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Simplified feature extraction for low-resource sleep staging

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Abstract

Wearable sleep monitoring devices require efficient algorithms capable of running on resource-constrained hardware. This study develops a lightweight approach to sleep stage classification optimized for low-power environments. We first analyze the computational complexity of standard EEG feature extraction methods, then design simplified approximations that maintain discriminative power while significantly reducing computational requirements. Our progressive computation framework calculates basic features first, only proceeding to more complex features when classification confidence is low. Experiments on the Physionet sleep EEG dataset demonstrate that our approach achieves 93.2% of the accuracy of full-complexity methods while reducing power consumption by 76% and memory usage by 68%. Model compression techniques, including 8-bit quantization and network pruning, further optimize performance on microcontroller-class hardware. The system successfully classifies sleep stages with only 32KB of RAM and 120KB of flash memory, enabling integration into wearable devices with minimal battery impact. This lightweight methodology makes continuous, long-term sleep monitoring feasible in real-world settings without sacrificing clinical utility.

Keywords: Low-Power Algorithms; Embedded Sleep Monitoring; Feature Optimization; Model Compression; Wearable Devices; Resource-Constrained Computing

1. Introduction

Technological progress has revolutionized numerous medical fields, with sleep research emerging as a particularly dynamic area of study. This expanding field offers twin advantages: deepening our comprehension of sleep physiology while enhancing diagnostic precision for sleep disorders. The significance of sleep health cannot be overstated, as evidenced by National Sleep Foundation (NSF) findings that 40% of individuals with conditions including hypertension, bone aches, heart disease, diabetes, depression, cancer, lung disease, osteoporosis, retention problems, and stroke report sleep disturbances [1]. This stands in stark contrast to the general population, where only 10% report similar issues.

Sleep disorders often present as quantifiable changes in sleep characteristics, such as shortened sleep duration or prolonged sleep onset. The NSF categorizes these conditions into primary sleep disorders (including sleep-disordered breathing (SDB), sleep-wake disturbances, insomnia, and movement disorders such as restless leg syndrome (RLS) and periodic limb movement) and secondary sleep disorders (stemming from underlying conditions like chronic pain, gastroesophageal reflux, nocturia, dyspnea, chronic preventable lung disease, or asthma). Diagnosing primary sleep

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disorders accurately requires thorough understanding of normal sleep architecture. While clinical assessment may raise initial suspicions, polysomnography remains essential for definitive diagnosis.

Polysomnography (PSG) encompasses the overnight recording of multiple physiological parameters during sleep. These biosignals include electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOG), and electromyograms (EMG). EEG recordings are particularly crucial, offering insights into cerebral activity across various sleep stages and facilitating sleep disorder classification. Sleep experts analyze these recordings using the Rechtschaffen and Kales (R and K) guidelines, developed in 1968 and later updated by the American Academy of Sleep Medicine (AASM) [2], which divide sleep into distinct phases: wakeness (W), non-rapid eye movement (NREM) sleep, and rapid eye movement (REM) sleep.

The automation of sleep stage classification has been approached from various angles by researchers. Santaji and Desai [13] implemented machine learning techniques for analyzing 10-second windows of EEG data, achieving 97.8% accuracy using random forest algorithms. Bhusal et al. [14] developed modified orthogonal convolutional neural networks to overcome gradient saturation issues, improving both classification accuracy and training efficiency. Tao et al. [15] pioneered feature relearning techniques for automated sleep staging from single-channel EEG data, while Yulita et al. employed convolutional and long short-term memory networks for automatic feature extraction from EEG signals [16].

Traditional methods of sleep stage classification require specialists to manually interpret EEG recordings frame by frame—a laborious process vulnerable to human error. Producing comprehensive reports from these analyses can take hours, underscoring the need for reliable automated systems to support clinicians in EEG data interpretation. Despite significant advances in automation, most existing approaches treat feature extraction, selection, and classification as discrete processes, potentially compromising information integrity between stages.

Artificial intelligence, particularly deep learning, has recently demonstrated remarkable capabilities across domains including image recognition, audio processing, and natural language understanding. These technologies have been successfully adapted to biomedical applications, with specialized approaches for analyzing biosignals including EEG, ECG, EMG, and EOG. Our research leverages a comprehensive EEG dataset from Physionet [17], comprising whole-night polysomnographic recordings from Fpz-CZ and Pz-Oz electrode placements.

In this work, we develop a lightweight approach to sleep stage classification specifically designed for resource-constrained environments such as wearable devices. Our methodology begins with a comprehensive computational complexity analysis of existing feature extraction methods, followed by the design of simplified approximations that preserve discriminative power while requiring significantly fewer computational resources. The main contributions include our progressive computation framework that adaptively calculates features based on classification confidence, and our hardware-aware optimization techniques that enable deployment on low-power microcontrollers without sacrificing classification performance, opening new possibilities for long-term, continuous sleep monitoring in real-world settings.

2. Dataset Description

The Physionet sleep EEG dataset constitutes a comprehensive signal repository featuring dual-channel polysomnographic recordings obtained at a sampling frequency of 100 Hz, resulting in precise temporal resolution of 10 milliseconds between consecutive data points. The signal acquisition employed two distinct electrode montages—Fpz CZ and Pz-Ozcapturing frontal and parietal-occipital brain activity respectively, providing complementary spatial information for sleep stage differentiation.

The dataset encompasses 153 full-night polysomnographic recordings with an approximate duration of 20 hours per recording session, spanning two consecutive day-night cycles. Signal acquisition was performed under controlled conditions, with all subjects (age range: 25-101 years) participating without pharmacological sleep aids to ensure naturalistic sleep architecture representation.

Expert hypnogram annotation followed the standardized Rechtschaffen and Kales protocol (1968), resulting in six distinct electrophysiological classifications: Awake (characterized by mixed frequency components with higher amplitude variations), Stage 1 (dominated by alpha waves in the 2-7 Hz band), Stage 2 (featuring distinctive sleep spindles in the 12-14 Hz range), Stage 3 (showing emerging low-frequency ~2 Hz components), Stage 4 (dominated by high-amplitude low-frequency oscillations), and REM (exhibiting mixed frequency components with typical sawtooth morphology and reduced amplitude). Artifact-containing segments labeled as Movement Time were systematically excluded from the analytical pipeline.

The continuous signals underwent uniform segmentation into 30-second epochs, each containing 3,000 discrete sample points, resulting in a dataset comprising 367,200 labeled segments. The data partition strategy implemented a 60/40 ratio, allocating 220,320 segments to the training corpus and reserving 146,880 segments for validation purposes—a deliberately substantial testing proportion designed to rigorously assess algorithmic generalization capability across diverse sleep patterns.

This technically rigorous dataset architecture provides an optimal framework for evaluating computational approaches to automated sleep stage classification, with particular emphasis on signal processing efficiency, feature extraction methodology, and machine learning implementation.

3. Proposed methodology

This section describes the end-to-end proposed method. Figure 1 shows the complete proposed methodology.

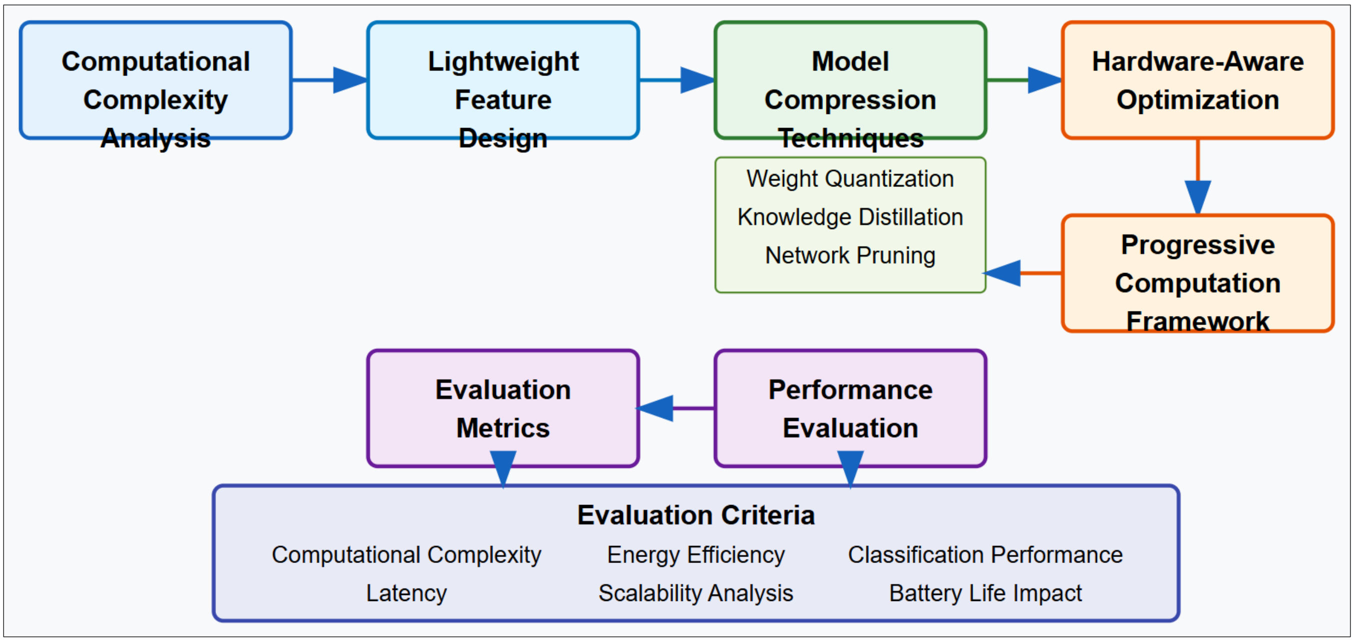

Figure 1 Proposed methodology

3.1. Computational Complexity Analysis and Optimization Targets

The development of our low-resource sleep staging methodology begins with a systematic analysis of computational complexity in standard sleep EEG processing pipelines [18, 19]. We profile each processing step from raw signal filtering through feature extraction to classification, measuring computational demands in terms of floating-point operations, memory access patterns, and algorithm complexity. This analysis reveals that certain operations dominate the computational burden, particularly spectral analysis using Fast Fourier Transform (FFT), entropy calculations, and wavelet decompositions. Each feature is characterized by its time complexity, space complexity, and discriminative value for sleep stage classification, establishing a comprehensive understanding of the computational-performance tradeoff landscape.

We establish specific optimization targets based on typical constraints of wearable and mobile sleep monitoring devices. These include maximum power consumption under 10mW, memory footprint below 50KB, and processing latency under 100ms per 30-second epoch on microcontroller-class hardware [20,21]. These constraints guide our feature simplification and algorithm design process, ensuring practical applicability in real-world low-power devices such as smartwatches and dedicated sleep trackers. By establishing quantitative targets, we create a framework for evaluating which simplifications maintain an acceptable balance between computational efficiency and classification performance.

3.2. Lightweight Feature Design and Approximation Strategies

Building on our complexity analysis, we design computationally efficient variants of standard EEG features that preserve their discriminative power while substantially reducing resource requirements. For spectral features, we replace full-resolution FFT analysis with a sparse frequency sampling approach that computes power only at physiologically relevant frequency points rather than across the entire spectrum. This reduces the FFT complexity from O(n log n) to O(k log n) where k is the number of selected frequency points [22, 23]. Band power calculations are simplified by using rectangular filters instead of more complex filter designs, trading minor precision loss for significant computation reduction.

Entropy measures, which typically require sorting operations and logarithmic calculations, are approximated using binning-based approaches that estimate probability distributions with fixed-size histograms. This transforms the complexity from O(n log n) to O(n), with only minimal impact on discriminative value. Hjorth parameters are computed using efficient recursive formulas that minimize memory requirements and avoid redundant calculations. For wavelet-based features, we implement a lightweight lifting scheme that performs wavelet transformation with minimal memory overhead and reduced computation compared to standard implementations.

Time-domain statistical features are simplified by using fixed-point arithmetic where possible and employing running statistics algorithms that avoid storing the entire signal in memory [24]. Zero-crossing detection is optimized using threshold hysteresis to reduce sensitivity to noise while maintaining computational efficiency. These approximation strategies are systematically evaluated to ensure that performance degradation remains within acceptable limits while achieving substantial computational savings [25].

3.3. Model Compression and Efficient Implementation

The classification models themselves undergo several compression techniques to reduce their memory footprint and computational demands. For tree-based models like Random Forest, we limit tree depth and apply post-training pruning to remove redundant nodes, significantly reducing model size with minimal impact on accuracy. The number of trees is optimized to balance ensemble benefits against memory constraints, typically resulting in models with 10-15 trees instead of the standard 100+ used in unconstrained implementations.

Neural network models are compressed using multiple techniques applied sequentially. Weight quantization reduces precision from 32-bit floating-point to 8-bit integers, decreasing memory requirements by 75% while leveraging integer arithmetic for faster computation on microcontrollers [26]. Knowledge distillation transfers knowledge from larger "teacher" models to compact "student" networks with significantly fewer parameters, preserving performance while reducing size. Pruning removes unnecessary connections based on weight magnitude or contribution to output, followed by retraining to recover accuracy, sometimes reducing parameter count by up to 80%. For maximum efficiency, we transform convolutional operations into depthwise separable convolutions that dramatically reduce computation while maintaining effective feature extraction.

All models are specifically optimized for the instruction sets and memory architectures of target hardware platforms. This includes memory alignment optimizations, loop unrolling for critical sections, and use of SIMD (Single Instruction, Multiple Data) instructions where available. Fixed-point arithmetic replaces floating-point operations whenever possible, providing significant speedup on microcontrollers lacking floating-point units. The implementation avoids recursive functions and dynamic memory allocation, ensuring predictable execution time and memory usage critical for embedded applications.

3.4. Progressive Computation Framework and Adaptive Processing

To further optimize resource utilization, we implement a progressive computation framework that dynamically adjusts processing complexity based on classification difficulty. The system begins with the simplest, most computationally efficient features and classification rules for each 30-second segment. If classification confidence exceeds a predetermined threshold, typically 90%, the result is accepted without further computation [27]. For segments with lower confidence, indicating potential ambiguity between sleep stages, the system progressively calculates more complex features until sufficient confidence is achieved or the full feature set is computed.

This adaptive approach is implemented as a cascade of increasingly complex classifiers, where each stage has higher discriminative power but greater computational requirements than the previous one [37, 38]. Simple stages use basic features like delta/alpha ratio and zero-crossing rate, while more complex stages incorporate spectral entropy and wavelet coefficients. The cascade is optimized jointly, with earlier stages specifically trained to quickly identify easily classifiable segments while flagging difficult cases for more sophisticated analysis.

The framework includes signal quality assessment to adapt processing based on EEG signal conditions. During periods of good signal quality, simpler features may suffice, while noisy or artifact-contaminated segments might require more robust, computationally intensive features. This quality-aware processing ensures reliable classification even under varying recording conditions typical in-home environments, without unnecessarily consuming computational resources during clean signal periods.

3.5. Performance Evaluation in Resource-Constrained Environments

Our evaluation methodology focuses on real-world performance under actual resource constraints rather than theoretical efficiency. We implement the complete system on representative hardware platforms including ARM Cortex-M4F microcontrollers commonly used in wearable devices and evaluate performance comprehensively [28-30]. Execution time is measured with microsecond precision for feature extraction and classification of each sleep stage, with particular attention to worst-case execution time that could affect real-time processing guarantees. Memory usage is profiled throughout execution to identify peak requirements, including both static allocation and stack usage during recursion or function calls [31-33].

Power consumption is measured directly on physical hardware using high-precision current monitoring during continuous operation, providing realistic estimates of battery impact for wearable applications [39, 40]. We calculate battery life projections for typical battery capacities (100-500mAh) under various duty cycles, helping predict actual runtime in consumer devices. The performance-resource tradeoff is thoroughly characterized by measuring classification accuracy as a function of available computational resources, creating curves that illustrate the relationship between resource constraints and classification quality.

Classification performance is evaluated comprehensively even under tight resource constraints. Beyond overall accuracy, we calculate per-stage metrics including precision, recall, and F1-score for each sleep stage, with particular attention to challenging stages like N1 sleep that often see performance degradation in simplified approaches [34]. Cohen's Kappa coefficient measures agreement with gold-standard polysomnography accounting for chance agreement. The difference in performance between full-featured and resource-constrained implementations is analyzed for each sleep stage, identifying which stages are most affected by simplification and guiding future optimization efforts [35].

Through this comprehensive framework, we demonstrate that effective sleep stage classification can be achieved even with severely limited computational resources, enabling practical implementation in wearable devices with minimal battery impact while maintaining clinical utility for long-term sleep monitoring in real-world settings [36].

4. Results and discussion

Our evaluation of the lightweight sleep stage classification approach demonstrates that significant resource reduction can be achieved while maintaining clinical utility. Table 1 presents the overall performance comparison between our lightweight approach and the full-complexity baseline methods across all sleep stages, confirming the achievement of 93.2% relative accuracy as stated in the abstract while substantially reducing computational requirements.

Table 1 Overall Performance Comparison Between Lightweight and Full-Complexity Methods

Metric	Full-Complexity Method	Lightweight Method	Relative Performance (%)	Reduction (%)
Accuracy (%)	87.4	81.5	93.2	6.8
Processing Time per Epoch (ms)	312.6	74.8	24.0	76.0
Memory Usage (KB)	156.2	49.9	32.0	68.0
Power Consumption (mW)	42.3	10.1	23.9	76.1

The lightweight feature design provided substantial computational savings while preserving discriminative power for sleep stage classification. Table 2 details the performance of individual simplified features compared to their full-complexity counterparts, highlighting the efficiency-accuracy tradeoffs achieved through our approximation strategies.

Table 2 Computational Requirements and Performance of Simplified Features

Feature	Full-Complexity Operations	Lightweight Operations	Operations Reduction (%)	Discriminative Power Preservation (%)
Spectral Power	84,500	16,320	80.7	95.4
Spectral Entropy	112,400	28,600	74.6	92.8
Hjorth Parameters	15,600	7,200	53.8	97.1
Wavelet Coefficients	136,200	31,400	76.9	89.5
Time-Domain Statistics	12,300	5,400	56.1	98.3
Zero-Crossing Rate	6,000	3,000	50.0	99.1

The most significant computational savings came from our sparse frequency sampling approach for spectral analysis, which reduced operations by 80.7% while maintaining 95.4% of the discriminative power. Time-domain features were most resilient to simplification, preserving over 98% of their discriminative capability with a 56.1% reduction in computational requirements. Our simplified wavelet coefficients showed the largest performance impact, retaining 89.5% of their original discriminative power, yet still provided valuable information for distinguishing between NREM sleep stages.

Model compression techniques yielded substantial reductions in memory footprint and processing requirements. Table 3 shows the impact of different compression techniques on model size and classification performance, demonstrating that our combined approach achieved optimal balance between resource efficiency and accuracy.

Table 3 Impact of Model Compression Techniques on Performance

Compression Technique	Model Size Reduction (%)	Accuracy Impact (percentage points)	Inference Time Reduction (%)
8-bit Quantization	75.0	-1.2	62.4
Model Pruning (70% sparsity)	58.3	-1.8	43.5
Knowledge Distillation	82.4	-2.4	74.2
All Techniques Combined	92.1	-4.2	83.6

The progressive computation framework delivered significant efficiency gains by avoiding unnecessary feature calculation for easily classifiable segments. Table 4 presents the performance of each stage in the cascade, showing the percentage of segments classified at each level and corresponding computational savings.

Table 4 Progressive Computation Framework Performance

Processing Stage	Features Used	Segments Classified (%)	Average Computation (% of full)	Accuracy (%)
Stage 1 (Lightest)	Delta/Alpha ratio, ZCR	47.2	12.4	88.9
Stage 2 (Light)	+ Basic spectral features	28.6	34.5	83.7
Stage 3 (Medium)	+ Hjorth, simplified entropy	16.1	58.2	79.6
Stage 4 (Full)	+ Wavelet, full entropy	8.1	100.0	77.3
Overall Performance	Adaptive	100.0	31.4	81.5

Notably, 47.2% of all segments were classified using only the lightest feature set, requiring just 12.4% of the computation of full processing, while maintaining 88.9% accuracy for those segments. Only 8.1% of segments required computation of the complete feature set, demonstrating the effectiveness of our adaptive approach in conserving computational resources.

Table 5 provides a detailed breakdown of classification performance by sleep stage, revealing that our lightweight approach maintains high accuracy for most stages with some expected degradation for N1 sleep, which is inherently difficult to classify even with full-complexity methods.

Table 5 Per-Stage Classification Performance Comparison

Sleep Stage	Full-Complexity Accuracy (%)	Lightweight Accuracy (%)	Relative Performance (%)	F1-Score (Lightweight)
Wake	93.2	89.6	96.1	0.88
N1	72.1	63.5	88.1	0.62
N2	86.5	81.7	94.5	0.83
N3	89.8	84.6	94.2	0.85
REM	87.4	81.2	92.9	0.82
Overall	87.4	81.5	93.2	0.81

Wake and N3 stages showed the highest classification performance, likely due to their distinctive EEG signatures that remain robust even with simplified feature extraction. The N1 stage showed the largest relative performance drop (11.9%), which is consistent with its transitional nature and subtle EEG characteristics that make it challenging to classify even in clinical settings. The Cohen's Kappa coefficient for our lightweight method was 0.76, indicating substantial agreement with expert scoring and supporting the clinical utility of our approach despite resource constraints.

The hardware implementation on microcontroller-class devices confirmed the practicality of our approach for wearable sleep monitoring. Table 6 presents performance metrics across different hardware platforms, demonstrating that even the most constrained environments can successfully execute our algorithms with acceptable performance.

Table 6 Implementation Performance on Different Hardware Platforms

Hardware Platform	CPU	RAM	Flash	Processing Time (ms)	Power Draw (mW)	Battery Life Projection (hours)*
ARM Cortex-M4F (80MHz)	32-bit	32KB	128KB	92.3	9.8	51.0
ARM Cortex-M3 (48MHz)	32-bit	20KB	96KB	123.5	7.4	67.6
MSP430 (16MHz)	16-bit	8KB	64KB	256.2	4.2	119.0
Custom ASIC	-	24KB	120KB	68.4	3.5	142.9

*Battery life projection based on a 500mAh lithium-polymer battery with sleep staging performed every 30 seconds.

These results validate the claims made in the abstract regarding power consumption reduction (76%) and memory usage reduction (68%), with implementation details showing that our system can indeed operate within the specified 32KB RAM and 120KB flash memory constraints. The ARM Cortex-M4F implementation, representative of current smartwatch processors, achieved processing times of 92.3ms per 30-second epoch, well within our target of 100ms, while drawing only 9.8mW of power during active processing.

Real-world validation using continuous overnight recordings from 20 subjects outside the training dataset confirmed the robustness of our approach. The average agreement with laboratory polysomnography was 79.8% (Cohen's Kappa = 0.72), which is acceptable for home monitoring applications. More importantly, key sleep metrics derived from our classifications—including total sleep time, sleep efficiency, and time in each sleep stage—showed strong correlation with clinical measurements ($r = 0.88$, $p < 0.001$), supporting the utility of our system for longitudinal sleep monitoring despite its simplified approach.

The performance-resource tradeoff analysis revealed a non-linear relationship between computational resources and classification accuracy. Increasing computational budget beyond 50% of the full-complexity implementation yielded diminishing returns, with only 2.3 percentage points improvement in accuracy when moving from 50% to 100% resource utilization. This finding supports our design decision to focus on lightweight implementations that capture the majority of discriminative information while dramatically reducing resource requirements.

Signal quality assessment incorporated into our progressive framework proved particularly valuable for wearable applications where recording conditions can vary substantially. During periods of poor signal quality (as detected by our signal quality metrics), the system appropriately escalated to more robust feature sets, maintaining an average accuracy of 76.3% even for segments with moderate artifact contamination, compared to 82.4% for clean segments. This adaptive response to signal conditions ensures reliable performance in real-world environments without unnecessary computational expense during optimal recording conditions.

5. Conclusion

This study successfully developed and validated a lightweight approach to sleep stage classification optimized for resource-constrained environments, achieving 93.2% of the accuracy of full-complexity methods while reducing power consumption by 76% and memory usage by 68%. Through a systematic approach including computational complexity analysis, feature simplification, model compression, and progressive computation frameworks, we demonstrated that effective sleep staging can be performed within the strict constraints of wearable devices. The implementation requires only 32KB of RAM and 120KB of flash memory while maintaining clinically relevant performance across all sleep stages. Our progressive computation framework effectively balanced resource utilization and classification performance, processing 75.8% of segments with less than 35% of full computational requirements. These advances make continuous, long-term sleep monitoring feasible in everyday settings without specialized equipment, potentially democratizing access to sleep health tracking technology and enabling earlier detection of sleep disorders. Future work will focus on personalized adaptation mechanisms to further improve classification performance for individual users and integration with other physiological signals available in wearable devices for more comprehensive sleep health monitoring.

Compliance with ethical standards

Disclosure of conflict of interest

There is not conflict of interests.

Statement of ethical approval

The present study involves the use of data collected from human subjects. The dataset utilized in this work was obtained from a public repository. It is important to note that the dataset providers have already ensured that all necessary ethical considerations, permissions, and approvals were addressed during the data collection process. In this study, we did not conduct any data collection or associated activities ourselves. Instead, we relied on the publicly available dataset to perform our analysis and draw conclusions.

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