still much to uncover about brain waves, significant research conducted in recent decades has shed light on their fundamental functions, the consequences of their disruption, and various approaches to effectively regulate them. This concise guide aims to provide an overview of brain waves, delving into different methodologies to identify and harness the frequencies required for specific purposes.

3.2.1 Finding Brain Waves

The discovery of neural oscillations, also known as brain waves, can be attributed to Hans Berger in 1924 when he invented the electroencephalogram (EEG). This device captures the electrical activity generated by clusters of neurons firing signals. The EEG records this electrical activity by placing multiple electrodes across the head, making it a non-invasive technique suitable for home use in commercial devices.
However, it is important to acknowledge that the EEG has limitations. It provides an overall measurement of the collective activity of numerous neurons throughout the brain's surface. This signal is further distorted by the skull and muscles that lie between the brain and the electrodes, re-

sulting in imprecision. Moreover, the EEG is unable to access individual neurons, smaller networks, or deeper brain regions, which often require invasive procedures for study.
Despite these constraints, the EEG yields valuable insights. By focusing on the broader scale of neuronal populations, we can observe their synchronization patterns, revealing intricate connections that might not be immediately apparent if we were overly fixated on minute details.

3.2.2 Range of the Brain

Brain waves are quantified in hertz (Hz), which represents the number of cycles occurring per second. Initially, when Hans Berger conducted his pioneering measurements of brain activity, he identified oscillations within the range of 8-12 Hz, which were initially referred to as the Berger wave but are now recognized as alpha waves.
Advancements in EEG technology have subsequently expanded its capability to detect a much broader spectrum of frequencies beyond the alpha band.Remarkably, the brain exhibits a wide range of frequencies, spanning from the low delta band of 1-4 Hz to the higher gamma activity ranging from 30-140 Hz.
By utilizing the EEG, researchers have made significant progress in uncovering the relationship between these distinct frequency bands and various psychological phenomena. Furthermore, individuals engaged in at-home experimentation have been exploring ways to influence their own brain activity by leveraging feedback from their personal devices.

3.2.3 The 5 Types of Brainwaves

Our thoughts, emotions, and behaviors are fundamentally shaped by the intricate communication between neurons in our brains. The prevailing frequency at which these neurons communicate determines our brainwave state. Let's explore the various brain waves into the insights gained from scientific studies regarding their distinctive features and characteristics. The following figure (Figure 4.1) describes The 5 types of Brainwaves:

- Gamma: 30–100 Hz
  Among the different brain wave frequencies, gamma waves occupy the highest range and exhibit the widest spectrum.Measuring gamma waves can pose a challenge due to their high frequency and the susceptibility of their small amplitude signals to interference from surrounding head muscles. Scientific investigations have revealed that gamma brain waves play a significant role in advanced cognitive processes, such as enhanced working memory and heightened concentration. Additionally, gamma waves, along with beta waves, are observed during REM sleep, the stage associated with vivid dreaming.

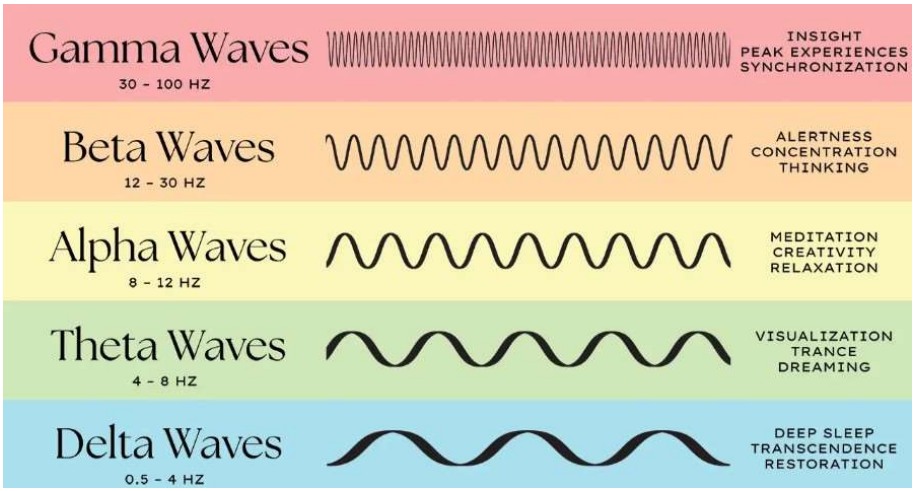


Figure 3.2: Five Types of Brainwaves

- Beta: 12–30Hz
  The beta brain wave range is often categorized into three bands: high beta, beta, and low beta. However, for the purpose of this discussion, we will consider the broader concept of the beta band. The beta brain wave range corresponds to a state of heightened mental activity and alertness, characterized by active thinking, concentration, decision-making, and problem-solving.Furthermore, beta activity increases when movement is resisted or suppressed, and artificially induced beta waves can lead to a slowing down of movements. This intricate relationship with movement underscores the involvement of beta brain waves in conditions such as Parkinson's disease.

- Alpha: 8–12 Hz
  The alpha state, the first brain wave discovered by Hans Berger, is typically observed when individuals are awake, alert, and in a state of calmness, often associated with minimal activity. Numerous studies have established a correlation between the alpha state and enhanced creativity.

- Theta: 4–8 Hz
  Similar to delta waves, theta brain waves are commonly observed during sleep, particularly during transitional phases such as falling asleep or waking up, rather than during deep sleep stages. Theta activity can also manifest while awake, but in a state of internal focus. During these times, individuals may experience drowsiness, daydreaming, relaxation, and a sense of being on "autopilot". Interestingly, a study has indicated that theta brain waves can contribute to positive emotional experiences, with participants describing it as a state of blissfulness.

- Delta: 0.5-4 Hz
  Delta brain waves occupy the slowest frequency band. It is not one

you'll have much conscious experience of, as mostly they're found in stage 3 non-REM sleep, also called slow-wave sleep. Delta brain waves are necessary for relaxing and restorative deep sleep. If they're inhibited or disrupted for some reason, you'll suffer from poor sleep and an inability to rejuvenate your body properly.

Chapter 4

Data and Preprocessing

Here we introduce the dataset used in this study, providing essential details about its origin and composition. We then discuss the preprocessing techniques employed, namely Independent Component Analysis (ICA) and Power Spectral Density (PSD). ICA helps separate mixed signals into independent components to identify and remove artifacts or noise. PSD provides a frequency-domain analysis, revealing the power distribution across frequency bands. By employing these techniques, this chapter ensures the reliability and validity of subsequent analyses in this thesis.

4.1 Data Description

The nature of the dataset is a Haaglanden Medisch Centrum sleep staging database that is collected from Physionet using the link : https://physionet.org/content/hmc-sleep-staging/1.0.1/ The data set content 154 subjects where each contain:

- EEG file: SN001.edf
- Annotation file: SN001-sleepscoring.edf
- Annotation file: SN001-sleepscoring.txt

The Sleep Physionet dataset is annotated using 8 labels: wakefulness(W), stages N1, N2, N3, and R, (M), and Stage (?) for any none scored segment. We are working with 5 stages: wake (W), stage N1, stage N2, stage N3, and REM sleep (R). The eventsid parameter in mne.Eventsfromannotations() to select which events are we interested in.

4.2 Preprocessing

Filtering the data to remove low-frequency drifts, which can negatively affect the quality of the ICA fit.The slow drifts are problematic because they reduce the independence of the assumed-to-be-independent sources making it harder for the algorithm to find an accurate solution.A high-pass filter with 1 hz cutoff frequency is recommended.

4.2.1 Independent Component Analysis (ICA)

In order to estimate distinct source signals from a collection of recordings in which the source signals were mixed together in unknown ratios, one method is known as independent components analysis (ICA). The sensor signal can be rebuilt using the ICA object's apply method after viewing the Independent Components (ICs) and removing any that capture artifacts you want to fix.
Signal reconstruction by default employs all ICs in addition to any PCs that were excluded from the ICA decomposition (i.e., the "PCA residual").The figure (Figure 4.1) below summarizes the fitting and reconstruction processes as well as the variables that affect dimensionality at different stages.

4.2.2 Power spectral density(PSD)

Power spectral density(psd) : the power spectral density (PSD) estimates for all available data channels provide a convenient way to check for spectral artifacts and, in some cases, bad channels.In order to forecast sleep stages using EEG signals, we will now develop a function (eegpowerband) to extract EEG features based on relative power in particular frequency bands.

$$PSD = powervalue/frequencyrange \tag{4.1}$$

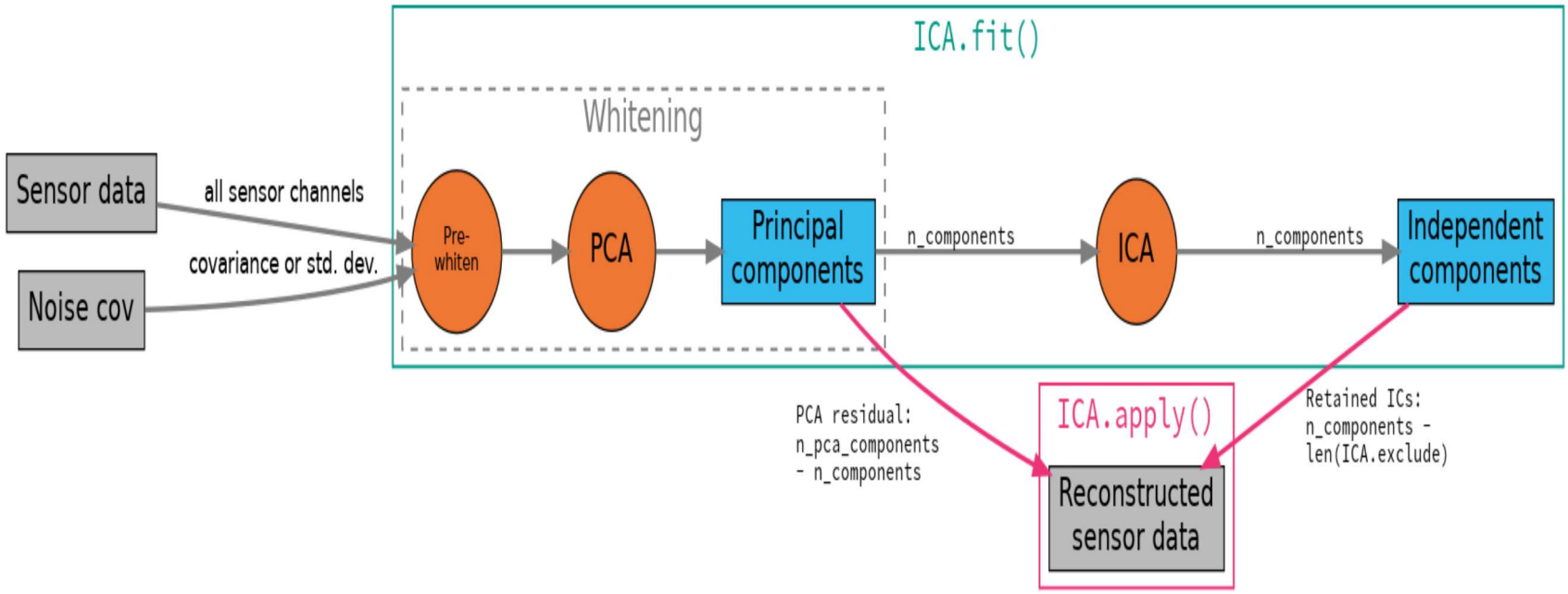


Figure 4.1: Working Procedure of ICA

Chapter 5

Experiment results and analysis

The analysis of EEG (Electroencephalography), the study of ERP (Event-Related Potentials), and the utilization of machine learning algorithms are pivotal in comprehending brain activity and cognitive processes. EEG analysis involves the collection and examination of the brain's electrical activity, which is captured through electrodes positioned on the scalp. This methodology grants valuable insights into brain functionality, enabling researchers to explore various cognitive states and disorders. ERP, which is a subset of EEG analysis, focuses on extracting and studying brain responses that are synchronized with specific stimuli or events. The integration of machine learning algorithms has brought about a revolution in EEG and ERP analysis, offering robust tools for processing data and recognizing patterns. These algorithms have significantly enhanced our ability to decipher EEG and ERP data, facilitating advanced data processing and pattern identification.

5.1 EEG analysis

5.1.1 EEG Connectivity

Measurements made using magnetoencephalography and electroencephalography (M/EEG) are made from the weak electromagnetic impulses produced by brain activity. Using these signals to characterize and identify neural activation in the brain is a challenge that requires expertise in physics, signal processing, statistics, and numerical methods. And in that way the EEG connectivity allows us to clarify the information processing mechanisms of neurons and neural networks and additional information like how they are located, named and how to identify each of them.
Process of montage:

1. Following standard 10-20 system to montage.
2. Compare the different channels of raw with different labels of 10-20 systems.

3. If it does not match, rename the channels according to labels.
4. Load the raw again with the new channels.
5. Plot the montage with the help of MNE function plotsensors().
6. The connectivity is visualized using a circular graph which is ordered based on the locations of the regions in the axial plane.
   The below montage(Figure 5.1) has been made with our raw with 4 EEG channels.

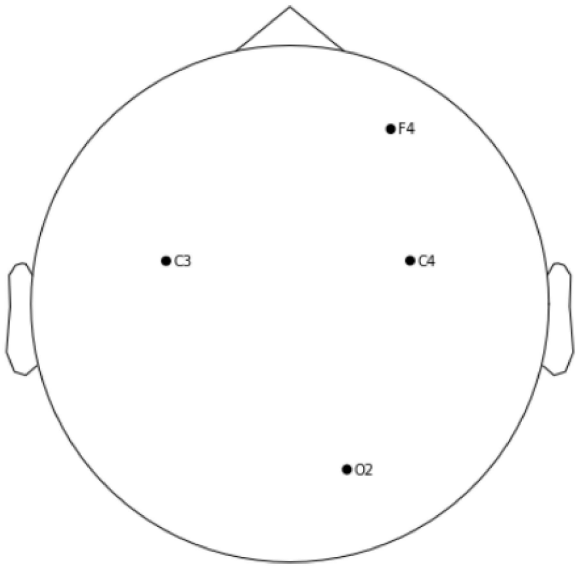


Figure 5.1: Process of montage

5.1.2 Event-Related Potentials (ERPs)

Event-related potentials (ERPs) are minute variations in the electroencephalogram (EEG) captured from the scalp and time-locked to the beginning of an event, such as a motor act or sensory stimulus.ERPs are derived from electroencephalographic (EEG) measurement of neural activity. The ERP is produced by taking multiple temporal segments that characterize the relevant event from the ongoing EEG and then averaging them. ERPs provide insight into a variety of cognitive functions, including perception, attention, emotion, action, and memory.
The Process:

1. Derived from EEG connectivity (selecting channels, rename it, 10-20 systems ..)
2. Creating dictionary containing different events name
3. Epoching
4. Plot base on differents epochs is shown Figure 5.2

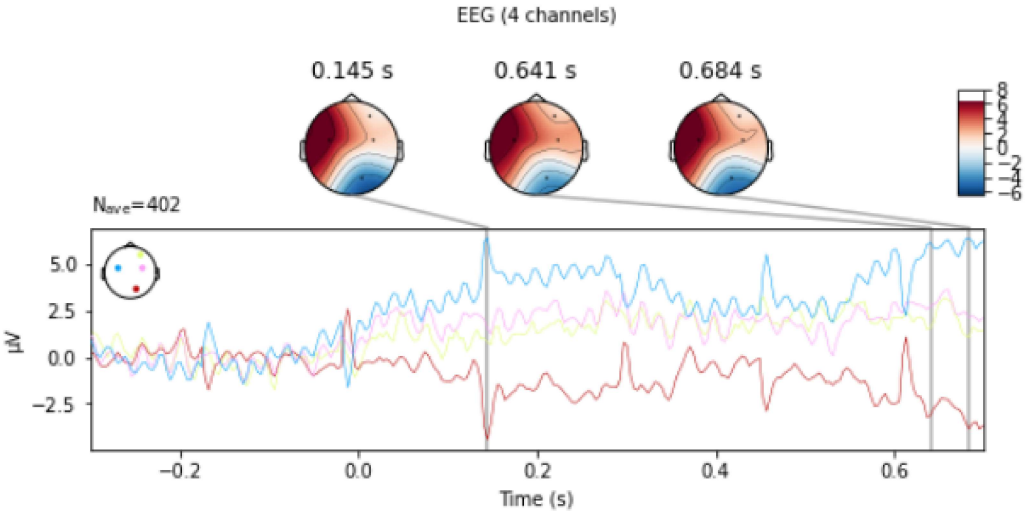


Figure 5.2: ERPs

If we wish to contrast auditory to visual stimuli, a helpful function is mne.viz.plot compare evokeds(). In this case, we stipulate to combine by averaging and limit it to a subset of channels by passing channel names. By default, this function will combine all channels in each evoked object using global field power (GFP or RMS for MEG channels). So, here we have combined our channels using mean and with helps of that function we plot the graph (Figure 5.3).

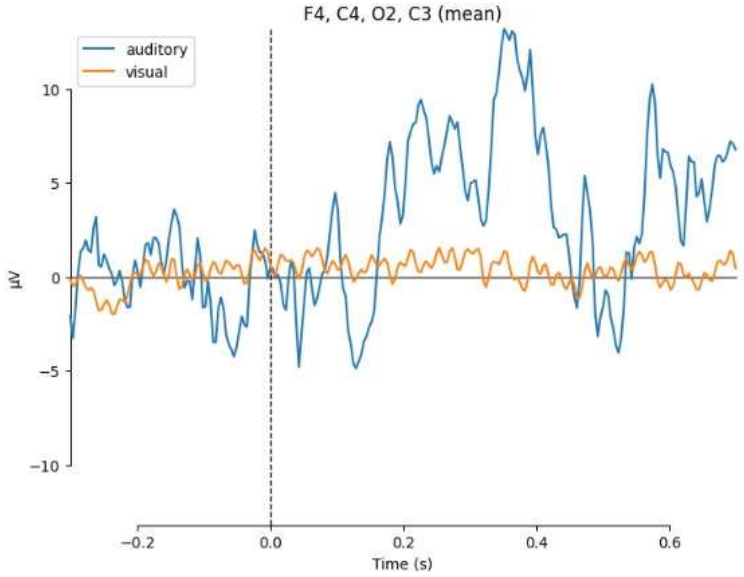


Figure 5.3: ERPs

5.2 Machine Learning

5.2.1 sklearn Pipeline

The purpose of the pipeline is to assemble several steps that can be cross-validated together while setting different parameters: Function transformer, Machine learning Algorithm.The following figure 5.4 detailed it:

5.2.2 Function transformer

The purpose of a function transformer is to pass its X (and potentially y) arguments to a user-defined function or function object and return the output of that function. In our case, the specific user-defined function we use is called "eegpowerband." This function operates on an "mne.Epochs" object and generates EEG features based on the provided input.on relative power in specific frequency bands that are compatible with scikit-learn

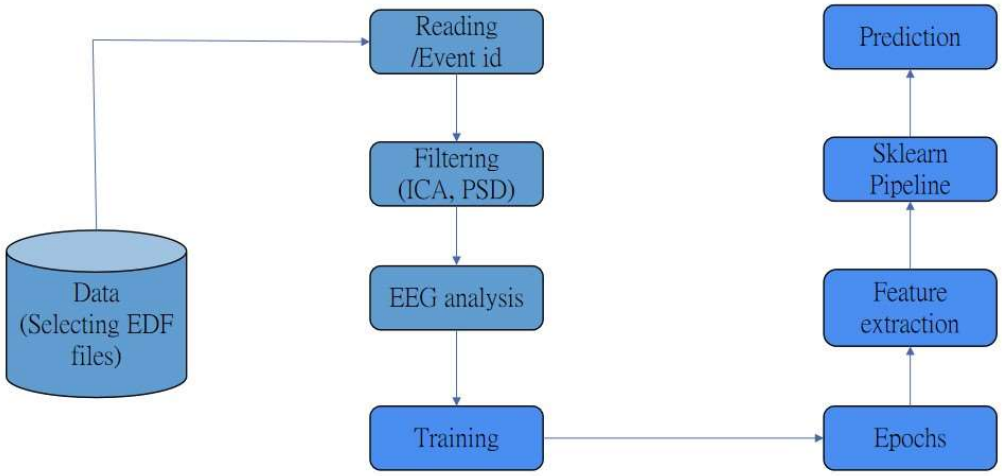


Figure 5.4: Methodologies

Parameters epochs : Epochs The data. Returns X : numpy array of shape [n samples, 5] Transformed data

5.2.3 Machine learning Algorithms

a. Random forest classifier

A random forest is a meta learner that builds multiple decision tree classifiers using different subsets of the dataset. It improves predictive accuracy and mitigates overfitting by averaging the predictions of these individual classifiers (Figure 5.5).

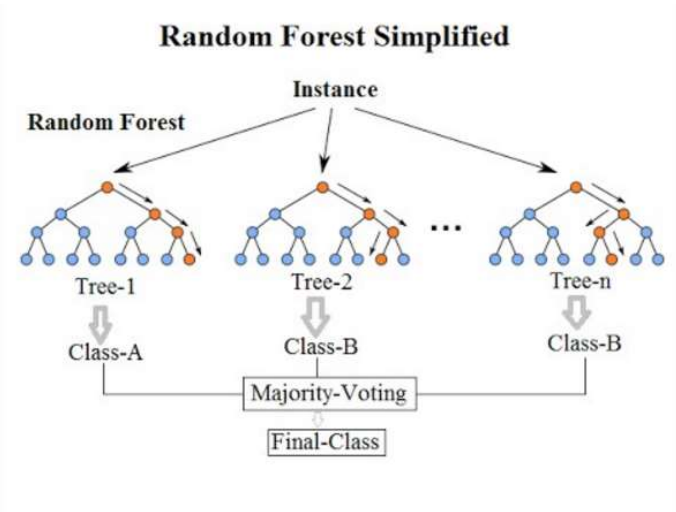


Figure 5.5: Random Forest simplified

b. XG Boost Classifier

This algorithm constructs an additive model incrementally, proceeding in a forward stage-wise manner. It offers the flexibility to optimize a wide range of differentiable loss functions (Figure 5.6).

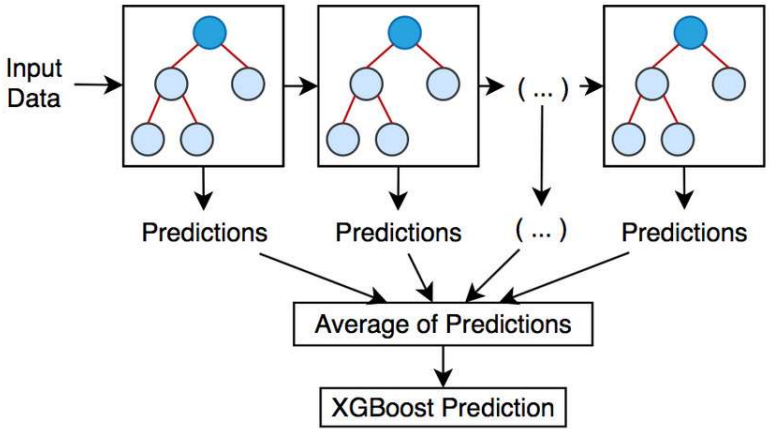


Figure 5.6: XG Boost Simplified

5.3 Evaluation Metrics

To evaluate our models, we have chosen four different evaluation metrics. They are: accuracy, precision, recall, F1- score. Here is brief introduction of these metrics: Here, TP = True Positive, FP = False Positive, FN = False Negative, TN = True Negative, P = Total Positive Predicted Class, N = Total Negative Predicted Class

5.3.1 Accuracy

It says how close a measured value is to the actual value

$$Accuracy = \frac{TP + TN}{P + N} \tag{5.1}$$

5.3.2 Precision

It says how close a measured values are to each other

$$Precision = \frac{TP}{TP + FP} \tag{5.2}$$

5.3.3 Recall

It is the ratio of all correctly predicted positive predictions. It measure how many the model missed.

$$Recall = \frac{TP}{P} \tag{5.3}$$

5.3.4 F1-Score

It is used when difficulties is faced to compare when model has low precision and high recall or vise-versa.

$$F1Score = \frac{2 * precistion * recall}{precistion + recall} \tag{5.4}$$

5.4 Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. It is also known as error matrix.
Confusion matrix of Random Forest Classifer:

2464	194	228	12	90
829	202	546	18	266
641	198	6640	571	300
308	10	1312	3074	38
276	135	1124	20	2452

Figure 5.7: Confusion matrix of Random Forest

Confusion matrix of XG Boost:

1756	112	123	10	70
673	122	430	18	230
641	198	5432	571	300
207	0	1312	2572	76
134	135	1124	20	1156

Figure 5.8: Confusion matrix of XG Boost

5.5 Result

5.5.1 Precision for all stages:

The precision rates, expressed as percentages, were determined for each sleep stage. For XG Boost, the precision values were as follows: Wake (W) - 48%, N1 - 16%, N2 - 60%, N3 - 68%, and REM (R) - 60%. Similarly, the Random Forest algorithm yielded the following precision rates: Wake (W) - 48%, N1 - 16%, N2 - 60%, N3 - 68%, and REM (R) - 60%. These precision values provide insights into the accuracy of the algorithms in classifying different sleep stages. Further analysis and comparison can help determine the most effective algorithm for sleep stage classification in this study (Table 5.1).

Table 5.1: Precision for all stages using XG Boost and Random forest Machine learning model

	XGBOOST	**RANDOM FOREST**
WAKE	48%	55%
N1	16%	27%
N2	60%	67%
N3	68%	83%
REM	69%	78%

5.5.2 Recall for all Stages

The recall rates, represented as percentages, were determined for each sleep stage. For XG Boost, the recall values were as follows: Wake (W) - 50%, N1 - 24%, N2 - 59%, N3 - 58%, and REM (R) - 49%. Likewise, the Random Forest algorithm yielded the following recall rates: Wake (W) - 82%, N1 - 11%, N2 - 80%, N3 - 65%, and REM (R) - 61%. These recall values provide insights into the algorithms' effectiveness in correctly identifying and capturing the different sleep stages (Table 5.2).

Table 5.2: Recall for all stages using XG Boost and Random forest Machine learning models

	XGBOOST	**RANDOM FOREST**
WAKE	58%	82%
N1	24%	11%
N2	59%	80%
N3	58%	65%
REM	49%	61%

5.5.3 Model Comparison

In the sleep study, a comparison was made between two machine learning algorithms, Random Forest and XG Boost, in terms of their performance metrics. The Random Forest algorithm achieved an accuracy of 68% and an F1-score of 60%. On the other hand, the XG Boost algorithm exhibited an accuracy of 54% and an F1-score of 50%.
The accuracy metric represents the overall correctness of the algorithm's predictions, indicating the percentage of correctly classified sleep stages. In this case, Random Forest outperformed XG Boost with a higher accuracy rate of 68% compared to 54%. The F1-score is a measure that considers both precision and recall, providing a balanced evaluation of the algorithm's performance. A higher F1-score indicates a better trade-off between precision and recall. In this study, Random Forest achieved an F1-score of 60%, while XG Boost obtained a lower score of 50%.
These results suggest that, in terms of accuracy and F1-score, Random Forest exhibited better performance in sleep stage classification compared to XG Boost.

Table 5.3: XG Boost and Random forest model comparison based on their Accuracy and F1 Score

	Accuracy	**F1-Score**
RANDOM FOREST	48%	55%
XG BOOST	16%	27%

5.5.4 Result for 50 Subjects

Prior to applying these filtering methods, the initial accuracy achieved was 68.45%. However, after implementing the filtering techniques, the accuracy significantly improved, reaching 82.62%.
This substantial increase in accuracy highlights the effectiveness of ICA and PSD in enhancing the precision of sleep stage classification. By utilizing ICA, the filtering process successfully extracted independent components from the original data, allowing for a more refined and accurate representation of the underlying sleep patterns. Additionally, the application of PSD provided further insights into the frequency characteristics of the sleep signals, enabling better discrimination between different sleep stages(Figure 5.9).

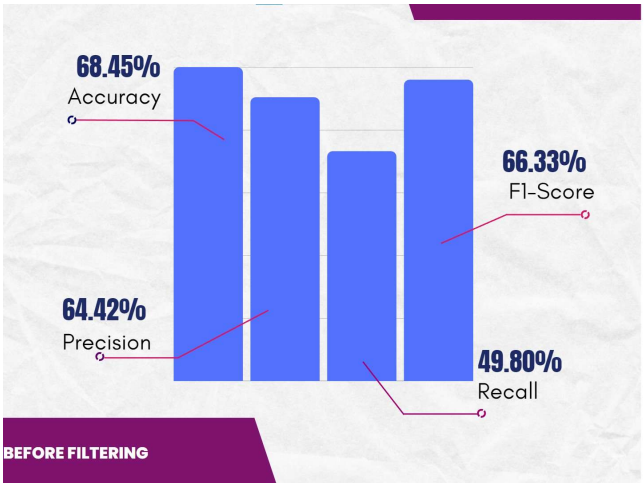


Figure 5.9: Before Filtering

The improved accuracy after applying ICA and PSD underscores the importance of preprocessing techniques in sleep studies. These findings contribute to the growing body of knowledge on signal processing approaches and their impact on sleep stage classification accuracy. The enhanced accuracy achieved through the filtering methods has implications for both clinical and research settings, as it can facilitate more reliable and precise sleep stage analysis (Figure 5.10).

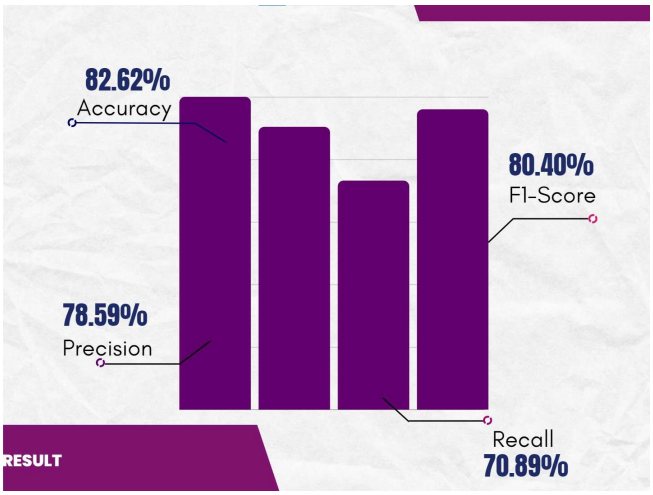


Figure 5.10: Result

Chapter 6

Conclusion

6.1 Challenges

Limited access to data: Obtaining a substantial amount of high-quality sleep data can be challenging. Sleep studies often require participants to spend nights in sleep laboratories, and access to such facilities and data may be restricted. Limited data can hinder the development and evaluation of sleep stage classification models.
Data variability and subjectivity: Sleep patterns and stages can vary significantly among individuals, making it difficult to establish universally applicable classification criteria. Different sleep laboratories may use different methodologies and scoring systems, leading to inconsistencies and subjectivity in data interpretation.
Complex data preprocessing: Sleep stage classification typically involves processing and analyzing large amounts of physiological data, including electroencephalography (EEG), electromyography (EMG), and electrooculography (EOG). Preprocessing this data can be challenging due to noise, artifacts, and individual differences, requiring careful filtering and normalization techniques.
Class imbalance: Sleep stages are often imbalanced, with some stages occurring more frequently than others.Imbalanced data can lead to biased model performance and difficulties in accurately classifying underrepresented stages.
Algorithm selection and evaluation: There are various algorithms and techniques available for sleep stage classification, such as rule-based methods, machine learning models, and deep learning approaches. Selecting the appropriate algorithm and evaluating its performance can be challenging, as each method has its strengths and limitations.
Feature selection and extraction: Choosing relevant features from raw sleep data and extracting meaningful information is crucial for accurate classification. Identifying informative features and optimizing feature extraction methods can be a time-consuming and complex task.

6.2 Summary

This thesis focused on sleep staging, an essential aspect of sleep assessment and disease diagnosis. The study aimed to predict five-class sleep stages using EEG data from the Haaglanden Medisch Centrum (HMC) dataset and explored the effectiveness of two machine learning models: Random Forest Classifier and XG Boost.The results of the study demonstrated the potential of machine learning techniques in accurately classifying sleep stages from PSG data.The Random Forest Classifier and XG Boost models achieved an accuracy above 80%, indicating their efficacy in identifying different sleep stages.

The study also addressed challenges in the dataset, including noise and preprocessing requirements. Through careful data preprocessing and selection, the models were able to produce accurate predictions, highlighting the importance of data quality and preprocessing techniques in sleep staging research.Overall, this research emphasizes the significance of automated sleep staging using machine learning and EEG data. The findings contribute to the field of sleep medicine, providing insights into the potential for improved sleep assessment, diagnosis, and treatment of sleep-related disorders.

In conclusion, this research advances the understanding of sleep staging and highlights the potential of machine learning techniques in accurately predicting sleep stages. The outcomes of this study pave the way for improved sleep assessment and personalized treatment strategies for sleep-related disorders, ultimately benefiting the health and well-being of individuals worldwide.

6.3 Future Work

It is important to acknowledge that further research is required to enhance the accuracy and generalizability of the models. Future studies can explore additional machine learning algorithms, incorporate more diverse datasets, and investigate the combination of multiple physiological signals for enhanced sleep staging performance.

Bibliography

[1] Jas, M., Larson, E., Engemann, D. A., Leppäkangas, J., Taulu, S., Hämäläinen, M., Gramfort, A. (2018). A reproducible MEG/EEG group study with the MNE software: recommendations, quality assessments, and good practices. Frontiers in neuroscience, 12, 530.

[2] Xu, M., Wang, X., Zhangt, X., Bin, G., Jia, Z., Chen, K. (2020, May). Computation-efficient multi-model deep neural network for sleep stage classification. In Proceedings of the 2020 Asia Service Sciences and Software Engineering Conference (pp. 1-8).

[3] Vilamala, A., Madsen, K. H., Hansen, L. K. (2017, September). Deep convolutional neural networks for interpretable analysis of EEG sleep stage scoring. In 2017 IEEE 27th international workshop on machine learning for signal processing (MLSP) (pp. 1-6). IEEE.

[4] 2018 Aug 6;12:530. doi: 10.3389/fnins.2018.00530. eCollection 2018.

[2] Xu, Mingkai, et al. "Computation-Efficient Multi-Model Deep Neural Network for Sleep Stage Classification." Proceedings of the 2020 Asia Service Sciences and Software Engineering Conference. 2020.

[5] 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI 2018)

[6] Z Jia, X. Cai, G. Zheng, J. Wang, and Y. Lin. Sleepprintnet: A multivariate multimodal neural network based on physiological time-series for automatic sleep staging. TAI, 2021

[7] Jia, Z., Lin, Y., Wang, J., Wang, X., Xie, P., Zhang, Y. (2021). Salientsleepnet: Multimodal salient wave detection network for sleep staging. arXiv preprint arXiv:2105.13864.

[8]Zhang, X., Kou, W., Eric, I., Chang, C., Gao, H., Fan, Y., Xu, Y. (2018). Sleep stage classification based on multi-level feature learning and recurrent neural networks via wearable device. Computers in biology and

medicine, 103, 71-81.

[9] Aboalayon, K. A. I., Faezipour, M., Almuhammadi, W. S., Moslehpour, S. (2016). Sleep stage classification using EEG signal analysis: a comprehensive survey and new investigation. Entropy, 18(9), 272..

[10] Aboalayon, K. A., Ocbagabir, H. T., Faezipour, M. (2014, May). Efficient sleep stage classification based on EEG signals. In IEEE Long Island Systems, Applications and Technology (LISAT) Conference 2014 (pp. 1-6). IEEE.

[11] Ebrahimi, F., Mikaeili, M., Estrada, E., Nazeran, H. (2008, August). Automatic sleep stage classification based on EEG signals by using neural networks and wavelet packet coefficients. In 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 1151-1154). IEEE.

[12] Dong, H., Supratak, A., Pan, W., Wu, C., Matthews, P. M., Guo, Y. (2017). Mixed neural network approach for temporal sleep stage classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(2), 324-333.

[13] Koley, B., Dey, D. (2012). An ensemble system for automatic sleep stage classification using single channel EEG signal. Computers in biology and medicine, 42(12), 1186-1195.

[14] Memar, P., Faradji, F. (2017). A novel multi-class EEG-based sleep stage classification system. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(1), 84-95.

[15]Eldele, E., Chen, Z., Liu, C., Wu, M., Kwoh, C. K., Li, X., Guan, C. (2021). An attention-based deep learning approach for sleep stage classification with single-channel EEG. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29, 809-818.

[16] Santaji, S., Desai, V. (2020). Analysis of EEG signal to classify sleep stages using machine learning. Sleep and Vigilance, 4, 145-152.

[17] Chambon, S., Galtier, M. N., Arnal, P. J., Wainrib, G., Gramfort, A. (2018). A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(4), 758-769.

[18] Ghimatgar, H., Kazemi, K., Helfroush, M. S., Pillay, K., Dereymaker,

A., Jansen, K., ... Aarabi, A. (2020). Neonatal EEG sleep stage classification based on deep learning and HMM. Journal of neural engineering, 17(3), 036031.

[19] Yildirim, O., Baloglu, U. B., Acharya, U. R. (2019). A deep learning model for automated sleep stages classification using PSG signals. International journal of environmental research and public health, 16(4), 599.

[20] Sekkal, R. N., Bereksi-Reguig, F., Ruiz-Fernandez, D., Dib, N., Sekkal, S. (2022). Automatic sleep stage classification: From classical machine learning methods to deep learning. Biomedical Signal Processing and Control, 77, 103751.

[21] Smith, A., Anand, H., Milosavljevic, S., Rentschler, K. M., Pocivavsek, A., Valafar, H. (2021, December). Application of Machine Learning to sleep stage classification. In 2021 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 349-354). IEEE.

[22] Ilhan, H. O., Bilgin, G. (2017). Sleep stage classification via ensemble and conventional machine learning methods using single channel EEG signals. Int. J. Intell. Syst. Appl. Eng, 5(4), 174-184.

[23] Mousavi, S., Afghah, F., Acharya, U. R. (2019). SleepEEGNet: Automated sleep stage scoring with sequence to sequence deep learning approach. PloS one, 14(5), e0216456. Aboalayon, K. A., Almuhammadi, W. S., Faezipour, M. (2015, May). A comparison of different machine learning algorithms using single channel EEG signal for classifying human sleep stages. In 2015 Long Island Systems, Applications and Technology (pp. 1-6). IEEE.

[24] Kim, H., Choi, S. (2018, July). Automatic sleep stage classification using eeg and emg signal. In 2018 Tenth International Conference on Ubiquitous and Future Networks (ICUFN) (pp. 207-212). IEEE.

[25] Korkalainen, H., Aakko, J., Nikkonen, S., Kainulainen, S., Leino, A., Duce, B., ... Leppänen, T. (2019). Accurate deep learning-based sleep staging in a clinical population with suspected obstructive sleep apnea. IEEE journal of biomedical and health informatics, 24(7), 2073-2081.

[26] Biswal, S., Kulas, J., Sun, H., Goparaju, B., Westover, M. B., Bianchi, M. T., Sun, J. (2017). SLEEPNET: automated sleep staging system via deep learning. arXiv preprint arXiv:1707.08262.

[27] Huang, J., Ren, L., Zhou, X., Yan, K. (2022). An improved neural network based on SENet for sleep stage classification. IEEE Journal of Biomedical and Health Informatics, 26(10), 4948-4956.

[28] Längkvist, M., Loutfi, A. (2018). A deep learning approach with an attention mechanism for automatic sleep stage classification. arXiv preprint arXiv:1805.05036.

[29] Craik, A., He, Y., Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: a review. Journal of neural engineering, 16(3), 031001. Prabhakar, S. K., Rajaguru, H., Ryu, S., Jeong, I. C., Won, D. O. (2022). A Holistic Strategy for Classification of Sleep Stages with EEG. Sensors, 22(9), 3557.

[30] Paisarnsrisomsuk, S., Ruiz, C., Alvarez, S. (2020, July). Improved deep learning classification of human sleep stages. In 2020 IEEE 33rd international symposium on computer-based medical systems (CBMS) (pp. 338-343). IEEE.