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TITLE

Multiparametric Study of Physiological Signals for the Recognition of Sleep Disorders

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DEDICACE

بسم الله الرحمن الرحيم

الله هو الذي سخر لي كل النعم ويسر لي السبل، فله الحمد والشكر على كل عطاياه.

قال تعالى: وَقُلْ رَبِ زِدْنِي عِلْمًا (طه: ١١٤)

À mes chers parents, vous êtes ceux qui ont peiné, veillé et sacrifié pour que j'atteigne ce que je suis aujourd'hui. Votre amour et votre soutien ont été la lumière qui a illuminé mon parcours. Vous êtes l'incarnation de l'amour véritable et du respect infini, le pilier inébranlable dans chaque étape de ma vie.

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الملخص

تتناول هذه الأطروحة دراسة متعددة المعايير للإشارات الفسيولوجية بهدف التعرف على اضطرابات النوم، والتي تُعتبر مشكلة صحية شائعة ذات تأثيرات خطيرة على جودة الحياة والصحة العامة. تشمل هذه الدراسة تحليلًا معمقًا لديناميكيات النوم، تصنيف مراحله، والاضطرابات المرتبطة به باستخدام تقنيات حديثة في معالجة الإشارات الحيوية والذكاء الاصطناعي.

يبدأ البحث باستعراض الجوانب الطبية للنوم، متناولًا تعريفه، مراحله المختلفة، وأهم الاضطرابات المرتبطة به مثل الأرق، وانقطاع التنفس أثناء النوم، واضطرابات الحركة خلال النوم. كما يُركز البحث على دور تخطيط النوم في تقييم هذه الاضطرابات من خلال تحليل إشارات تخطيط الدماغ الكهربائي، وتخطيط القلب الكهربائي، وتخطيط حركة العين، وتخطيط العضلات.

تعتمد الدراسة على نهج متعدد الإشارات لتصنيف مراحل النوم بدقة، حيث يتم استخدام تقنيات الذكاء الاصطناعي المتقدمة مثل خوارزمية الجار الأقرب، والتحليل الموجي لاستخراج الخصائص الحيوية المهمة. كما يتم تحسين دقة التصنيف من خلال اختيار الميزات المثلى باستخدام الشبكات العصبية العميقة، وتعزيز أداء النماذج باستخدام تقنيات مثل إضافة الضوضاء العشوائية.

أظهرت النتائج أن الجمع بين الإشارات الفسيولوجية المختلفة وتحليلها المتعدد المستويات يعزز بشكل كبير دقة تصنيف مراحل النوم واكتشاف الاضطرابات المرتبطة به. يُعتبر هذا النهج خطوة واعدة نحو تطوير أدوات تشخيصية ذكية، أقل تكلفة وأكثر كفاءة، مما يسهم في تحسين تشخيص وعلاج اضطرابات النوم

الكلمات اللمفتاحية : اضطرابات النوم، تخطيط النوم، تخطيط الدماغ الكهربائي، تخطيط القلب الكهربائي، تخطيط حركة العين، تخطيط العضلات، الذكاء الاصطناعي، تصنيف مراحل النوم، معالجة الإشارات الحيوية.

ABSTRACT

This dissertation presents a multiparametric study of physiological signals for the recognition of sleep disorders, which are common health issues with severe impacts on quality of life and public health. This study involves an in-depth analysis of sleep dynamics, classification of its stages, and associated disorders using advanced techniques in biosignal processing and machine learning.

The research begins by examining the medical context of sleep, including its definition, different stages, and major related disorders such as insomnia, sleep apnea, and movement disorders during sleep. The study also focuses on the role of polysomnography (PSG) in evaluating these disorders through the analysis of electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), and electromyography (EMG) signals.

This study adopts a multi-signal approach for accurate sleep stage classification, utilizing advanced machine learning techniques such as the K-Nearest Neighbors (KNN) algorithm and wavelet functions for feature extraction. Classification accuracy is further improved by selecting optimal features using deep learning networks and enhancing model performance through techniques such as Gaussian noise augmentation.

The results show that integrating multiple physiological signals and analyzing them at different levels significantly enhances sleep stage classification accuracy and the detection of associated disorders. This approach represents a promising step toward developing intelligent, cost-effective, and highly efficient diagnostic tools, contributing to improved diagnosis and treatment of sleep disorders.

Keywords: Sleep disorders, polysomnography (PSG), electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), electromyography (EMG), machine learning, automatic sleep stage classification.

RÉSUMÉ

Cette thèse présente une étude multiparamétrique des signaux physiologiques pour la reconnaissance des troubles du sommeil, un problème de santé courant ayant des répercussions graves sur la qualité de vie et la santé publique. Cette étude comprend une analyse approfondie de la dynamique du sommeil, la classification de ses différentes phases, ainsi que l'identification des troubles associés, en utilisant des techniques avancées de traitement des signaux biologiques et d'apprentissage automatique.

La recherche commence par une exploration du contexte médical du sommeil, en abordant sa définition, ses différents stades, ainsi que les principaux troubles qui y sont associés, tels que l'insomnie, l'apnée du sommeil et les troubles moteurs nocturnes. L'étude met également l'accent sur le rôle de la polysomnographie (PSG) dans l'évaluation de ces troubles, à travers l'analyse des signaux électroencéphalographiques (EEG), électrocardiographiques (ECG), électro-oculographiques (EOG) et électromyographiques (EMG).

Cette étude adopte une approche multisignal pour une classification précise des stades du sommeil, en exploitant des techniques avancées d'apprentissage automatique, telles que l'algorithme des plus proches voisins (KNN) et les fonctions ondulatoires pour l'extraction des caractéristiques. La précision de la classification est ensuite améliorée grâce à une sélection optimale des caractéristiques à l'aide des réseaux de neurones profonds et à l'amélioration des performances des modèles par des techniques telles que l'ajout de bruit gaussien.

Les résultats montrent que l'intégration de plusieurs signaux physiologiques et leur analyse à différents niveaux améliorent considérablement la précision de la classification des stades du sommeil et la détection des troubles associés. Cette approche représente une avancée prometteuse vers le développement d'outils de diagnostic intelligents, moins coûteux et plus efficaces, contribuant ainsi à l'amélioration du diagnostic et du traitement des troubles du sommeil.

Mots clés: Troubles du sommeil, polysomnographie (PSG), électroencéphalographie (EEG), électrocardiographie (ECG), électro-oculographie (EOG), électromyographie (EMG), apprentissage automatique, classification automatique des stades du sommeil.

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ACRONYMS

AASM American Academy of Sleep Medicine

CAP Cyclic Alternating Pattern

CNN Convolutional Neural Network

DL Deep Learning

DT Decision Tree

DWT Discret Wavelet Transform

ECG Electrocardiogram

EEG Electroencephalogram

EMG Electromyogram

EOG Electrooculogram

KNN K-Nearest Neighbors

Physionet Publicly available database for sleep-related data

PSG Polysomnography

R&K Rechtschaffen and Kales

SVM Support Vector Machine

GENERAL INTRODUCTION

General Introduction: Sleep plays a vital role in maintaining physical and cognitive well-being. It is a complex physiological state governed by intricate interactions between neurological, cardiovascular, and muscular systems. The recognition and classification of sleep stages are crucial for diagnosing sleep disorders, optimizing treatment strategies, and understanding the intricate mechanisms governing sleep-related processes. Over the years, advancements in biomedical signal processing and machine learning have significantly improved the accuracy of sleep analysis, particularly through the use of electrophysiological signals such as electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), and electromyography (EMG). This thesis focuses on a multiparametric study of physiological signals for the automatic recognition of sleep disorders, providing a comprehensive framework for sleep stage classification and disorder detection.

Research Context and Justification: Sleep disorders, including insomnia, sleep apnea, restless leg syndrome, and narcolepsy, affect millions worldwide, impacting health, productivity, and quality of life.

Traditional diagnostic methods rely on polysomnography (PSG), a gold standard technique involving overnight monitoring of multiple physiological parameters in sleep laboratories. However, PSG is expensive, time-consuming, and often inconvenient for patients. The increasing prevalence of sleep-related disorders necessitates the development of automated, efficient, and accessible diagnostic tools.

Recent research has demonstrated that machine learning and deep learning models can significantly enhance sleep classification accuracy, reducing reliance on manual sleep scoring performed by clinicians. By leveraging EEG, ECG, EOG, and EMG signals, researchers have developed algorithms capable of recognizing sleep stages and detecting abnormalities with high precision.

This study builds upon existing methodologies by integrating multiple physiological signals and advanced feature extraction techniques to improve sleep stage classification and disorder

recognition. The ultimate goal is to develop a robust, automated system for sleep analysis that enhances clinical decision-making and facilitates early diagnosis of sleep disorders.

Objectives of the Study: The primary objective of this thesis is to develop a multiparametric framework for sleep stage classification and sleep disorder detection using physiological signals. Specifically, the study aims to:

- Investigate the role of different physiological signals (EEG, ECG, EOG, and EMG) in sleep stage classification.
- Develop feature extraction techniques to enhance the representation of sleep-related characteristics from these signals.
- Implement and compare various machine learning algorithms for sleep stage classification, including K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and deep learning models.
- Evaluate the impact of combining multiple physiological signals on classification accuracy and robustness.
- Propose an optimized model for automated sleep staging that can serve as a foundation for future real-time and wearable sleep monitoring solutions.

Research Questions and Hypotheses: To achieve these objectives, the study seeks to answer the following research questions:

- How effectively can EEG, ECG, EOG, and EMG signals be utilized for automated sleep stage classification?
- What are the optimal feature extraction methods for enhancing the classification accuracy of sleep stages?
- How does the combination of multiple physiological signals improve sleep stage differentiation compared to single-signal approaches?
- What are the limitations of current machine learning models in sleep stage classification, and how can they be addressed?
- Can an optimized model be developed to facilitate real-time, wearable-based sleep monitoring solutions?

Based on these questions, the study hypothesizes that:

- The combination of EEG, ECG, EOG, and EMG signals will yield higher classification accuracy than individual signal-based models.

- Advanced feature extraction techniques, such as wavelet transforms and deep learning-based feature selection, will enhance classification performance.
- Machine learning models, particularly ensemble methods and deep learning architectures, will outperform traditional classifiers in sleep stage recognition.
- The integration of multiparametric signals will improve the differentiation of light sleep stages, reducing misclassification errors commonly observed in previous studies.

Contributions of the Thesis: This thesis presents several key contributions to the field of sleep research and biomedical signal processing:

- Development of an innovative multiparametric sleep classification framework integrating EEG, ECG, EOG, and EMG signals.
- Proposal of novel feature extraction techniques tailored for sleep stage recognition, leveraging both time-frequency and statistical signal characteristics.
- Comparative analysis of different machine learning classifiers, highlighting the effectiveness of KNN, SVM, and deep learning models.
- Demonstration of the advantages of multi-signal fusion in improving classification robustness, particularly for complex sleep stages such as REM sleep.
- Recommendations for future development of wearable and real-time sleep monitoring systems based on the proposed classification methodologies.

Structure of the Thesis: This thesis is structured as follows:

- **Chapter 1: Medical Context of Sleep** – This chapter provides an overview of sleep physiology, including the definition of sleep, sleep stages, and common sleep disorders. It also introduces polysomnography (PSG) and its role in clinical sleep diagnosis.
- **Chapter 2: Related Work** – This chapter reviews previous research on sleep stage classification, focusing on different physiological signals and machine learning methodologies.
- **Chapter 3: Sleep Stage Detection Using EEG and ECG Signals** – This chapter presents the methodologies and results of sleep stage classification using EEG and ECG signals. It discusses feature extraction techniques, machine learning models, and evaluation metrics.

- **Chapter 4: Sleep Stage Detection Using Combined Physiological Signals** – This chapter explores the integration of multiple signals (EEG, ECG, EOG, EMG) for enhanced classification accuracy. It evaluates the impact of deep learning-based feature selection and noise augmentation techniques.
- **Chapter 5: Conclusion and Perspectives** – The final chapter summarizes the key findings of the study, highlights its contributions, and outlines potential future research directions, including real-time applications and wearable technologies.

Through this comprehensive study, the thesis aims to advance the field of sleep research by providing an automated, accurate, and clinically relevant framework for sleep disorder diagnosis.

CHAPTER 1

MEDICAL CONTEXT OF SLEEP

1.1 Introduction

Sleep is a critical physiological process that supports overall health, cognitive function, and bodily restoration. emotional stability, immune defence, and metabolic regulation. Despite its importance, sleep is often neglected in contemporary lifestyles, contributing to a rising prevalence of sleep disorders[1]. These disorders, ranging from insomnia and sleep apnea to parasomnias and hypersomnia, can severely impact an individual's quality of life. A thorough understanding of sleep physiology, its regulation, associated disorders, and available diagnostic tools is crucial for advancing public health and clinical interventions.

This chapter provides an in-depth examination of sleep mechanisms, including their physiological processes, classification of sleep disorders, and the significance of diagnostic techniques such as polysomnography in assessing and managing sleep-related conditions. Given that sleep is fundamental to overall health, cognitive performance, and homeostasis, disturbances in its structure or quality can contribute to various complications, including cardiovascular diseases, mental health disorders, and cognitive impairments. By exploring the regulation of sleep, its stages, and modern approaches to sleep monitoring and analysis[2], this chapter aims to highlight the crucial role of sleep research in improving clinical outcomes and public health strategies.

1.2 Definition of Sleep

Sleep is a fundamental biological process essential for human survival, profoundly affecting physical health, cognitive function, and emotional well-being. Extensive research has demonstrated that high-quality sleep is associated with enhanced overall health, improved cognitive performance, and greater physiological resilience[3].

Sleep is a complex, highly regulated process that influences multiple key physiological systems, as illustrated in Figure 1.

Key Functions of Sleep:

Metabolic Regulation and Energy Balance: Sleep plays a fundamental role in maintaining metabolic stability and energy homeostasis. It regulates the secretion of key hormones such as leptin, which signals satiety, and ghrelin, which stimulates hunger. Disruptions in sleep patterns can lead to hormonal imbalances, resulting in increased appetite, food cravings, and a heightened risk of obesity and metabolic disorders.

Cognitive Function and Memory Processing:

Sleep plays a crucial role in neurocognitive functions such as memory consolidation, learning, and executive processing. During key sleep stages, particularly slow-wave sleep (SWS) and rapid eye movement (REM), the brain strengthens and reorganizes synaptic connections, improving problem-solving abilities and decision-making skills. Chronic sleep deprivation can lead to attention deficits, reduced cognitive flexibility, and diminished mental performance.

Immune System Support: Sleep plays a crucial role in modulating immune responses, strengthening the body's ability to resist infections and recover from illnesses. Slow-wave sleep (NREM stage 3) enhances cytokine production, essential for immune regulation, inflammation control, and tissue repair. Conversely, chronic sleep deprivation weakens immune defences, increasing susceptibility to infections and delaying recovery.

Emotional Stability and Mental Health: Sleep is closely linked to emotional regulation and psychological resilience. Insufficient sleep contributes to mood disorders, including anxiety and depression, by impairing the brain's ability to process emotions and manage stress. Restorative sleep is essential for maintaining mental well-being, reducing emotional volatility, and enhancing the ability to cope with daily challenges.

Cardiovascular and Metabolic Health: Adequate sleep is vital for cardiovascular function and metabolic homeostasis. During deep sleep, the autonomic nervous system regulates blood pressure, heart rate, and vascular tone, promoting cardiovascular recovery and stability. Chronic sleep deprivation is associated with increased risks of hypertension, endothelial dysfunction, systemic inflammation, and a higher incidence of cardiovascular diseases such as heart disease and stroke[4].

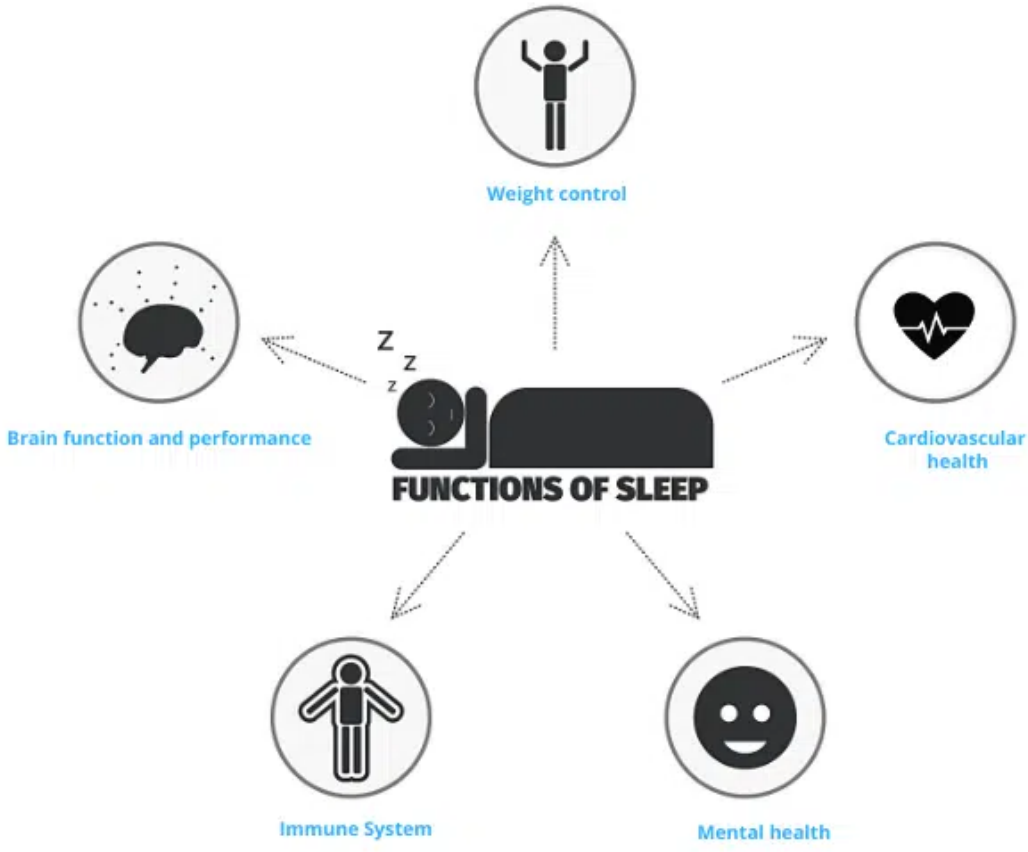

Figure 1.1: Functions of Sleep

1.3 Sleep Stages

Sleep is a complex and essential biological process that plays a critical role in maintaining physical health, cognitive function, and emotional regulation. Distinct stages characterize it, each exhibiting specific patterns of brain activity, physiological responses, and restorative functions. Sleep cycles alternate between two primary categories: Non-Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep, which recur cyclically throughout the night. The classification of these sleep stages has evolved, with the Rechtschaffen and Kales (R&K) criteria and the American Academy of Sleep Medicine (AASM) guidelines being the most widely recognized frameworks. While both systems have contributed to sleep research, the AASM classification has become the standard in contemporary sleep medicine and clinical practice [5].

The Rechtschaffen and Kales (R&K) Sleep Classification System The R&K system, developed in 1968,[6] categorizes sleep into four distinct stages: Stage 1 (N1), Stage 2 (N2), Stage 3 (N3), and REM sleep.

Stage 1 (N1): This is the lightest sleep stage, marking the transition from wakefulness

to sleep. It is characterized by slow eye movements, reduced muscle activity, and decreased responsiveness to external stimuli. This phase is brief, typically lasting only a few minutes. Stage 2 (N2): This stage represents deeper sleep and is identified by the presence of sleep spindles (bursts of high-frequency brain activity) and K-complexes (sharp waveforms that help maintain sleep stability and filter external disturbances). Stage 2 accounts for a significant portion of total sleep time. Stage 3 (N3): Also known as slow-wave sleep (SWS) or deep sleep, this stage is dominated by delta waves, the slowest and highest-amplitude brain waves. This phase is crucial for physical recovery, immune function, and the secretion of Growth hormones, which play a vital role in cellular repair and metabolic regulation. REM Sleep: is characterized by rapid eye movements, vivid dreaming, and near-complete muscle atonia, preventing physical movement during dreams. REM sleep is essential for memory consolidation, emotional regulation, and neural plasticity. The American Academy of Sleep Medicine (AASM) Sleep Classification System The AASM sleep staging system, introduced in 2007, refined the R&K classification by simplifying NREM sleep into three distinct stages (N1, N2, and N3) instead of four. In this system, Stage 3 (N3) combines the former Stages 3 and 4 of the R&K system, creating a more precise and standardized framework for sleep assessment [7].

Stage N1 (N1): The lightest sleep stage, transitioning from wakefulness to sleep. Stage N2 (N2): The most predominant sleep stage in adults, accounting for 45-55% of total sleep time, is characterized by sleep spindles and K-complexes that play a role in sensory processing and maintenance. Stage N3 (N3): Deep sleep (formerly Stages 3 and 4 in the R&K system), where slow-wave activity (delta waves) dominates. This stage is critical for physiological restoration, immune system modulation, and metabolic homeostasis. REM Sleep: Similar to the R&K system, REM sleep in the AASM framework is distinguished by high-frequency brain activity, vivid dreams, and muscle paralysis, which serve key functions in memory consolidation, learning, and emotional processing.

Comparison and Significance of Sleep Staging Systems: The R&K and AASM classification systems have significantly contributed to the scientific understanding of sleep architecture. The AASM system has become the gold standard in clinical settings, offering a more precise and standardized approach to sleep evaluation. It is widely used in diagnosing sleep disorders, research, and therapeutic interventions. Meanwhile, the R&K system remains an important historical reference that laid the foundation for modern sleep medicine.

By advancing the understanding of NREM and REM sleep dynamics, these classification systems have provided valuable insights into the role of sleep in physical health, cognitive performance, and emotional well-being. Ongoing research continues to refine sleep staging methodologies, integrating advanced neurophysiological techniques to enhance sleep disor-

der diagnostics and treatment strategies further Sleep-related movement disorders include periodic limb movements (PLM) and restless legs syndrome (RLS), which interfere with sleep continuity. Periodic Limb Movements (PLM): Characterized by involuntary, repetitive movements of the lower limbs during NREM sleep, PLM can lead to micro-arousals, fragmented sleep, and subsequent daytime fatigue. Restless Legs Syndrome (RLS): A neurological disorder marked by an overwhelming urge to move the legs, often accompanied by uncomfortable sensations that worsen during inactivity, particularly at night. RLS is strongly linked to dopaminergic dysfunction and iron metabolism abnormalities, and it is frequently associated with insomnia and increased cardiovascular risk .

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1.4 Sleep disorders

Sleep Disorders and Their Impact on Health Sleep disorders constitute a diverse group of conditions that disrupt the normal sleep cycle, impairing sleep quality and overall physiological functioning. Among the most prevalent categories are sleep-disordered breathing (SDB), insomnia, movement disorders, parasomnias, epilepsy-related sleep disturbances, and hypersomnia syndromes. These conditions affect sleep patterns and contribute to systemic health complications, cognitive impairment, and reduced quality of life.[8]

1. Sleep-disordered breathing (SDB): Sleep-disordered breathing (SDB) encompasses conditions such as obstructive sleep apnea (OSA) and central sleep apnea (CSA), both of which are characterized by recurrent episodes of apnea and hypopnea during sleep.

These disruptions result in oxygen desaturation, sleep fragmentation, and increased sympathetic nervous system activity. OSA, the most common form, arises from upper airway obstruction due to pharyngeal collapse, whereas CSA stems from dysregulated respiratory control by the central nervous system. The consequences of untreated SDB are far-reaching, including excessive daytime sleepiness (EDS), cardiovascular complications (hypertension, arrhythmias, and stroke), and neurocognitive impairments .

2. Insomnia and Its Consequences: Insomnia is a highly prevalent sleep disorder characterized by difficulty initiating, maintaining, or achieving restorative sleep.

Early-morning awakenings and significant daytime dysfunction often accompany it. Chronic insomnia is associated with increased stress responses, heightened sympathetic activity, and neuroinflammatory processes, contributing to mood disorders, cognitive decline, and metabolic disturbances. The aetiology of insomnia is multifactorial, involving psychological, neurological, and environmental factors, necessitating an individualized approach to diagnosis and treatment .

3. Sleep-Related Movement Disorders: Sleep-related movement disorders include periodic limb movements (PLM) and restless legs syndrome (RLS), which interfere with sleep continuity.

Periodic Limb Movements (PLM): Characterized by involuntary, repetitive movements of the lower limbs during NREM sleep, PLM can lead to micro-arousals, fragmented sleep, and subsequent daytime fatigue. Restless Legs Syndrome (RLS): A neurological disorder marked by an overwhelming urge to move the legs, often accompanied by uncomfortable sensations that worsen during inactivity, particularly at night. RLS is strongly linked to dopaminergic dysfunction and iron metabolism abnormalities, and it is frequently associated with insomnia and increased cardiovascular risk .

4. Parasomnias: Abnormal Behaviors During Sleep: Parasomnias are disorders characterized by unusual or disruptive behaviours occurring during sleep, often involving incomplete transitions between sleep stages.

One significant parasomnia is REM sleep behaviour disorder (RBD), in which individuals physically act out vivid dreams due to the absence of normal muscle atonia during REM sleep. This disorder is of particular clinical importance as it is strongly correlated with neurodegenerative diseases such as Parkinson's disease, dementia with Lewy bodies, and multiple system atrophy

5. Epileptic Sleep Disorders: Specific epileptic syndromes, such as nocturnal frontal lobe epilepsy (NFLE), manifest with seizure-like motor behaviours during sleep, often mistaken for parasomnias. These episodes typically occur during NREM sleep and involve abrupt, stereotyped movements caused by abnormal electrical discharges in the frontal cortex. NFLE is distinct from other sleep disorders due to its epileptiform nature, requiring polysomnographic evaluation with electroencephalography (EEG) for differential diagnosis .

6. Hypersomnia and Narcolepsy: Hypersomnia disorders are characterized by excessive daytime sleepiness (EDS) despite sufficient or extended sleep duration. One of the most well-documented hypersomnia conditions is narcolepsy, a neurological disorder associated with dysregulation of the sleep-wake cycle.

Narcolepsy Type 1 (NT1): Characterized by excessive daytime sleepiness, cataplexy (sudden loss of muscle tone triggered by emotions), sleep paralysis, and hypnagogic hallucinations. NT1 is linked to hypocretin (orexin) deficiency, a neuropeptide responsible for maintaining wakefulness.

Narcolepsy Type 2 (NT2): Similar to NT1, but lacks cataplexy and typically has normal hypocretin levels. Idiopathic Hypersomnia (IH): A distinct condition involving prolonged, unrefreshing sleep and severe daytime sleepiness, often associated with altered cerebral arousal patterns and prolonged sleep inertia.

Polysomnography (PSG) and the Multiple Sleep Latency Test (MSLT) are essential for diagnosing hypersomnia syndromes, differentiating narcolepsy from other causes of excessive sleepiness.

The complexity and heterogeneity of sleep disorders highlight the intricate interactions between neurological, cardiovascular, and metabolic systems in regulating sleep. The accurate

classification, diagnosis, and management of these disorders are crucial for mitigating their impact on long-term health and improving quality of life.
Advances in sleep medicine, neurophysiology, and biomarker-based diagnostics continue to refine treatment strategies, ensuring personalized interventions tailored to the specific pathophysiology of each disorder.

1.5 Polysomnography (PSG)

1.5.1 Definition

Polysomnography (PSG) is a comprehensive diagnostic technique that involves the simultaneous recording, analysis, and interpretation of multiple physiological and electrophysiological parameters during sleep. It serves as the gold standard for evaluating sleep disorders, enabling the detection of abnormalities related to sleep architecture, respiratory function, cardiovascular activity, and neuromuscular control. PSG provides a detailed assessment of sleep physiology, facilitating accurate diagnosis and individualized treatment strategies [9].

1.5.2 PSG Customization and Data Acquisition

A key advantage of PSG is its customizable monitoring approach, allowing technicians to select specific channels, adjust electrode derivations, modify sensitivity settings, and configure filter parameters. Each physiological parameter can be analyzed using tailored settings, including labelling, colour coding, and individualized analysis properties. This flexibility enables precise real-time monitoring of sleep patterns and facilitates identifying pathological events.
Key Sensors and Monitoring Components in PSG
Polysomnography incorporates a variety of specialized sensors Figure 2. to capture and analyze multiple physiological signals:

Electroencephalogram (EEG)
Records brainwave activity, distinguishing between wakefulness, NREM, and REM sleep stages. Essential for assessing sleep architecture and identifying abnormal neurophysiological patterns in disorders such as insomnia, narcolepsy, and epilepsy-related sleep disturbances.
Electrooculogram (EOG)
Tracks eye movements, differentiating REM sleep (characterized by rapid eye movements) from NREM sleep stages. Crucial for identifying sleep-onset REM periods (SOREMPs), commonly seen in narcolepsy and REM behaviour disorder (RBD).
Electrocardiogram (ECG)

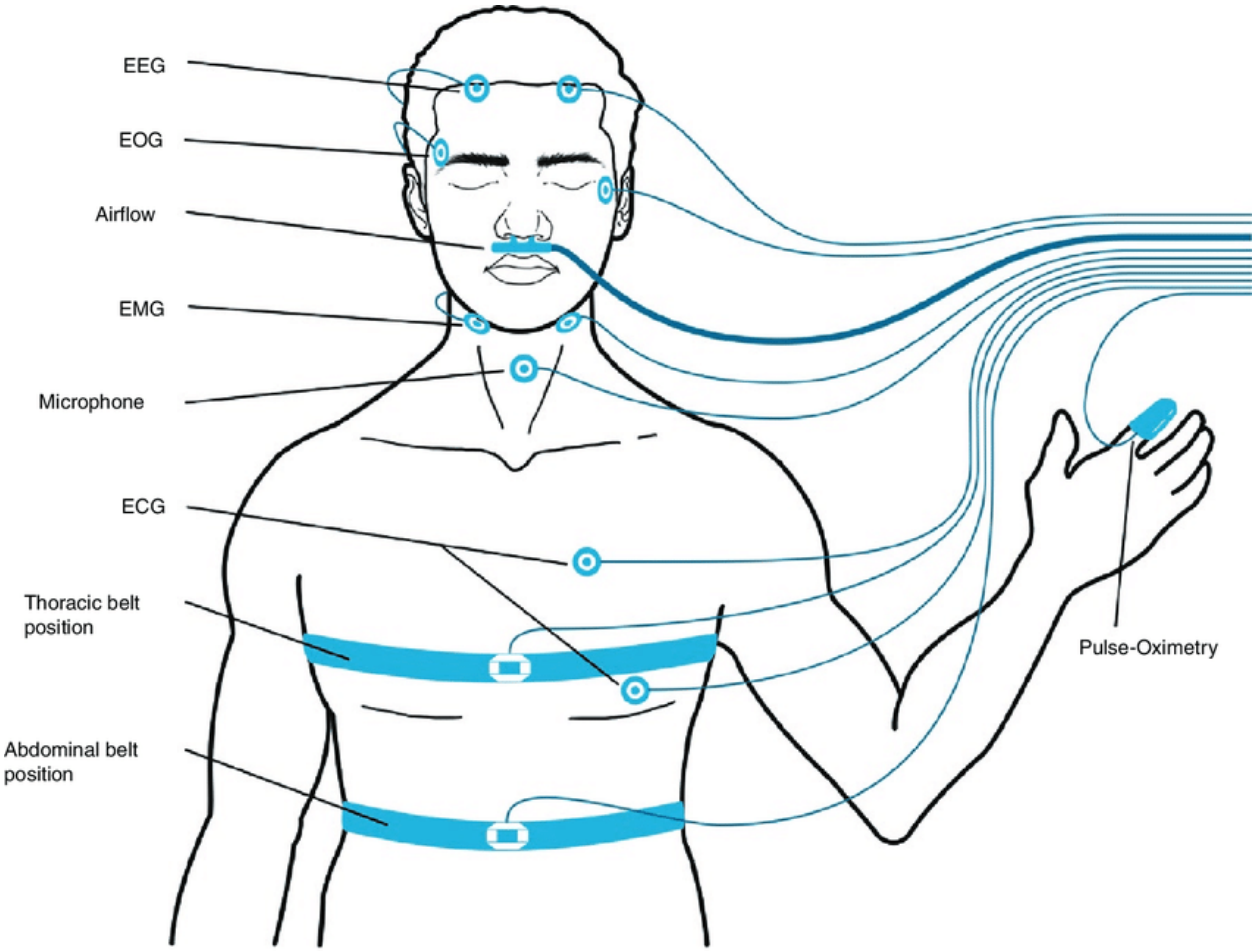

Figure 1.2: Polysomnography (PSG)
1

Records cardiac activity, assessing heart rate variability (HRV) and cardiovascular function during sleep. Detects arrhythmias, bradycardia, and tachycardia, often linked to sleep-disordered breathing (SDB) and autonomic dysfunction.

Electromyogram (EMG)

Measures muscle tone and activity, particularly in the chin and limb muscles. Differentiates between REM sleep (characterized by muscle atonia) and wakefulness. Detects periodic limb movements (PLM) and muscle twitches associated with restless legs syndrome (RLS) and REM behaviour disorder (RBD). **Oxygen Saturation (SpO) – Oximetry** Measures blood oxygen levels, detecting desaturation events linked to apneas and hypopneas. Uses infrared and red light transmission to assess oxygen saturation, providing crucial data for diagnosing obstructive sleep apnea (OSA).

Photoplethysmography (PPG)

A non-invasive optical sensor that measures peripheral arterial blood flow. Complements oximetry in evaluating circulatory dynamics and autonomic regulation during sleep.

Airflow Measurement

Detects breathing irregularities using thermistors and nasal pressure transducers. Helps

classify apneas (complete cessation of airflow) and hypopneas (partial airway obstruction), which are crucial for diagnosing SDB, including OSA and CSA.

Respiratory Effort

Assesses thoracic and abdominal movements via respiratory inductance plethysmography (RIP) belts. Differentiate obstructive and central sleep apnea by evaluating respiratory effort during apneic events.

Body Position Monitoring

It uses accelerometers to determine sleep posture and its impact on respiratory function. It is essential for detecting positional obstructive sleep apnea, where apneic events are more frequent in supine positions.

Audio Recording

Captures snoring patterns, a hallmark of obstructive sleep apnea. Analyzes snoring frequency, intensity, and variability, assisting in SDB diagnosis.

Video Recording

Enables direct behavioural observation during sleep. It helps diagnose parasomnias, nocturnal seizures, and movement

1.5.3 Comparison of Sleep Stages in Normal and Abnormal Sleep Patterns

Sleep architecture consists of distinct stages that alternate throughout the night, forming a structured cycle in healthy individuals. Abnormal sleep patterns, as observed in various sleep disorders, disrupt this architecture, leading to significant deviations. Below is a detailed comparison[10].

Normal Sleep Stages NREM Sleep Stage N1 (Light Sleep): The transitional phase between wakefulness and sleep represents 5-10% of total sleep time. Stage N2 (Deeper Sleep): Accounts for 45-55% of total sleep, characterized by sleep spindles and K-complexes, essential for maintaining stable sleep. Stage N3 (Deep Sleep): Comprising 15-25% of total sleep, this stage is crucial for physical restoration and immune function, marked by slow delta waves. REM Sleep Represents 20-25% of total sleep time. Associated with vivid dreaming, memory consolidation, and emotional regulation. Alternates with NREM sleep in cycles of approximately 90 minutes. Healthy individuals experience consistent cycles of these stages, leading to optimal restorative and cognitive functions.

Abnormal Sleep Patterns in Disorders

Sleep-Disordered Breathing (SDB): Characterized by frequent apneas (pauses in breathing) and hypopneas (shallow breathing). Results in disrupted N3 (deep sleep) and REM stages due to frequent arousals. Sleep efficiency is reduced, with an increased proportion of light sleep (Stage N1).

Insomnia: Difficulty falling or staying asleep leads to reduced total sleep time. Increased time spent in Stage N1, with frequent arousals disrupting deeper NREM and REM stages. Sleep fragmentation leads to non-restorative sleep.
Sleep Movement Disorders (PLM and RLS):

Periodic Limb Movements (PLM): Repeated limb jerks during sleep cause frequent micro-arousals, reducing N3 and REM sleep. Restless Leg Syndrome (RLS): Discomfort in the legs delays sleep onset, increasing time in Stage N1 and reducing sleep efficiency.
Parasomnias (e.g., REM Behavior Disorder - RBD):

In RBD, the muscle atonia typical of REM sleep is absent, leading to the physical enactment of dreams. PSG shows elevated muscle tone during REM, disrupting the normal REM stage.
Epileptic Disorders (e.g., Nocturnal Frontal Lobe Epilepsy - NFLE):

Seizures disrupt sleep continuity, particularly during NREM stages. PSG reveals epileptiform activity during sleep, often associated with fragmented sleep architecture. Hypersomnias of Central Origin (e.g., Narcolepsy) table(1).

Feature	**Normal Sleep**	**Abnormal Sleep (Examples)**
Stage N1	5-10% of total sleep	Increased in insomnia, SDB, and movement disorders.
Stage N2	45-55% of total sleep	Reduced in SDB, PLM, and RLS due to arousals.
Stage N3 (Deep Sleep)	15-25% of total sleep	Reduced in SDB, insomnia, and hypersomnias.
REM Sleep	20-25% of total sleep	Reduced in SDB, RBD, and narcolepsy; disrupted.
Arousals and Awakenings	Minimal, ensuring sleep continuity	Frequent in most sleep disorders.
Sleep Efficiency	85%	Often reduced ($< 80\%$) in disorders like SDB.

Table 1.1: Comparison of Sleep Features in Normal and Abnormal Conditions

1.5.4 Physiological Signals in Polysomnography

Polysomnography (PSG) relies on the simultaneous recording of multiple physiological signals to analyze sleep stages, identify abnormalities, and diagnose a wide range of sleep disorders. The primary signals include the electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), respiratory signals, and blood

oxygen saturation (SpO2). Each of these signals provides unique insights into specific physiological processes during sleep, contributing to a comprehensive understanding of sleep architecture and pathology[9].
The EEG is essential for monitoring brain activity, recorded via electrodes placed on the scalp, typically following the 10-20 International System. It helps differentiate between various sleep stages by analyzing brainwave patterns such as alpha, delta, theta, and beta waves. For example, delta waves dominate during deep sleep (Stage N3), while rapid, low-amplitude beta waves characterize wakefulness or arousal during sleep. These signals provide valuable insights into sleep quality and are crucial for diagnosing disorders like insomnia and sleep-related epilepsy. The EOG, on the other hand, captures eye movements through electrodes placed near the eyes. It is particularly useful for distinguishing between light sleep (NREM) and REM sleep, where rapid eye movements are a defining characteristic. By identifying abnormalities in eye movement patterns, the EOG plays a critical role in diagnosing conditions such as REM behavior disorder (RBD) and narcolepsy.

The EMG records muscle activity, typically using electrodes placed on the chin and limbs. It is indispensable for detecting changes in muscle tone across sleep stages. For instance, during REM sleep, muscle atonia (a near-complete loss of muscle tone) occurs as a protective mechanism to prevent individuals from acting out their dreams. The EMG also identifies periodic limb movements (PLM) and conditions like restless legs syndrome (RLS), which can significantly disrupt sleep quality. Complementing this, the ECG tracks heart activity and detects irregularities in cardiac rhythms during sleep. Sleep disorders such as obstructive sleep apnea (OSA) often cause cardiovascular changes, including arrhythmias and heart rate variability, which are captured by the ECG and provide critical diagnostic information.

Respiratory signals, including nasal airflow, thoracic and abdominal movements, and oxygen saturation (SpO2), are fundamental in identifying sleep-disordered breathing (SDB). Nasal airflow is measured using pressure transducers or thermistors, detecting apneas (complete cessation of airflow) and hypopneas (partial reduction of airflow). Respiratory effort is monitored using thoraco-abdominal belts, distinguishing between obstructive and central apneas. Additionally, SpO2 levels, measured via pulse oximetry, are vital for detecting oxygen desaturation events caused by apneas or hypopneas, which are common in OSA. Together, these respiratory signals provide a detailed picture of breathing patterns during sleep and help classify the severity of sleep-related breathing disorders.

By integrating these signals, PSG offers a holistic view of sleep physiology and is considered the gold standard for diagnosing sleep disorders. The simultaneous analysis of brain, eye, muscle, heart, and respiratory activity enables clinicians to identify disruptions

in normal sleep architecture and tailor interventions to improve patient outcomes. This multi-parametric approach ensures precise and reliable assessments, making PSG an indispensable tool in sleep medicine.

Electroencephalogram (EEG)

The electroencephalogram (EEG) is a fundamental component of polysomnography (PSG), providing crucial insights into brain activity during sleep. The EEG measures electrical activity in the brain by detecting voltage fluctuations generated by neuronal activity in the cortex. Electrodes are strategically placed on the scalp, typically following the 10-20 International System, which ensures standardized coverage of key brain regions, including the frontal, central, parietal, and occipital areas.
These recordings are instrumental in identifying sleep stages by analyzing distinct brainwave patterns. For instance, alpha waves (8–13 Hz) are commonly observed during wakefulness and relaxed states, while theta waves (4–7 Hz) are associated with light sleep (Stage N1). During deep sleep (Stage N3), delta waves (0.5–4 Hz) dominate, indicating restorative processes in the body. In contrast, beta waves (13–30 Hz), often linked to active thinking and arousal, may appear during wakeful interruptions or sleep disorders[11].

The EEG's ability to capture these brainwave patterns allows for the differentiation of NREM (non-rapid eye movement) and REM (rapid eye movement) sleep stages, as well as the transitions between them. This is essential for diagnosing a range of sleep disorders. For example, disrupted delta waves might indicate sleep fragmentation in obstructive sleep apnea (OSA), while irregular EEG patterns during sleep-onset periods can help diagnose conditions like insomnia or narcolepsy. Furthermore, the EEG is indispensable in detecting nocturnal epilepsy, as it can reveal abnormal electrical discharges in the brain during sleep.

The EEG also plays a critical role in understanding the architecture and quality of sleep, providing data for calculating sleep latency, total sleep time, and sleep efficiency. These parameters are vital for assessing the impact of sleep disorders and evaluating treatment outcomes. As a non-invasive and highly sensitive tool, the EEG not only facilitates the diagnosis of sleep disorders but also deepens our understanding of brain activity and its regulation during sleep.figure3

Electrocardiogram (ECG)

An electrocardiogram (ECG) is a medical test that records the heart's electrical activity. In polysomnography (PSG), the ECG monitors heart rhythms and identifies abnormalities that may affect sleep, such as arrhythmias, heart rate variability, and other cardiovascular

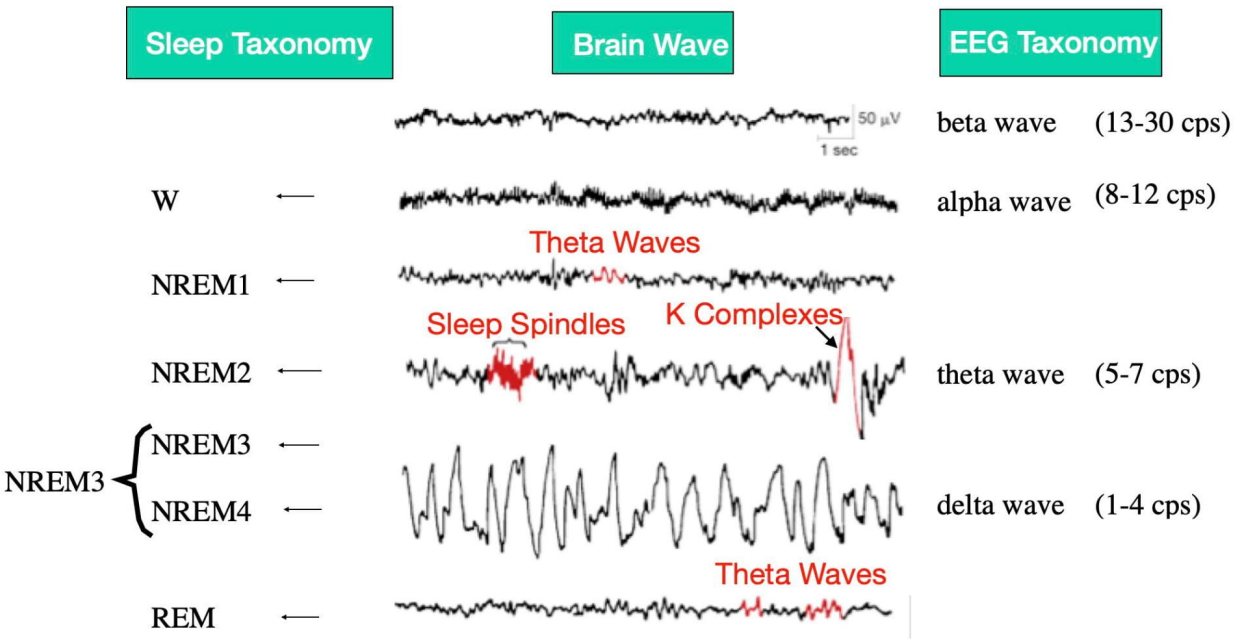

Figure 1.3: EEG Patterns During Sleep Stages
1

issues. The ECG sensor detects electrical signals produced by the heart, which are recorded as waveforms[12].

During sleep, heart rate and rhythm can fluctuate based on the body's sleep stages. For example, during REM sleep, heart rate variability increases due to sympathetic nervous system activation, while during NREM sleep, the parasympathetic system typically lowers the heart rate. Monitoring the ECG during sleep helps assess:

Heart rate variability:

Variations in time intervals between heartbeats are associated with autonomic nervous system activity and may provide insights into overall health and sleep quality. Arrhythmias: The detection of abnormal heart rhythms, which can interfere with sleep and indicate underlying conditions such as sleep apnea or heart disease. Sleep-related cardiac events: Certain sleep disorders, like obstructive sleep apnea (OSA), trigger brief episodes of irregular heart rhythms (e.g., bradycardia, tachycardia, or atrial fibrillation) during apneic events.

Integrating ECG data with other PSG parameters provides a comprehensive view of how heart function interacts with sleep stages and potential disorders. Notable sleep disorders that can be detected or exacerbated by ECG monitoring include:

Obstructive Sleep Apnea (OSA):

ECG can reveal irregularities in heart rate that may coincide with apneic events, helping to confirm the presence and severity of OSA. Central Sleep Apnea: Unlike OSA, central sleep apnea involves a lack of respiratory effort. ECG can detect specific patterns related to

the absence of heart rate acceleration during these events. Cardiovascular Diseases: Sleep disturbances are linked to conditions like hypertension, heart Failure, and atrial fibrillation, which can be assessed through ECG during sleep studies. ECG Interpretation in PSG When analyzing ECG in PSG, clinicians look for:

Heart rate patterns:
Identifying significant shifts in heart rate can indicate disturbances or stress caused by sleep disorders. Long QT intervals:
A prolonged QT interval may suggest potential risks for arrhythmias, particularly in people with sleep disorders like narcolepsy or insomnia. Ischemic events: Any evidence of reduced blood flow to the heart during sleep could indicate undiagnosed cardiac issues.

Electromyogram (EMG)

An electromyogram (EMG) is a diagnostic tool that evaluates the electrical activity generated by muscle fibres during contraction and relaxation. Within polysomnography (PSG), EMG is employed to monitor muscle activity throughout sleep, providing valuable insights into muscle tone variations and aiding in detecting movement-related sleep disorders. This assessment is essential for analyzing sleep architecture and identifying abnormalities associated with conditions such as REM sleep behaviour disorder (RBD) and restless legs syndrome (RLS)[13]

Role of EMG in Sleep Studies:

EMG electrodes are commonly positioned on the chin (mentalis muscle) and lower limbs to measure muscle tone across different sleep stages:

- **Muscle Tone During NREM Sleep:** During non-rapid eye movement (NREM) sleep, muscle tone typically decreases, although occasional muscle activity can still be observed.
- **Muscle Tone During REM Sleep:** Rapid eye movement (REM) sleep is marked by muscle atonia, where voluntary muscles become temporarily paralyzed to prevent physical reactions to dreams. Deviations from this atonia are critical indicators when diagnosing disorders such as RBD.

EMG in Diagnosing Sleep Disorders:

EMG plays a pivotal role in identifying and monitoring various sleep-related movement disorders that affect muscle tone:

- **REM Sleep Behavior Disorder (RBD):** Characterized by a Failure of the typical muscle paralysis during REM sleep, individuals with RBD may physically act out vivid dreams. EMG recordings reveal excessive muscle activity, facilitating the diagnosis of this condition.
- **Restless Legs Syndrome (RLS):** RLS is a neurological disorder marked by an irresistible urge to move the legs, especially during rest, often accompanied by Discomfort. EMG helps quantify leg muscle activity, aiding in the assessment of symptom severity.
- **Periodic Limb Movement Disorder (PLMD):** This condition involves repetitive, involuntary leg movements during sleep, which can disrupt sleep continuity. EMG effectively tracks these periodic movements, usually observed during NREM sleep stages.
- **Sleep Bruxism:** Characterized by involuntary teeth grinding or jaw clenching during sleep, sleep bruxism is identified through EMG monitoring of the masseter muscle, where heightened activity indicates the presence of this condition.

EMG Interpretation in PSG: When interpreting EMG data in a polysomnographic setting, the following aspects are considered:

Muscle tone assessment: Muscle tone should be minimal (muscle atonia) in REM sleep, while some degree of muscle activity may still be seen in NREM sleep. Deviations from these norms are significant in identifying disorders like RBD. Abnormal muscle activity: In RLS, PLMD, and sleep bruxism, EMG detects repetitive muscle contractions that interfere with sleep, providing insight into the severity of these conditions. Clustering of movements: Repetitive movements seen in PLMD or RLS are tracked in terms of their timing and frequency, which can be quantified to aid diagnosis and treatment.

Electrooculogram (EOG):

The EOG measures eye movements using electrodes near the eyes, typically on the outer canthi. It provides critical information about sleep stages, particularly in distinguishing between REM and NREM sleep:

NREM Sleep: Eye movements are slow or absent. Slow-rolling eye movements characterize Stage N1. REM Sleep: Defined by rapid eye movements, this stage's hallmark indicates dreaming and heightened brain activity. Abnormalities in EOG signals contribute to diagnosing:

REM Sleep Behavior Disorder (RBD): Normal rapid eye movements are accompanied by excessive muscle activity due to the absence of muscle atonia. Narcolepsy: Increased rapid

eye movement density during daytime sleep episodes. The EOG is essential for identifying sleep-stage transitions and detecting conditions like parasomnias or ocular abnormalities affecting sleep quality[14].

1.6 Challenges in Sleep Diagnosis:

Despite advancements in sleep medicine, the diagnosis of sleep disorders remains complex and challenging due to multiple factors:

Variability in Sleep Patterns: Individual differences in sleep architecture and circadian rhythms make it difficult to establish universal diagnostic criteria.

Overlapping Symptoms: Many sleep disorders share common symptoms, such as excessive daytime sleepiness, making differential diagnosis challenging.

Limitations of Polysomnography (PSG): While PSG is the gold standard, it requires overnight monitoring in specialized laboratories, which may not capture habitual sleep patterns.

Home Sleep Testing Constraints: Portable monitoring devices provide convenience but may not accurately detect complex disorders like parasomnias and narcolepsy.

Patient Compliance and Subjectivity: Self-reported sleep patterns and compliance with monitoring protocols can influence diagnostic outcomes.

Influence of Comorbidities: Sleep disturbances often coexist with psychiatric, metabolic, or neurological conditions, complicating accurate diagnosis and treatment planning.

Addressing these challenges requires continued innovation in sleep monitoring technology, improved diagnostic algorithms, and personalized approaches to sleep disorder assessment.

1.7 Cultural, Social, and Economic Factors

Cultural, social, and economic factors are crucial in shaping sleep patterns and quality, directly impacting overall health. Sleep habits and rest practices vary across cultures and societies, influencing sleep in the following ways:

Cultural Factors: Cultural beliefs and traditions surrounding sleep, such as the preference for naps in some societies or customary bedtime and wake-up schedules, significantly affect sleep duration and quality. While some cultures emphasize adequate sleep as essential for well-being, others may undervalue it due to fast-paced lifestyles.

Social Factors: Social stressors, long working hours, and family obligations can reduce sleep duration and quality. Factors such as shift work, exposure to artificial lighting from screens, and societal expectations can disrupt the biological sleep rhythm, leading to sleep disorders.

Economic factors play a significant role in sleep quality, as individuals with limited financial resources may face unsuitable sleeping conditions due to overcrowding, excessive noise, or substandard living environments. Additionally, financial strain can lead to psychological distress, increasing the risk of conditions like stress, emotional instability, and mood disorders, all of which are strongly associated with sleep disturbances, including insomnia[15].

1.8 Conclusion

Understanding sleep physiology, its regulation, and the disorders that disrupt it is critical in advancing sleep medicine and improving patient outcomes. This chapter highlighted the fundamental aspects of sleep architecture, the role of various physiological signals in diagnosing sleep disorders, and the influence of cultural, social, and economic factors on sleep quality. Despite significant advancements in sleep research and diagnostic techniques, challenges remain in accurately diagnosing and treating sleep disorders due to overlapping symptoms, patient variability, and technological limitations. Future research should focus on improving diagnostic methodologies, personalizing treatment approaches, and integrating innovative technologies such as artificial intelligence in sleep analysis. Addressing sleep health at individual and societal levels will contribute to overall well-being, disease prevention, and enhanced quality of life.

CHAPTER 2

RELATED WORK

2.1 Introduction

Sleep stage classification and detecting sleep disorders have been extensively studied in recent years due to their critical implications for health and well-being. Numerous methodologies have been developed, leveraging different physiological signals such as electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG), and electromyography (EMG). These studies have explored various machine learning and deep learning approaches to enhance the accuracy and efficiency of sleep stage classification.

This chapter reviews literature on sleep stage detection and disorder diagnosis using individual physiological signals and multimodal approaches. We first examine sleep classification techniques based on EEG, the primary signal used in sleep studies. Subsequently, we explore methods employing ECG, EOG, and EMG, assessing their contributions to sleep analysis. Additionally, we review studies that integrate multiple physiological signals, aiming to improve classification performance through feature fusion and advanced machine learning models.

By analyzing these contributions, this chapter provides insights into current advancements, highlights the strengths and limitations of existing approaches, and identifies potential research gaps that need further exploration. The discussion in this chapter serves as a foundation for developing more robust and efficient sleep stage classification techniques using advanced signal processing and artificial intelligence

2.2 Sleep Stage Detection Using EEG Signal

Table 2.1: Summary 1 of the Sleep Stage Classification Study Using EEG

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Pejman Memar (2017)[16]	Develop an EEG-based automated system for sleep stage classification	25 disorder & 20 healthy subjects. Kruskal-Wallis test Random forest classifier	95.31% accuracy (nested 5-fold CV).	Single EEG channel limitation.
Tzimourta et al. (2018)[17]	Develop an EEG-based classification system for sleep stage analysis to aid sleep disorder diagnosis.	ISRUC Sleep Database (100 patients). FIR filters for feature extraction from six EEG channels. Naïve Bayes, knn, and Random Forests.	Random Forests achieved 75.29% accuracy.Awake stage (90.43%) ower accuracy for N1 and REM.	Misclassification issues for N1 and REM.
Mohammed Diyk (2019)[18]	Develop a more accurate EEG-based sleep stage classification method to reduce misclassification.	Data from ISRUC-Sleep and Sleep-EDF databases. Leave-One-Out Cross-Validation (LOSO) . Network analysis for sleep stage differences.	96.74% accuracy (C3-A2 channel, ISRUC-Sleep), 96% (Pz-Oz channel, Sleep-EDF).	Deep sleep stages show lower communication efficiency.
Sharma et al. (2020)[19]	Develop a wavelet-based automated classification system for sleep stages.	Sleep-EDF database (98 subjects, 127,512 EEG segments). Two-band wavelet decomposition SVM	Gaussian SVM yielded 91.5% .	Class imbalance, limited generalization to other datasets.

Table 2.2: Summary 2 of the Sleep Stage Classification Study Using EEG

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Sharma et al. (2021)[20]	Automate sleep stage detection using wavelet-based features.	CAP Sleep Database (80 subjects with sleep disorders and healthy individuals). Wavelet-based EEG feature extraction (F4-C4 and C4-A1 channels), Bagged Trees.	Bagged Trees achieved 92.8%	Class imbalance affecting accuracy, generalization issues.
Murarka et al. (2022)[21]	Develop a CNN-based classifier for CAP phases detection.	CAP Sleep Database (healthy and sleep disorder patients). 1D CNN trained on EEG signals for classification of CAP phases (A/B).	Accuracy: 78.84% (healthy), 70.88–82.21% (disorders).	Performance variability across disorders, reliance on single-channel EEG.
Shahab Abdulla et al. (2023)[22]	Develop an intelligent model for automatic sleep stage classification using EEG signals with multi-channel spectral pattern-based features.	-Short-Time Fourier Transform (STFT) is applied to convert EEG signals into spectrum images. -Multiple Channels Information Local Binary Pattern (MILBP) is used to extract texture-based features.	Accuracy: 0.96 F1-score: 0.94	The model's generalizability to different EEG datasets is unverified, limiting its robustness across diverse populations and recording conditions
Hamidreza Jalali et al[23]	Develop a novel method for classifying sleep stages by mapping EEG signals	CAP Sleep Database Adaptive Common Spatial Patterns (ACSP) and Particle Swarm Optimization (PSO) are used.SVM	CAP Sleep Database: 89.5%	The impact of EEG artifacts and noise on classification accuracy is not extensively analyzed.

Accurate classification of sleep stages is essential for diagnosing sleep disorders and understanding sleep patterns. Recent advancements in machine learning and signal processing have led to the development of automated classification methods using EEG signals. Various studies have explored different feature extraction techniques, including wavelet decomposition, frequency domain transformations, and deep learning models to enhance classification accuracy. However, challenges such as dataset variability, class imbalance, and the impact of EEG artifacts remain significant limitations in these methods. This section provides a summary of recent research on EEG-based sleep stage classification, highlighting the methodologies, datasets used, classification results, and potential limitations. Table 2.1 and Table 2.2 summarize these studies.

2.3 Sleep Stage Detection Using ECG Signal

Precise classification of sleep stages is vital for diagnosing sleep disorders and gaining insights into sleep patterns. Recent advancements in machine learning and signal processing have facilitated the development of automated methods for classifying sleep stages, particularly using ECG signals. Various studies have explored different approaches, including feature extraction techniques such as wavelet decomposition, frequency domain analysis, and deep learning models to enhance classification accuracy. These approaches aim to address the complexity of ECG signals and improve performance across various sleep stages. However, challenges such as dataset variability, class imbalance, and the quality of ECG signals continue to pose significant obstacles to achieving reliable results. Despite these difficulties, recent studies have made considerable progress in ECG-based sleep stage classification, with the use of advanced techniques providing notable improvements in accuracy. This summary highlights the key methodologies, results, and limitations found in recent research on ECG-based sleep stage classification, as detailed in Table 2.3.

Table 2.3: Summary of the Sleep Stage Classification Study Using ECG

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Kurniawan et al. (2019)[24]	To develop an automatic sleep stage classification model based on ECG signals	MIT-BIH Polysomnographic Database, Particle Swarm Optimization (PSO),Weighted Extreme Learning Machine (WELM)	(NREM, REM, Wake): Mean accuracy of 78.78%	The model's performance may vary with different datasets beyond MIT-BIH due to dependency on data distribution and feature relevance.
Edita et al. (2020)[25]	method for classifying sleep disorders	Cyclic Alternating Pattern (CAP) sleep data,Spectral feature extraction,using Decision-Tree-Based Support Vector Machine (DTB-SVM)	Sensitivity: 84.01% Specificity: 94.17% Overall Accuracy: 86.27%	The method's effectiveness is limited by the quality of ECG signals
Mustafa et al. (2021)[26]	o explore a deep transfer learning approach for wearable sleep stage classification.	292 participants, 584 recordings with ECG and polysomnography (PSG) data, annotated according to the (R&K) rules. Long Short-Term Memory (LSTM) network.	Cohen's Kappa: 0.65 $\pm$ 0.11 Accuracy: 76.36 $\pm$ 7.57%	The model was evaluated on healthy individuals.
Pragati Tripathi et al. (2022)[27]	The paper aims to develop an automatic insomnia detection system using ECG signals.	ECG signals from the PhysioNet database,Linear Discriminant Analysis (LDA),Decision Tree (DT) and Random Forest (RF)	Sleep Stage-based Classification: 96% sensitivity, specificity, and accuracy.	The method was applied to a limited dataset from the PhysioNet database,

2.4 Sleep Stage Detection Using EOG Signal

The use of Electrooculogram (EOG) signals for sleep stage classification has gained attention due to their ability to provide valuable information about eye movement during sleep. Recent studies have demonstrated the potential of EOG in accurately classifying sleep stages, often in conjunction with other physiological signals like EEG and ECG.

For instance, Mosheyur et al. (2019) used a small dataset from the Sleep-EDF database and applied Wavelet Transform (DWT) with Extreme Gradient Boosting (XGBoost), achieving an accuracy of 83%. However, the study acknowledged that the small dataset size could limit the generalizability of the findings. Similarly, Chih-En Kuo et al. (2020) developed a short-time insomnia detection system using single-channel EOG signals, reporting high accuracy (89.31%) with sensitivity of 96.63% and specificity of 82%. Despite the promising results, this study was focused solely on primary insomnia, excluding other sleep disorders, which may affect its applicability to broader conditions.

Jiahao Fan et al. (2021) proposed a deep learning model, EOGNet, for sleep stage classification, achieving an accuracy of 81.2% on the MASS database. This study highlighted the limitation of limited generalizability to populations with sleep disorders, which could reduce the model's effectiveness in real-world scenarios. Lastly, Hans van Gorp et al. (2022) focused on sleep stage classification across a heterogeneous cohort with various sleep disorders. They reported high accuracy (85.0% for left EOG and 85.2% for right EOG), but the use of full PSG-derived EOG channels limits the model's scalability for systems relying on fewer channels.
These studies show that while EOG-based methods have potential for sleep stage classification, challenges such as dataset limitations, generalizability to diverse populations, and reliance on complex systems remain significant hurdles table 2.4.

Table 2.4: Summary of the Sleep Stage Classification Study Using EOG

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Mosheyur et al. (2019)[28]	method for sleep stage classification using single-channel Electrooculogram (EOG) signals	Sleep-EDF database ,Wavelet Transform (DWT),Extreme Gradient Boosting (XGBoost)	Accuracy 0.83	The proposed method relies on a small dataset, and further validation with larger databases
Chih-En Kuo et al. (2020)[29]	To develop a short-time insomnia detection system using single-channel sleep EOG	16 healthy individuals and 16 insomnia patient,Refined composite multiscale entropy (RCMSE),Svm	accuracy of 89.31%, with sensitivity of 96.63% and specificity of 82%.	The study focused on primary insomnia and did not include patients with other sleep disorders
Jiahao Fan et al. (2021)[30]	To propose a novel deep learning model, EOGNet, for sleep stage classification.	data Sleep-EDF, convolutional neural network (CNN)	81.2% accuracy on the MASS database and 76.3%	Limited generalization to sleep-disordered populations..
Hans van et al. (2022)[31]	It focuses on achieving reliable sleep staging for a heterogeneous cohort of subjects with various sleep disorders.	SOMNIA dataset,A neural network	85.0% for the left EOG and 85.2% for the right	The model used full PSG-derived EOG channels,

2.5 Sleep Stage Detection Using EMG Signal

Sleep stage detection using electromyography (EMG) signals has shown promising results in recent years, with several studies developing methods to improve classification accuracy. Yong et al. (2019) proposed a method for classifying hand gestures using EMG signals, achieving an accuracy of 96% with the use of scale average wavelet transform (SAWT) and convolutional neural networks (CNN). However, challenges such as variability in signal quality and the need for large, diverse datasets remain significant hurdles.

Sezgin et al. (2015) focused on classifying EMG signals from patients using the Wavelet Packet Transform (WPT), achieving an accuracy of 96.85%. A limitation in this study was the reliance on EMG signals alone, without incorporating other physiological signals, which may have improved classification performance.

In a similar vein, M. Karuna et al. (2024) developed a method for classifying hand movements by combining Empirical Mode Decomposition (EMD) and Complex Continuous Transform (CCT) for feature extraction, achieving an accuracy of 94.63%. The study noted that electrode placement could significantly affect system accuracy, which is a common challenge in EMG-based signal classification. Lastly, Adil Rehman et al. (2025) explored the use of chin EMG for sleep stage classification, achieving an accuracy of 82.2% with the Random Forest model. However, the model struggled with classifying the N2 sleep stage, highlighting the limitations of EMG for accurate classification of certain stages. These studies collectively demonstrate the potential of EMG for sleep stage classification, but also emphasize the challenges related to signal quality, electrode placement, and the use of EMG alone without combining it with other physiological signals like EEG or EOG for more robust classification results table 2.5

Table 2.5: Summary of the Sleep Stage Classification Study Using EMG

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Yong et al. (2019)[32]	To develop an effective method for classifying hand gestures using EMG	scale average wavelet transform,CNN	96 %	challenges in EMG-based gesture recognition include variability in signal quality and the need for large, diverse datasets.
Sezgin et al. (2015)[33]	The paper aims to classify electromyogram (EMG) signals of patients	Wavelet Packet Transform (WPT)	accuracy of 96.85%,%.	The study's limitation is that it used only EMG signals and did not explore other physiological signals
M. Karuna et al. (2024)[34]	To develop a method for classifying hand movements	combining Empirical Mode Decomposition (EMD) and Complex Continuous Transform (CCT) for feature extraction,linear discriminant analysis (LDA)	accuracy of 94.63%.	Electrode placement affects system accuracy.
Adil Rehman et al. (2025)[35]	Chin EMG aids in sleep stage classification.	,Sleep-EDFx,Surface electromyography (sEMG),Random Forest (RF)	accuracy of 82.2%	Chin EMG struggles with N2 classification.

2.6 Sleep Stage Detection Using Combined Physiological Signals (EEG, ECG, EOG, EMG)

Tables 2.6 and 2.7 provide a comprehensive summary of recent studies on sleep stage classification using combined physiological signals, including EEG, ECG, EOG, and EMG. These studies utilize advanced techniques and multi-signal approaches to improve the accuracy and reliability of sleep stage detection.

Yildirim et al. (2019) proposed a deep learning model using 1D-CNN for classification, applying the Sleep-EDF dataset with EEG and EOG signals. The model achieved high accuracy (98.06% for two classes, 94.64% for three classes, and 92.36% for six classes). However, its effectiveness for sleep disorders was limited, and the generalizability to other datasets remained a challenge.

Alexandra et al. (2020) focused on combining EEG, ECG, EMG, and respiratory signals for sleep stage detection using time and frequency-domain features. Using the Physionet You Snooze dataset, they achieved an accuracy of 93% with the Random Forest (RF) classifier. A limitation noted was the impact of class imbalance, despite using data balancing techniques. Zhao et al. (2021) aimed to combine the strengths of EEG and ECG signals for improved sleep stage classification. Using the MIT-BIH dataset and a deep residual network (ResNet), the model performed well, with 97.97% accuracy for light sleep vs. deep sleep and 98.84% accuracy for NREM vs. REM stages. However, the dataset imbalance limited the generalizability of the results.

Hyungjik et al. (2022) developed an automatic sleep stage classification model using EEG and EMG signals, trained on the Sleep-EDF dataset. They achieved an accuracy of 87.2%. A limitation of this study was the use of a single dataset, which impacts the model's generalizability to other populations or conditions. Sharma et al. (2022) explored an automated system for identifying sleep disorders using EMG and EOG signals. They used the CAP sleep dataset and achieved an accuracy of 94.3% for a six-class classification. The limitation was the influence of factors like signal quality and the need for larger and more diverse datasets.

Haifa et al. (2023) proposed a novel sleep staging method integrating EEG and ECG signals using multiscale entropy (MSE) and SVM. They achieved the highest accuracy of 84.3%. However, the model struggled with N1 classification due to the small sample size of the dataset.

Zhang et al. (2024) aimed to determine if multi-channel data improves classification accuracy. Using the Sleep-SC dataset and a hybrid attention neural network, they achieved 87.18% accuracy by combining EEG and dual-channel EOG signals. Dataset variability and classification complexity were noted as limitations.

Furutani et al. (2025) developed an automated system for classifying sleep-wake states

using EEG and EMG signals. The system achieved an accuracy of 97.1%, but the SAC model misclassified REM sleep as NREM in some cases, which highlights the challenges in accurately detecting certain sleep stages.

These studies collectively illustrate the potential and challenges of using combined physiological signals for sleep stage classification. While the integration of multiple signals has improved accuracy.

Table 2.6: Summary 1 of the Sleep Stage Classification Study Using Combined Physiological Signals (EEG, ECG, EOG, EMG)

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Yildirim et al. (2019)[36]	The study proposes a deep learning model using 1D-CNN for classification	Sleep-edf,the 1D-CNN model,and EEG&EOG	98.06% accuracy for two classes, 94.64% for three classes, and 92.36% for six classes	Limited effectiveness for sleep disorders.
Alexandra et al. (2020)[37]	The study combines EEG, ECG, EMG, and respiratory signals for sleep stage detection	Physionet You Snooze,Time and frequency-domain	accuracy of 93% using the RF classifier.%.	Class imbalance affected performance despite balancing.
Zhao et al. (2021)[38]	he aim is to combine the strengths of both signals to improve sleep stage classification	MIT-BIH,deep residual network (ResNet)	97.97% for light sleep vs. deep sleep, 98.84 % for NREM vs. REM, and 80.40% for the four-class classification.	Limited generalizability due to dataset imbalance..
Hyungjik et al. (2022)[39]	automatic sleep stage classification using (EEG) and (EMG) .	CNN Sleep-EDF for multi-signal data.	accuracy of 87.2%,	Evaluated on single dataset, limits generalizability.

Table 2.7: Summary 2 of the Sleep Stage Classification Study Using Combined Physiological Signals (EEG, ECG, EOG, EMG)

Authors	**Aim**	**Data & Methods**	**Classification Results**	**Limitations**
Sharma et al. (2022)[40]	Automated system identifies sleep disorders use EMG AND EOG	CAP sleep dataset,biorthogonal wavelet filter bank	94.3% for a six-class classification	EOG, EMG signals influenced by factors..
Haifaet et al . (2023)[41]	The study proposes a novel sleep staging method that integrates EEG and ECG multimodal	PThe study used the ISRUC-S3 dataset,ultiscale entropy (MSE),svm	the highest accuracy of 84.3%	N1 classification struggled due to small sample size.
Zhanget al. (2024)[42]	It aims to determine whether multi-channel data improves classification accuracy, EEG&EOG	Sleep-SC DATASET, A hybrid attention neural network,	the combination of EEG and dual-channel EOG achieved an accuracy of 87.18%	Dataset variability limits generalizability and classification complexity.
Furutani et al. (2025)[43]	Automated system for classifying sleep-wake states using (EEG) and (EMG) .	wild-type (WT) dataset,multiscale entropy (MSE) and detrended fluctuation analysis (DFA). .	accuracy of 97,1%,	SAC model misclassified REM as NREM.

2.7 Discusion

Chapter 2 provides an in-depth review of the latest methodologies and findings in sleep stage classification using a range of physiological signals such as EEG, ECG, EOG, and EMG. This section highlights various machine learning and signal processing techniques used to enhance the accuracy and reliability of automated sleep stage classification systems.

The studies reviewed indicate that EEG-based sleep stage classification has become the most widely explored method due to its direct measurement of brain activity. Research has shown significant advancements in the use of wavelet transforms, frequency-domain analysis, and deep learning techniques, leading to impressive accuracy levels. However, despite these advancements, challenges persist in terms of dataset variability, class imbalance, and the impact of EEG artifacts, which can significantly affect classification performance. For example, Pejman Memar (2017) and Tzimourta et al. (2018) demonstrated good classification results using the Kruskal-Wallis test and random forests, achieving accuracies up to 95%, but limitations in generalizability and misclassification of certain stages such as N1 and REM were highlighted. Similarly, Mohammed Diyk (2019) showed that deep sleep stages exhibited lower communication efficiency, which could lead to misclassification of these stages. Thus, while EEG provides rich information for sleep stage classification, addressing these challenges remains an ongoing concern.

In contrast, ECG, EOG, and EMG signals, while not as commonly used, also offer promising results in enhancing the performance of sleep stage classification. These signals have the advantage of being more easily accessible in clinical settings, particularly for patients with sleep disorders. For example, studies by Kurniawan et al. (2019) and Edita et al. (2020) used ECG and EMG signals to classify various sleep stages, with the former achieving a mean accuracy of 78.78% and the latter showing high specificity and sensitivity. However, the effectiveness of these methods is often constrained by factors such as signal quality, small sample sizes, and the need for better feature extraction techniques to address the complexity of these signals.

The integration of multiple signals, as explored in studies using combined physiological signals (EEG, ECG, EOG, EMG), has shown substantial improvements in classification accuracy. For instance, Yildirim et al. (2019) achieved high classification accuracy with a deep learning model that combined EEG and EOG signals, reaching 98.06% accuracy for two classes. This trend was further confirmed by Haifa et al. (2023) and Zhao et al. (2021), where the fusion of multiple signals helped mitigate the limitations inherent in single-signal approaches. Combining EEG with other signals such as EOG and EMG leads to better detection of difficult-to-classify stages such as REM and N1. However, the challenges associated with class imbalance and dataset variability remain significant concerns, as these issues can limit the generalizability of the models across diverse populations and datasets.

Despite the significant advances, the literature reveals several common limitations in

the field of sleep stage classification. The reliance on small or single-dataset studies often hinders the applicability of models to diverse real-world scenarios. Furthermore, the need for larger and more diverse datasets to address class imbalance is an ongoing challenge. While several methods have demonstrated improved performance using feature fusion and advanced machine learning algorithms, the quality of the physiological signals and the choice of signal processing techniques continue to affect the final classification accuracy.

2.8 Conclusion

In conclusion, sleep stage classification using various physiological signals such as EEG, ECG, EOG, and EMG has seen considerable advancements with the use of machine learning and signal processing techniques. Each signal offers distinct advantages and limitations in classifying sleep stages, with EEG leading the field due to its direct measurement of brain activity. However, challenges such as dataset variability, signal quality, and class imbalance persist across all methods. The integration of multiple signals has shown promise in overcoming some of these challenges by improving classification accuracy and providing more robust systems. The studies reviewed in this chapter highlight the ongoing evolution of sleep stage classification and the need for further research to address existing limitations, particularly in terms of generalizability, feature extraction, and dataset diversity.

The field would benefit from further exploration of hybrid models that combine multiple physiological signals and more sophisticated signal processing techniques. Additionally, the use of deep learning approaches, particularly convolutional neural networks (CNNs), has proven effective, and the integration of more advanced techniques such as multi-scale entropy or wavelet transforms could further enhance classification performance. Finally, future research should focus on improving the generalizability of these models by using diverse datasets, applying transfer learning techniques, and incorporating data from different populations with various sleep disorders.

CHAPTER 3

SLEEP STAGE DETECTION USING EEG AND ECG SIGNALS

3.1 Introduction

Sleep is a fundamental biological process essential for cognitive function, physical health, and overall well-being. Accurate sleep stage classification plays a crucial role in diagnosing and treating sleep-related disorders such as insomnia, sleep apnea, and narcolepsy. Traditionally, sleep staging has been performed manually by trained clinicians using (PSG), which records multiple physiological signals, including (EEG), (ECG), (EOG), and (EMG). However, this manual process is **time-consuming, subjective, and prone to inter-expert variability**, necessitating the development of automated approaches for sleep stage classification.

Among the various physiological signals used for sleep analysis, EEG and ECG have gained significant attention due to their strong correlation with sleep stages. EEG reflects brain activity, capturing key transitions between wakefulness and different sleep stages, whereas ECG provides valuable insights into autonomic nervous system responses during sleep. The integration of EEG and ECG signals enhances the robustness of sleep stage classification, improving accuracy and generalizability across diverse populations.

In recent years, machine learning and deep learning techniques have demonstrated remarkable success in automating sleep stage classification. Feature-based machine learning approaches, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and ensemble learning methods (Bagging and Boosting), have been widely explored. These models utilize extracted features from EEG and ECG signals, such as time-domain statistical measures, frequency-domain spectral components, and wavelet transform-based features, to classify sleep stages accurately.

This chapter presents a comprehensive framework for sleep stage classification using EEG and ECG signals.

3.2 Sleep Stage Detection from EEG Signals Using the KNN Algorithm

3.2.1 Objective

The main contributions of this work can be summarized as follows:

Development of an Automated Sleep Stage Classification Model: This study implements a robust sleep stage classification model utilizing the K-Nearest Neighbors (KNN) algorithm. The model is trained on EEG signals extracted from the CAP Sleep Database, offering a significant improvement in sleep staging accuracy and reliability.

EEG-Based Feature Extraction and Preprocessing: The EEG data undergoes comprehensive signal preprocessing, including filtering, segmentation into 30-second epochs, and wavelet decomposition. This ensures optimal feature extraction for accurate classification.

Enhanced Sleep Stage Discrimination Using Machine Learning: A feature-based machine learning approach is employed to differentiate between wakefulness (W), light sleep (N1, N2), deep sleep (N3), and REM sleep (R). The KNN classifier achieves a high classification accuracy of 95.5%, outperforming traditional manual scoring methods.

Validation on a High-Resolution EEG Dataset: The study utilizes high-resolution C4-A1 EEG channels with a sampling frequency of 512 Hz from the CAP Sleep Database, ensuring the robustness and generalizability of the results. The dataset includes individuals with various sleep disorders, such as insomnia, narcolepsy, and nocturnal frontal lobe epilepsy, enabling comprehensive performance evaluation.

Comparison with Other Machine Learning Models: In addition to KNN, other classifiers such as Support Vector Machines (SVM), Ensemble Bagged Trees (EBagT), and Boosted Trees (EBoostT) are evaluated. The KNN classifier demonstrates superior accuracy, highlighting its effectiveness for sleep stage classification.

Potential Applications in Sleep Medicine: This work presents an automated, efficient, and accurate sleep staging method that reduces the time-consuming and error-prone nature of manual sleep stage classification. The findings offer valuable insights for clinicians and researchers working on sleep disorder diagnosis, polysomnography analysis, and wearable sleep monitoring technologies.

3.2.2 Materiel and Methods

Dataset

In this study, the dataset was sourced from the CAP Sleep Database, a publicly accessible resource on PhysioNet that provides a comprehensive collection of physiological signals.[44]

The CAP database originates from the Sleep Disorder Center at Ospedale Maggiore in Parma, Italy, and includes polysomnographic (PSG) recordings from 108 subjects, comprising both healthy individuals and patients with various sleep disorders Table 4.1. The dataset includes EEG, EOG, ECG, SpO (oxygen saturation), and respiratory signals,

Table 3.1: CAP Sleep Database.

Subject type	**Subject available**	**Male & Female**	**Age (in years)**
Healthy	16	7M & 9F	24-42
Insomnia	9	4M & 5F	47-82
Bruxism	2	2M	23-34
Narcolepsy	5	2M & 3F	18-44
NFLE	40	21M & 19F	14-67
PLM	10	7M & 3F	40-62
RBD	22	19M & 3F	58-82
SBD	4	4M	65-78
Total	**108**	**66M & 42F**	**14-82**

offering a rich foundation for sleep stage analysis. The EEG recordings were obtained from multiple channels, including F4-C4, C4-A1, C4-P4, P4-O2, Fp2-F4, Fp1-F3, C3-P3, and P3-O1, with a common reference at A1/A2. These channels were sampled at varying frequencies, ranging from 100 Hz to 512 Hz, ensuring high-resolution signal acquisition.

For this study, we focused on EEG and EOG signals due to their critical role in sleep stage classification and diagnosis of sleep disorders. A subset of 10 participants was selected, including individuals diagnosed with insomnia, narcolepsy, and nocturnal frontal lobe epilepsy (NFLE). Among the available EEG channels, the C4-A1 channel, sampled at 512 Hz, was chosen for its high signal fidelity and relevance in sleep staging. This selection provided a balanced dataset for evaluating sleep patterns and a robust foundation for developing automated classification models.

3.2.3 Methods

The proposed system employed EEG signal-based sleep stage classification, following the AASM (American Academy of Sleep Medicine) standard for sleep staging. From the CAP Sleep Database, the C4-A1 EEG channel was selected due to its high reliability in distinguishing sleep stages. The EEG signals were preprocessed, removing noise and artifacts through filtering techniques, and subsequently segmented into 30-second epochs, as per AASM guidelines. Feature extraction included power spectral density, statistical features, and wavelet

transforms, providing a robust representation of sleep patterns. Various classifiers—SVM, KNN, ensemble bagged trees (EBagT), and ensemble boosted trees (EBoosT)—were tested, with KNN achieving the highest accuracy of 95.5%. The dataset was carefully curated by selecting 10 participants, including cases of insomnia, narcolepsy, and nocturnal frontal lobe epilepsy, ensuring a balanced dataset for effective model training and evaluation.figure 1.

Extraction of EEG from PSG Data:

Polysomnographic (PSG) recordings contain multiple physiological signals, including EEG, ECG, EOG, and EMG, which must be carefully processed to isolate the relevant EEG signal for sleep stage classification. The EEG extraction process consists of the following steps:

Signal Selection and Acquisition

The C4-A1 EEG channel was extracted from PSG recordings due to its strong correlation with sleep stages. EEG was sampled at 512 Hz, ensuring a high-resolution signal for analysis.

Butterworth Filtering:

To reduce high-frequency noise without altering the fundamental characteristics of the signals, a Butterworth filter is applied. The Butterworth filter is particularly advantageous due to its maximally flat frequency response in the passband, ensuring minimal signal distortion. It effectively removes unwanted noise while preserving the essential frequency components relevant for sleep stage classification[45].

The Butterworth filter is mathematically defined by the following transfer function:

$$H(f) = \frac{1}{\sqrt{1 + \left(\frac{f}{f_c}\right)^{2N}}} \tag{3.1}$$

where:

- $H(f)$ is the filter's frequency response.
- f_c is the cutoff frequency, which determines the passband limits.
- f represents the frequency component of the EEG signal.
- N is the filter order, which controls the sharpness of the transition between the passband and stopband.

In this study, a band-pass Butterworth filter is applied to retain the critical EEG frequency components while suppressing noise. The band-pass filtering process is represented as:

$$H(f) = \frac{1}{\sqrt{1 + \left(\frac{f}{f_L}\right)^{2N}}} \times \frac{1}{\sqrt{1 + \left(\frac{f_H}{f}\right)^{2N}}} \tag{3.2}$$

where:

- $f_L = 0.5$ Hz is the lower cutoff frequency, removing slow baseline drift.
- $f_H = 45$ Hz is the upper cutoff frequency, eliminating high-frequency artifacts such as muscle (EMG) noise.

The filter order N is unspecified in this paper, allowing for optimization based on signal characteristics. Typically, N is set between 2 and 4 to ensure a balance between sharp cutoff and minimal signal distortion.

By applying a Butterworth band-pass filter (0.5–45 Hz), EEG waves in the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and low gamma (30–45 Hz) bands are retained, ensuring proper sleep stage classification. This preprocessing step enhances signal integrity, facilitating accurate feature extraction and classification.

Segmentation:

Adhering to the standards set by the American Academy of Sleep Medicine (AASM), the EEG signals are segmented into fixed-length epochs of 30 seconds. This standardized segmentation ensures a consistent methodology for identifying and classifying different sleep stages, including rapid eye movement (REM) sleep, non-REM sleep (stages N1, N2, and N3), and wakefulness[46].

Mathematically, the segmentation process can be represented as:

$$S_i = S(t)_{i \times L:(i+1) \times L} \tag{3.3}$$

where:

- S_i represents the i^{th} segmented EEG epoch.
- $S(t)$ is the continuous EEG signal.
- L is the window length, set to 30 seconds.
- The EEG signal is sampled at 512 Hz, resulting in $L = 30 \times 512 = 15,360$ samples per epoch.

This segmentation technique ensures that each epoch contains a sufficient number of samples to capture sleep dynamics while maintaining consistency across different sleep stages. Each segment is subsequently labeled according to its corresponding sleep stage, facilitating accurate classification and analysis.

Continuous Wavelet Transform (CWT):

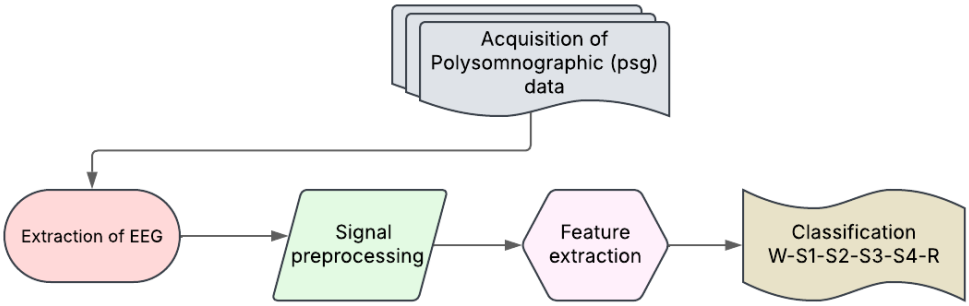

Figure 3.1: schematic of methods

The Continuous Wavelet Transform (CWT) is a mathematical tool well-suited for analyzing non-stationary signals, where the spectral content varies over time . Unlike traditional Fourier Transform (FT), which provides only a global frequency representation, the CWT allows for a time-frequency decomposition of a signal, making it particularly effective for EEG signal analysis[47].

The CWT is computed using a mother wavelet function $\psi(t)$, which is scaled and translated to analyze the signal at different resolutions. The wavelet family is defined as:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{3.4}$$

where:

- s is the scale parameter, which determines the dilation (expansion) or compression of the wavelet.
- τ is the translation parameter, which shifts the wavelet in time.
- The factor $\frac{1}{\sqrt{s}}$ normalizes the wavelet energy across different scales.

Given a mother wavelet, the Continuous Wavelet Transform (CWT) of a signal $f(t)$ is defined as the convolution of $f(t)$ with the complex conjugate of the wavelet function:

$$W(s,\tau) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{3.5}$$

where:

- $W(s,\tau)$ represents the **wavelet coefficients**, which quantify the similarity between $f(t)$ and $\psi(t)$ at different scales.
- $\psi^*(t)$ is the **complex conjugate** of the wavelet function.

These wavelet coefficients provide a time-frequency representation of the signal, enabling the identification of transient features and localized frequency variations. Instead of working

directly with scales, it is often useful to express them in terms of **pseudo-frequencies, which can be computed using the following equation:

$$f_s = \frac{f_c}{s \cdot \Delta} \tag{3.6}$$

where:

- f_s is the **pseudo-frequency** associated with a given scale.
- f_c is the **central frequency** of the chosen wavelet.
- Δ is the **sampling period** of the EEG signal.

By applying the CWT, EEG signals can be analyzed at multiple resolutions, allowing for the extraction of sleep-related features across different frequency bands. This multi-resolution analysis is crucial for distinguishing various sleep stages based on EEG spectral characteristics.

Feature Extraction from Wavelet Coefficients

For each level of decomposition in wavelet analysis, essential statistical features are computed from the wavelet coefficients. These features provide critical insights into the characteristics of the signal at different frequency bands and play a fundamental role in classification tasks. The primary statistical features extracted from the wavelet coefficients include[48]:

Mean (μ)

The mean represents the arithmetic average of the wavelet coefficients at each decomposition level, reflecting the central tendency of the signal within the specific frequency band. Mathematically, it is computed as:

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{3.7}$$

where:

- N is the total number of wavelet coefficients.
- x_i denotes each individual wavelet coefficient.

Maximum (Max)

The maximum value among the wavelet coefficients signifies the peak amplitude within the frequency band, indicating the strongest signal component at a given level. It is determined by:

$$Max = \max(x_1, x_2, ..., x_N) \tag{3.8}$$

where x_i represents each coefficient.

Minimum (Min)

The minimum value among the wavelet coefficients represents the smallest amplitude within the frequency band. It is calculated as:

$$Min = \min(x_1, x_2, ..., x_N) \tag{3.9}$$

Standard Deviation (Std)

Standard deviation measures the variability or dispersion of the wavelet coefficients, indicating how widely the values are spread within the frequency band. It is given by:

$$Std = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{3.10}$$

where:

- μ denotes the mean of the coefficients.

Kurtosis

Kurtosis evaluates the degree of peakedness in the distribution of wavelet coefficients. A high kurtosis value indicates the presence of outliers or extreme values, suggesting a distribution with heavy tails. A low kurtosis value signifies a more **evenly spread distribution**. It is defined as:

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2\right)^2} - 3 \tag{3.11}$$

where:

- μ represents the mean of the coefficients.

These statistical features play a crucial role in characterizing the distribution, variability, and amplitude of EEG signals at different frequency bands, enabling a comprehensive analysis within the domain of wavelet-based signal processing.

Classification Methods

The extracted features were used to train various classifiers, including K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Ensemble Bagged Trees (EBagT), and Ensemble Boosted Trees (EBoosT). Each classifier applies a different learning approach, contributing to the robustness of the sleep stage classification process.

K-Nearest Neighbors (KNN)

KNN is a non-parametric, instance-based learning algorithm that classifies data based on similarity. It operates by comparing an unknown test sample with training samples stored in an n-dimensional space, determining its closeness to existing labeled samples using distance

metrics such as Euclidean and Mahalanobis distances. The test sample is assigned to the most prevalent class among its nearest neighbors, allowing for effective classification. KNN is particularly useful for sleep stage classification due to its ability to capture nonlinear relationships in EEG data. In this study, KNN achieved the highest classification accuracy of 95.5%, demonstrating its effectiveness in distinguishing sleep stages[49].

Support Vector Machines (SVM)

SVM is a supervised learning algorithm that identifies an optimal hyperplane to separate different classes with the maximum margin. It is particularly effective in high-dimensional spaces and is widely used in EEG classification tasks. When data is not linearly separable, SVM employs kernel functions such as the Radial Basis Function (RBF) kernel to map the data into a higher-dimensional space where it becomes separable. SVM has shown strong performance in sleep stage classification by handling complex patterns and minimizing classification errors[50].

Bagging (Bootstrap Aggregation)

Bagging, also known as bootstrap aggregation, is an ensemble learning technique designed to improve classification robustness by combining multiple weak learners. It operates by creating multiple subsets of the training dataset through random sampling with replacement. A weak learner, typically a decision tree, is trained on each subset independently, and during classification, the final prediction is obtained through majority voting. This approach reduces variance and mitigates the risk of overfitting, making it particularly beneficial for EEG-based classification tasks. Bagging has demonstrated improved stability and accuracy compared to individual classifiers[51].

Boosting (EBoosT)

Boosting is another ensemble learning method that focuses on sequentially improving weak learners. Unlike bagging, where models are trained independently, boosting adjusts the weights of misclassified samples to improve performance in subsequent iterations. This approach enhances the predictive power of weak learners by progressively refining their decision boundaries. Popular boosting algorithms such as AdaBoost and Gradient Boosting have been widely used in EEG classification tasks due to their ability to enhance classification accuracy. Boosting effectively reduces bias and improves model generalization, making it a valuable technique in sleep stage detection[52].

Comparison of Classifier Performance

Among the classifiers evaluated, the KNN classifier demonstrated the highest classification accuracy of 95.5%, followed by SVM, EBagT, and EBoosT. Ensemble-based models such as bagging and boosting showed improved classification stability and reduced variance, but KNN outperformed them in terms of accuracy. The results highlight the effectiveness of different classification techniques in EEG-based sleep stage detection, emphasizing the importance of selecting an appropriate model for optimal performance figure 2.

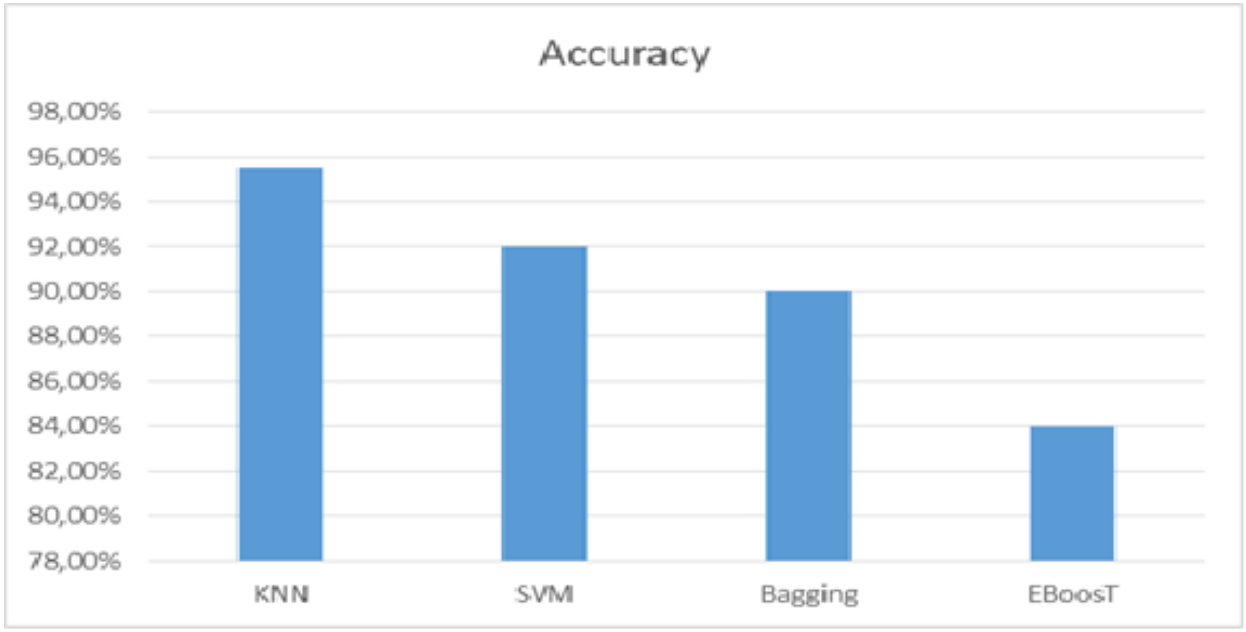

Figure 3.2: EEG Classification Accuracy)

3.2.4 Results and Discusion

The proposed EEG-based automatic sleep stage classification system, utilizing the C4-A1 EEG channel from the CAP Sleep Database, demonstrated high accuracy in identifying sleep stages using the K-Nearest Neighbors (KNN) classifier. The confusion matrix (Figure 5) revealed an overall classification accuracy of 98.0%, with wake and REM sleep achieving the highest accuracy (98.0%), followed by N2 sleep (97.1%) and N1 sleep (95.6%). However, N3 sleep exhibited the lowest accuracy (88.1%), highlighting the challenge of distinguishing deep sleep stages. These findings confirm the reliability of wavelet-based feature extraction and KNN classification in sleep analysis. This method offers a highly accurate, efficient, and automated approach to sleep stage classification, addressing the limitations of manual scoring, which is often time-consuming and error-prone. The results signify a significant advancement in sleep medicine, paving the way for more precise and scalable diagnostic tools for sleep disorder assessment figure 3.

The findings underscore the efficacy of EEG-based analysis in automating sleep stage classification, offering a fast, accurate, and scalable alternative to traditional manual scoring. Since manual sleep stage assessment is labour-intensive and prone to errors, this method provides a promising solution for enhanced sleep monitoring and disorder diagnosis.

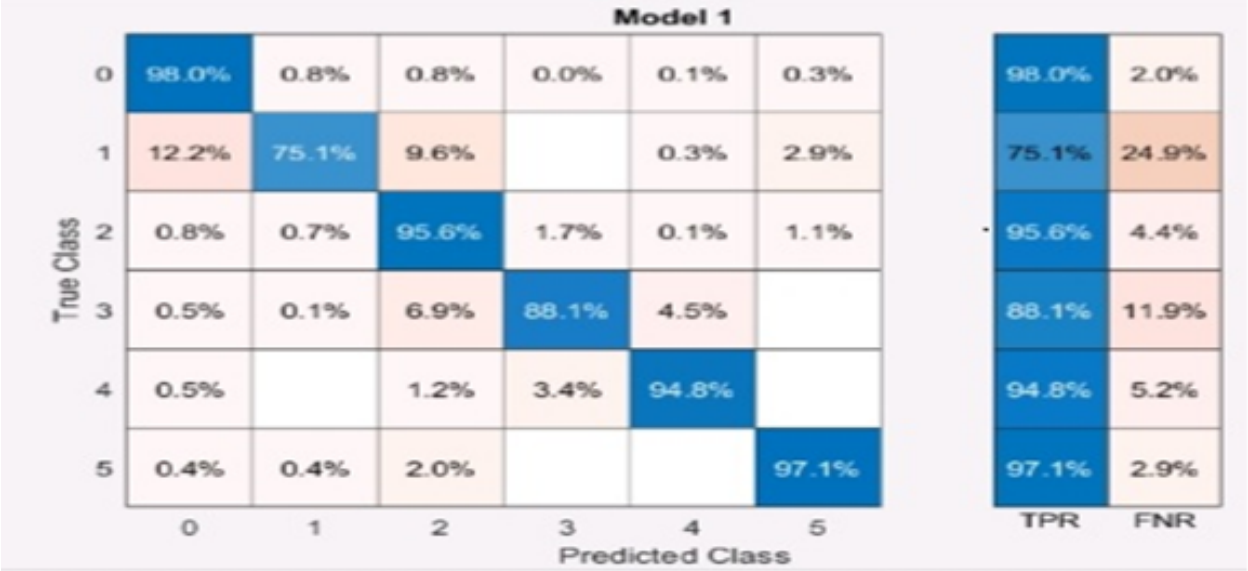

Figure 3.3: Confusion matrix for EEG

3.3 Sleep Stage Identification Using Hjorth Parameters and Signal Energy: An Analysis of PhysioNet's CAP Database.

3.3.1 Objective

The primary objective of this study is to develop an automated sleep stage classification system utilizing EEG signals from the CAP Sleep Database, applying the K-Nearest Neighbors (KNN) algorithm combined with wavelet-based feature extraction. This research aims to enhance the accuracy and efficiency of sleep stage classification by leveraging Hjorth parameters and signal energy while following the K&R segmentation method for preprocessing.

The key contributions of this work include:
Implementing the KNN Algorithm for Sleep Staging: Developing a robust classification model that can effectively differentiate between various sleep stages (Wake, N1, N2, N3, and REM). EEG-Based Signal Processing and Feature Extraction: Applying wavelet decomposition, Hjorth parameters, and energy-based features to optimize classification accuracy.

Use of the K&R Method for Segmentation: Ensuring standardized 30-second epoch segmentation for reliable feature extraction and classification.

Evaluation of a High-Quality EEG Dataset: Utilizing C4-A1 EEG recordings from the CAP Sleep Database, focusing on individuals diagnosed with insomnia, narcolepsy, and nocturnal frontal lobe epilepsy. Achieving High Classification Accuracy: Demonstrating that the proposed KNN-based system achieves 96.3% accuracy, surpassing traditional manual

sleep scoring techniques.

This study aims to provide an efficient and scalable approach to sleep disorder diagnosis and monitoring by automating sleep stage classification, reducing reliance on time-consuming manual scoring while improving clinical decision-making.

3.3.2 Dataset

This study focuses on EEG-based sleep stage classification, utilizing data from the CAP Sleep Database. A subset of 10 participants was selected, including individuals with insomnia, narcolepsy, and nocturnal frontal lobe epilepsy. The C4-A1 EEG channel, sampled at 512 Hz, was chosen due to its high reliability in detecting sleep stage transitions.

3.3.3 Methods

The proposed methodology for sleep stage classification using EEG signals is illustrated in Figure 4 , which outlines the sequential steps involved in processing and analyzing the CAP sleep database. The process begins with EEG signal extraction from the CAP dataset, followed by segmentation into 30-second epochs based on the Rechtschaffen & Kales (R&K) system. Subsequently, the segmented signals undergo bandpass filtering to eliminate unwanted frequency components and retain relevant sleep-related frequencies. A wavelet transform is then applied to analyze time-frequency domain characteristics. Feature extraction is performed using Hjorth parameters and signal energy, capturing essential characteristics of EEG signals. Finally, the extracted features are fed into a K-Nearest Neighbors (KNN) classifier to classify sleep stages.

Detailed Explanation of Each Step

1. EEG Signal Extraction

EEG signals are extracted from the CAP sleep database containing annotated sleep recordings. These signals provide critical neurophysiological insights for sleep stage classification.

2. Segmentation (30s using R&K System)

The EEG recordings are segmented into 30-second epochs according to the Rechtschaffen & Kales (R&K) sleep scoring system, standardizing sleep stage classification.

3. Filtering (Bandpass)

A bandpass filter is applied to retain frequencies relevant to sleep analysis, typically in the range of 0.5 Hz to 30 Hz, corresponding to delta, theta, alpha, and beta bands [53].

4. Wavelet Transform

The wavelet transform decomposes the EEG signal into different frequency subbands, enabling effective time-frequency analysis crucial for detecting sleep stage variations.

5. Feature Extraction: Energy & Hjorth Parameters

The feature extraction process involves two key metrics:

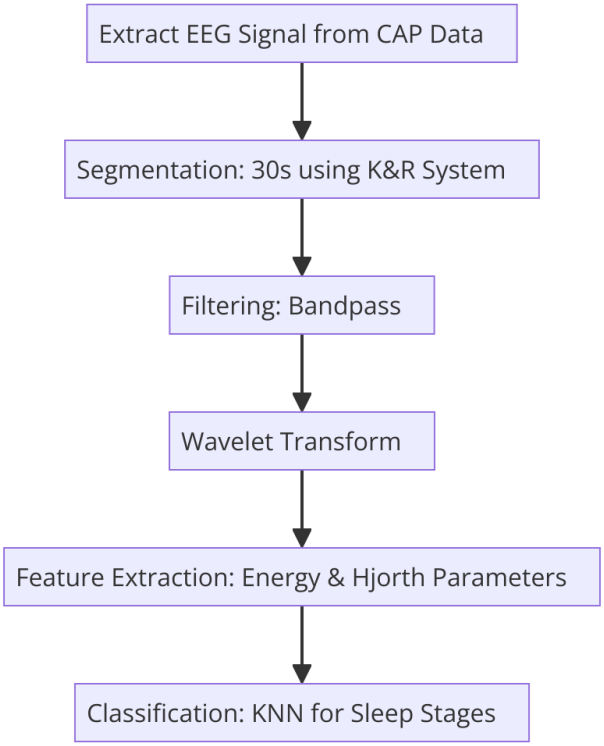

Figure 3.4: Flowchart of Sleep Stage Classification Process Using EEG Signals

Signal Energy: Measures the power distribution and frequency of the EEG signal over time. The energy of a signal $x(t)$ over time T is defined as:

$$E = \int_0^T x^2(t)dt \tag{3.12}$$

High-energy EEG signals often correspond to wakefulness or active sleep stages, whereas low-energy signals indicate deep sleep[54].

Hjorth Parameters: These are statistical descriptors of EEG signals used for feature extraction[55]:

Activity (A): Measures signal power, representing the variance of the EEG signal:

$$A = \text{var}(x(t)) \tag{3.13}$$

Mobility (M): Represents the frequency content of the signal:

$$M = \sqrt{\frac{\text{var}(dx/dt)}{\text{var}(x(t))}} \tag{3.14}$$

Complexity (C): Measures the change in frequency components, giving insights into signal smoothness:

$$C = \frac{M(dx/dt)}{M(x)} \tag{3.15}$$

These parameters effectively capture EEG signal dynamics, distinguishing different sleep stages.

6. Classification Using KNN

The extracted features are fed into a K-Nearest Neighbors (KNN) classifier, which assigns sleep stages based on feature similarity. KNN is chosen for its simplicity and effectiveness in sleep stage classification.

3.3.4 Result and Discussion

The confusion matrix presented in Figure 5, provides a detailed performance assessment of Model 2 in classifying sleep stages based on EEG features. The matrix displays the true class labels (ground truth) on the y-axis and the predicted class labels on the x-axis, with each cell showing the percentage of instances classified into the respective category. Additionally, the True Positive Rate (TPR) and False Negative Rate (FNR) for each class are provided in a separate summary panel to the right.

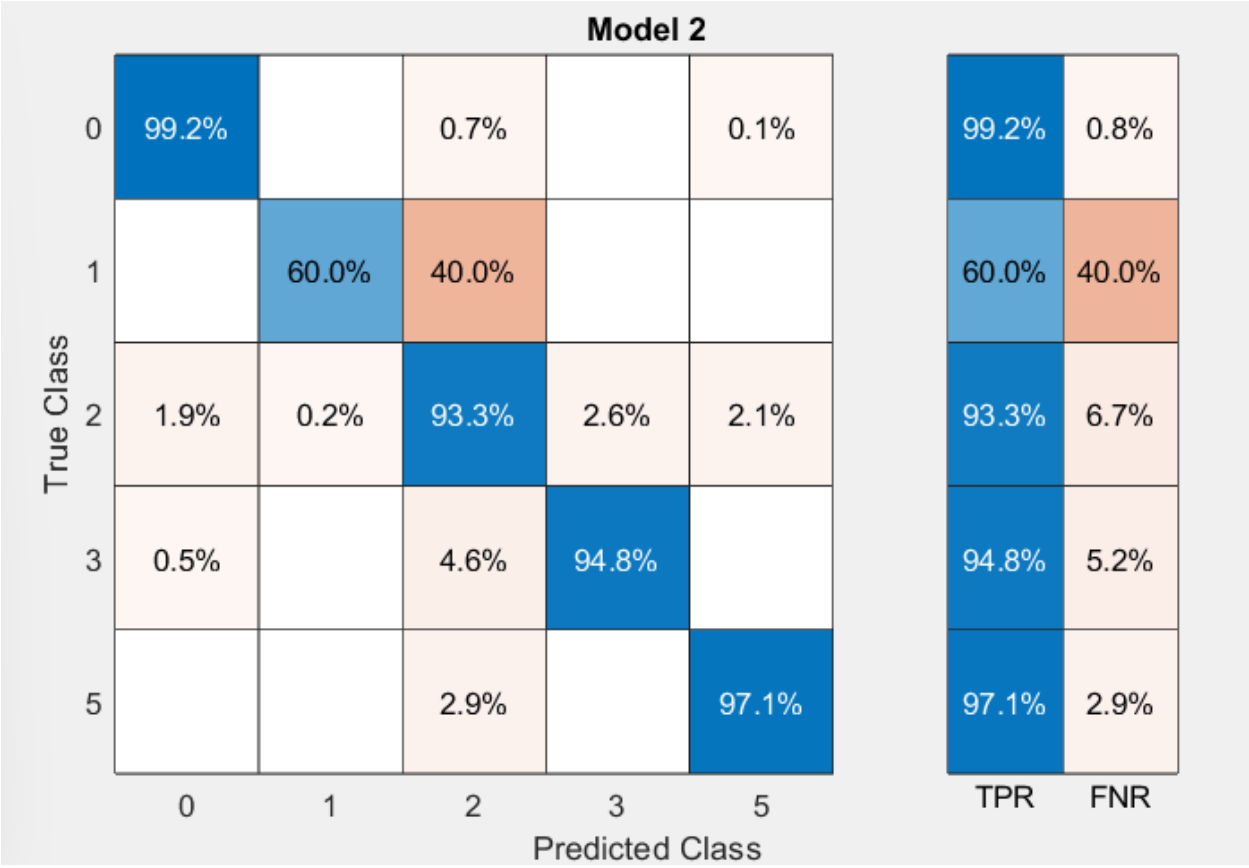

Figure 3.5: EEG-Based Sleep Stage Classification Matrix

Key Observations and Discussion

The classification model demonstrated outstanding performance in distinguishing most sleep stages. Specifically, it achieved high accuracy for classes **0, 2, 3, and 5**, with accuracy rates of **99.2%, 93.3%, 94.8%, and 97.1%**, respectively. These results indicate the

model's strong ability to correctly classify these sleep stages, as confirmed by the high **True Positive Rate (TPR)** values. The minimal misclassification in these classes highlights the effectiveness of the extracted features and classification approach.

However, the model exhibited notable challenges in classifying **class 1**, with only **60.0%** of instances correctly classified. A significant proportion (**40.0%**) of class 1 samples were misclassified as class 2, suggesting that these two stages may share overlapping feature representations. This misclassification trend is particularly pronounced between adjacent sleep stages, indicating that additional feature refinement is necessary to improve class separability. Conversely, classes 3 and 5 showed very low misclassification rates, demonstrating that the model effectively differentiates deep sleep and REM sleep from other stages.

The analysis of the **True Positive Rate (TPR)** and **False Negative Rate (FNR)** further confirms these observations. The TPR values are consistently high for most stages, ensuring reliable detection. However, **class 1 exhibits an FNR of 40.0%**, meaning a significant portion of class 1 samples are misclassified. This suggests that refining the feature extraction process could help mitigate misclassification and enhance overall model robustness.

Receiver Operating Characteristic (ROC) Curve Analysis

Definition of the ROC Curve

The Receiver Operating Characteristic (ROC) curve is a fundamental tool used to evaluate the performance of a classification model. It provides a graphical representation of the trade-off between sensitivity (true positive rate) and specificity (1 - false positive rate) across different decision thresholds. The ROC curve is especially valuable in biomedical applications, such as EEG-based sleep stage classification, where precise discrimination between different states is crucial.

The ROC curve plots the following two key metrics:

- **True Positive Rate (TPR) – Sensitivity or Recall:** This metric measures the proportion of correctly identified positive cases (correctly classified sleep stages).

$$TPR = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \tag{3.16}$$

- **False Positive Rate (FPR):** This metric measures the proportion of negative cases incorrectly classified as positives.

$$FPR = \frac{\text{False Positives (FP)}}{\text{False Positives (FP)} + \text{True Negatives (TN)}} \tag{3.17}$$

The Area Under the Curve (AUC) is a quantitative measure derived from the ROC curve

that represents the overall discriminative ability of the classifier:

$$AUC = \int_0^1 TPR(FPR)\, dFPR \tag{3.18}$$

where an AUC value of 1.0 represents a perfect classifier, while 0.5 suggests a classifier performing at random chance.

Interpretation of the ROC Curves for Sleep Stage Classification

In this study figure 6, ROC curves were generated for five sleep stages: **S0, S1, S2, S3, and S5**. These curves allow us to assess the model's capability in distinguishing between these sleep phases based on EEG signal analysis.

1. High Classification Performance with Strong AUC Values

The classification model demonstrated outstanding performance, with *AUC values exceeding 0.95 for most sleep stages. Specifically:

- S0 and S5 achieved an AUC of 0.98, indicating near-perfect classification accuracy. This suggests that the EEG features extracted for these stages are highly distinct and that the classifier can identify them with almost no ambiguity.
- S2 and S3 obtained AUC values of 0.96–0.97, further reinforcing the robustness of the model. These stages, which correspond to intermediate sleep states, are also well-recognized by the classification model.
- Stage S1, while slightly lower (AUC = 0.87), still demonstrated strong classification ability. This result suggests that Stage 1 shares overlapping characteristics with adjacent stages, making it more challenging to classify accurately.

2. Sensitivity and Specificity Trade-off

The ROC curves provide insights into the classifier's ability to balance sensitivity and specificity:

- The high **sensitivity (TPR)** observed for most stages confirms that the classifier correctly identifies sleep stages with minimal false negatives.
- The low **false positive rate (FPR)** suggests that the classifier is highly selective, avoiding misclassifications.
- The classifier maintains a strong balance between sensitivity and specificity, demonstrating its applicability to real-world scenarios, such as clinical sleep monitoring and automated sleep tracking systems.

3. Stage S1 Performance and Potential for Improvement

Although Stage S1 (AUC = 0.87) performed slightly lower than the other stages, it still demonstrates significant classification ability. Several factors may explain this behavior:

- Feature Overlap with Adjacent Stages: Stage S1 represents a transition between wakefulness and deeper sleep, and its EEG characteristics often resemble those of neighboring stages.
- Data Distribution: If fewer training samples were available for Stage 1, the classifier may not have learned its distinguishing features as effectively.
- Potential Enhancement Strategies: To further improve Stage 1 classification, future work could explore:
  - Using deep learning techniques to automatically extract more discriminative features.
  - Incorporating multi-modal data (e.g., ECG, EMG signals) to supplement EEG-based classification.
  - Refining feature selection techniques to emphasize non-overlapping spectral characteristics.

Practical Implications and Real-World Applications

The exceptional performance of this classification model positions it as a promising tool for various practical applications, including:

- **Clinical Sleep Disorder Diagnosis:** High classification accuracy can aid in detecting and diagnosing sleep disorders such as insomnia and sleep apnea.
- **Wearable Sleep Trackers:** The model's efficiency makes it suitable for implementation in consumer-grade wearable devices for sleep monitoring.
- **Biomedical Research:** Neuroscientific studies on sleep patterns can benefit from the high-precision classification offered by this approach.
- **AI-Based Health Systems:** Integrating this classifier into smart health monitoring systems can enhance patient care by providing continuous sleep quality assessments.

Conclusion: A Strong and Reliable Sleep Classification Model

The results of this study provide clear evidence of the effectiveness, reliability, and robustness of the developed sleep stage classification model. The consistently high AUC values underscore its ability to accurately distinguish between sleep stages, making it a powerful tool for both clinical and consumer applications.

While **Stage S1 presented a minor challenge, the overall classification accuracy remains exceptionally strong, showcasing the success of the methodology used. Future refinements—such as the integration of deep learning, multi-modal data, and enhanced feature selection—could further optimize the model's performance, particularly for transitional sleep stages.

In summary, this work represents a significant step forward in EEG-based sleep classification, offering high-precision, reliable results that can contribute to advancements in both medical diagnostics and personal health monitoring.

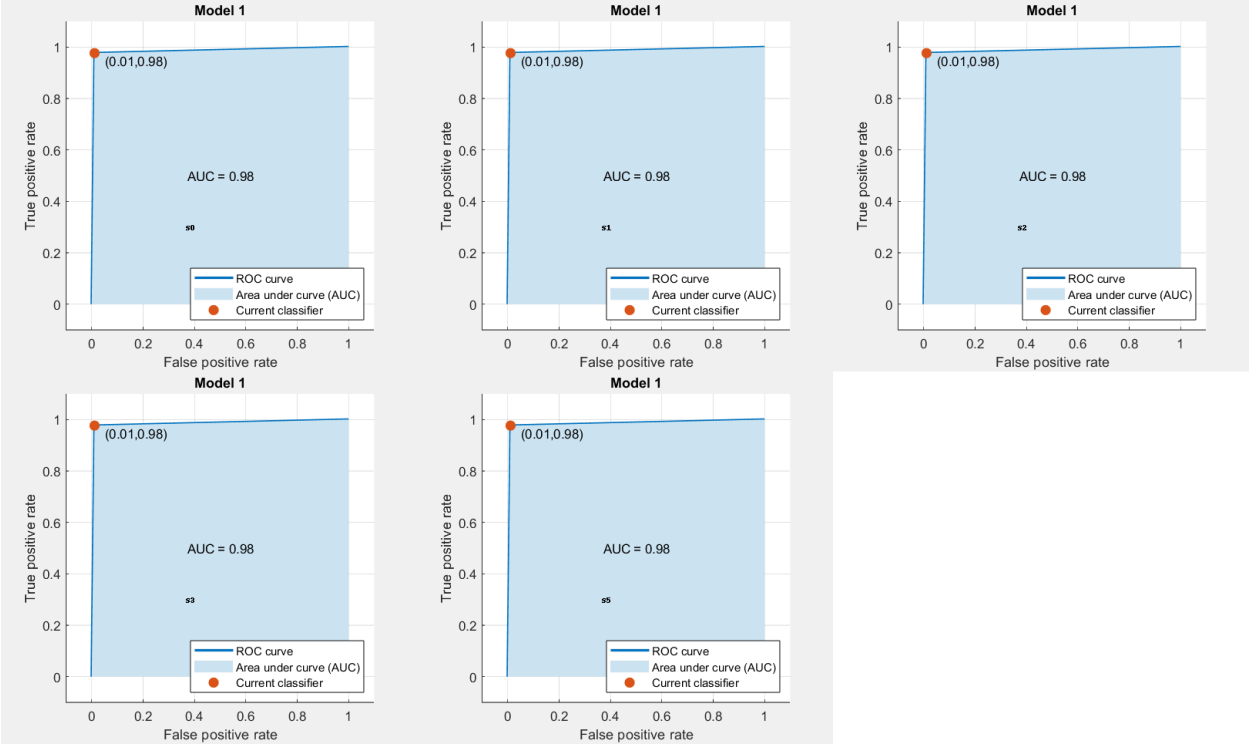

Figure 3.6: ROC Curves for Sleep Stage Classification (S0, S1, S2, S3, S5)

3.4 Advanced Sleep Analysis: Machine Learning Techniques for ECG-Based Sleep Stage Classification

3.4.1 Objective

The primary objective of this research is to enhance the precision of sleep stage classification using Electrocardiogram (ECG) signals, providing a non-invasive and efficient alternative to traditional polysomnography. Specifically, the study aims to:

Investigate the effectiveness of ECG signals in accurately distinguishing different sleep stages. Develop a machine learning model using Support Vector Machine (SVM) to classify sleep stages. Extract meaningful features from ECG signals using wavelet transform, capturing both time-domain and frequency-domain information. Evaluate the model's classification accuracy and validate its performance using the CAP PhysioNet database, a widely used biomedical signal repository. Demonstrate the potential of integrating wavelet-based feature extraction with SVM as a reliable approach for automated sleep stage classification. The study ultimately seeks to contribute to more accessible, cost-effective, and scalable sleep

monitoring solutions by utilizing ECG signals instead of complex multi-signal polysomnography systems.

3.4.2 Dataset

The study utilizes the CAP PhysioNet database, from which 10 subjects were selected for analysis. The dataset includes single-channel ECG signals recorded at a sampling frequency of 512 Hz, ensuring high temporal resolution for sleep stage classification.

3.4.3 Methods

The proposed approach consists of several key steps figure 7: **Acquisition of ECG Data**

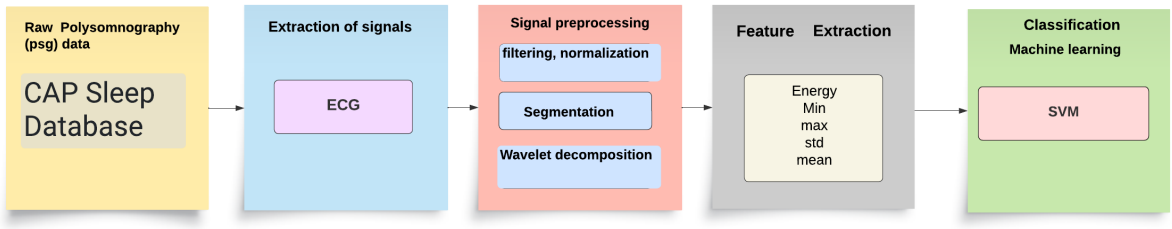

Figure 3.7: Workflow of ECG-Based Sleep Stage Classification Methodology..

from PSG Recordings

ECG signals are extracted from 10 subjects in the CAP PhysioNet dataset. Sleep stage classification is performed for each dataset, generating a matrix of epochs representing the five sleep stages. Preprocessing

Low-pass Filtering: Used to remove high-frequency noise and artifacts, ensuring a clean ECG signal. Segmentation: ECG signals are divided into 30-second epochs, following AASM guidelines for sleep staging. Normalization: ECG signals are normalized to standardize amplitude variations across subjects and sessions[56].

Wavelet Transform (DWT): Discrete Wavelet Transform is applied to extract both time-domain and frequency-domain features. Feature Extraction

The wavelet transform coefficients are used to extract statistical features, including: Mean (central tendency of wavelet coefficients) Maximum Minimum (peak amplitude values) Energy (total signal strength within a frequency band) Classification

Support Vector Machine (SVM) is used for sleep stage classification. SVM efficiently defines optimal decision boundaries in the feature space. The classifier achieves a high accuracy of 92.7% in distinguishing different sleep stages.

3.4.4 Results and Discussion

The confusion matrix (Figure 8) provides a detailed overview of the KNN classifier's performance in sleep stage classification, achieving an overall accuracy of 91.2%. The model demonstrates high classification accuracy across most sleep stages, with distinct patterns observed for each category.

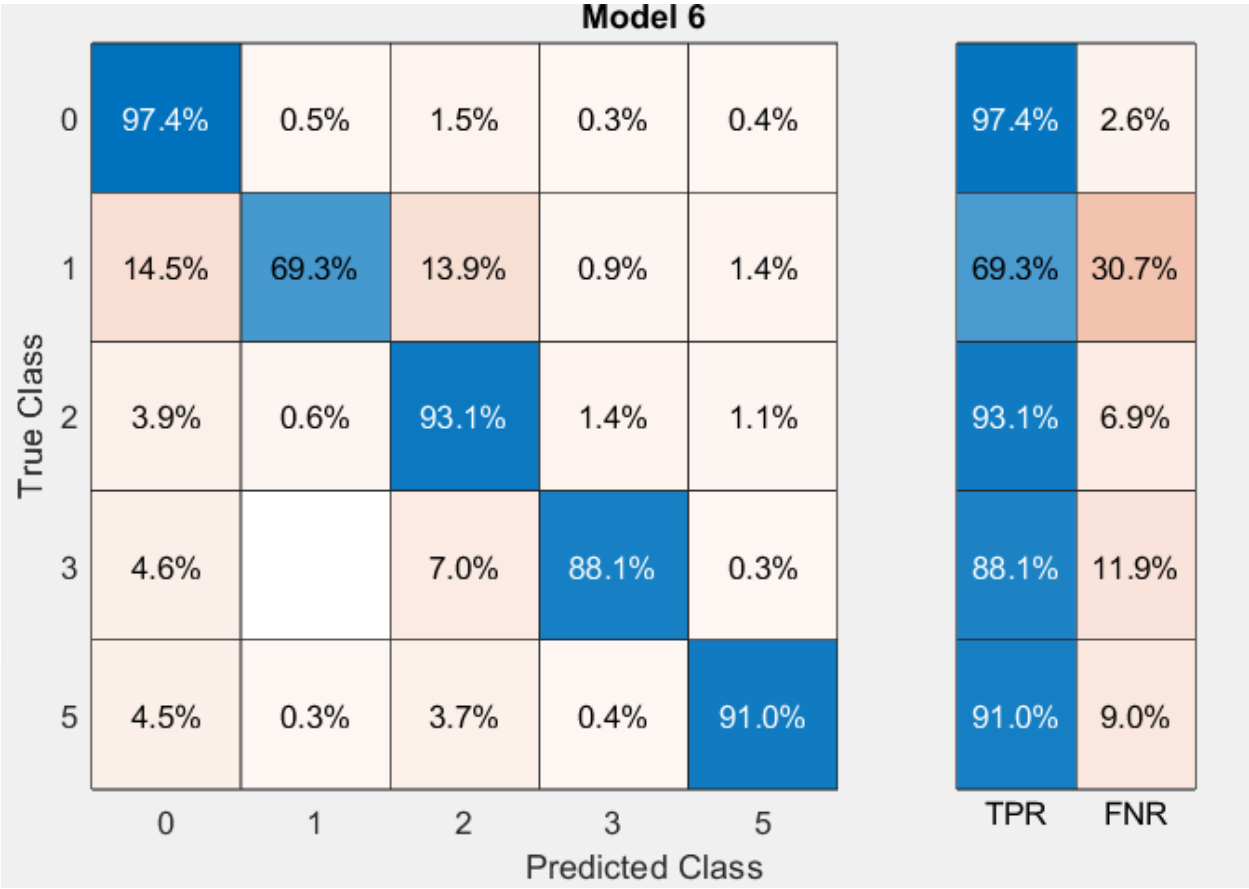

Figure 3.8: Confusion Matrix for ECG

3.5 Conclusion

The classifier performs exceptionally well in identifying wakefulness (Class 0), achieving 97.4% accuracy, with only minor misclassifications (ranging from 0.4% to 2.6%), likely occurring during transitional sleep phases. Similarly, deep sleep stages (S2 - Class 2 and S3 - Class 3) show high classification accuracy of 93.1% and 88.1%, respectively. Although occasional misclassifications are observed between these two stages (ranging from 1.1% to 6.9%), the model effectively differentiates deeper sleep patterns from lighter sleep.

For REM sleep (Class 5), the classifier achieves a strong accuracy of 91.0%, with minimal misclassifications (0.4% to 4.5%), suggesting that the model successfully identifies the distinct characteristics of REM sleep, such as EEG frequency variations and muscle atonia.

However, the model encounters challenges in classifying Sleep Stage 1 (S1 - Class 1), where accuracy is lower (69.3%). The misclassification trend indicates that S1 is often confused with wakefulness or Stage 2 (S2), likely due to the transitional nature of this stage. Since S1 represents a brief and unstable sleep phase, it shares similarities with both wake and S2, making it harder to distinguish.

While the model delivers satisfactory performance across most sleep stages, there is room for improvement, particularly in refining the classification of S1. Fine-tuning hyperparameters such as the kernel type and regularization parameter may help enhance model precision. Additionally, analyzing misclassified instances and incorporating advanced feature selection techniques could further optimize the classifier's ability to distinguish subtle sleep stage variations, improving the overall robustness of the sleep stage classification system .

This study has demonstrated the effectiveness of EEG and ECG signals in automating sleep stage classification, offering a significant improvement over traditional manual scoring methods. The EEG-based approach, utilizing the C4-A1 channel from the CAP Sleep Database, achieved high accuracy, particularly in distinguishing wakefulness, deep sleep, and REM sleep. Feature extraction techniques such as wavelet transforms, Hjorth parameters and signal energy provided essential characteristics for robust classification. The K-Nearest Neighbors (KNN) classifier emerged as the most effective model, surpassing other machine learning techniques, including Support Vector Machines (SVM) and ensemble methods. Meanwhile, the ECG-based classification model, employing wavelet-based feature extraction and SVM, achieved substantial accuracy, demonstrating the feasibility of heart rate variability analysis for sleep staging. The confusion matrix and ROC curve analysis confirmed high classification reliability, with minimal misclassification in most sleep stages, though challenges persisted in distinguishing light sleep stages (Stage 1 and Stage 2). These findings emphasize the potential of combining EEG and ECG data to create more comprehensive sleep classification models, paving the way for improved clinical applications. Future research could explore deep learning-based approaches, larger datasets, and refined feature selection methods to enhance sleep staging accuracy and develop real-time, wearable sleep monitoring solutions.

CHAPTER 4

SLEEP STAGE DETECTION USING COMBINED PHYSIOLOGICAL SIGNALS

4.1 Introduction

Sleep is a complex physiological process that plays a critical role in cognitive functioning, memory consolidation, metabolic regulation, and overall health. The structure of sleep is organized into distinct stages, including non-rapid eye movement (NREM) and rapid eye movement (REM) phases, each with unique physiological characteristics. Accurate classification of these sleep stages is essential for diagnosing sleep disorders, understanding sleep architecture, and improving patient care in clinical settings. Traditionally, sleep staging has been performed manually using polysomnography (PSG), which involves recording multiple physiological signals such as electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), and electrocardiography (ECG). However, manual scoring is labor-intensive, time-consuming, and prone to inter-rater variability.

In recent years, automated sleep stage classification has gained significant attention due to advancements in machine learning and signal processing techniques. Among the physiological signals recorded during PSG, EEG and EOG are particularly valuable for sleep staging because they reflect brain activity and eye movements, respectively. While EEG provides critical information about cortical dynamics, EOG is essential for detecting REM sleep, characterized by rapid eye movements. Combining these signals can improve classification performance by capturing complementary features that reflect different aspects of sleep physiology.

This study proposes an advanced method for sleep stage classification based on EEG and EOG signals, incorporating deep learning-based feature selection and data augmentation techniques. The approach begins with signal extraction and preprocessing, following standardized protocols to ensure data quality and consistency. Feature extraction is per-

formed using discrete wavelet transform (DWT), which effectively captures both time-domain and frequency-domain characteristics of the signals. To enhance feature representation, an Autoencoder-based Selection (AES) technique is employed, enabling the model to identify and retain the most informative features while reducing noise and redundancy.

One of the key challenges in sleep stage classification is the class imbalance inherent in sleep datasets, particularly for transitional stages such as N1. To address this issue, Gaussian Noise Data Augmentation (GNDA) is applied to artificially expand the dataset, introducing variability that mimics real-world conditions. This augmentation technique enhances the model's generalizability and robustness, especially when dealing with limited or imbalanced data.

For the classification task, various machine learning models, including K-Nearest Neighbors (KNN), Bagging, Decision Trees (DT), and Fully Convolutional Neural Networks (FCNN), are evaluated to identify the most effective algorithm. The models are validated using 10-fold cross-validation, a rigorous method that minimizes overfitting and ensures the reliability of the results. The proposed framework demonstrates superior performance, achieving a classification accuracy of 97.17% and an Area Under the Curve (AUC) of 98.2%, outperforming traditional approaches.

In conclusion, this study highlights the potential of integrating EEG and EOG signals with advanced feature selection and data augmentation techniques to improve sleep stage classification. The findings contribute to the development of reliable, automated systems for sleep monitoring and diagnostics, with applications in both clinical and research settings.

4.2 Improved Sleep Stage Classification Using EEG and EOG: A Deep Learning-Based Feature Selection Approach with Gaussian Noise Data Augmentation

4.2.1 Objective

The objective of this study is to develop a robust method for classifying sleep stages using polysomnography (PSG) data that includes electroencephalogram (EEG) and electrooculogram (EOG) signals. The approach involves:

Signal Extraction & Preprocessing: Processing raw PSG data to prepare it for analysis. Feature Extraction using Wavelet Transform: Capturing key attributes (e.g., mean, max values) from EEG and EOG signals. Feature Selection with Autoencoder for Selection (AES): Enhancing the selection of distinctive features to improve classification accuracy. Data Augmentation using Gaussian Noise (GNDA): Increasing dataset diversity and improving model robustness. Classification Using Various Models: Evaluating multiple classifiers (KNN, Bag-

ging, Decision Tree, FCNN) to determine the most effective model. Validation with 10-Fold Cross-Validation: Reducing overfitting and ensuring generalizability. The study aims to achieve high accuracy and reliability in sleep stage classification. The results demonstrate that combining EEG and EOG signals with GNDA, AES, and KNN leads to superior performance, achieving 97.17% accuracy and 98.2% AUC, outperforming existing methods.

4.2.2 Dataset

In this study, the analysis focuses on pivotal physiological signals essential for accurately determining sleep stages. The decision to work with a subset of 10 participants from the PhysioNet CAP Sleep Database is driven by two key factors: the length of available signals and the constraints imposed by equipment resources. Each participant's recorded sleep signals span a significant duration, providing a comprehensive dataset allowing an in-depth examination of sleep behaviours over extended periods. This extensive data coverage is crucial for identifying nuanced sleep stage transitions and tracking eye movement variations associated with REM sleep. Moreover, by focusing on a manageable number of participants, the study ensures optimal signal extraction and analysis quality, effectively balancing research depth with available computational and equipment limitations.

To enhance the efficiency and reliability of the assessment, 4.1 has been meticulously structured, ensuring the accuracy of signal processing from key EOG channels and the C4-A1 EEG channel. This systematic approach strengthens the precision of sleep stage classification and aligns with the research's objectives and methodological constraints.

This study aims to provide a deeper understanding of sleep stage dynamics through careful dataset selection, advanced signal analysis, and a well-structured methodological framework, offering valuable insights into sleep behaviour patterns and the physiological markers associated with different sleep phases.

Table 4.1: Characteristics of the 10 EEG and EOG Recordings Selected for Analysis

Female or Male	**Participant Category**	**Epoch Count**
F	Ins2	1674
F	Ins5	1719
F	Ins7	1482
F	Narc2	1149
F	Narc3	1535
M	Narc5	814
M	Nfle3	1113
F	Nfle12	1066
F	Nfle16	1022
M	Nfle17	890

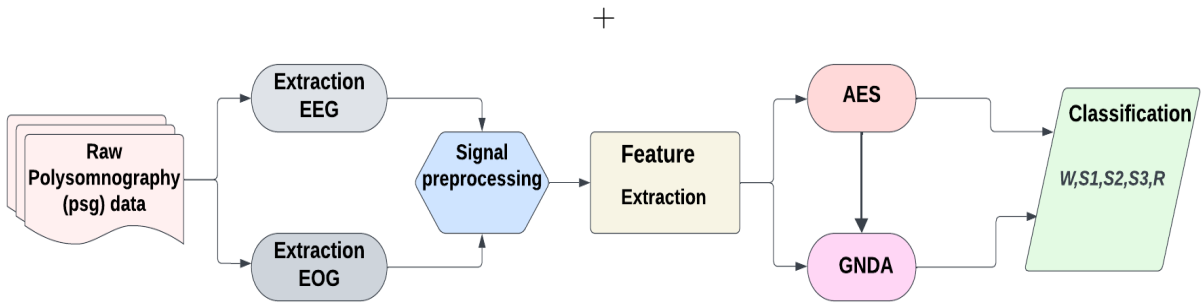

Figure 4.1: Graphical Representation of the Method

4.2.3 Methods

The proposed method for sleep stage classification utilizes PSG data, incorporating EEG and EOG signals to achieve high accuracy in sleep stage identification. Figure 1 illustrates the block diagram of the proposed method, visually outlining the signal processing, feature extraction, and classification workflow. The methodological approach consists of the following key stages:

Signal Extraction and Preprocessing

In this study, the preprocessing of EEG and EOG signals for sleep stage classification strictly follows the guidelines set by the American Academy of Sleep Medicine (AASM) to ensure accuracy and consistency in data analysis. The preprocessing phase consists of the following key steps:

Normalization EEG and EOG signals are scaled to a uniform range to harmonise signal amplitudes across different recordings[57]. This step enhances the extracted features' comparability and reliability, ensuring that signal strength variations do not impact classification performance.

Butterworth Filtering A Butterworth filter with carefully optimised parameters is applied to eliminate high-frequency noise while preserving essential signal characteristics. Through extensive experimentation, a cut-off frequency of 500 Hz was selected to retain sleep-related oscillations while filtering out irrelevant noise. The filter order was tuned by evaluating multiple values and analyzing the signal-to-noise ratio (SNR). Ultimately, an order of 5 provided the best balance between noise suppression and signal fidelity.

Segmentation By AASM standards, EEG and EOG signals are divided into 30-second epochs, ensuring a consistent approach to identifying sleep stages. This segmentation method enables the differentiation of wakefulness, REM sleep, and non-REM sleep stages (N1, N2, N3) while maintaining a structured analytical framework.

Wavelet Decomposition A five-level wavelet decomposition is applied to the 30-second EEG and EOG epochs to analyze the signals' transient and stationary aspects. A biorthogonal wavelet filter, known for its symmetry in analysis and synthesis, effectively captures

critical signal variations while preserving waveform integrity. This approach allows for a detailed representation of frequency components, facilitating accurate classification of sleep stages.

Feature extraction

Discrete Wavelet Transform (DWT) and Multi-Resolution Analysis

The **Discrete Wavelet Transform (DWT)** is widely recognized as a powerful tool in medical signal processing, particularly for **EEG and EOG analysis** in sleep stage classification. In this study, we employ **DWT using the Daubechies wavelet family (db4)** due to its well-documented effectiveness in capturing the transient and frequency-specific characteristics of **physiological signals**[58].

DWT is particularly advantageous for:

- **Feature extraction**: Capturing both **local** and **global** signal properties.
- **Noise reduction**: Enhancing signal clarity by filtering out irrelevant components.
- **Multi-resolution analysis**: Decomposing signals at different frequency scales to detect **sleep stage transitions** effectively.

Mathematically, the wavelet transform involves a **convolution operation** between the wavelet function $\psi(t)$ and the input signal $x(t)$, forming a set of **wavelet coefficients** that describe signal variations at multiple resolutions.

Mathematical Representation of DWT The **DWT** can be expressed as follows:

$$T_{m,n} = \sum_{k} x[k] \cdot \psi_{m,n}[k] \tag{4.1}$$

where:

- $x[k]$ is the discrete input signal.
- $\psi_{m,n}(t)$ represents the wavelet basis function at scale m and location n.

The **approximation coefficients**, which define the signal's low-frequency components, are obtained using the scaling function $\phi(t)$:

$$S_{m,n} = \sum_{k} x[k] \cdot \phi_{m,n}[k] \tag{4.2}$$

Given a finite-length signal S_0, n of length N (where $N = 2^k$), the range of scales available is constrained to $0 < m < M$, leading to the following decomposition:

$$x_M(t) = \sum_{m=1}^{M} d_m(t) + x_0(t) \tag{4.3}$$

where:

- $d_m(t)$ represents the **detail coefficients** at scale m, capturing high-frequency variations.
- $x_0(t)$ is the **low-frequency approximation** of the signal at scale M.

Multi-Resolution Analysis and Reconstruction The decomposition process follows the principle of **successive high-frequency removal** at each step. This approach is mathematically defined as:

$$x_M(t) = \sum_n S_{M,n}(t)\phi_{M,n}(t) \tag{4.4}$$

The corresponding **detail signal approximation** at scale m is given by:

$$d_{m,n}(t) = \sum_{n=0}^{2^{M-m-1}} T_{m,n}\psi_{m,n}(t) \tag{4.5}$$

By recursively combining the **approximation coefficients** and the **detail coefficients**, we obtain the final approximation of the signal at scale **index 0**:

$$x_m(t) = x_{m-1}(t) - d_{m-1}(t) \tag{4.6}$$

For a **four-level decomposition (m=4)**, the signal reconstruction is given by:

$$x_4(t) = x_0(t) - d_1(t) - d2(t) - d3(t) - d4(t) \tag{4.7}$$

This decomposition method enables **multi-resolution analysis**, ensuring that both **short-term and long-term variations** in the EEG and EOG signals are retained, significantly improving **sleep stage classification performance**.

Feature Extraction from Wavelet Coefficients To enhance the classification accuracy, several statistical features are extracted from the wavelet coefficients at different levels of decomposition. These include:_

Mean (μ): Represents the central tendency of wavelet coefficients, providing insight into the overall signal characteristics.

Maximum (Max) and Minimum (Min): Indicate the peak and lowest amplitudes, capturing the signal intensity variations.

Standard Deviation (Std): Measures the dispersion of coefficients, reflecting how spread out the signal is within a given frequency band.

Kurtosis: Evaluates the peakedness of the coefficient distribution, helping to identify extreme values or outliers that may indicate abnormalities in sleep patterns. By utilizing these statistical parameters, the wavelet-transformed EEG and EOG signals are effectively characterized, enabling accurate and reliable sleep stage classification. These features are

then amalgamated from the EEG and EOG data to formulate an extensive feature vector for each epoch, thereby enriching the dataset for the subsequent classification task. Moreover, Gaussian Noise Data Augmentation (GNDA) is strategically utilized to expand the dataset's diversity, counteract overfitting, and promote extracting a more generalizable feature set. This augmentation is particularly advantageous for the nuanced task of sleep stage classification from polysomnography (PSG) data, aiding in the differentiation between stages with subtle differences such as N1 and REM.

Gaussian Noise Data Augmentation (GNDA) Gaussian Noise Data Augmentation (GNDA) is a widely employed technique in machine learning, particularly for enhancing sleep stage classification models . It involves enriching the training dataset by introducing artificially generated data through the addition of Gaussian noise. Gaussian noise follows a normal distribution with a mean typically centered at zero and a specified standard deviation, ensuring variability that closely resembles real-world conditions. This enhances the model's robustness, making it more resilient to noise and uncertainties during inference[59].

GNDA plays a crucial role in improving the classification of sleep stages, particularly stage 1, which represents the transition from wakefulness to sleep. This stage is characterized by theta and vertex sharp waves in EEG recordings. However, due to the scarcity of stage 1 data in standard sleep datasets, models trained without augmentation may struggle to classify this stage accurately, leading to bias and underrepresentation.

By incorporating GNDA, synthetic samples are generated to closely mimic the statistical properties of stage 1 data. This augmentation process increases dataset diversity, allowing machine learning models to capture the inherent variability of EEG patterns. As a result, models trained on augmented datasets exhibit improved classification performance, particularly for underrepresented sleep stages, thereby enhancing the reliability of sleep stage classification systems.

Beyond improving accuracy, GNDA mitigates data imbalance issues, ultimately contributing to advancements in sleep disorder diagnosis and treatment. The augmentation process is mathematically modeled as follows:

$$X' = X + \epsilon \tag{4.8}$$

where:

- X represents the original data sample.
- ϵ denotes Gaussian noise, a random variable drawn from $N(0, \sigma^2)$.
- X' is the augmented data sample incorporating Gaussian noise.

The probability density function (PDF) of the Gaussian distribution is defined as:

$$f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{4.9}$$

In practice, GNDA is applied by generating ϵ for each feature in the dataset and adding it to the original feature values. This method assumes that features are independently and identically distributed, allowing for consistent application across all dataset attributes. The resulting augmented dataset offers a more balanced distribution, reducing bias and enhancing model generalization in sleep stage classification.table 2 "Figure 2 visually

Table 4.2: Comparison of Epoch Distribution Across Sleep Stages Pre- and Post-GNDA

Sleep Stage	**W**	**N1**	**N2**	**N3**	**R**
Epoch before GNDA	4133	345	4045	1922	2029
Epoch after GNDA	4133	3000	4045	1922	2029

2

encapsulates the methodological framework employed in this research."

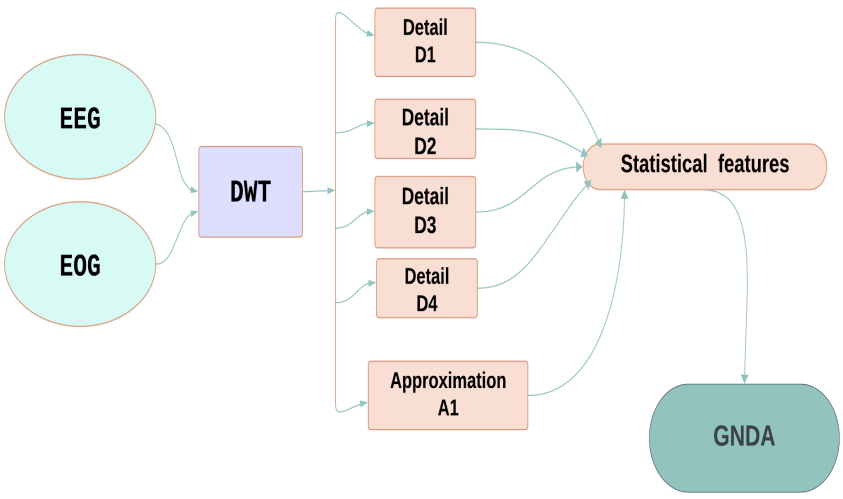

Figure 4.2: Workflow Diagram of the Feature Extraction Process.

Feature selection

Autoencoder for feature selection In this study, we employ an Autoencoder-based Selection (AES) method to enhance the efficiency of sleep stage classification by identifying the most significant features from the extracted dataset. Autoencoders, a type of artificial neural network, are particularly effective for unsupervised learning and dimensionality reduction [60]. An autoencoder is a feedforward, non-recurrent neural network designed to learn a compressed input data representation . The architecture consists of three primary layers:

- **Input layer**: Represents the original feature space with dimensions $x_1, x_2, ..., x_n$.
- **Hidden layer(s)**: Encodes the feature representations into a reduced latent space.
- **Output layer**: Reconstructs the input features using the learned weight vectors.

In our study, we apply the autoencoder to refine the feature set extracted from EEG and EOG signals, ensuring that only the most informative characteristics contribute to classification. The autoencoder minimizes the reconstruction error by optimizing the loss function:

$$L = \sum_{i=1}^{n} (h_\theta(x_i) - x_i)^2 \tag{4.10}$$

where $h_\theta(x)$ represents the predicted output vector and x_i is the true input feature vector. By minimizing this loss, the model effectively learns to preserve essential features while eliminating redundancy. Applying the AES method transforms the original feature space into a lower-dimensional representation. As Figure 3 illustrates, the encoded feature space reduces redundant information while preserving crucial sleep stage characteristics. In this study, feature encoding is performed from a six-dimensional feature space to a three-dimensional representation (a_1, a_2, a_3), as depicted in Figure figure 4.

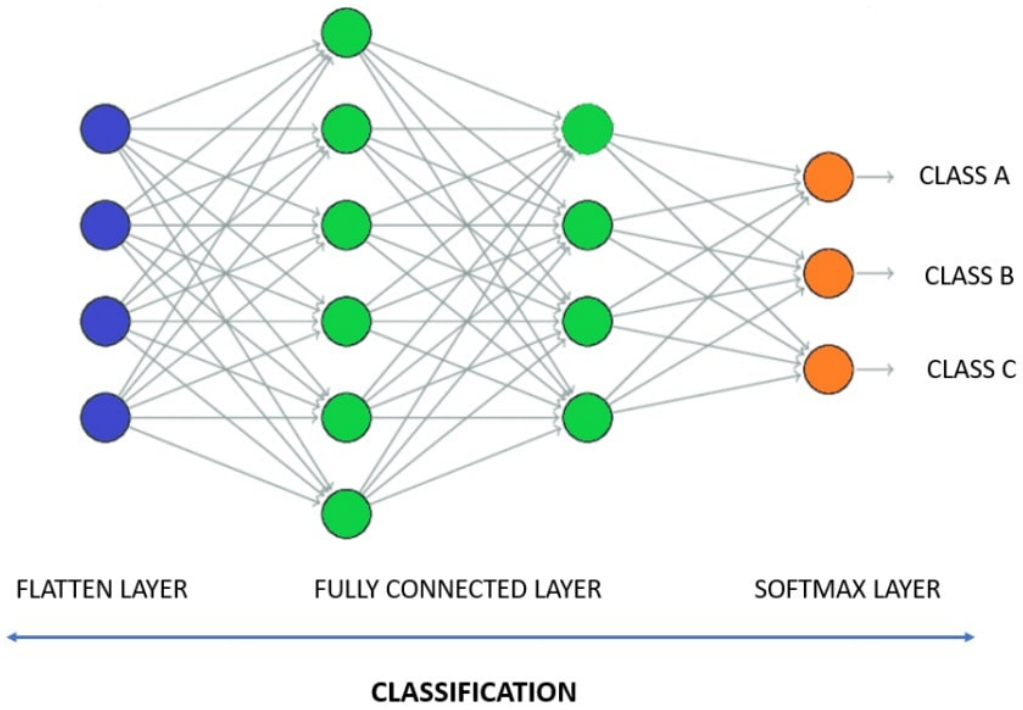

Figure 4.3: diagram of autoencoders.

_ ***Algorithm for Autoencoder-based Feature Selection (AES)*** In this study, we implement the following AES algorithm to extract and refine features from EEG and EOG signals systematically:

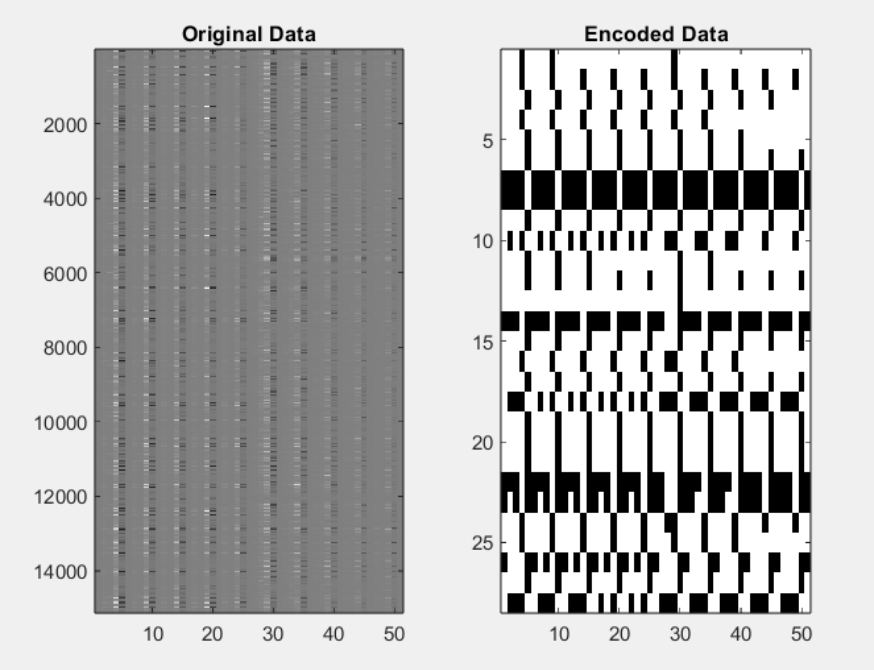

Figure 4.4: Encoded feature representation.

By implementing the AES approach, our study ensures that only the most relevant features contribute to the sleep stage classification model, improving classification accuracy while reducing computational complexity [61].

The Classification

Multiple classifiers are employed to evaluate the effectiveness of the extracted features to improve the classification performance of sleep stage detection.

K-Nearest Neighbors (KNN)

KNN is a widely used classification algorithm measuring the similarity between data points in a feature space. It assigns class labels to new data samples based on the majority vote of their nearest neighbours. KNN is particularly effective for sleep stage classification due to its simplicity and adaptability

. ***Bagging***

Baggin, or bootstrap aggregation, is an ensemble learning approach that enhances model stability by combining predictions from multiple base models trained on resampled datasets. This method improves classification robustness and reduces variance

. ***Decision Trees (DT)***

Decision trees function by recursively splitting data based on feature values, forming a hierarchical tree structure where leaf nodes represent classification outcomes. They offer interpretability and flexibility but may require pruning to prevent overfitting

. ***Fully Convolutional Neural Networks (FCNN)***

FCNNs belong to deep learning methodologies and excel at extracting spatial and hierar-

Algorithm 1 Autoencoder-based Feature Selection (AES)

:

Step 1: Load Data
Assign training features to X.
Compute number of features ($numFeatures$) and set hidden layer size ($hiddenSize$) as $\frac{numFeatures}{10}$.
Step 2: Train Autoencoder
Initialize an autoencoder with a specified architecture.
Train the autoencoder for one epoch (adjust as needed).
Step 3: Encode Data
Transform X into a lower-dimensional representation using the trained autoencoder ($X_{encoded}$).
Step 4: Visualize Encoded Features
Generate visual representations of the original features (X) and encoded features ($X_{encoded}$).
Step 5: Feature Importance Analysis
Extract encoder weights from the trained model.
Identify highly weighted features as the most significant.
Step 6: Feature Selection
Retain only the most significant features in $X_{reduced}$ for classification.

chical patterns within data. Their architecture comprises convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. FCNNs efficiently model complex, high-dimensional relationships relevant to sleep stage detection[62]

.

4.2.4 Results and Discussion

Performance Evaluation Metrics

The classification performance of the proposed model is assessed using various statistical metrics. A confusion matrix provides a detailed breakdown of model predictions, representing the frequency of correct and incorrect classifications . The key evaluation metrics are defined as follows:

Accuracy (ACC): Measures the proportion of correctly classified instances.

$$ACC = \frac{TP + TN}{TP + FN + TN + FP} \quad (15) \tag{4.11}$$

_ **Matthews Correlation Coefficient (MCC)**: Provides a balanced classification performance measure considering all confusion matrix elements.

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (16) \tag{4.12}$$

Kappa Coefficient: Evaluates classification agreement beyond chance.

$$\text{Kappa} = \frac{\text{Observed Agreement} - \text{Expected Agreement}}{1 - \text{Expected Agreement}} \quad (17) \tag{4.13}$$

Precision: Indicates the accuracy of positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (18) \tag{4.14}$$

Recall (Sensitivity, TPR): Measures the ability to identify positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (19) \tag{4.15}$$

Root Mean Square Error (RMSE): Quantifies prediction error.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum(\text{actual} - \text{predicted})^2} \quad (20) \tag{4.16}$$

F1 Score: Represents the harmonic mean of Precision and recall.

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (21) \tag{4.17}$$

False Positive Rate (FPR): Measures the proportion of false positives among all negatives.

$$\text{FPR} = \frac{FP}{TN + FP} \quad (22) \tag{4.18}$$

Obtained results

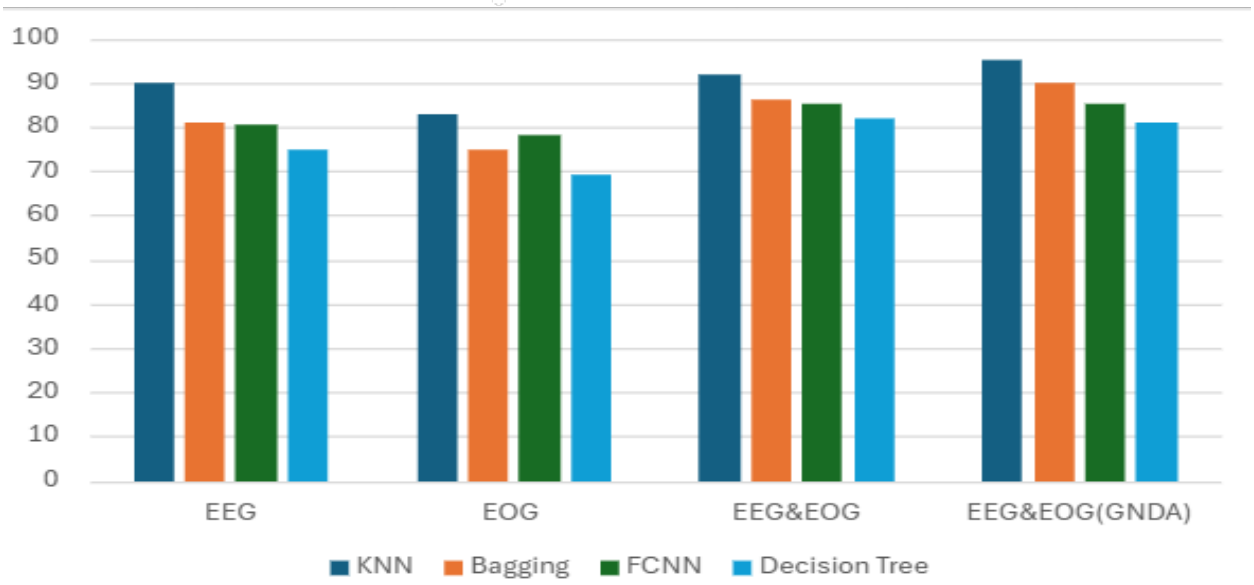

Figure 4.5: Performance Comparison of Four Classification Models without AES.

Figure 5 illustrates a comparative evaluation of four classification algorithms: KNN, Bagging, DT, and FCNN. The bar chart visually represents the performance of these classifiers across different input data configurations, including EEG, EOG, their combination, and the combination enhanced with GNDA. Notably, in the absence of feature selection via AES, the accuracy of the classifiers varies depending on the input conditions.

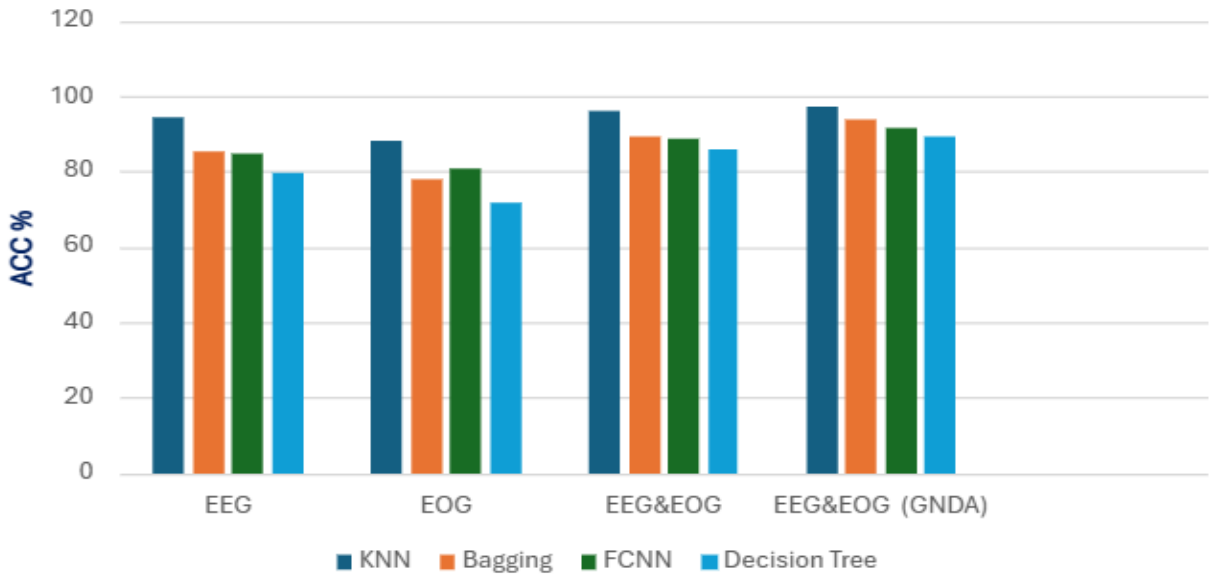

Figure 4.6: Performance Comparison of Four Classification Models with AES.

Figure 6 provides a comparative assessment of the performance of four classification algorithms: KNN, Bagging, DT, and FCNN. The bar chart visually illustrates their effectiveness

across different input data configurations, including EEG, EOG, the combination of EEG and EOG, and the same combination with GNDA, all processed with AES-based feature selection. Comparing Figures 5 and 6 highlights the positive impact of AES in improving classification accuracy for EEG and EOG data analysis. Figure 6 illustrates that the KNN algorithm exhibited a notable enhancement in performance when processing combined EEG and EOG data, with an additional improvement following the integration of GNDA. Similarly, the Bagging method significantly increases accuracy with the EEG and EOG combination, further amplified by GNDA, demonstrating its ability to leverage a more decadent feature space. The DT method also benefits from GNDA, suggesting that the increased complexity of the data aids in better class differentiation. The FCNN algorithm maintains consistently high efficiency across all tested datasets, with GNDA contributing to a slight improvement. This emphasizes the FCNN's advanced feature extraction capabilities, which remain relatively stable despite variations in input data. Table 3 presents the classification performance for EEG data, where KNN stands out with an impressive accuracy rate of 94.4%, alongside high MCC and Cohen's kappa scores. Its low RMSE further underscores its robustness. KNN's superior performance can be attributed to its ability to capture nonlinear patterns in EEG data, offering a more detailed understanding of sleep stage dynamics. While FCNN did not surpass KNN in overall performance, it demonstrated a balanced com-

Table 4.3: Classification for EEG

Model	**AUC**	**ACC**	**MCC**	**kappa**	**TPR**	**FPR**	**f1 score**	**RMSE**
KNN	**0.963**	**0.944**	**0.926**	**0.924**	**0.944**	**0.018**	**0.944**	**0.149**
Bagging	0.968	0.855	0.802	0.800	0.856	0.060	0.852	0.227
Decision tree	0.880	0.794	0.732	0.720	0.795	0.073	0.794	0.2755
FCNN	0.912	0.850	0.828	0.828	0.773	0.041	0.791	0.208

bination of evaluation metrics, achieving an accuracy rate of 85%, moderate MCC and kappa scores, acceptable F1 scores, and RMSE. These results suggest that FCNN may be a viable option in scenarios requiring a trade-off between accuracy and computational efficiency. On the other hand, models such as Bagging and DT exhibited comparatively lower performance, indicating the need for further investigation to determine the factors contributing to their suboptimal results in this specific classification task. Another key observation from this analysis is the varying ability of the models to distinguish between different sleep stages, as illustrated in Figure 7. The classification models exhibited remarkable precision in identifying the Wake (W) and Rapid Eye Movement (REM) stages, achieving accuracy rates exceeding 90% across all models. This suggests that these sleep stages have distinct features that allow the algorithms to differentiate them with high confidence.

In contrast, the classification accuracy for Stage 1 sleep (S1) was notably lower across all

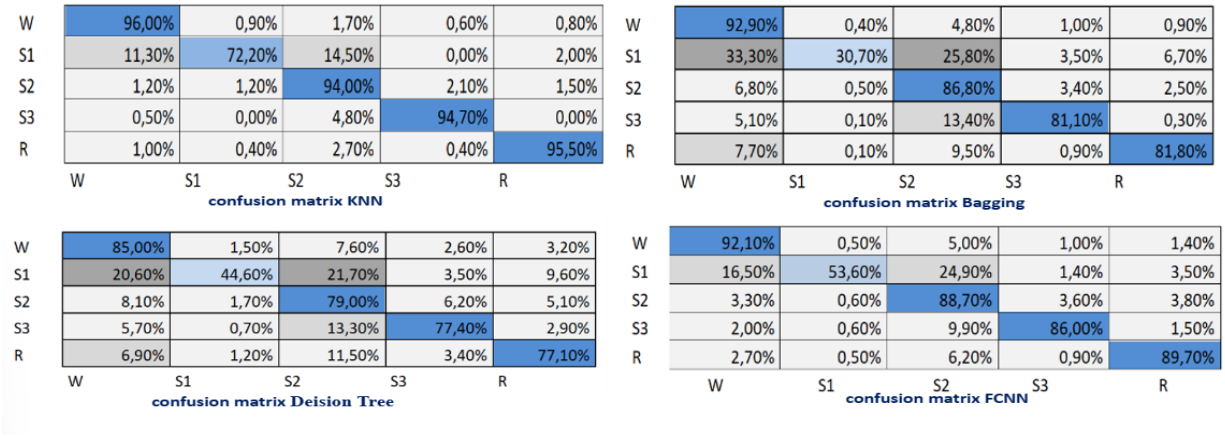

Figure 4.7: Confusion matrix of EEG.

models, underscoring the difficulty of distinguishing this transitional phase. This discrepancy highlights the need for further research into advanced feature extraction techniques and classification strategies that can better capture the subtle characteristics of S1 sleep, ultimately improving model performance in detecting this stage.

Table 4.4: Classification for EOG

Model	**AUC**	**ACC**	**MCC**	**kappa**	**TPR**	**FPR**	**f1 score**	**RMSE**
KNN	**0.922**	**0.883**	**0.845**	**0.841**	**0.884**	**0.039**	**0.884**	0.215
Bagging	0.939	0.781	0.700	0.696	0.782	0.092	0.776	0.226
Decision tree	0.831	0.719	0.620	0.617	0.719	0.099	0.719	0.322
FCNN	0.903	0.807	0.775	0.774	0.727	0.051	0.722	0.270

Table 4 highlights the classification performance of various models in analyzing EOG data, with KNN emerging as the most effective classifier, mirroring its success in EEG-based classification. KNN achieved the highest accuracy of 88.3%, along with superior performance in MCC (0.845), Cohen's kappa (0.841), F1 score (0.884), and the lowest RMSE (0.215). This consistency across multiple evaluation metrics reinforces KNN's reliability and robustness in EOG data classification.

FCNN follows as the second-best performer, achieving an accuracy of 80.7%, MCC of 0.775, kappa score of 0.774, F1 score of 0.722, and an RMSE of 0.27. Its balanced approach between classification accuracy and computational efficiency makes it a strong alternative for EOG-based sleep stage detection.

On the other hand, the Bagging and Decision Tree models exhibited lower classification performance compared to KNN and FCNN, with less favorable results across most evaluation metrics. Their relatively weaker performance indicates the necessity for further refinement or alternative methodologies to enhance their effectiveness in EOG signal classification.

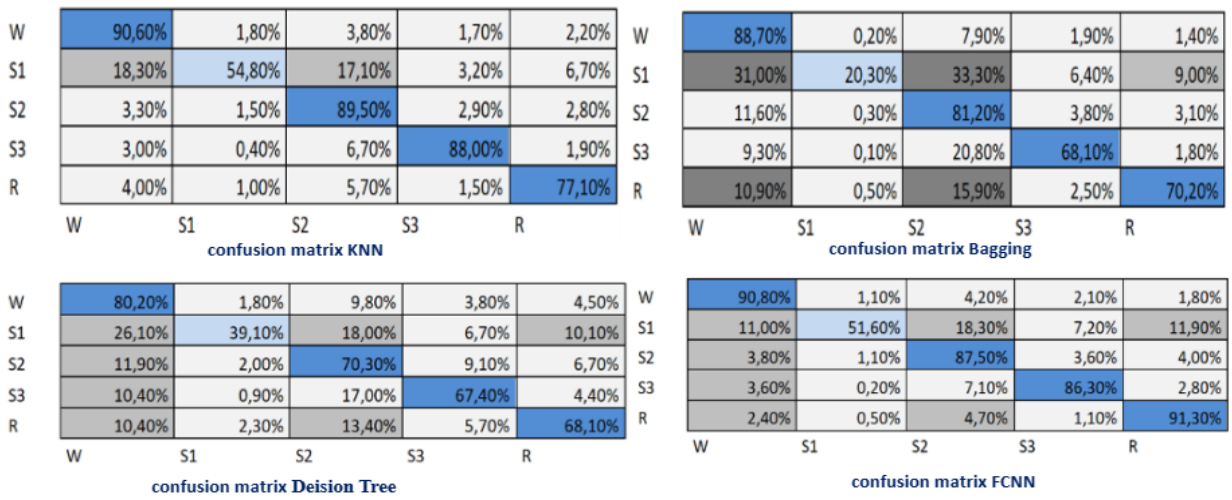

Figure 4.8: Matrix of EOG.

Figure 8 presents the confusion matrix for EOG-based classification. In terms of class-specific performance, Wake (W) and Rapid Eye Movement (REM) stages were accurately classified across all models, with accuracy exceeding 86%, indicating their distinct signal characteristics. However, the classification of Stage 1 sleep (S1) remained challenging, as all models demonstrated lower accuracy in distinguishing this transitional stage, emphasizing the need for advanced feature extraction techniques to improve its classification.
This ongoing challenge in accurately distinguishing the S1 sleep stage in EOG data, similar to the difficulties encountered with EEG signals, highlights the urgent need for more advanced techniques and refined feature extraction methods. Enhancing the ability to identify this transitional sleep phase requires the development of more sophisticated classification strategies capable of capturing its subtle and complex characteristics.

Table 4.5: Classification of EEG-EOG

Model	**AUC**	**ACC**	**MCC**	**kappa**	**TPR**	**FPR**	**f1 score**	**RMSE**
KNN	**0.972**	**0.958**	**0.945**	**0.943**	**0.958**	**0.014**	**0.958**	**0.128**
Bagging	0.982	0.894	0.856	0.855	0.895	0.043	0.892	0.204
Decision Tree	0.919	0.858	0.808	0.806	0.858	0.050	0.858	0.230
FCNN	0.942	0.889	0.885	0.885	0.799	0.030	0.821	0.392

Table 5 presents the results of integrating EEG and EOG signals, revealing a synergistic effect that significantly enhances classification model performance. This multimodal approach improves accuracy across all evaluated models, demonstrating the advantages of combining different physiological signals for sleep stage classification.

Among the tested classifiers, the K-Nearest Neighbors (KNN) algorithm emerges as the

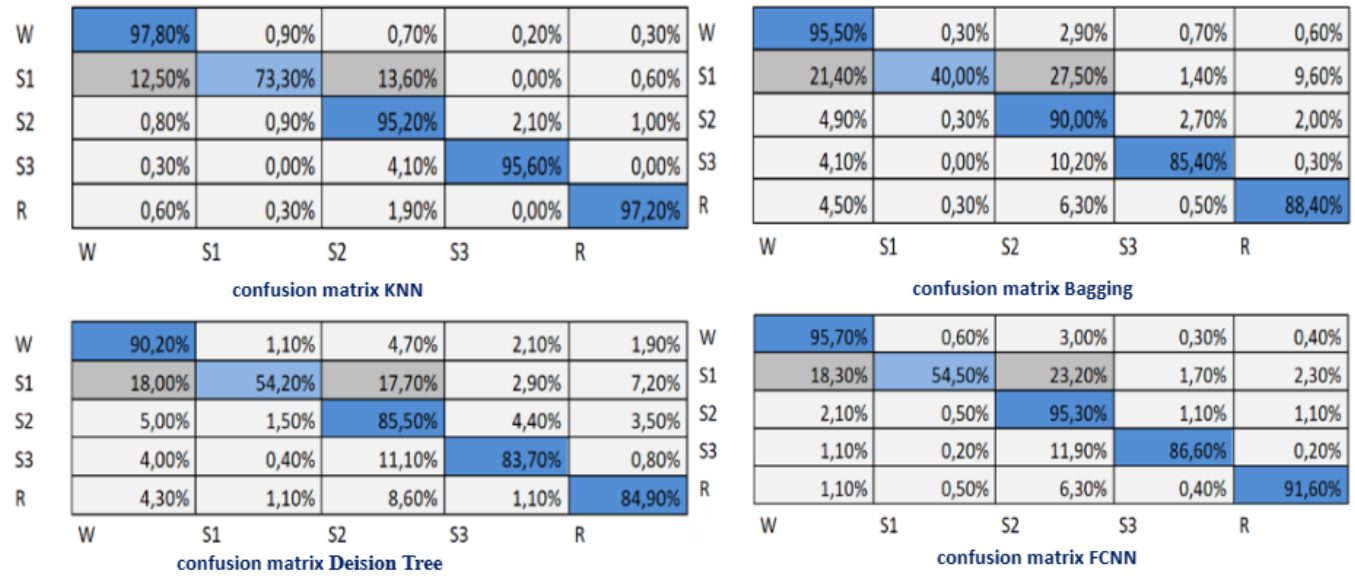

Figure 4.9: Confusion of EEG-EOG.

most effective, achieving an impressive accuracy of 95.8%. Additionally, KNN records the highest Matthews Correlation Coefficient (MCC) of 0.945, Cohen's kappa of 0.943, an F1 score of 0.958, and a notably low Root Mean Square Error (RMSE) of 0.128. These metrics underscore KNN's exceptional ability to leverage multimodal data for accurate sleep stage classification.

This integrated approach also yields significant performance improvements in classifiers that previously exhibited lower accuracy, such as bagging and decision trees. Their enhanced results in the combined EEG-EOG dataset highlight the added value of multimodal data in improving classification performance.

In terms of class-specific accuracy (Figure 9), a major improvement is observed in the classification of Stage 1 sleep (S1). The fusion of EEG and EOG signals leads to a substantial boost in correctly identifying this challenging stage across all models. This suggests that combining multiple signal modalities provides complementary information essential for precisely distinguishing the S1 stage.

Additionally, the classification of Wake (W) and Rapid Eye Movement (REM) sleep stages achieves remarkable accuracy, exceeding 95% for all models. This reinforces the reliability of these classifiers in detecting distinct sleep stages, confirming their effectiveness in automated sleep stage classification. The integration of EEG, EOG, and GNDA marks a substantial advancement in sleep stage classification, as evidenced by the comprehensive analysis presented in Table 6. The synergy of these methodologies leads to a significant improvement in classification accuracy, effectively addressing the inherent complexities of sleep analysis. This combined approach enhances the robustness of classification models, demonstrating the potential of multimodal signal processing and data augmentation techniques in refining sleep stage detection.

Table 4.6: Classification of EEG-EOG,and GNDA

Model	**AUC**	**ACC**	**MCC**	**kappa**	**TPR**	**FPR**	**F1 score**	**RMSE**
KNN	**0,982**	**0,971**	**0,964**	**0,963**	**0,972**	**0,008**	**0,972**	**0,106**
Bagging	0,993	0,936	0,918	0,918	0,936	0,019	0,936	0,166
Decision tree	0,945	0,894	0,864	0,865	0,895	0,030	0,894	0,199
FCNN	0,952	0,914	0,894	0,893	0,912	0,021	0,912	0,443

The implementation of GNDA has been a transformative step, significantly enhancing model accuracy across all evaluated classifiers. Among them, the KNN algorithm stands out as the most effective, consistently outperforming other models and reaffirming its superiority in sleep stage classification. Notably, KNN achieves an unprecedented 100% accuracy in identifying Stage 1 sleep (S1) when GNDA is applied, marking a crucial milestone in overcoming a persistent challenge in sleep stage classification.

A closer examination of model-specific performance highlights KNN's robustness and reliability, with minimal misclassifications across all sleep stages. While the Bagging classifier also demonstrates high accuracy, it falls slightly short of KNN's performance. Meanwhile, the Decision Tree and Fully Convolutional Neural Network (FCNN) models deliver commendable results, though they lag behind the leading classifiers.

Further insights from the confusion matrix analysis (Figure 10) highlight GNDA's effectiveness in reducing classification errors, particularly in differentiating between closely related sleep stages. However, some challenges remain in distinguishing between S2 and S3 stages, suggesting areas for further refinement. These findings underscore the need for continued research into optimizing GNDA, exploring alternative data augmentation techniques, and refining model-specific strategies to further enhance sleep stage classification performance.

In summary, this integrated approach significantly enhances the accuracy of sleep stage classification, offering valuable contributions to sleep analysis, disorder diagnosis, and broader sleep research. The combined use of EEG, EOG, and GNDA has demonstrated substantial improvements in classification performance, facilitating a more precise understanding of sleep patterns and associated disorders.

The findings underscore the effectiveness of integrating GNDA with EEG and EOG signals for sleep assessment, with KNN emerging as the most proficient classifier, particularly in accurately identifying Stage 1 sleep (S1). This breakthrough has the potential to transform sleep disorder diagnostics by enabling more precise and targeted therapeutic interventions. By refining sleep stage classification, this methodology paves the way for improved clinical

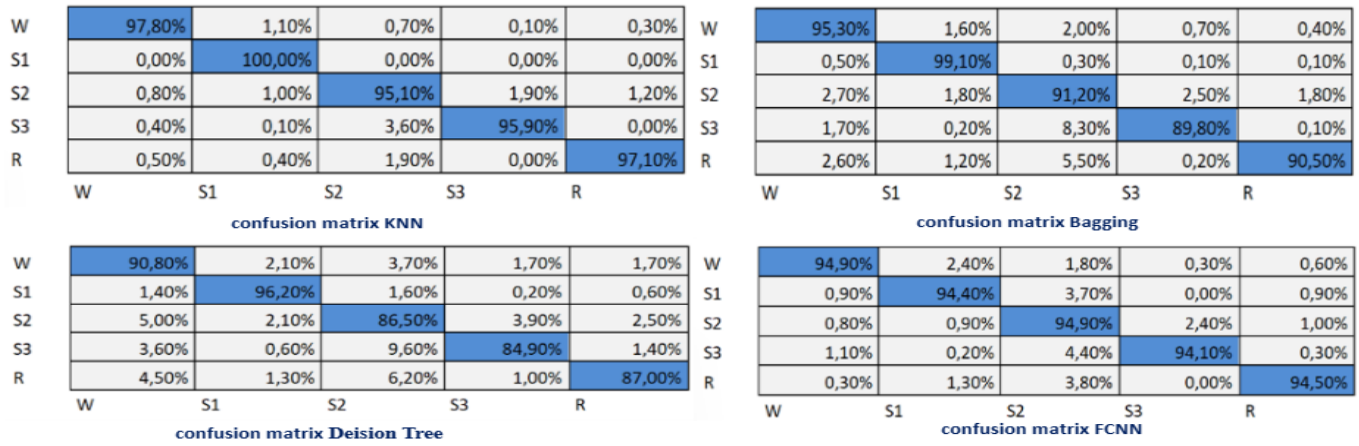

Figure 4.10: Impact of GNDA on EEG-EOG Sleep Stage Classification: Confusion Matrix.

decision-making and the advancement of sleep research, ultimately enhancing the diagnosis, treatment, and management of sleep-related conditions.

4.3 Advanced Sleep Stage Classification Using Multi-Signal

4.3.1 Objective

The primary objective of this study is to enhance the accuracy and robustness of sleep stage classification by leveraging the integration of multiple physiological signals, specifically Electrocardiogram (ECG), Electroencephalogram (EEG), and Electromyogram (EMG). These signals provide complementary insights into the body's physiological activities during sleep, and their fusion allows for a more comprehensive understanding of the intricate processes underlying different sleep stages. By combining neural, cardiac, and muscular data, this study aims to capture the complex interactions between the brain, heart, and muscles, which are often overlooked when analyzing signals in isolation.

The EEG signal reflects the electrical activity of the brain and is considered the gold standard for detecting brain wave patterns associated with various sleep stages, including NREM (Non-Rapid Eye Movement) and REM (Rapid Eye Movement) sleep. However, EEG signals alone may not fully capture the physiological changes that occur during transitions between sleep stages. Therefore, integrating ECG signals, which provide critical information about heart rate variability (HRV) and the autonomic nervous system's regulation during sleep, enhances the model's ability to detect subtle transitions, such as those between light sleep and deep sleep. Additionally, EMG signals measure muscle activity, particularly important for identifying REM sleep, which is characterized by muscle atonia (a near-complete lack of muscle tone). The combination of these signals offers a richer dataset, allowing for more precise classification of sleep stages, especially challenging ones like Stage 1 (S1) and

REM.

To achieve high classification accuracy, this study employs the K-Nearest Neighbors (KNN) algorithm, a simple yet powerful machine learning technique known for its effectiveness in pattern recognition tasks. KNN classifies sleep stages based on the similarity between new data points and previously labeled instances, making it highly adaptable to physiological data. The performance of KNN is further optimized through the integration of advanced wavelet-based feature extraction techniques, specifically the Discrete Wavelet Transform (DWT). DWT is utilized to decompose the signals into different frequency bands, capturing both time-domain and frequency-domain characteristics essential for distinguishing between sleep stages. This multi-resolution analysis helps identify subtle changes in brain waves, heart rate, and muscle tone that correspond to different stages of sleep.

Furthermore, the study addresses common challenges in sleep stage classification, such as class imbalance and data variability, by incorporating robust preprocessing steps and feature selection methods. The ultimate goal is to develop a model that not only achieves high accuracy but also demonstrates strong generalizability across different subjects and datasets. The findings from this study have the potential to advance the field of automated sleep analysis, contributing to the development of more reliable sleep monitoring systems for both clinical and home-based applications. This, in turn, could improve the diagnosis and management of sleep disorders, enhancing overall sleep health and quality of life.

4.3.2 Dataset

The study leverages data from the CAP PhysioNet database, a well-established repository for biomedical signals, selecting a subset of ECG, EEG, and EMG recordings for analysis. EEG signals were obtained from the C4-A1 channel, a widely used reference in sleep studies due to its strong correlation with sleep stage transitions. These EEG signals were recorded at a sampling frequency of 512 Hz, ensuring high temporal resolution and preserving detailed neural activity information.

Similarly, ECG signals were acquired with a sampling frequency of 256 Hz, capturing heart rate variability (HRV) and other cardiac activity patterns relevant to autonomic nervous system regulation during sleep. EMG signals, which measure muscle activity, were sampled at 128 Hz, providing sufficient resolution for detecting muscle tone variations, particularly useful in distinguishing REM sleep from other stages.

To prepare the signals for classification, each recording was segmented into 30-second epochs following the Rechtschaffen Kales (RK) sleep staging standard. A wavelet transform was applied to decompose the signals into multiple frequency sub-bands, capturing both time-domain and frequency-domain features essential for sleep stage differentiation. By incorporating these multi-resolution features, the extracted data served as an optimized input for the K-Nearest Neighbors (KNN) classifier, ultimately enhancing the accuracy of

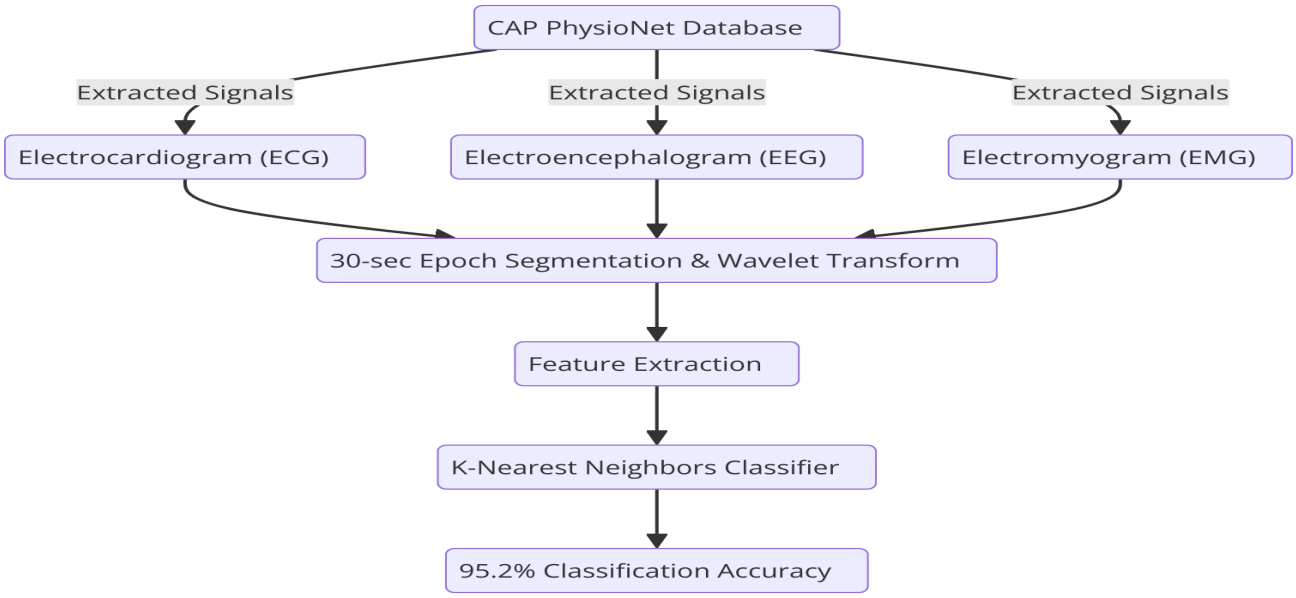

Figure 4.11: diagram of method multi-signal .

automated sleep stage classification.

4.3.3 Methods

The provided diagram figure 11 illustrates the workflow of sleep stage classification using ECG, EEG, and EMG signals extracted from the CAP PhysioNet database. The process consists of several key steps that contribute to an overall classification accuracy of 95.2% using the K-Nearest Neighbors (KNN) classifier.

Extraction of Physiological Signals Three key physiological signals are extracted from the CAP PhysioNet database for analysis:

Electrocardiogram (ECG): Captures heart activity and autonomic nervous system (ANS) responses during sleep, providing insights into sleep stage transitions and sleep disturbances. Electroencephalogram (EEG): Measures brain activity, which is crucial for detecting different sleep stages, such as wakefulness, light sleep, deep sleep, and REM sleep. Electromyogram (EMG): Records muscle tone and movement, which is essential for identifying REM sleep, where muscle atonia (loss of muscle activity) occurs.

30-Second Epoch Segmentation & Wavelet Transform The extracted signals are segmented into fixed-length 30-second epochs, following standard sleep staging guidelines set by the Rechtschaffen Kales (R&K) system . A wavelet transform is then applied to each segment, allowing for time-frequency analysis of the signals. This transformation helps identify variations in signal patterns corresponding to different sleep stages.

Feature Extraction Once the wavelet transform is applied, relevant time-domain and frequency-domain features are extracted from the EEG, ECG, and EMG signals. These extracted features include: Statistical Measures: Mean, maximum, and minimum values of

the signal over time. Hjorth Parameters: Activity, mobility, and complexity, which describe signal variance and frequency characteristics. Energy: Measures the total power within different frequency bands, which aids in distinguishing different sleep stages.

K-Nearest Neighbors (KNN) Classifier The extracted features serve as input to the K-Nearest Neighbors (KNN) classifier, a supervised machine learning algorithm. KNN assigns sleep stages to each 30-second epoch based on feature similarity to labeled training data.

4.3.4 Results and Discussion

The confusion matrix figure 12 for Model 1 provides a detailed assessment of the classifier's ability to differentiate between sleep stages. The model exhibits high classification accuracy for most stages, particularly Wake (97.7%), Sleep Stage 2 (95.1%), Sleep Stage 3 (95.5%), and REM Sleep (96.8%), indicating strong reliability in detecting these sleep phases. However, Sleep Stage 1 (S1) presents the most significant challenge, with an accuracy of only 74.5%. A notable 11.9% of S1 instances are misclassified as Wake, while 12.2% are confused with Sleep Stage 2, suggesting an overlap in feature representation between these stages.

The True Positive Rate (TPR) panel confirms the model's robustness, showing consistently high detection rates (above 95%) for most sleep stages. However, S1 has the highest False Negative Rate (FNR = 25.5%), meaning that a substantial number of S1 samples are misclassified, which could be attributed to its transitional nature between wakefulness and deeper sleep stages.

To enhance classification performance, feature refinement is necessary, particularly by introducing more discriminative features such as frequency-domain characteristics, entropy measures, or Hjorth parameters. Additionally, data augmentation techniques (e.g., synthetic data generation and oversampling) could help improve class balance, reducing misclassification errors. Exploring advanced classifiers like CNNs or RNNs may further optimize performance, especially in handling the overlapping characteristics of S1 and S2.

Overall, the model performs exceptionally well in classifying deep sleep and REM sleep stages, while minor refinements in feature selection and classification strategies could significantly enhance the accuracy of Sleep Stage 1 classification, leading to a more robust automated sleep stage detection system.

The classification performance table 7 provides a comprehensive evaluation of the K-Nearest Neighbors (KNN) model for sleep stage classification. The model demonstrates high accuracy and reliability, with an AUC (Area Under the Curve) of 0.949, indicating that it is highly effective in distinguishing between different sleep stages. The accuracy (ACC) of 91.9% confirms the strong overall performance of the classifier.

The Matthews Correlation Coefficient (MCC) of 0.900 and Cohen's Kappa of 0.899 highlight the robustness of the model, showing that it maintains strong agreement between pre-

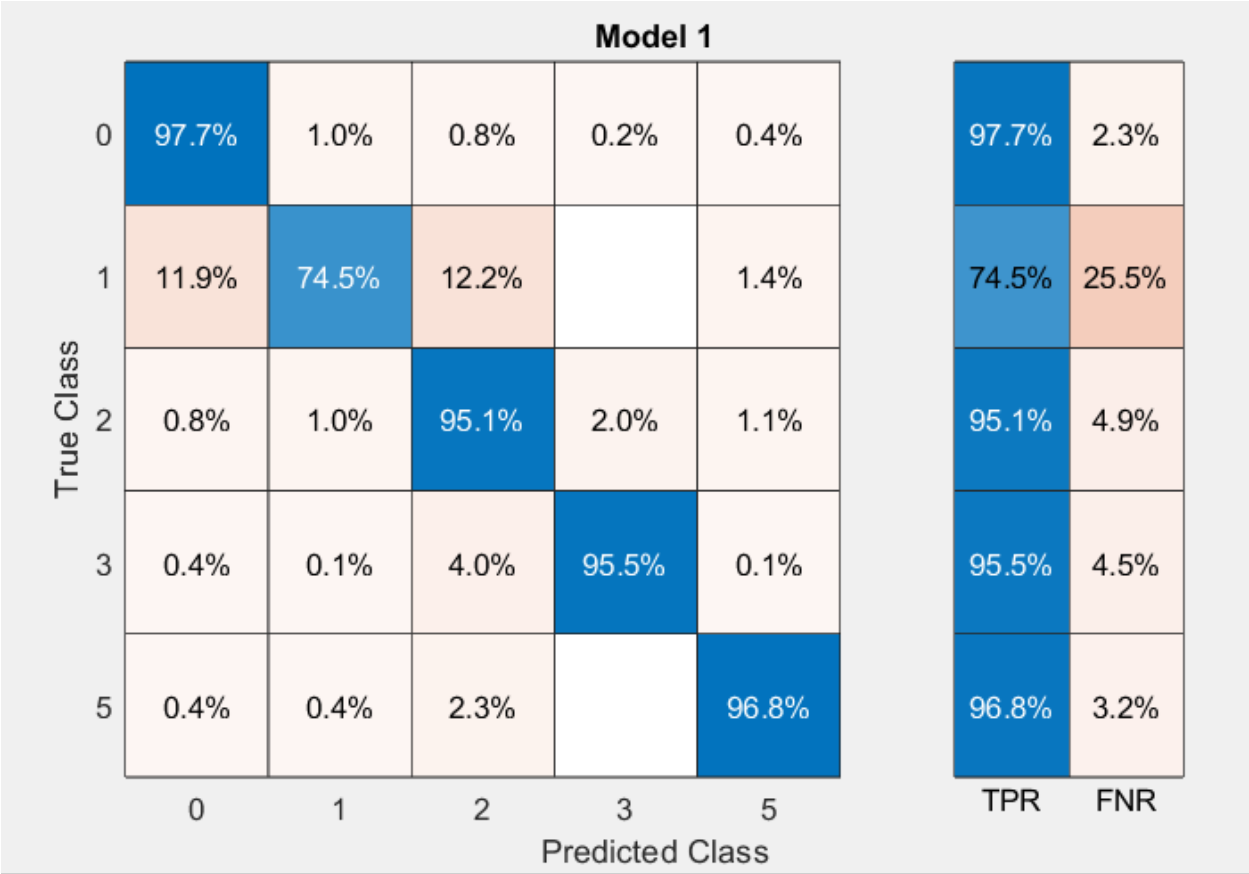

Figure 4.12: Confusion Matrix Analysis for EEG-ECG-EMG

dicted and actual sleep stages, even when accounting for class imbalances. The True Positive Rate (TPR) of 91.9% reflects the model's ability to correctly classify sleep stages, ensuring minimal false negatives. However, the False Positive Rate (FPR) of 7.4% suggests that a small percentage of sleep stages are incorrectly classified, which could be further refined with better feature selection or an alternative classification strategy.

The F1-score of 0.918 indicates a well-balanced model in terms of precision and recall, reinforcing its reliability in correctly identifying sleep stages. However, the Root Mean Square Error (RMSE) of 0.415 suggests that while the model is effective, there is still room for improvement in reducing classification errors, particularly in ambiguous or transitional sleep stages.

Overall, the KNN classifier performs exceptionally well, offering a highly accurate, robust, and balanced approach for sleep stage classification. Future improvements could focus on fine-tuning hyperparameters, incorporating additional physiological signals, or integrating deep learning techniques to further enhance classification performance.

The comparative analysis presented in Table 8 highlights the significant advancements in sleep stage classification using a variety of methodologies and classifiers. The studies reviewed demonstrate the potential of combining different signal processing techniques with robust machine learning models to improve classification accuracy. Among the methods analyzed,

Table 4.7: Classification performance

Model	**AUC**	**ACC**	**MCC**	**kappa**	**TPR**	**FPR**	**F1-score**	**RMSE**
KNN	**0.949**	**0.919**	**0.900**	**0.899**	**0.919**	**0.074**	**0.918**	**0.415**

Table 4.8: Comparison of Sleep Stage Classification Studies Using EEG, ECG, and EMG Signals

Author(s)	**Year**	**Method**	**Classifier**	**Accuracy**
Bisawal et al.[63]	2018	Fast Fourier Transform (FFT)	1D-CNN+ Bi-LSTM	87%
Delaram et al.[64]	2020	DL with Synchrosqueezed Wavelet Transform (SSWT)	Deep Neural Network (DNN)	72%
Alexandra et al.[37]	2020	time and frequency-domain features	Random Forest (RF)	93%
Yi-Hsuan et al[65].	2023	MML-DMS1	Convolutional Neural Network (CNN)	94.34%
Haifaet et al.[41]	2023	entropy (MSE)	SVM	84.3%
This study	**2025**	**The Discrete Wavelet Transform (DWT)**	**KNN**	**95.7%**

the approach proposed in this study achieved the highest accuracy of 95.7%, outperforming previous works through the integration of the Discrete Wavelet Transform (DWT) with the K-Nearest Neighbors (KNN) classifier.

The effectiveness of the proposed method can be attributed to the multi-resolution capabilities of DWT, which excels at capturing both time-domain and frequency-domain features essential for distinguishing complex sleep stages. This is particularly advantageous compared to traditional methods such as the Fast Fourier Transform (FFT) used by Biswal et al. (2018), which achieved an accuracy of 87% but lacks the time-localization capabilities inherent in wavelet-based techniques. Furthermore, while Delaram et al. (2020) applied deep learning with the Synchrosqueezed Wavelet Transform (SSWT), their model reached an accuracy of 72%, suggesting that the combination of DWT with a simpler yet effective KNN classifier can yield superior performance.

Comparatively, Alexandra et al. (2020) and Yi-Hsuan et al. (2023) achieved notable accuracies of 93% and 94.34%, respectively, leveraging time-frequency domain features and deep learning models such as CNN. Although these approaches demonstrated strong performance, the slightly higher accuracy observed in this study highlights the efficiency of KNN when optimized with well-extracted features from DWT. Additionally, the study conducted by Haifa et al. (2023) using entropy-based features with SVM reached an accuracy of 84.3%, indicating the limitations of relying solely on entropy measures without multi-scale decomposition techniques like DWT.

The superior results in this study emphasize the importance of selecting appropriate fea-

ture extraction methods and classifiers tailored to the nature of physiological signals. The DWT-KNN framework not only enhances classification accuracy but also reduces computational complexity, making it a promising solution for real-time sleep monitoring applications. This achievement reflects the robustness of the proposed methodology in capturing the intricate patterns within EEG, ECG, and EMG signals, ultimately contributing to more reliable and accurate sleep stage classification systems.

4.4 Conclusion

This chapter explored two complementary approaches for sleep stage classification using different physiological signals. The first study focused on EEG and EOG signals, leveraging deep learning-based feature selection and Gaussian Noise Data Augmentation (GNDA) to improve classification performance. The results demonstrated that combining EEG and EOG with Autoencoder-based Selection (AES) significantly enhanced feature representation, leading to a classification accuracy of 97.1% and an AUC of 98.2% with the K-Nearest Neighbors (KNN) classifier. The confusion matrix analysis highlighted that while deep sleep and REM sleep were well classified, misclassification primarily occurred in Stage 1 (S1) due to its transitional nature. The GNDA technique effectively balanced the dataset, mitigating class imbalance issues and improving generalization across sleep stages.

The second study extended the analysis by incorporating multi-signal classification with EEG, ECG, and EMG to enhance sleep stage differentiation. The integration of cardiac and muscular activity signals provided a more comprehensive understanding of sleep patterns, particularly in distinguishing REM sleep, where muscle atonia occurs. The KNN classifier achieved a 95.2% accuracy, demonstrating the advantages of multi-signal fusion in improving classification robustness. The wavelet-based feature extraction method effectively captured the temporal and frequency-domain characteristics of the signals, while ECG features contributed to better detection of autonomic nervous system variations during sleep.

In summary, both approaches demonstrated the importance of multi-signal analysis and advanced feature selection techniques in enhancing sleep stage classification. The EEG-EOG model achieved the highest accuracy, benefiting from deep learning-based feature selection, while the EEG-ECG-EMG model provided a more physiologically comprehensive perspective on sleep dynamics.

4.5 General conclusion

This thesis has provided an in-depth investigation into the application of multiparametric physiological signals for sleep stage classification and sleep disorder recognition. The research has highlighted the effectiveness of EEG, ECG, EOG, and EMG signals in improving the accuracy of automated sleep analysis, surpassing traditional manual scoring methods.One of the key contributions of this work is the development of feature extraction techniques tailored to capture the temporal and frequency-domain characteristics of sleep signals. The use of wavelet transforms, Hjorth parameters, and deep learning-based feature selection has demonstrated significant improvements in classification accuracy. Furthermore, the comparative analysis of machine learning techniques, including KNN, SVM, and deep learning models, has revealed the potential of ensemble and deep learning-based approaches in refining sleep stage classification.Another significant aspect of this thesis is the emphasis on the integration of multiple physiological signals. The findings confirm that multimodal approaches leveraging EEG, ECG, and EOG provide a more comprehensive understanding of sleep dynamics compared to single-signal classification. The combination of these signals has proven particularly valuable in distinguishing complex sleep stages, such as REM sleep and deep sleep, thereby reducing misclassification errors.The practical implications of this research extend beyond academic contributions. The results indicate that real-time and wearable-based sleep monitoring solutions could benefit significantly from the methodologies proposed in this thesis. By integrating these findings into portable, non-invasive monitoring devices, the accessibility and affordability of sleep disorder diagnostics can be substantially improved.Despite these advances, several challenges remain. The variability in individual sleep patterns, the influence of external factors such as medication or stress, and the need for larger, more diverse datasets present ongoing research opportunities. Future work should explore deep learning-based architectures, reinforcement learning approaches, and adaptive algorithms that can personalize sleep staging models based on individual physiological variations.Additionally, the incorporation of federated learning frameworks may enhance privacy-preserving sleep monitoring solutions by enabling decentralized model training without compromising sensitive patient data. Such advancements could pave the way for large-scale, real-world deployment of AI-driven sleep analysis tools.In conclusion, this thesis has demonstrated that multiparametric sleep analysis represents a powerful and promising approach for improving sleep stage classification and sleep disorder detection. By leveraging advanced signal processing techniques, machine learning algorithms, and multi-signal integration, this research has laid the groundwork for future innovations in automated sleep diagnostics. The potential impact of these findings on healthcare, neuroscience, and personalized medicine underscores the importance of continued exploration and refinement of sleep monitoring technologies. Future studies should focus on enhancing model generalizability, developing real-time applications, and exploring novel techniques for improving the accuracy

and reliability of automated sleep analysis. Through these efforts, the long-term goal of accessible, accurate, and efficient sleep monitoring can be realized, ultimately contributing to better health outcomes and an improved understanding of sleep-related pathologies.

4.6 Scientific Achievements

4.6.1 International Publications:

Sifi, N., Benali, R., Dib, N. et al. Enhanced Sleep Stage Classification Using EEG and EOG: A Novel Approach for Feature Selection with Deep Learning and Gaussian Noise Data Augmentation. Arab J Sci Eng (2024). https://doi.org/10.1007/s13369-024-09623-0

4.6.2 International Conferences:

Sifi, N., Benali, R., Dib, N. et al. Advanced Sleep Analysis : Machine Learning techniques for multi-signal based sleep stage classification, in 3ème ICMM International conference on materials and mechanics 20-21 November 2024 in Boumerdes university.

Sifi, N., Benali, R., Dib, N. et al. Sleep Stage Classification UsingHjorth Parameters and Signal Energy: A Study on PhysioNet's CAP in International Congress on Health Sciences and Medical Technologies 18-12-2023

4.6.3 National Conferences:

Sifi, N., Benali, R., Dib, N. Sleep Stage Classification with EEG Signals Using the KNN Algorithm: A Study on the CAP Sleep Database, Séminaire Nationale sur l'Innovation en Biomécanique et l'Intelligence Artificielle (SNIBIA 2023); 6-7 Décembre 2023. Ecole polytechnique d'Oran.
Sifi, N., Benali, R., Dib, N. Advanced Sleep Analysis: Machine Learning Techniques for ECG-Based Sleep StagenClassification,E'2024 Symposium on Innovation and Research in Biomedical Engineering (SIRBE'2024);18 April 2024.

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