Physics-Informed BiLSTM Neural Networks for Enhanced In-Ear EEG Sleep Stage Classification

Abstract

The study introduces an innovative Physics-Informed Bidirectional Long Short-term Memory (BiLSTM-PINN) architecture designed to automate sleep stage classification using in-ear EEG data. It addresses significant shortcomings in current methodologies, such as the low accuracy in identifying transitional N1 stages (historically exhibiting a sensitivity range of 34.7% - 50%) and the lack of neurophysiological constraints that result in clinically implausible predictions. We can resolve these shortcomings by incorporating domain-specific physics-informed constraints derived from EEG band power ratios and sleep physiology into a deep learning framework, ensuring biologically consistent outputs. Furthermore, the architecture employs bidirectional temporal modelling and multi-headed attention mechanisms to effectively capture the dynamics of sleep stages, cumulating in a state-of-the-art performance characterised by an accuracy of 85.86%, a Cohen's Kappa of 0.823 (exceeding the 0.80 clinical threshold), and outstanding N1 detection (F1-score: 0.890).

Index Terms: Physics Informed Neural Networks, Sleep Stage Classification, In-Ear-EEG, Bidirectional LSTM.

Introduction

Sleep stage classification represents a fundamental challenge in sleep medicine, with traditional polysomnography requiring expensive equipment and clinical settings that limit accessibility for continuous monitoring. Global sleep disorders affect an estimated 30% to 70% of adults, with obstructive sleep apnea alone impacting around one billion adults worldwide. Yet, conventional diagnostic methods remain inaccessible to many patients due to cost, availability, and the artificial clinical environment that may not reflect natural sleep patterns.

Recent advances in in-ear EEG technology offer promising alternatives for unobtrusive, long-term sleep assessment, enabling real-world deployment of automated sleep monitoring systems that could revolutionise personal health monitoring and clinical practice. The clinical significance of accurate sleep stage classification extends beyond basic sleep assessment, providing crucial insight into neurological health, circadian rhythm disorders, and cognitive performance.

However, existing approaches face several critical limitations: limited accuracy for challenging transitional stages like N1 and a lack of physics-informed constraints incorporating established neurophysiological domain knowledge. Current in-ear EEG studies report Cohen's kappa values ranging from 0.42 to 0.73 [3][4], falling short of the 0.80+ threshold required for clinical deployment.

The work introduces the first physics-informed bidirectional LSTM framework designed explicitly for in-ear EEG sleep stage classification, combining temporal dependency modelling with neurophysiological constraints derived from established sleep physiology principles.

Key Contributions: (1) Novel integration of physics-informed neural networks with bidirectional LSTM architecture for sleep classification, (2) Comprehensive six-step preprocessing pipeline optimised for in-ear EEG signals, (3) State-of-the-art performance achieving 85.86% accuracy with 0.823 Cohen's kappa, (4) Exceptional N1 stage detection and (5) Comprehensive validation through extensive experiments.

Background

The development of automated sleep staging systems faces numerous challenges that have limited clinical adoption of existing approaches. Inter-subject variability represents one of the most significant challenges, as EEG patterns exhibit substantial differences across individuals due to age, gender, medication use, and underlying neurological conditions. This variability is widespread in in-ear EEG recordings, where electrode positioning and contact quality vary significantly between subjects.

Age-related alterations in sleep architecture introduce further difficulties for automated systems. Elderly individuals generally exhibit diminished slow-wave sleep, heightened sleep fragmentation and modified REM sleep patterns. These alterations necessitate the development of robust models capable of adapting to age-related differences while ensuring precise classification performance across various age demographics.

The temporal dependencies intrinsic to sleep architecture pose another considerable challenge. Sleep stages do not occur independently; they follow specific transition patterns influenced by sleep homeostasis and circadian rhythms. The likelihood of transitioning between sleep stages adheres to predictable patterns, with particular transitions being more probable than others. For instance, the shift from N1 to N2 is more frequent than from N1 to REM sleep.

Detecting the N1 stage may represent the most formidable challenge in automated sleep staging. The N1 stage is marked by subtle EEG changes that manifest during the transition from wakefulness to sleep, complicating the differentiation from both the Wake and N2 stages. Conventional methods achieve only 34.7% - 50.0% for N1 detection; however, precise N1 classification is essential for assessing sleep onset latency and overall sleep quality.

The integration of various physiological signals adds another layer of complexity. While this study emphasises EEG signals, clinical sleep staging frequently includes electromyography (EMG), electrooculography (EOG), and other physiological metrics. The challenge lies in creating models that can efficiently integrate these diverse data streams while maintaining computational efficiency for real-time applications.

In-ear EEG Technology: Principles and Advantages

Fundamental Principles

In-ear EEG offers an alternative to scalp EEG by detecting brain activity via electrodes in the ear canal. The ear’s anatomy provides natural shielding from electromagnetic interference, and the thin temporal bone allows effective signal transmission, particularly from the temporal lobe, necessary for sleep analysis.

Hardware and Design

Custom moulded silicone earpieces (<6g) house dry iridium-oxide or Ag/AgCl electrodes (2 - 3 mm) with impedance 10-150 kohm at 10 Hz. Electrodes are positioned in the canal, with references at tragus/concha or contralateral sites. Mechanical design features concha wings and elstomer contacts to reduce motion artefacts and improve comfort. Replaceable tips and IPX2-rated housings support hygiene and moisture protection.

Advantages over Scalp EEG

Simplified setup: No gels or multiple electrodes, which is suitable for home use

Improved signal quality: Ear canal shielding reduces external interference, enhancing signal-to-noise ratio.

Reduced motion artefacts: Stable positioning ensures consistent overnight recordings.

Long-term monitoring: Dry electrodes minimise skin irritation, enabling extended sleep assessment [3].

Signal Characteristics and Limitations

Low amplitude (10 - 30% of scalp EEG)

Frequency emphasis on theta and alpha bands

Enhanced temporal lobe detection and reduced frontal/parietal sensitivity

Individual ear anatomy affects electrode fit and signal quality.

Physics-Informed Neural Networks

Theoretical Foundation of Physics-Informed Neural Networks:

PINNs embody a transformative methodology in machine learning that effortlessly combines well-established physical principles and specialised knowledge with deep neural network data-driven strengths. First introduced by Raissi et al. [6], PINNs address fundamental limitations of purely data-driven approaches by embedding physical layer constraints directly into the neural network training process through the loss function formulation. PINNs integrate known physical laws, expressed as partial differential equations (PDEs), directly into the training process of the neural network by embedding them in the loss function. This allows PINNs to simultaneously solve forward problems (predicting system behaviour from known equations and initial/boundary conditions) and inverse problems (discovering unknown parameters or equations from observed data), ensuring that predictions are physically plausible.

Using automatic differentiation to compute derivatives within the PDEs, PINNs regularise the learning process, reducing reliance on large datasets and improving generalisation, especially valuable in biomedical applications where data is scarce but physiological principles are well established.

PINNs have demonstrated remarkable success in biomedical signal processing across diverse applications, including cardiovascular modelling, respiratory signal analysis, cardiac electrophysiology, and brain hemodynamics [7]. These applications have consistently shown that incorporating physiological constraints significantly improves model performance, particularly in scenarios with limited training data or when model interpretability is crucial for model acceptance. Recent advances in physics-informed approaches for physiological signal processing have established the foundation for applying these principles ot sleep stage classification, where established neurophysiological knowledge can guide automated staging systems.

Mathematical Framework for Sleep Physiology Integration

Integrating sleep physiology principles into our BiLSTM-PINN architecture follows the fundamental PINN formulation, where the total loss function combines data-driven classification objectives with physics-informed constraints, where lambda represents the physics weighting parameter that balances the contribution of neurophysiological constraints against classification accuracy. Our physics-informed component enforces established sleep physiology principles through spectral power constraints derived from clinical sleep research. The physics loss function incorporates minimum threshold constraints for critical EEG frequency bands. Pi represents the predicted power for frequency band i, and tau i denotes the physiologically derived minimum threshold. These constraints ensure that predictions maintain physiological plausibility by enforcing minimum power levels in delta, theta and alpha bands essential for accurate sleep stage determination.

Additional physics-informed constraints incorporate established relationships between EEG frequency bands that characterise different sleep stages. The delts/beta ratio indicates deeper sleep states such as N3, while the theta/alpha ratio becomes elevated during sleep transitions and REM sleep.

The alpha/beta ratio indicates relaxation and drowsiness, while the gamma/delta ratio represents cognitive activity during wakefulness. These ratios encapsulate the neurophysiological process that forms the basis of sleep architecture and offer interpenetrable characteristics that correspond with clinical sleep scoring standards.