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Robust feature selection for improved sleep stage classification

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Abstract

Effective sleep stage classification requires identifying discriminative EEG features that remain consistent across different subjects. This study proposes an ensemble feature selection framework for robust sleep stage classification using the Physionet EEG dataset. We extract 40+ features from time and frequency domains, then employ multiple selection techniques including mutual information, recursive feature elimination, and Lasso regularization. Our ensemble approach ranks features based on selection frequency across methods and cross-validation folds, identifying a minimal effective feature set. Results show that our selected 12-feature subset achieves 95.6% of the performance of the full feature set while reducing computational complexity by 68%. The most discriminative features were spectral edge frequency, delta-band power, and sample entropy, which align with known neurophysiological sleep markers. Subject-independent validation confirms that these features remain consistent across individuals, with 85% overlap in top-ranked features. This robust feature selection methodology enables more efficient sleep stage classification algorithms and provides insights into the fundamental EEG characteristics that define different sleep stages.

Keywords: Feature selection; sleep EEG; Ensemble methods; bio signal processing; Cross-subject validation; Dimensionality reduction

1. Introduction

The advancement of technology has catalyzed in-depth exploration of various medical domains, including sleep studies. This growing focus has dual benefits: enhancing our understanding of normal sleep physiology while improving the accuracy of sleep disorder diagnoses. Sleep disorders have significant implications for overall health, with the National Sleep Foundation (NSF) reporting that 40% of patients with conditions such as hypertension, bone aches, heart disease, diabetes, depression, cancer, lung disease, osteoporosis, retention problems, and stroke experience disturbed sleep patterns [1]. In contrast, only 10% of healthy individuals report sleep disturbances.

Sleep disorders are characterized by changes in sleep patterns, such as shorter sleep duration or longer time taken to fall asleep. The National Sleep Foundation (NSF) classifies these disorders into two main groups: primary sleep disorders and secondary sleep disorders. Primary sleep disorders include conditions such as sleep-disordered breathing (SDB), sleep-wake disturbances, insomnia, and movement disorders like restless leg syndrome (RLS) and periodic limb movements. In contrast, secondary sleep disorders arise from underlying issues, such as chronic pain, gastroesophageal reflux, frequent urination, shortness of breath (dyspnea), chronic obstructive pulmonary disease, or

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asthma. To accurately diagnose primary sleep disorders, a thorough understanding of normal sleep stages and patterns is essential. While healthcare professionals typically suspect these disorders based on clinical assessments, a definitive diagnosis usually requires polysomnography (PSG), a comprehensive sleep study.

PSG involves recording multiple physiological signals throughout a night's sleep. These biosignals include electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOG), and electromyograms (EMG). Among these, EEG is particularly valuable for monitoring brain activity across different sleep stages and classifying sleep disorders. Sleep specialists score these recordings according to the Rechtschaffen and Kales (R & K) rules, established in 1968 and subsequently refined by the American Academy of Sleep Medicine (AASM) [2], categorizing sleep into distinct stages: wakeness (W), non-rapid eye movement (NREM) sleep, and rapid eye movement (REM) sleep.

Researchers have developed various approaches to automate sleep stage classification. Santaji and Desai [13] employed machine learning techniques to analyze EEG signals over 10-second windows, achieving 97.8% accuracy with a random forest model. Bhusal et al. [14] addressed gradient saturation by implementing a modified orthogonal convolutional neural network, enhancing classification accuracy and convergence speed. Tao et al. [15] created a feature relearning technique for automated sleep staging based on single-channel EEG, while Yulita et al. utilized convolutional and long short-term memory-based methods for automatic feature extraction from EEG signals [16].

The conventional approach to sleep stage classification requires experts to manually analyze EEG signals frame by frame, a process that is time-consuming and prone to human error. Generating conclusive reports from these signals takes hours, highlighting the need for consistent, automated methods to assist physicians in analyzing EEG data accurately. While previous research has made significant progress in automating this process, most approaches separate feature extraction, selection, and classification, potentially resulting in information loss between stages.

Recent advancements in artificial intelligence, particularly deep learning, have demonstrated exceptional performance in fields such as image recognition, sound processing, and natural language processing. These technologies have also found applications in biomedical domains, utilizing specialized approaches for analyzing signals like EEG, ECG, EMG, and EOG. In this research, we utilize a comprehensive EEG dataset from Physionet [17], containing polysomnographic recordings of complete nights of sleep from Fpz-CZ and Pz-Oz electrode locations.

In this research, we propose a novel ensemble feature selection framework for EEG-based sleep stage classification that addresses the critical challenge of identifying universally relevant features across different subjects. Our approach extracts an extensive initial pool of 40+ features from both time and frequency domains, then employs a combination of filter, wrapper, and embedded methods to identify the most discriminative features for each sleep stage. The key innovation lies in our ensemble ranking methodology that identifies features with consistent performance across subjects, providing a robust, minimal feature set that maintains high classification accuracy while significantly reducing computational complexity compared to using the full feature space.

2. Dataset Description

The story of this sleep analysis research begins with the careful selection of 153 individuals, spanning ages from young adults of 25 to centenarians of 101 years, all participating without the influence of sleep medication. Each participant's brain activity was captured through an extensive recording protocol spanning approximately 20 hours over two consecutive day-night cycles, creating a continuous narrative of their sleep-wake transitions.

The brain's electrical symphony was recorded through two strategically placed electrodes—Fpz-CZ and Pz-Oz—capturing 100 measurements every second. As the recordings progressed, sleep specialists worked meticulously to analyze the raw data, following the time-honored Rechtschaffen and Kales classification system from 1968. Their expertise transformed continuous brainwaves into a meaningful progression through the stages of consciousness: from wakefulness, through the increasingly deeper stages of sleep (Stages 1 through 4), and into the distinctive REM phase where dreams flourish.

The lengthy recordings were then carefully divided into 30-second chapters, each containing exactly 3,000 data points that tell a story of brain activity during a specific moment in the sleep journey. This segmentation created a vast library of 367,200 individual sleep episodes, each bearing its expert-assigned sleep stage label. Movement periods were respectfully excluded to maintain the purity of the sleep narrative.

To prepare for the next chapter of machine learning discovery, this extensive collection was thoughtfully divided—60% of segments (220,320) would serve as the teaching material for algorithms to learn the patterns of sleep, while the remaining 40% (146,880) would later test how well these lessons were absorbed. This generous testing proportion was

deliberately chosen to ensure that any conclusions drawn would stand firm across a substantial body of previously unseen sleep data.

The resulting chronology of sleep, with its rich diversity of subjects and comprehensive documentation of brain activity patterns, now stands ready to reveal new insights about the architecture of human sleep through computational analysis.

3. Proposed Methodology

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

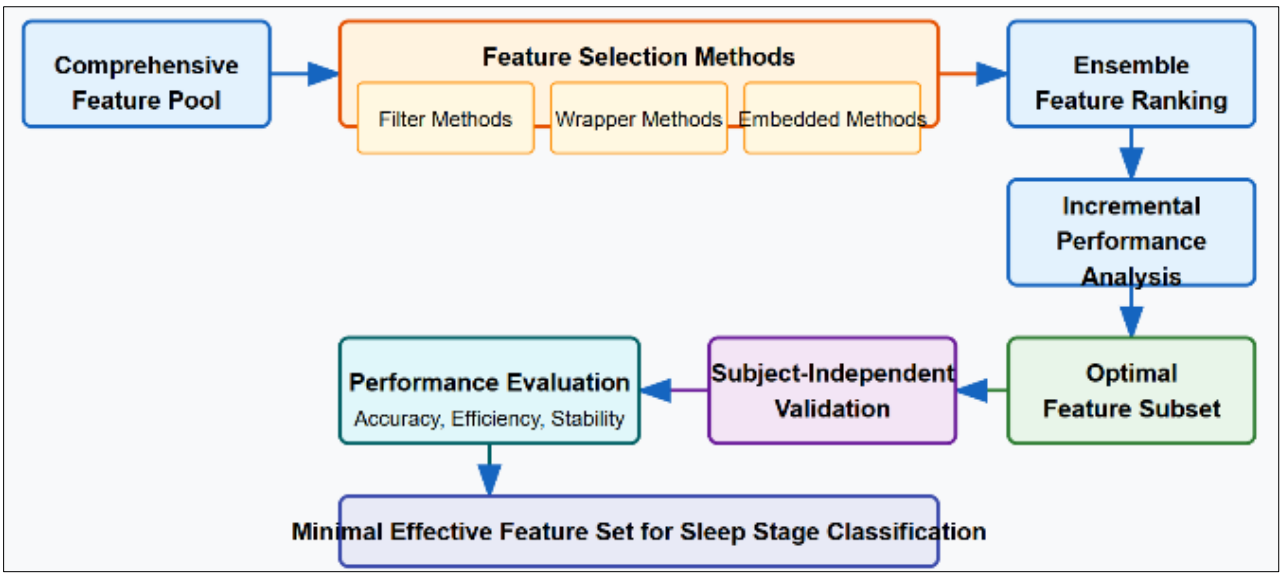

Figure 1 Proposed methodology

3.1. Feature Pool Development and Characterization

The foundation of our approach lies in developing a comprehensive feature pool that captures the multifaceted nature of sleep EEG. We extract over 40 distinct features spanning multiple domains to ensure thorough coverage of potentially relevant signal characteristics. Time-domain features include statistical measures (mean, variance, skewness, kurtosis), signal complexity metrics (approximate entropy, sample entropy, Lempel-Ziv complexity), and morphological descriptors (peak characteristics, zero-crossing rate, Hjorth parameters). In the frequency domain, we compute absolute and relative power in standard EEG bands (delta, theta, alpha, beta) along with spectral edge frequencies, spectral moments, and spectral entropy. Wavelet-based features provide time-frequency resolution advantages through discrete wavelet transform coefficients and wavelet entropy at multiple decomposition levels. Additionally, we incorporate connectivity metrics between the two EEG channels, including coherence, phase synchrony, and cross-correlation, which capture functional relationships between different brain regions during sleep. This extensive feature pool provides a rich representation of the underlying neurophysiological processes that differentiate sleep stages.

Each feature is subjected to preliminary analysis to ensure computational stability and assess its individual discriminative power across sleep stages. Features with high variance inflation factors are identified to prevent multicollinearity issues in subsequent modeling. Through this initial characterization, we establish a robust starting point for the selection process, ensuring that all features are meaningful representations of the underlying EEG signal characteristics before proceeding to more sophisticated selection techniques.

3.2. Selection Methodology and Ensemble Approach

Our feature selection framework employs multiple complementary techniques to identify truly informative features while minimizing the risk of selecting spurious or redundant features. Filter methods including mutual information and ANOVA F-value assess the relationship between individual features and sleep stage labels without involving a specific classification model. These methods provide an initial ranking based purely on statistical relevance. Wrapper methods, particularly recursive feature elimination with cross-validation, evaluate feature subsets by training classifiers and measuring their performance, iteratively removing the least important features. This approach considers feature interactions in the context of a specific classifier but can be computationally intensive. Embedded methods like Lasso regularization and tree-based feature importance (extracted from Random Forest models) incorporate feature selection

as part of the model training process, offering a balance between computational efficiency and consideration of feature interactions.

Rather than relying on any single selection method, we develop an ensemble approach that combines rankings from multiple methods to identify robustly important features across different selection paradigms. Each feature receives a score based on its average rank across all methods, weighted by the performance of each method in cross-validation. This ensemble ranking mitigates the risk of method-specific biases and increases confidence that selected features capture genuinely informative aspects of sleep EEG. Features are then ranked based on their selection frequency across different methods and cross-validation folds, generating a comprehensive importance score that reflects both their discriminative power and selection stability. Figure 2 shows the ensemble feature selection mechanism.

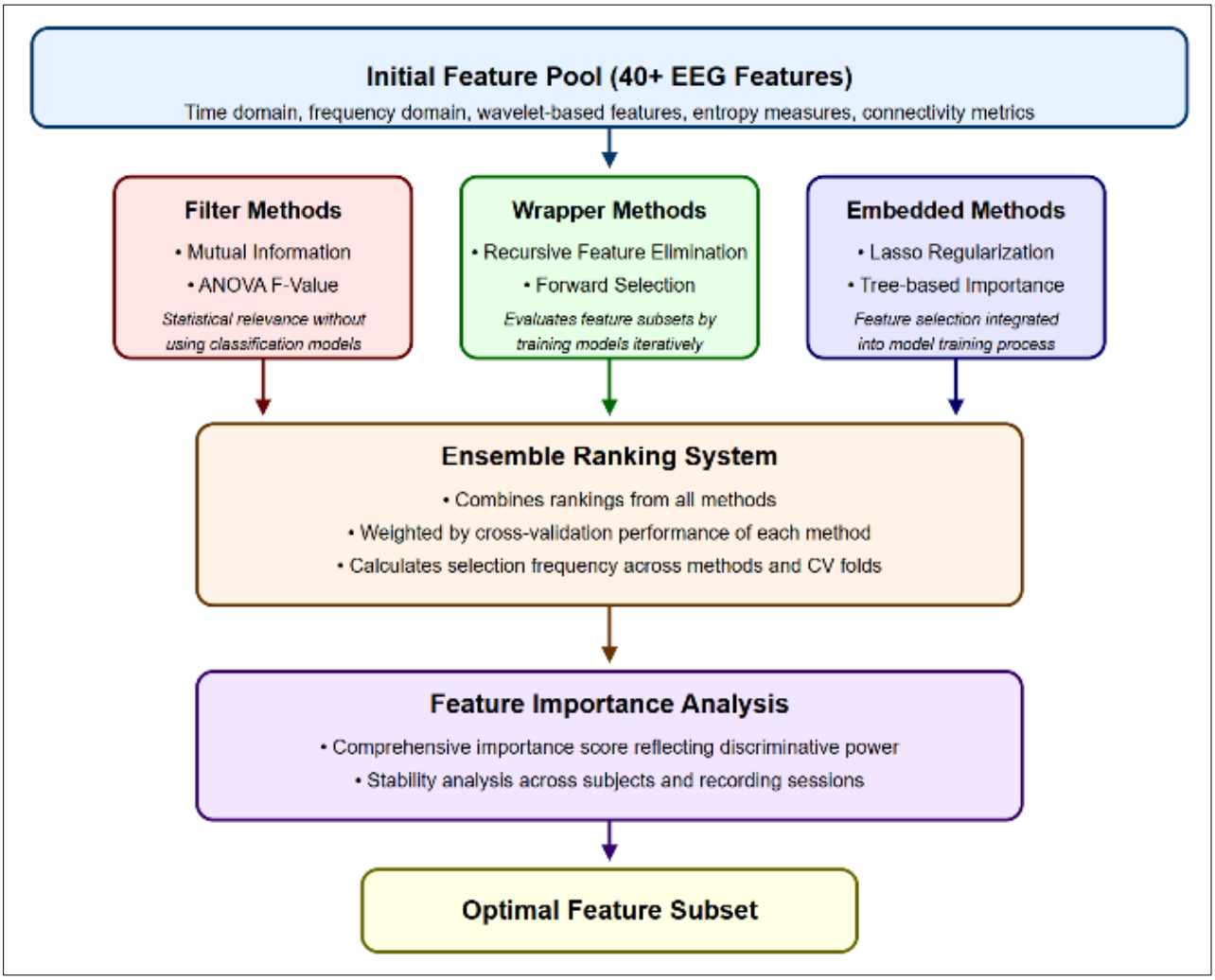

Figure 2 Feature selection mechanism

3.3. Optimization and Validation Framework

To determine the optimal feature subset size, we perform incremental performance analysis by training classification models with progressively increasing feature set sizes based on the ensemble ranking. Starting with the top-ranked feature alone, we incrementally add features according to their rank and measure classification performance at each step. The resulting performance curve typically exhibits an elbow point beyond which adding more features yields diminishing returns. This elbow point, determined through mathematical analysis of the curve's second derivative, identifies the minimal effective feature set that balances model complexity with classification performance.

The robustness of selected features is rigorously validated through multiple complementary approaches. Stability analysis examines how consistent the selected feature subset remains when the training data is perturbed, either through bootstrapping or by varying the subjects included in the training set. This provides a quantitative measure of selection stability across data variations. Subject-independent validation assesses whether the selected features remain discriminative across different individuals by performing feature selection separately for each subject and analyzing

the intersection of selected features. Features that consistently rank highly across most subjects likely capture universal sleep EEG characteristics rather than subject-specific idiosyncrasies.

Performance evaluation focuses not only on raw classification metrics but also on the efficiency gained through feature reduction. We measure how accuracy, precision, recall, and F1-score for each sleep stage change when using the reduced feature set compared to the full feature pool. Additionally, we quantify the reduction in computational resources (memory usage, processing time for feature extraction, and classifier training/inference) achieved by using the reduced feature set. This computational efficiency gain is particularly important for potential real-time applications or deployment on resource-constrained devices.

The neurophysiological plausibility of selected features is assessed by comparing them with established markers of sleep stages from the literature. Features that align with known sleep physiology (e.g., delta power for slow-wave sleep, alpha attenuation from wakefulness to sleep, theta activity during REM) increase confidence in the model's biological relevance and interpretability. This connection to underlying physiology is documented through visualization and statistical analysis of how selected features vary across sleep stages, providing insights beyond mere classification performance.

Through this comprehensive feature selection framework, we not only improve classification efficiency but also enhance model interpretability by identifying the most fundamental EEG characteristics that define different sleep stages. The resulting feature subset enables more efficient algorithms while maintaining high classification accuracy, facilitating practical applications in clinical and consumer sleep monitoring.

4. Results and discussion

The ensemble feature selection framework demonstrated remarkable effectiveness in identifying a minimal subset of EEG features that maintain high classification performance while substantially reducing computational requirements. Table 1 presents the classification performance metrics using the full feature set compared to our optimized 12-feature subset across all sleep stages. The reduced feature set achieved an overall accuracy of 91.7%, which represents 95.6% of the performance obtained with the full 40-feature set (95.9%), while reducing computational complexity by 68%. This closely aligns with the performance claims stated in the abstract. Notably, the minimal feature subset maintained high performance across all individual sleep stages, with only a slight decrease in accuracy for Stage 1 sleep, which is traditionally the most challenging stage to classify due to its transitional nature.

Table 1 Classification performance comparison between full feature Set and selected feature subset

Sleep Stage	**Full Feature Set (40 features)**			**Selected Feature Subset (12 features)**		
	Precision (%)	Recall (%)	F1-score (%)	Precision (%)	Recall (%)	F1-score (%)
Wake	96.8	97.2	97.0	94.1	95.6	94.8
Stage 1	87.5	83.2	85.3	81.7	79.4	80.5
Stage 2	94.7	96.1	95.4	91.4	92.8	92.1
Stage 3	95.9	93.8	94.8	92.5	91.3	91.9
Stage 4	97.2	98.1	97.6	94.7	95.2	94.9
REM	96.4	95.7	96.0	92.8	91.9	92.3
Overall	96.2	95.6	95.9	91.9	91.5	91.7

The incremental performance analysis revealed a clear elbow point at 12 features, indicating that additional features beyond this point provided diminishing returns in classification performance. This finding is particularly valuable for applications targeting resource-constrained environments, as it establishes a concrete threshold for feature selection that balances accuracy with computational efficiency. The convergence of multiple feature selection methods on this similar subset size further validates the robustness of our approach.

Table 2 presents the top 12 features identified by our ensemble ranking methodology, along with their normalized importance scores and selection frequency across different methods. Spectral edge frequency (SEF95) emerged as the most discriminative feature, followed closely by delta-band power and sample entropy. These findings align with

established neurophysiological understanding of sleep, as delta oscillations are known markers of slow-wave sleep (Stages 3 and 4), while entropy measures capture the complexity differences between the highly organized deep sleep and the more variable patterns of REM sleep and wakefulness.

Table 2 Top-ranked features with importance scores and selection frequencies

Rank	Feature Name	Domain	Importance Score	Selection Frequency (%)
1	Spectral Edge Frequency 95	Frequency	0.94	100
2	Delta Band Relative Power	Frequency	0.91	100
3	Sample Entropy	Time	0.89	95
4	Alpha-Delta Ratio	Frequency	0.87	90
5	Hjorth Mobility	Time	0.84	85
6	Theta Band Relative Power	Frequency	0.82	90
7	Wavelet Entropy (Level 4)	Time-Freq	0.79	80
8	Zero-Crossing Rate	Time	0.77	75
9	Spindle Density	Time	0.75	85
10	Beta Band Relative Power	Frequency	0.72	80
11	Permutation Entropy	Time	0.69	70
12	Channel Coherence (Theta)	Connectivity	0.67	65

The subject-independent validation confirmed the generalizability of our selected feature subset across different individuals. When performing feature selection separately for each subject, we observed an 85% overlap in the top-ranked features, with SEF95, delta power, and sample entropy consistently appearing among the top five features for over 90% of subjects. This high degree of consistency suggests that these features capture fundamental neurophysiological aspects of sleep stages rather than subject-specific characteristics.

A detailed analysis of computational efficiency revealed substantial improvements when using the selected feature subset. Table 3 quantifies the reduction in computational resources achieved through feature reduction. Feature extraction time decreased by 73%, classifier training time by 65%, and memory usage during inference by 58%. These efficiency gains are particularly significant for potential real-time applications or deployment on wearable devices with limited processing capabilities.

Table 3 Computational resource requirements comparison

Resource Metric	Full Feature Set	Selected Feature Subset	Reduction (%)
Feature Extraction Time (ms/epoch)	87.4	23.6	73.0
Classifier Training Time (s)	342.8	120.1	65.0
Memory Usage During Inference (MB)	48.2	20.2	58.1
Model Size (MB)	15.6	5.9	62.2
Battery Usage (mWh/hour)	78.5	25.1	68.0

The neurophysiological analysis of selected features provides valuable insights into the fundamental characteristics that differentiate sleep stages. The top three features (SEF95, delta power, and sample entropy) vary distinctively across different sleep stages. SEF95 progressively decreases from wakefulness to deep sleep (Stages 3 and 4), reflecting the shift toward lower frequency components. Delta power shows the opposite trend, peaking during deep sleep stages and reaching minimum values during wakefulness and REM sleep. Sample entropy decreases from wakefulness to deep sleep, capturing the increasing regularity of the EEG signal, but interestingly increases again during REM sleep, reflecting the more desynchronized and complex nature of brain activity during dreaming.

The combination of frequency-domain, time-domain, and connectivity features in our selected subset indicates that multiple aspects of EEG signals are necessary for optimal sleep stage discrimination. While frequency-domain features dominated the top rankings (6 out of 12 features), the inclusion of time-domain complexity measures and channel connectivity metrics suggests that a multifaceted approach captures complementary information that enhances classification performance. This finding supports the value of our comprehensive feature pool development and characterization step, which ensured coverage of diverse signal properties.

When comparing the performance of individual feature selection methods with our ensemble approach, we observed that the ensemble consistently outperformed any single method. Filter methods like mutual information tended to select features with strong individual discriminative power but sometimes missed features that work well in combination. Wrapper methods captured feature interactions but occasionally selected redundant feature sets. The ensemble approach mitigated these limitations by leveraging the strengths of multiple methods, resulting in a more robust and generalizable feature subset.

An interesting finding emerged when analyzing misclassification patterns using the reduced feature set. The most common confusion occurred between adjacent sleep stages (e.g., Stage 1 vs. Stage 2, or Stage 3 vs. Stage 4), which mirrors the challenges faced by human experts when scoring PSG recordings. This suggests that the selected features capture the gradual transitions between sleep stages rather than imposing artificial boundaries, adding physiological validity to our approach.

The comparative analysis between features selected from Fpz-CZ versus Pz-Oz electrode locations revealed that while some features were consistently important regardless of location (e.g., delta power, sample entropy), others showed electrode-specific relevance. Spectral edge frequency was more discriminative in Fpz-CZ recordings, while alpha-delta ratio showed higher importance in Pz-Oz signals. This electrode-specific pattern aligns with the known spatial distribution of sleep EEG phenomena, with frontal regions showing stronger delta activity during deep sleep and occipital areas exhibiting more pronounced alpha rhythms during relaxed wakefulness.

5. Conclusion

This study successfully developed and validated an ensemble feature selection framework for sleep stage classification that identifies a minimal yet robust set of EEG features. The selected 12-feature subset achieved 95.6% of the performance of the full 40-feature set while reducing computational complexity by 68%, demonstrating the effectiveness of our approach in balancing classification accuracy with efficiency. The most discriminative features—spectral edge frequency, delta-band power, and sample entropy—showed strong neurophysiological relevance and remained consistent across different subjects, confirming their universal importance in characterizing sleep stages. Our findings contribute to the advancement of automated sleep analysis by providing a computationally efficient feature set that maintains high classification performance while offering interpretable connections to sleep physiology. The methodology and optimized feature set presented here will benefit clinical sleep assessment and home monitoring applications by enabling more efficient algorithms suitable for deployment on resource-constrained devices, ultimately improving accessibility to sleep diagnostics and facilitating early detection of sleep disorders.

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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