University of Essex

School of Computer Science &
Electronic Engineering

CE903 - Group Project

Automated Sleep Stage Classification

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Abstract

This project investigates the use of machine learning algorithms to classify sleep stages using polysomnography (PSG) data, employing advanced models such as XGBoost, Random Forest, and Convolutional Neural Networks (CNN) to analyze sleep data with a detailed 13-channel feature extraction process. The methodology includes thorough data preparation, cross-validation, and performance assessment, addressing the challenge of imbalanced datasets through class-weight adjustments to enhance model performance. Principal Component Analysis (PCA) was conducted using both Python and MATLAB to reduce dimensionality and improve feature selection. Additionally, feature selection methods are explored to identify the most significant contributors to classification accuracy, optimizing model efficiency. The results indicate that XGBoost surpasses both CNN and Random Forest in performance, demonstrating its potential as a powerful tool for sleep stage classification. The research also underscores the importance of hyperparameter tuning in improving model accuracy and reliability. This study not only advances the field of biomedical signal processing but also has significant implications for clinical practices in sleep medicine, suggesting that integrating machine learning models like XGBoost into clinical workflows can potentially improve the diagnosis and treatment of sleep disorders, offering more precise and automated analysis of sleep patterns.

Keywords: machine learning, sleep stage classification, polysomnography, XGBoost, Random Forest, Convolutional Neural Networks, feature extraction, class imbalance, hyperparam

Contents

CHAPTER 1

Introduction

Have you ever wondered about the enigmatic journey we undertake each night when we fall asleep? You're not alone. The realm of sleep is incredibly fascinating, with its intricate dance of phases like REM and non-REM playing crucial roles in our well-being. Understanding these sleep stages isn't just an academic curiosity; it's a vital key to unlocking deep insights into our physical and mental health. However, decoding these sleep phases has historically been akin to detective work in the dark. Traditional methods, relying on sleep studies and human analysis, are useful but come with significant challenges. That's where Machine Learning steps in as our modern-day hero. Picture this dissertation as a spotlight in the darkness, illuminating those elusive sleep phases. We're delving into the exciting convergence of sleep science and machine learning, with a clear mission: to create intelligent models capable of interpreting the language of sleep. Why does this matter? Because cracking this code could revolutionize our understanding of sleep patterns and ultimately enhance our quality of rest.

1.1 Critical Role of Sleep Stages

The sleep cycle, with its distinct stages, is essential for various bodily functions. Non-REM sleep, including light (N1, N2) and deep sleep (N3), is crucial for physical repair, immune function, and hormone balance. REM sleep, characterized by intense brain activity and vivid dreams, is key for cognitive functions like memory consolidation. Interruptions in these stages are linked to numerous health problems, highlighting the need for precise identification. Conditions like insomnia and sleep apnea often disrupt REM and non-REM balance, making accurate stage differentiation crucial for early diagnosis and treatment.

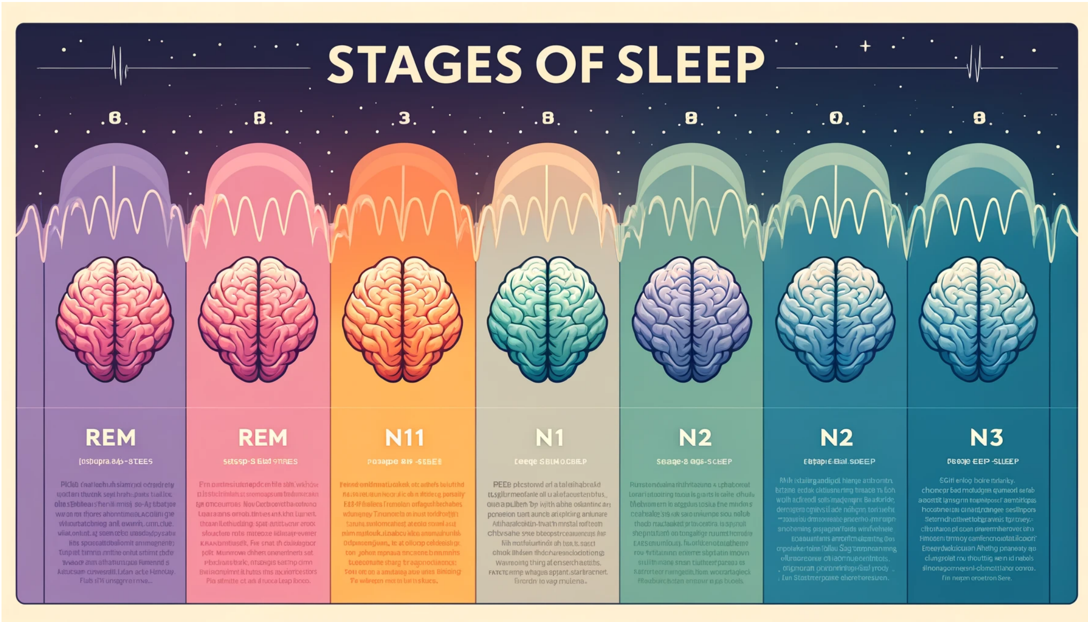

Figure 1.1: Sleep Stages

1.2 Traditional Sleep Monitoring

Although polysomnography (PSG) provides detailed data, its use outside labs is limited due to logistical challenges. The requirement for specialized equipment and expert interpretation, along with the subjectivity in manual scoring, restricts its scalability and real-world application. This creates a need for innovative, scalable methods in sleep research.

1.3 Machine Learning in Sleep Studies

Machine learning is emerging as a powerful tool in sleep research. These algorithms can analyze large datasets and detect complex patterns, addressing traditional monitoring limitations. With the rise of wearable devices that offer continuous, unobtrusive monitoring, the integration of machine learning in sleep science is set to transform the field. Machine learning in sleep stage detection involves extracting key features from physiological signals, training models on labeled data, and validating against benchmarks to surpass human scoring and overcome traditional method limitations.

1.4 Objectives

Against this backdrop, the primary objectives of this project become clear. First, it aims to thoroughly review the existing literature on sleep phase classification, covering both traditional techniques and the latest advancements in machine learning. This comprehensive review will provide a solid foundation for understanding the current state of the field and identify gaps that the project seeks to address. Second, the project intends to develop and rigorously evaluate machine learning models designed for automated sleep phase classification. This involves navigating the complexities of feature extraction from polysomnography (PSG) data, meticulous model training, and robust validation processes. The focus will be on assessing the practical implications of these methodologies in real-world applications, ensuring the models' scalability and accessibility.

By embarking on this academic journey, the project aspires to deepen the understanding of sleep dynamics and contribute to the development of scalable and accessible sleep monitoring solutions. The following sections will explore the detailed methodologies employed, the challenges faced, and the broader implications of the findings in the context of sleep research. Through this scientific endeavor, we aim to bridge the gap between data-driven machine learning approaches and the intricate nature of human sleep, ultimately paving the way for more accurate and practical solutions in sleep medicine.

1.5 Acknowledgments

The successful completion of this project is the result of collaborative efforts and dedication from our team of six members, who have contributed their expertise and time to this extensive research endeavor. We would like to express our sincere gratitude to all those who played a role in making this research possible. First and foremost, we extend our appreciation to our team members. Each team member brought a unique set of skills and perspectives, enriching the overall quality of the research. Their collective efforts have been instrumental in the various stages of this project, from literature review to model development and evaluation. We are grateful to our advisors and mentors, Dr. Vito De Feo and Jose Luis, for their guidance, encouragement, and valuable insights throughout the entire research process. Their expertise and unwavering support have been indispensable in shaping the direction and success of this project. Additionally, we would like to acknowledge the support received from the University of Essex. The resources, facilities, and academic environment provided by the institution have been essential in facilitating our research endeavors. Their support has enabled us to conduct this study with the rigor and depth required to achieve our objectives.

CHAPTER 2

Related Works

Embarking on the journey into the mysterious world of sleep science and the cutting-edge domain of machine learning starts with delving into the wealth of existing knowledge and scholarly discussions. This chapter, aptly named "Background Research and Literature Review," forms the foundation upon which all our subsequent analysis and experiments are constructed. It intricately weaves together the strands of previous research, theoretical foundations, and technological breakthroughs, creating a vivid and coherent backdrop that frames our study. Through this exploration, we set the stage for our investigation, connecting past insights with new discoveries to push the boundaries of what is known about sleep and its classification through machine learning.

2.1 Sleep Cycles

Sleep, a fascinating state of reduced awareness and minimal interaction with the environment, is divided into two primary phases: Rapid Eye Movement (REM) and Non-Rapid Eye Movement (Non-REM). These phases alternate throughout the night, each playing a crucial role in our overall health.

Non-REM Sleep: The Backbone of Restorative Sleep Non-REM sleep consists of three stages, each progressively deeper than the last:

N1 (Initial Sleep): This stage marks the transition from wakefulness to sleep and typically lasts between 5 and 10 minutes. Characterized by the emergence of theta brain waves, N1 involves a gradual reduction in heart rate, breathing, and body temperature.

This stage makes up about 5

N2 (Light Sleep): Lasting around 20 minutes, N2 represents the onset of true sleep. It features sleep spindles and K-complexes, which are thought to assist in memory consolidation and reduce sensitivity to external stimuli. N2 accounts for approximately 45-55

N3 (Deep Sleep): Also known as slow-wave sleep, N3 is the deepest and most restorative sleep stage. It lasts between 20 to 40 minutes, decreasing with age, and is vital for physical recovery and growth hormone release. This stage is marked by delta waves and is the hardest to wake from due to minimal responsiveness to external stimuli.

REM Sleep: The Dreaming Phase After about 90 minutes of sleep, REM sleep begins, marked by rapid eye movements and heightened brain activity. REM periods lengthen throughout the night, with the longest occurring just before waking.

Physiological Aspects: REM sleep, discovered by Aserinsky and Kleitman, is characterized by brain activity similar to wakefulness but with muscle atonia to prevent acting out dreams. This stage involves irregular breathing and heart rates and is essential for cognitive functions like learning and memory.

Dreaming and Cognitive Processes: REM sleep is associated with vivid dreaming. The activation-synthesis hypothesis suggests that dreams are the brain's way of making sense of random neural activity. REM is crucial for memory consolidation and emotional regulation.

The Rhythmic Pattern of Sleep Throughout the night, sleep stages follow a cyclical pattern, typically repeating every 90 to 120 minutes. The proportion of REM sleep increases as the night progresses, supporting various restorative functions for the brain and body.

Understanding the detailed structure of sleep stages is fundamental to sleep science. It provides insights into critical physiological and psychological processes and is essential for diagnosing and treating sleep disorders. Ongoing research continues to shed light on the complexities of these stages, revealing more about our nocturnal activities.

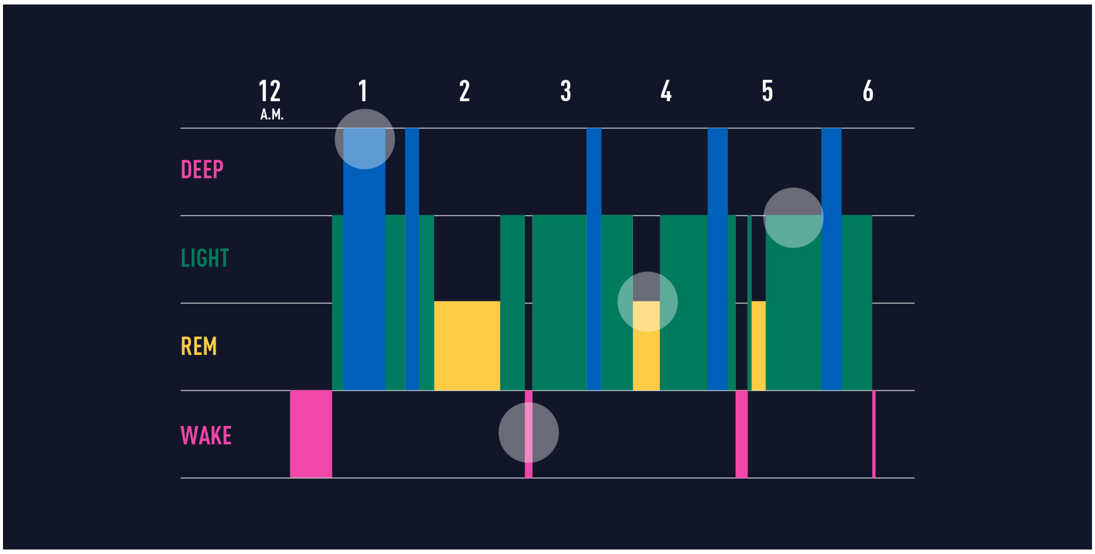

Figure 2.1: Sleep Hypnogram

2.2 Impact of Sleep

Sleep is crucial for maintaining overall health and well-being, affecting a range of physiological and psychological processes. Interruptions in normal sleep patterns are associated with various health issues.

Physical Health Impacts:

- **Cardiovascular Health:** Poor sleep quality and disorders such as sleep apnea are strongly linked to an increased risk of cardiovascular diseases. Sleep disruptions can lead to conditions like hypertension, arrhythmias, and even heart failure.
- **Metabolic Function:** Lack of sleep adversely affects glucose metabolism and appetite regulation, increasing the risk of obesity and type 2 diabetes.

Mental Health Connections:

- **Cognitive Functioning:** Adequate sleep is essential for cognitive processes including learning, memory, and problem-solving. Impaired sleep can lead to deficits in these areas, affecting daily functioning and overall quality of life.
- **Psychiatric Disorders:** There is a strong correlation between sleep disturbances and psychiatric conditions such as depression and anxiety. Disrupted sleep can worsen these conditions, creating a vicious cycle of deteriorating mental health and sleep problems.

2.3 Polysomnography (PSG)

Polysomnography (PSG) is a comprehensive and multifaceted diagnostic tool utilized in sleep medicine to evaluate and diagnose sleep disorders. This test records multiple physiological parameters during sleep, offering crucial insights into various aspects of sleep architecture and quality. Below is a detailed examination of the components and functions of PSG.

2.3.1 Components

1. **Electroencephalogram (EEG):**

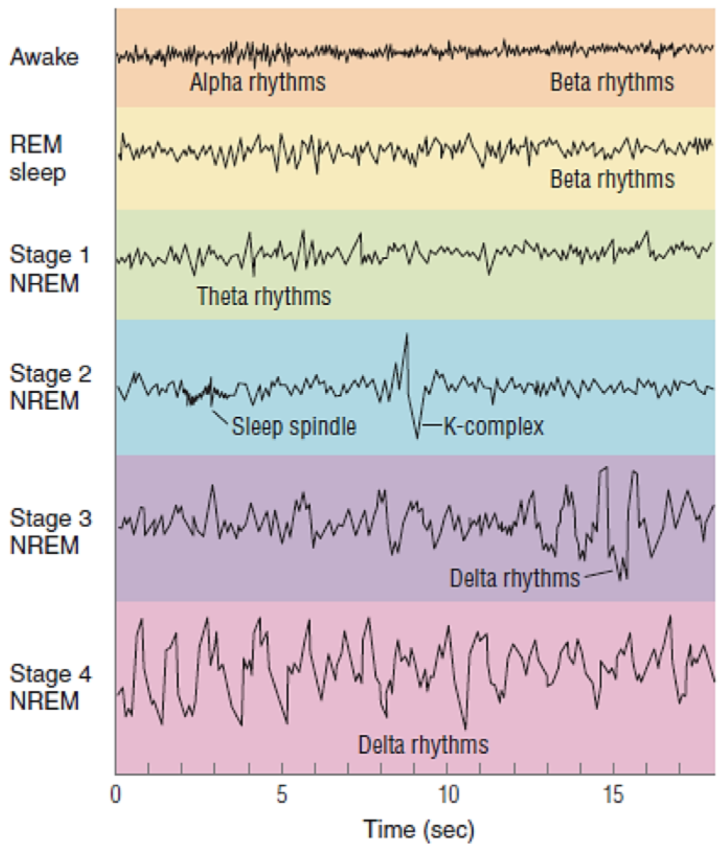

Figure 2.2: EEG brain wave patterns

Function: The EEG monitors and records the brain's electrical activity, which is essential for identifying and differentiating between various sleep stages (N1, N2, N3, and REM). The EEG helps determine the depth and continuity of sleep, as well as detect any abnormal brain activity. Implementation: Electrodes are strategically placed on the scalp according to the 10-20 system, a standardized method for electrode placement in EEG recordings. This ensures accurate and consistent data collection. Data Interpretation: EEG traces display different brain wave patterns characteristic of each sleep stage. For example, theta waves are seen in light sleep (N1), sleep spindles and K-complexes occur during N2, and delta waves are present in deep sleep (N3). During REM sleep, the EEG shows patterns similar to wakefulness.

2. **Electrooculogram (EOG):**

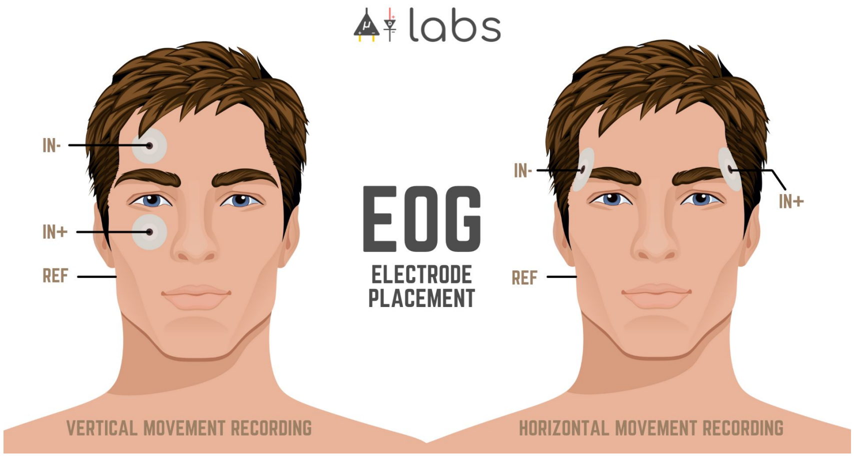

Figure 2.3: EOG Electrode placements

Function: The EOG records eye movements, which are particularly significant in distinguishing REM sleep from other stages. Rapid eye movements are a hallmark of REM sleep, while slow rolling eye movements are indicative of N1. Implementation: Electrodes are placed near the eyes to detect and measure these movements accurately. Data Interpretation: The EOG helps to identify the onset of REM sleep and track its duration, contributing to a comprehensive understanding of sleep cycles.

3. **Electromyogram (EMG):**

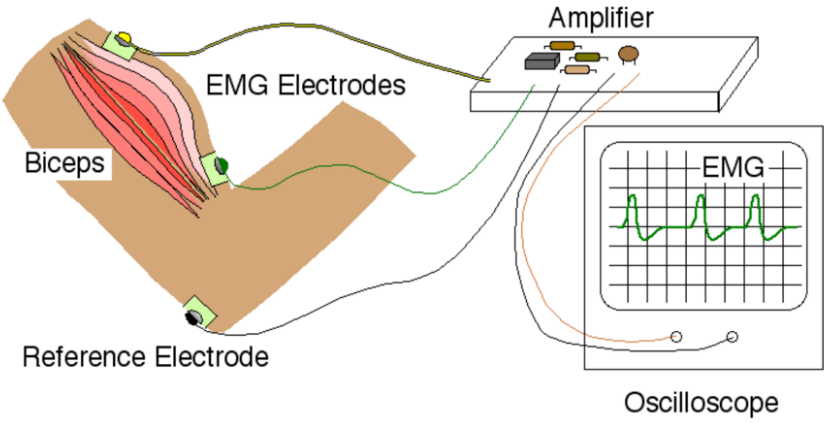

Figure 2.4: EMG Electrode placements

Function: The EMG measures muscle activity and tone, which is vital for detecting muscle relaxation during different sleep stages. It is also used to identify periods of muscle atonia during REM sleep. Implementation: Electrodes are placed on the chin, legs, or other relevant muscle groups. Data Interpretation: The EMG shows reduced muscle activity during sleep, with complete atonia during REM sleep to prevent the body from acting out dreams. Increased muscle activity may indicate movement disorders or disturbances such as restless leg syndrome.

4. **Electrocardiogram (ECG):**

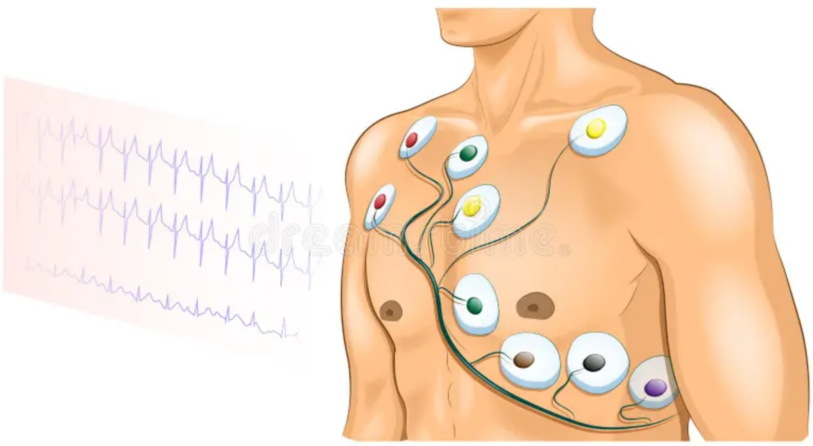

Figure 2.5: ECG Electrode placements

Function: The ECG records heart rate and rhythm, providing information about cardiovascular function during sleep. Implementation: Electrodes are attached to the chest to monitor the heart's electrical activity. Data Interpretation: The ECG helps identify cardiac arrhythmias and other heart-related issues that may occur during sleep.

5. **Respiratory Channels:**

   Function: These channels measure breathing patterns and airflow to detect respiratory disorders such as sleep apnea. Implementation: Sensors are placed near the nose and mouth to measure airflow, and belts are placed around the chest and abdomen to monitor respiratory effort. Data Interpretation: The respiratory channels provide data on breathing regularity, the presence of apneas or hypopneas, and oxygen saturation levels in the blood.

6. **Pulse Oximetry:**

   Function: This component measures the oxygen saturation of the blood, which is crucial for identifying hypoxemia (low blood oxygen levels) during sleep. Implementation: A sensor is placed on a fingertip or earlobe to continuously monitor oxygen levels. Data Interpretation: Pulse oximetry helps in diagnosing conditions like obstructive sleep apnea by showing drops in blood oxygen levels during apneic events.

7. **Body Position Sensors:**

   Function: These sensors detect the sleeper's body position, as certain sleep disorders may be position-dependent. Implementation: Sensors are attached to the body to track movements and positions during sleep. Data Interpretation: Understanding body position can help in diagnosing positional obstructive sleep apnea and other movement-related sleep disorders.

2.3.2 Purpose and Applications of Polysomnography

Polysomnography is primarily used to diagnose and evaluate various sleep disorders, including:

1. **Obstructive Sleep Apnea (OSA):** By monitoring breathing patterns, airflow, and oxygen levels, PSG can identify episodes of apnea and hypopnea, helping to

diagnose OSA.

2. **Insomnia:** PSG can provide insights into sleep architecture and detect underlying causes of insomnia, such as periodic limb movements or sleep-disordered breathing.

3. **Narcolepsy:** By observing REM sleep patterns and sleep onset REM periods, PSG aids in diagnosing narcolepsy.

4. **Restless Leg Syndrome (RLS) and Periodic Limb Movement Disorder (PLMD):** The EMG component helps detect involuntary limb movements during sleep.

2.4 Literature Review

The field of Automated Sleep Stage Classification (ASSC) has seen significant advancements through the application of machine learning techniques. This literature review highlights ten seminal papers that have contributed to this progress, providing detailed insights into various methodologies and their effectiveness.

1. **Shallow Learning for Sleep Stage Classification,** Van Der Donckt et al. [1] developed a feature extraction process utilizing a shallow learning technique. They extracted 131 features, including multi-domain and multi-resolution features, to create a detailed representation of sleep data. These features encompass various aspects of the EEG signal, such as time-domain statistics, frequency-domain measures, and non-linear dynamics. By using classical machine learning algorithms like Random Forests and Support Vector Machines, they demonstrated that a well-engineered feature vector could achieve performance comparable to deep learning models. The study's pipeline consisted of preprocessing, feature extraction, and classification. This approach highlighted the importance of domain knowledge in creating effective features for sleep stage classification. The results showed that their method could reliably classify sleep stages, achieving competitive accuracy rates. Their work suggests that, despite the rise of deep learning, shallow learning with expertly crafted features remains a viable approach for tasks like sleep stage classification.

2. **Shallow Learning Approaches to Sleep Stage Classification,** Giri et al.[2] introduced a methodology that extracted 28 features based on prior research, utilizing classifiers like Naive Bayes, k-NN, Neural Network, SVM, and classification trees. They focused on features such as relative power in different frequency bands (delta, theta, alpha, beta, and gamma), spectral mean, and kurtosis. By employing k-fold cross-validation (5-fold), they evaluated the performance of each classifier. Their study demonstrated that shallow learning techniques, which involve manually engineered features, are effective for sleep stage classification. They used an 80-20 split for training and testing in their experiments, ensuring robust evaluation of their models. The findings emphasized that even simple classifiers could achieve high accuracy when coupled with relevant features. This study reinforced the potential of shallow learning methodologies in providing interpretable and effective solutions for sleep stage classification.

3. **Comparison of Feature Extraction and Classification Algorithms for Sleep Stage Classification,** Aboalayon et al.[3] conducted a comparative study on various feature extraction and classification algorithms for ASSC using a single EEG signal. They focused on time domain, frequency domain, and non-linear features. The classifiers evaluated included Random Forests (RF) and Support Vector Machines (SVM). Their study highlighted that RF models trained on linear spectral features from a frontal EEG channel achieved the best results. This research emphasized the importance of feature selection in improving classification performance. They demonstrated that even with a single EEG channel, significant insights could be gained through careful feature engineering and selection. The study's results indicated that Random Forests, with their ability to handle a large number of features and their robustness against overfitting, were particularly effective for this task.

4. **A Two-Part System for Enhanced Sleep Stage Classification,** Sousa et al.[4] introduced a two-part system designed to improve the accuracy of sleep stage classification. Their system generated two types of outputs: epochs with high confidence of accurate classification and epochs with a high likelihood of misclassification. Dubious classification epochs were identified and corrected using a post-processing algorithm. This post-processing step involved heuristic rules

and expert validation to refine the initial automatic classifications. The system utilized electroencephalographic (EEG) and electrooculographic (EOG) channels to categorize five sleep stages: Wake, NREM sleep (N1, N2, N3), and REM sleep. Their approach aimed to offer a versatile solution applicable to patients with various sleep disorders. The results showed promising accuracy for wake and REM stages, though challenges remained in handling limited training data for certain stages and variations among sleep disorders. This study highlighted the potential benefits of combining automatic classification with expert validation to enhance the reliability of sleep stage scoring.

5. **Deep Convolutional Neural Networks for Sleep Stage Classification,** Sokolovsky et al.[5] explored the use of deep Convolutional Neural Networks (CNN) for sleep stage classification using multi-channel polysomnography (PSG) data, focusing on EEG and EOG signals. Their proposed CNN achieved an 81% classification accuracy, significantly outperforming previous single-channel models. The study involved training the CNN on a large dataset, allowing the model to learn complex patterns associated with different sleep stages. The authors compared their CNN with a more complex CNN-LSTM hybrid model and found that their simpler CNN was more efficient while maintaining high accuracy. This research demonstrated the potential of deep learning to improve sleep stage classification by leveraging multi-channel data and advanced neural network architectures. The study also highlighted the importance of sufficient training data and the potential limitations posed by the scarcity of certain sleep stages' epochs.

6. **DeepSleepNet: A Model for Automatic Sleep Stage Scoring,** Supratak et al.[6] developed DeepSleepNet, a deep learning model designed for automated sleep stage scoring using raw single-channel EEG. The model employs Convolutional Neural Networks (CNNs) to extract invariant features from the EEG signals and bidirectional Long Short-Term Memory Networks (LSTMs) to capture the transitions between sleep stages. DeepSleepNet addresses class imbalance issues and encodes temporal information through a two-step training approach. The model adapts to different EEG datasets and properties while capturing features consistent with the American Academy of Sleep Medicine (AASM) manual. This automated feature learning approach allows DeepSleepNet to generalize across

various datasets, making it a strong candidate for remote sleep monitoring. The study's results demonstrated that DeepSleepNet achieved high accuracy and robustness, outperforming traditional hand-engineered methods.

7. **An Automatic Sleep Staging System Using Single-Channel EEG** Zhou et al.[7, **?**] focused on automating sleep stage classification using a single-channel EEG signal. They developed a two-layer stacked ensemble model combining Random Forest (RF) and LightGBM (LGB) algorithms. This approach aimed to reduce model variance and address bias, respectively. The study introduced a class balance strategy to improve the recognition of the N1 stage, which is often underrepresented in datasets. The system's performance was evaluated on the Sleep-EDF and Sleep-EDF Expanded databases, showing competitive accuracy and recognition rates. The results indicated that their model could robustly classify sleep stages, particularly improving the identification of the challenging N1 stage. This study demonstrated the feasibility of using single-channel EEG for practical sleep monitoring applications, reducing the complexity and intrusiveness of traditional multi-channel PSG setups.

8. **XSleepNet: Multi-View Sequential Model for Automatic Sleep Staging,** Phan et al.[8] introduced XSleepNet, a multi-view sequential model for automatic sleep staging that integrates various types of sleep-related data. This model combines multiple views, such as EEG, EOG, and EMG signals, to provide a comprehensive analysis of sleep stages. The sequential aspect of the model captures temporal dependencies in sleep data, which are critical for accurate classification. XSleepNet employs advanced machine learning techniques, including deep learning and sequence modeling, to achieve high accuracy in sleep stage classification. The model was rigorously evaluated across five different databases, demonstrating its robustness and generalizability. The study's results indicated that XSleepNet outperformed existing methods, providing a new benchmark for sleep staging performance. This research highlighted the importance of multi-view frameworks in enhancing the accuracy and reliability of sleep stage classification.

9. **SleePyCo: Automatic Sleep Scoring with Feature Pyramid and Contrastive Learning,** Lee et al.[9] presented SleePyCo, a model that combines feature pyra-

mid networks and contrastive learning for automatic sleep scoring. The feature pyramid structure captures information at various scales, which is crucial for accurately distinguishing between different sleep stages. Contrastive learning helps the model learn discriminative features by simultaneously reducing intra-class feature distances and maximizing inter-class feature distances. This innovative approach addresses some of the key limitations of previous machine learning methods, such as the need for large amounts of labeled data and the challenge of generalizing across different patient populations. The study's results demonstrated that SleePyCo could significantly improve sleep stage classification accuracy, particularly in distinguishing between N1 and REM stages. This research contributes to the advancement of automated sleep staging by providing a robust and adaptable methodology.

10. **A Comprehensive Approach to EEG-Based Sleep Stage Classification,** Sen et al.[10] proposed a comprehensive method for EEG-based sleep stage classification, involving feature extraction, selection, and classification. The feature extraction phase employed 20 attribute algorithms across four categories, yielding 41 feature parameters. Feature selection was critical in enhancing prediction accuracy and reducing computational load by eliminating irrelevant and redundant features. The study used various practical feature selection algorithms, including mRMR, FCBF, ReliefF, t-test, and Fisher score, to identify the most representative features. These selected features were then input into different classification algorithms, such as Random Forests, Feedforward Neural Networks, Decision Trees, SVM, and Radial Basis Function networks. The results demonstrated high classification accuracy, underscoring the importance of effective feature selection and the potential of combining multiple algorithms for sleep stage classification. This study provides a solid foundation for developing intelligent sleep scoring systems.

CHAPTER 3

Methodology

3.1 Physionet 2018 Challenge Dataset

The dataset used in this project, titled 'You Snooze, You Win: the PhysioNet/Computing in Cardiology Challenge 2018,' is a rich source of polysomnography (PSG) recordings aimed at advancing sleep stage classification techniques. This challenge dataset comprises a total of 1983 PSG recordings collected from the Massachusetts General Hospital's (MGH) Sleep Lab in the Sleep Division, in collaboration with the Computational Clinical Neurophysiology Laboratory and the Clinical Data Animation Center.

The recordings were conducted following the standards set by the American Association of Sleep Medicine (AASM). The dataset includes thirteen distinct signals:

- Electroencephalography (EEG): Six channels recorded at F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, and O2-M1 positions based on the International 10/20 System.
- Electrooculography (EOG): Measured on the left side.
- Electromyography (EMG): Recorded at the chin.
- Respiration: Two channels capturing signals from the abdomen and chest.
- Airflow and Oxygen Saturation (SaO2): Measured for assessing breathing and oxygen levels during sleep.
- Electrocardiogram (ECG): Recorded below the right clavicle near the sternum.

All signals, except the SaO2, were recorded with a sampling frequency of 200Hz. To ensure synchronization, the SaO2 was upsampled to 200Hz using a sample-and-hold method. This comprehensive set of signals, measured in microvolts, provides detailed physiological data essential for accurate sleep stage classification.

The dataset was annotated by seven different scorers, with each PSG recording being scored by a single scorer. The EEG signals were segmented into non-overlapping 30-second epochs and annotated according to AASM standards into one of the following five sleep stages:

1. Wake (W)
2. Rapid Eye Movement (REM)
3. Non-REM Stage 1 (N1)
4. Non-REM Stage 2 (N2)
5. Non-REM Stage 3 (N3)

Originally, the PhysioNet 2018 Challenge was published to classify arousal regions accurately. However, this project focuses on utilizing the detailed annotations provided for sleep stages to enhance the accuracy of sleep stage classification models. The aim is to leverage the high-quality PSG data to train and evaluate machine learning models that can reliably classify sleep stages, thereby contributing to the broader field of sleep research and improving diagnostic tools for sleep disorders.

The availability of such a comprehensive and well-annotated dataset allows for the application of various machine learning techniques, including traditional machine learning classifiers and deep learning models. The detailed signal data facilitates the extraction of relevant features necessary for accurate classification. Moreover, the high sampling rate ensures that subtle changes in physiological signals can be captured, which is critical for distinguishing between different sleep stages.

By focusing on this dataset, the project aims to push the boundaries of current sleep stage classification techniques, offering insights into both the efficacy of different machine learning approaches and the practical applications of these models in clinical settings.

3.2 Feature Extraction

In this project, the feature extraction process from polysomnography (PSG) data is a comprehensive and meticulous task, designed to ensure the data is prepared adequately for machine learning models aimed at sleep stage classification.

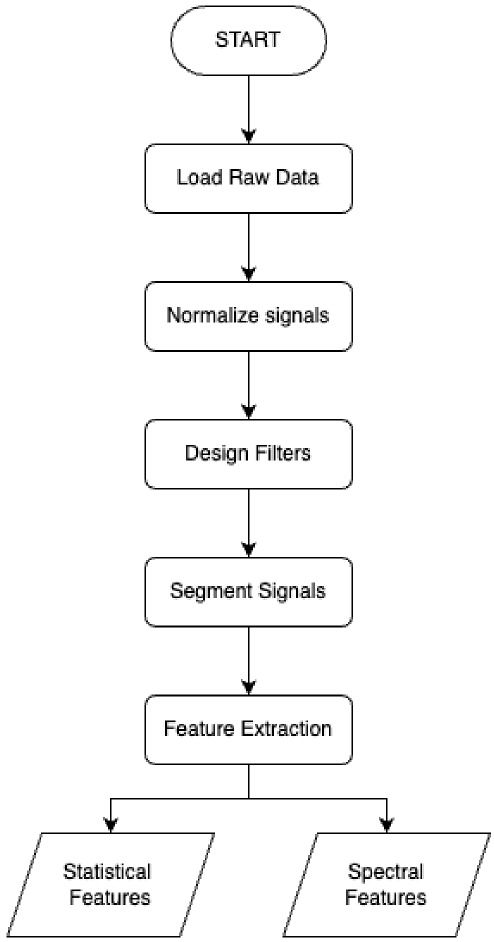

Figure 3.1: Feature Extraction

1. **Loading Data** The process begins with the load data function, which is designed to handle .mat files and extract necessary signals from specified channels. This function reads the file, extracts the data array, and selects specific channels based on the number of channels present. It then transposes the signals to align them properly for feature extraction. This careful handling ensures that all relevant physiological signals like EEG, EOG, and EMG are correctly oriented and prepared for subsequent processing.

2. **Importing Labels** The get labels function imports sleep stage labels associated

with each PSG recording. These labels, derived from expert annotations, are critical as they provide the target outcomes for supervised machine learning models. The extract window labels function further processes these labels to match the 30 second epochs of the PSG data, ensuring each segment of data is accurately labeled for model training.

3. **Filtering and Normalization** Given the presence of noise and artifacts in PSG signals, the normalize signals function is used to standardize the data. This function normalizes each signal to have zero mean and unit standard deviation, which is essential to reduce variability and ensure consistent signal quality across different recordings. The check standard deviations function checks the standard deviations of the signals to ensure they are above a minimal threshold, thus validating the quality of the data before further processing.

4. **Statistical Features:** The extract stat features function focuses on extracting statistical parameters such as interquartile range (IQR), skewness, kurtosis, and standard deviation. These features provide a quantitative overview of the distribution and variability of the physiological signals, offering valuable insights into different sleep stages.

5. **Spectral Features:** The frequency domain transform function employs Welch's method to compute the power spectral density (PSD) across various frequency bands (delta, theta, alpha, sigma, beta). These frequency bands are crucial in sleep science as they correlate with different sleep stages. This function also normalizes the PSD and handles outliers to ensure the reliability of the spectral features extracted.

3.3 Feature Reduction Using PCA

In this project, Principal Component Analysis (PCA) is used for feature reduction to manage the high-dimensional data extracted from PSG recordings.

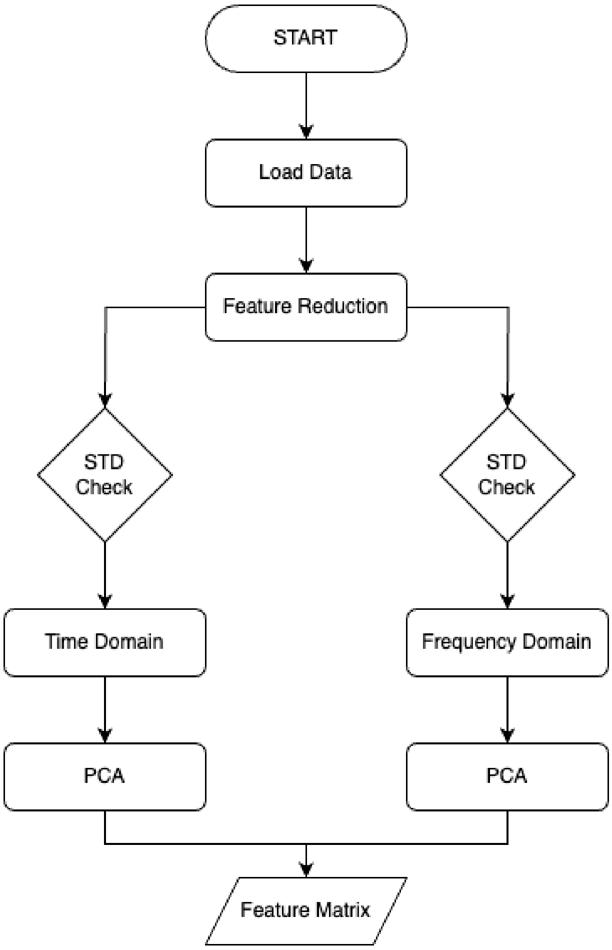

Figure 3.2: Feature Reduction

3.3.1 PCA Time Domain

1. The 'time domain transform' function is designed to process and normalize time-domain signals, segmenting them into windows suitable for further analysis. This function begins by iterating through each channel of the input data, which is assumed to be a two-dimensional array with samples along one dimension and channels along the other. For each channel, it first eliminates extreme outliers by setting values greater than ten times the standard deviation of the channel to zero. This step helps mitigate the influence of unusually high values that could skew the analysis.

2. Next, the function normalizes the data for each channel using the 'normalize data time' function, which adjusts the data to have a zero mean and scales it appropriately. This normalization ensures that the data from different channels

are on a comparable scale, which is crucial for accurate analysis. The normalized data is then segmented into windows of a specified size using the 'reshape channel data' function. This segmentation divides the continuous time-series data into manageable chunks, making it easier to extract meaningful features from each window.

3. After processing all channels, the function concatenates the windowed data from each channel along the first axis to form a single two-dimensional array. This array, 'reshaped data', represents the transformed and segmented time-domain data for all channels. By normalizing and reshaping the data into windows, the 'time domain transform' function prepares the input signals for feature extraction and machine learning tasks, ensuring that the data is clean, consistent, and structured appropriately for subsequent analysis.

3.3.2 PCA Frequency Domain

1. The 'frequency domain transform' function is designed to convert time-domain signals into frequency-domain representations using the Welch method. This transformation is crucial for analyzing the frequency characteristics of physiological signals, which are important in sleep stage classification. The function begins by setting parameters for the Welch method, including the window size ('pwelch window'), overlap size ('pw overlap'), and the number of FFT points ('NFFT'). It also calculates the number of samples corresponding to 40 Hz ('sample 40Hz'), ensuring that the transformation captures the relevant frequency range.

2. The function processes each channel of the input data individually. For each channel, it reshapes the data into windows of the specified size using the 'reshape channel data' function. It then applies the Welch method to compute the power spectral density (PSD) of the windowed data. To handle zero values in the PSD, the function replaces them with the minimum non-zero value, ensuring that the logarithmic transformation does not result in undefined values.

3. The function further processes the PSD by eliminating outliers, normalizing the PSD values, and subtracting the mean to center the data. These steps are essential to enhance the robustness and consistency of the frequency-domain features. After

processing, the function concatenates the transformed data from all channels into a single array. This array, ‘data all win freq‘, represents the frequency-domain features for all channels, providing a comprehensive set of features for subsequent analysis and classification tasks.

3.3.3 Output and Storage

PCA scores and coefficients are stored in .mat files due to the large size of the datasets, which makes CSV files impractical. This structured storage allows for easy access and further analysis, ensuring that the reduced feature set is ready for machine learning model training.

3.4 Classification Models

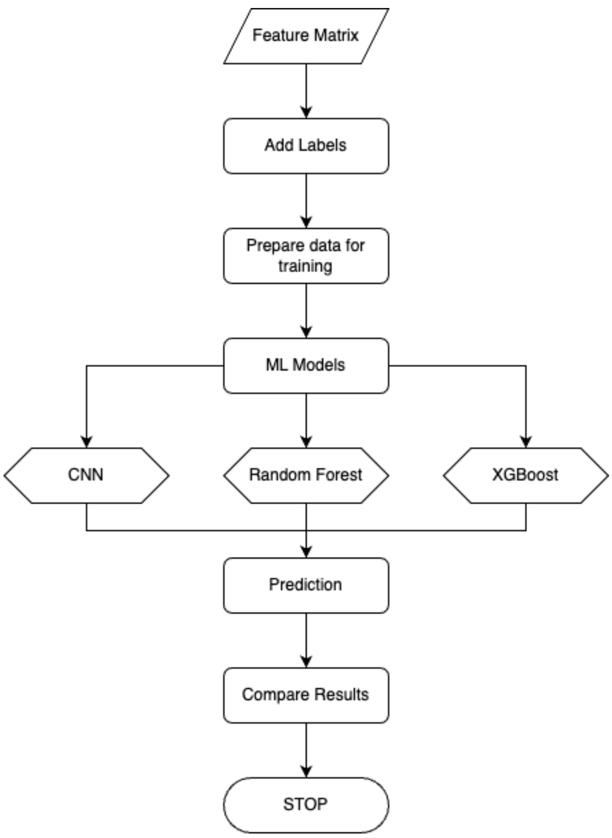

Figure 3.3: Classification models

3.4.1 Random Forest Classifier

The Random Forest classifier was selected due to its robustness and effectiveness in handling high-dimensional data, making it well-suited for the PCA-transformed data used in this study. Random Forest is an ensemble learning method that operates by constructing a multitude of decision trees during training and outputting the mode of the classes as the final prediction. This approach helps in reducing overfitting and provides a high level of accuracy, which is crucial for the complex task of sleep stage classification.

The significance of using Random Forest lies in its ability to handle large datasets with numerous variables without overfitting. It provides insights into the importance of different features for classification, helping understand the underlying patterns in the data. Additionally, its inherent ability to perform both classification and regression tasks makes it a versatile tool in various domains.

In the implementation, the Random Forest classifier is integrated into a pipeline that includes feature scaling using 'StandardScaler' to ensure all features contribute equally to the model's performance. Hyperparameter tuning is conducted through a grid search with cross-validation, ensuring the optimal combination of parameters such as the number of trees, depth of the trees, and minimum samples required for splitting and leaf nodes. The model is evaluated using a stratified K-Folds cross-validator, which helps in ensuring that each fold is representative of the overall data distribution. The final evaluation is performed on a test set, and the results are summarized in a classification report that provides a detailed performance assessment of the model.

3.4.2 XGBoost Classifier

XGBoost, or eXtreme Gradient Boosting, is chosen for its high performance and efficiency in handling large and complex datasets, such as those encountered in sleep stage classification. XGBoost is an implementation of gradient boosting algorithms designed to be highly efficient, flexible, and portable. It is known for its speed and accuracy, especially in scenarios where computational resources and time are critical constraints.

The key advantage of XGBoost is its ability to handle missing values and its robustness to overfitting, thanks to the regularization terms in its objective function. This makes it particularly suitable for datasets with many features and potential noise, as seen in the transformed polysomnography (PSG) data. XGBoost also allows for custom optimization objectives and evaluation metrics, offering flexibility in tuning the model to specific requirements.

In this study, XGBoost is applied through a pipeline that includes feature scaling to standardize the data. The labels are encoded to ensure compatibility with the model's requirements. The model undergoes hyperparameter tuning using a grid search over parameters such as the number of estimators, maximum tree depth, learning rate, subsample ratio, and column sampling ratio. This comprehensive tuning ensures that the model is optimized for the specific characteristics of the dataset. The model's performance is validated using stratified K-Folds cross-validation, and the final evaluation is conducted on a separate test set. The results, including precision, recall, and F1-score, are detailed in a classification report.

3.4.3 Convolutional Neural Network (CNN)

CNNs are particularly advantageous because they can effectively capture local dependencies and patterns within the time-series data of the polysomnography (PSG) recordings. CNNs are composed of multiple layers, including convolutional layers that apply filters to the input data, pooling layers that reduce dimensionality, and fully connected layers that perform the classification. The model used in this study includes several convolutional layers with filters of increasing size, each followed by batch normalization and dropout layers to prevent overfitting and improve generalization. The final layers are fully connected and output the classification results.

The significance of using a CNN in this study is its ability to learn complex patterns and features from the raw data, which might not be easily captured by traditional machine learning models. The CNN model is trained and evaluated using k-fold cross-validation to ensure robustness and generalizability. Each fold involves training the model on a subset of the data and testing it on a separate subset, with the results averaged across all folds. This approach ensures that the model's performance is not biased by any particular subset of the data. The results are then compiled into a comprehensive classification report, providing insights into the model's accuracy, precision, recall, and other performance metrics.

By employing these three diverse machine learning models, the study aims to leverage the strengths of each approach to achieve a comprehensive and accurate classification of sleep stages from PSG data. The combination of ensemble learning with Random Forest, gradient boosting with XGBoost, and deep learning with CNN provides a robust framework for tackling the complexities inherent in sleep stage classification.

3.5 The Complete Architecture

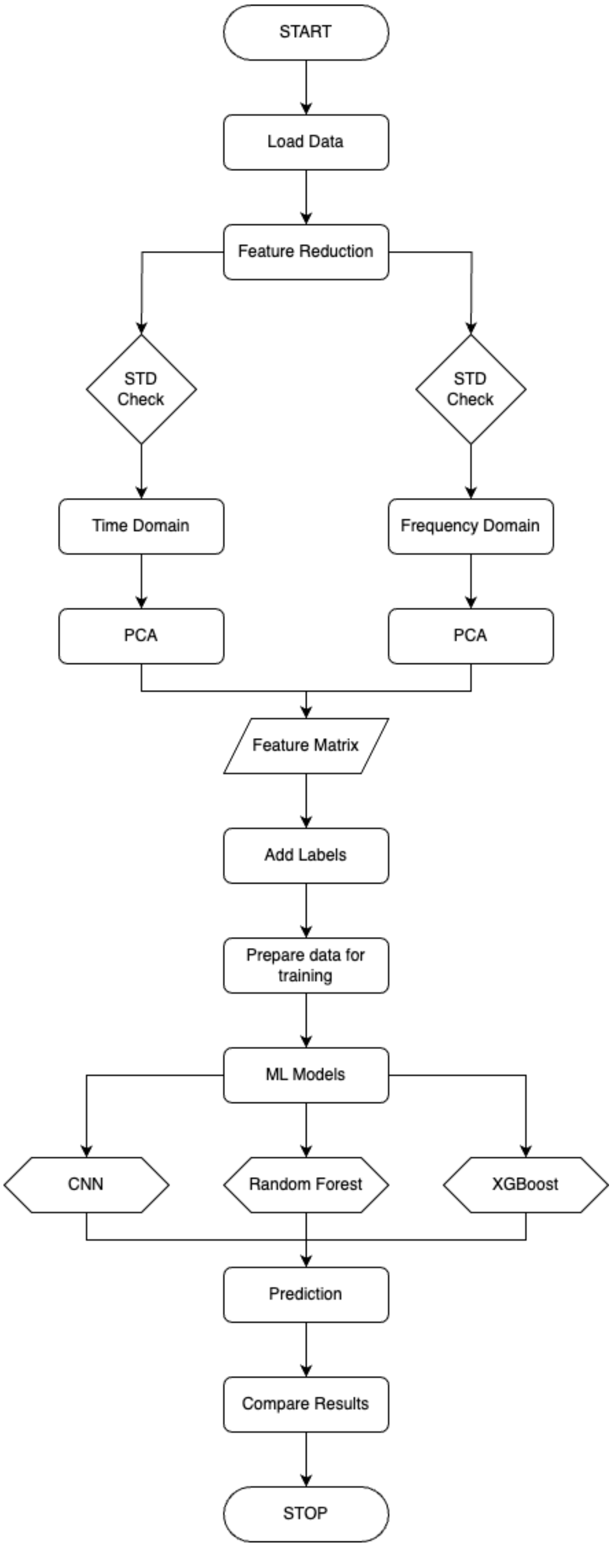

Figure 3.4: The Complete Architecture

Chapter 4

Results and Discussion

This section presents and discusses the results of training our machine learning models with two different datasets: PCA-transformed data with statistical features and PCA-transformed data without statistical features. We employed Random Forest and XGBoost classifiers to evaluate the performance across these datasets. The results are summarized below.

4.1 Random Forest Results

1. **Random Forest with PCA Data and Statistical Features**

   The performance of the Random Forest classifier trained on PCA data with additional statistical features showed a mixed outcome:

   - **Precision:** The precision values varied significantly across different sleep stages, with the highest precision for stage 6 (0.818) and the lowest for stage 2 (0.765).
   - **Recall:** The recall values were generally low, with stage 3 showing the highest recall (0.913) but others, like stage 2 and stage 4, showing extremely low recall.
   - **F1-score:** The f1-scores mirrored the precision and recall trends, with stage 3 having the highest f1-score (0.603) and stage 2 the lowest (0.002).
   - **Accuracy:** The overall accuracy was 0.451, indicating that the model correctly classified 45.13

The macro and weighted averages indicate a disparity in performance across classes, with macro average precision at 0.621 and recall at 0.233, highlighting significant variation in model performance across different sleep stages.

2. **Random Forest with PCA Data Without Statistical Features**

   The performance of the Random Forest classifier improved markedly when trained on PCA data without statistical features:

   - **Precision:** Higher precision was observed across most stages, with stage 6 showing the highest precision (0.980) and stage 2 the lowest (0.671).
   - **Recall:** The recall values improved, particularly for stage 1 (0.884) and stage 3 (0.938), though stage 6 still had a low recall (0.081).
   - **F1-score:** The f1-scores were higher, with stage 3 achieving the highest (0.792) and stage 2 the lowest (0.335).
   - **Accuracy:** The overall accuracy was 0.710, indicating that the model correctly classified 71.02

   The macro and weighted averages show a significant improvement, with macro average precision at 0.799 and recall at 0.546, reflecting a more balanced performance across all sleep stages.

4.2 XGBoost Results

1. **XGBoost with PCA Data and Statistical Features**

   The performance of the XGBoost classifier on PCA data with statistical features was relatively modest:

   - **Precision:** The precision values were generally low, with stage 1 having the highest precision (0.452) and stage 2 the lowest (0.329).
   - **Recall:** Recall was highest for stage 3 (0.905) but extremely low for stages 2 and 4.
   - **F1-score:** The f1-scores were also low, with stage 3 having the highest (0.603) and stage 2 the lowest (0.004).

- **Accuracy:** The overall accuracy was 0.452, similar to the Random Forest model with statistical features.

The macro and weighted averages indicate poor performance with macro average precision at 0.476 and recall at 0.236, showing the model's difficulty in effectively classifying all sleep stages.

2. **XGBoost with PCA Data Without Statistical Features**

   When trained on PCA data without statistical features, the XGBoost classifier exhibited substantial improvements:

   - **Precision:** Precision values were notably higher, with stage 1 having the highest precision (0.734) and stage 2 the lowest (0.633).
   - **Recall:** Recall values improved significantly, with stage 1 at 0.876 and stage 3 at 0.893.
   - **F1-score:** The f1-scores showed considerable enhancement, with stage 3 achieving the highest (0.850) and stage 2 the lowest (0.554).
   - **Accuracy:** The overall accuracy was 0.787, reflecting a strong performance with 78.70% correct classifications.

   The macro and weighted averages show a balanced performance with macro average precision at 0.790 and recall at 0.696, indicating the model's effectiveness across different sleep stages.

4.3 Discussion

The results demonstrate that both Random Forest and XGBoost classifiers perform better when trained on PCA-transformed data without statistical features. The inclusion of statistical features seems to introduce noise or complexity that hinders the models' ability to learn effectively. XGBoost, in particular, showed a significant improvement in both precision and recall across all stages when statistical features were excluded, suggesting that the simpler feature set allowed the model to generalize better and capture the essential patterns in the data.

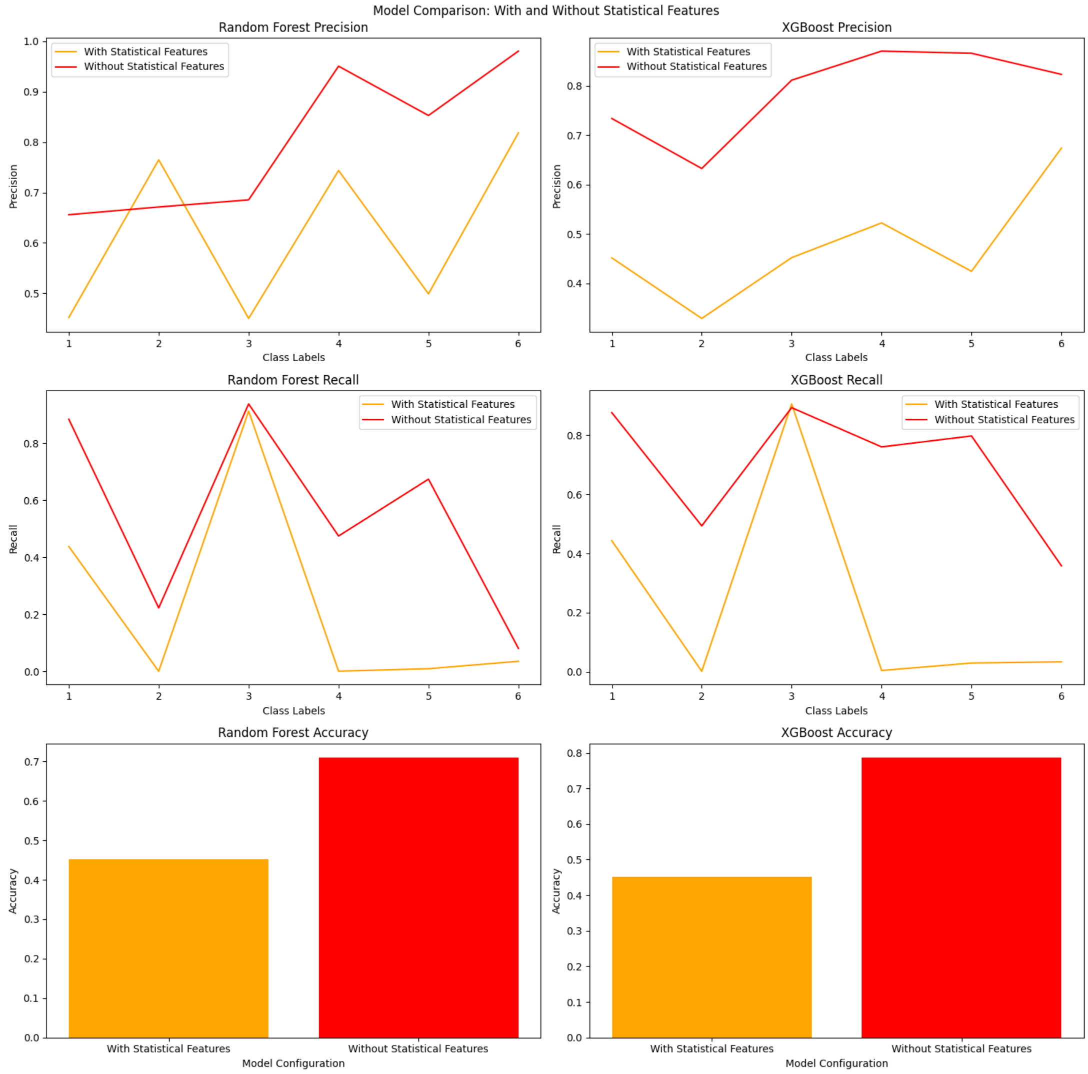

Figure 4.1: Comparisons

Random Forest also benefited from the exclusion of statistical features, though the improvement was not as pronounced as in XGBoost. This indicates that while Random Forest can handle high-dimensional data well, it might still struggle with the noise introduced by additional features.

Overall, the findings suggest that PCA-transformed data alone, without supplementary statistical features, provides a more robust and effective feature set for sleep stage classification. This insight is crucial for future studies and applications in sleep research, emphasizing the importance of feature selection and dimensionality reduction in enhancing model performance.

CHAPTER 5

Conclusion

In this project, we embarked on the challenging task of classifying sleep stages using polysomnography (PSG) data by leveraging machine learning models. Our approach focused on reducing the high dimensionality of the data through Principal Component Analysis (PCA) and evaluating the impact of including statistical features on model performance. The classifiers employed in this study included Random Forest and XGBoost, alongside a Convolutional Neural Network (CNN), each chosen for their unique strengths in handling complex datasets.

The results demonstrated a clear preference for PCA-transformed data without the inclusion of additional statistical features. Both Random Forest and XGBoost classifiers exhibited significant improvements in precision, recall, and overall accuracy when trained on this streamlined feature set. Specifically, XGBoost showed remarkable performance, achieving an accuracy of 78.70% when statistical features were excluded, underscoring its robustness in dealing with large, complex datasets.

A key insight from this study is the potential negative impact of extraneous statistical features, which may introduce noise and complicate the learning process for machine learning models. This finding underscores the importance of careful feature selection and dimensionality reduction in sleep stage classification tasks.

Moreover, the inclusion of spectral feature extraction should not be overlooked. Spectral features play a critical role in capturing the frequency characteristics of physiological signals, which are pivotal in accurately identifying sleep stages. Future research should delve deeper into spectral feature extraction techniques, as these can enhance the granularity and accuracy of the classification models. By integrating advanced spectral analysis methods, it is possible to achieve a more nuanced understanding of the underlying sleep patterns, leading to improved classification performance.

In conclusion, this project highlights the efficacy of PCA in simplifying complex sleep data and the superior performance of models trained on PCA-transformed data without statistical features. The insights gained here pave the way for future studies to refine feature selection processes further and integrate spectral feature extraction to boost model accuracy. These advancements will significantly contribute to the field of sleep research, providing more accurate and reliable tools for diagnosing and understanding sleep disorders.

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