Real-Time Sleep Stage Monitoring Using Neural Networks For Optimal Wake-Up Timing

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Abstract

Background: Human sleep architecture is cyclic, oscillating between Non-Rapid Eye Movement (NREM) stages and Rapid Eye Movement (REM). NREM sleep progresses from light sleep (Stages N1 and N2) to deep, slow-wave sleep (Stage N3). Awakening during deep N3 or intense REM sleep often results in sleep inertia, a physiological state characterized by grogginess, disorientation, and cognitive impairment. Conversely, waking up during light sleep stages (N1 or N2) significantly reduces these symptoms, leading to improved alertness and morning functionality. While clinical polysomnography provides high diagnostic accuracy, it is intrusive and unsuitable for long-term home use. This creates a need for comfortable, automated sleep monitoring systems that can identify optimal wake-up moments. *Methods*: We propose a low-cost system combining a minimalist 3-electrode EEG headband with a wrist-worn unit containing PPG, EDA, and accelerometer sensors. An MSC-Transformer neural network, trained on the DREAMT dataset, fuses these multimodal signals to classify sleep stages in 30-second windows. A smart alarm algorithm utilizes this classification to trigger wake-up within a user-defined window, specifically targeting light sleep stages (N1/N2). Thus, our specific goal is to implement a neural network-based algorithm that performs continuous sleep stage classification, allowing for a "smart wake-up" mechanism that significantly reduces the grogginess associated with waking from deep sleep or REM. *Results*: The model was evaluated using a subject-independent split on 100 subjects (68 training, 12 validation, 20 test). On a 4-class classification task (Wake, Light, Deep, REM), the model achieved 79.27% test accuracy, with 91% precision and 83% recall for detecting light sleep—the critical class for smart alarm applications. Merging N1 and N2 into a single "Light" class improved accuracy by 6% compared to the traditional 5-class approach. *Conclusion*: Our results demonstrate promising classification performance for sleep stage detection using a reduced sensor setup. However, real-world validation in home environments and empirical testing of the smart wake-up mechanism are needed before the system can be considered a practical alternative to clinical polysomnography.

Keywords: Sleep stage classification; Electroencephalography (EEG); Photoplethysmography (PPG); Multi-modal bio signals; Smart wake-up system.