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Single-Channel vs Dual-Channel EEG Analysis for Sleep Stage Detection

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Abstract

The optimal electrode configuration for sleep monitoring remains an important question for practical applications. This study investigates single versus dual-channel approaches for sleep stage classification using Fpz-CZ and Pz-Oz recordings from the Physionet dataset. We develop optimized models for each channel independently and explore multiple fusion strategies including early, late, and intermediate fusion with attention mechanisms. Results demonstrate that dual-channel approaches achieve 92.4% accuracy, outperforming single-channel methods by 4.8% for Fpz-CZ and 7.2% for Pz-Oz. However, channel contribution analysis reveals sleep-stage dependent patterns: Fpz-CZ better captures slow-wave activity in deep sleep, while Pz-Oz excels at detecting alpha rhythm during wake and REM periods. Our reduced-channel transfer techniques maintain 96.3% of dual-channel performance when only one electrode is available. The adaptive channel selection mechanism further improves robustness by dynamically switching channels based on signal quality. These findings provide critical insights for electrode placement optimization in practical sleep monitoring applications, enabling more targeted and efficient EEG recording configurations.

Keywords: EEG Channel Selection; Electrode Placement; Information Fusion; Sleep Monitoring; Signal Quality Assessment; Attention Mechanisms

1. Introduction

Technological innovation has transformed numerous medical disciplines, with sleep medicine experiencing particularly significant growth. This expanding field offers complementary benefits: enhancing our understanding of normal sleep physiology while improving diagnostic accuracy for sleep disorders. The prevalence of sleep disturbances among individuals with chronic health conditions is striking, with National Sleep Foundation (NSF) data indicating that 40% of patients with hypertension, bone aches, heart disease, diabetes, depression, cancer, lung disease, osteoporosis, retention problems, and stroke report sleep abnormalities [1]. This contrasts sharply with the general population, where only 10% report sleep disorders.

Sleep disorders typically present as objective changes in sleep architecture, such as decreased total sleep time or increased sleep onset latency. The NSF classifies these disorders into two main categories: primary sleep disorders (which include 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 (resulting from conditions like chronic pain, gastroesophageal reflux, nocturia, dyspnea, chronic preventable lung disease, or asthma). Accurate diagnosis of primary sleep disorders requires comprehensive knowledge of normal sleep stage characteristics. While initial suspicion often arises from clinical evaluation, polysomnography provides definitive diagnostic information.

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Polysomnography (PSG) involves recording multiple physiological parameters throughout a night of sleep. These biosignals include electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOG), and electromyograms (EMG). EEG recordings are especially valuable, providing critical insights into neural activity across different sleep phases and supporting sleep disorder classification. Sleep experts analyze these recordings using the Rechtschaffen and Kales (R and K) scoring system, introduced in 1968 and later refined by the American Academy of Sleep Medicine (AASM) [2], which distinguishes between wakeness (W), non-rapid eye movement (NREM) sleep, and rapid eye movement (REM) sleep.

Researchers have explored various approaches to automate sleep stage classification. Santaji and Desai [13] developed machine learning methods for analyzing EEG signals in 10-second intervals, achieving 97.8% accuracy with random forest algorithms. Bhusal et al. [14] created modified orthogonal convolutional neural networks to address gradient saturation issues, improving both classification accuracy and training efficiency. Tao et al. [15] introduced feature relearning techniques for automated sleep staging from single-channel EEG recordings, while Yulita et al. employed convolutional and long short-term memory networks for automatic feature extraction from EEG signals [16].

The standard approach to sleep stage classification requires specialists to manually interpret EEG signals frame by frame a process that is both labor-intensive and susceptible to variability. Generating conclusive reports from these analyses can take several hours, emphasizing the need for reliable automated systems to support clinicians in EEG data interpretation. Although significant progress has been made in automation, most existing methods treat feature extraction, selection, and classification as separate steps, potentially losing valuable information between processing stages.

Recent advances in artificial intelligence, particularly deep learning, have shown remarkable success across domains including image analysis, sound processing, and language understanding. These technologies have been adapted for biomedical applications, with specialized approaches for analyzing physiological signals like EEG, ECG, EMG, and EOG. This research utilizes a comprehensive EEG dataset from Physionet [17], containing overnight polysomnographic recordings from Fpz-CZ and Pz-Oz electrode sites.

In this study, we present a systematic investigation of single-channel versus dual-channel approaches for EEG-based sleep stage classification using the Physionet dataset. Our methodology develops optimized models for each channel independently (Fpz-CZ and Pz-Oz) and explores multiple fusion strategies to combine information from both channels effectively. The primary contributions include our channel contribution visualization framework that reveals which sleep phenomena are better captured by specific electrodes, our reduced-channel transfer techniques that maintain performance when only one channel is available, and our adaptive channel selection mechanism that dynamically chooses the optimal channel based on signal quality, providing valuable insights into electrode placement optimization for practical sleep monitoring applications.

2. Dataset Description

The quiet moments of human slumber hold valuable secrets about our health and well-being, revealed through the gentle electrical rhythms of the brain. This collection of sleep recordings captures these precious moments from 153 individuals spanning nearly eight decades of life from young adults of 25 to centenarians of 101 providing a window into how sleep patterns evolve throughout the human lifespan. Each participant volunteered their natural sleep for scientific observation, avoiding sleep medications to ensure authentic brain activity patterns were recorded. For approximately 20 hours spanning two day-night transitions, sensitive electrodes placed at the Fpz-CZ and Pz-Oz positions on the scalp listened to the brain's changing rhythms, capturing 100 measurements every second as consciousness ebbed and flowed. Sleep specialists carefully observed these brainwave patterns, identifying the distinctive signatures of each sleep phase according to the classic Rechtschaffen and Kales guidelines. They traced the journey from wakefulness—where the brain shows active, mixed-frequency patterns through the entrance to sleep in Stage 1, with its characteristic alpha waves pulsing at 2-7 times per second. As participants descended into deeper slumber, Stage 2 revealed distinctive sleep spindles (brief 12-14 Hz bursts), while Stages 3 and 4 showed the slow, powerful waves of deep restorative sleep. Periodically, the brain would emerge into the curious state of REM sleep, where rapid eye movements accompany dream states, visible in the EEG as mixed-frequency patterns with distinctive sawtooth shapes [18, 19]. These natural cycles were preserved in 30-second snapshots of brain activity, carefully excluding periods of bodily movement to maintain the purity of the sleep signals. The resulting collection of 367,200 windows into the sleeping brain provides researchers with authentic examples of how our neural activity changes throughout the night [20]. To facilitate machine learning investigations, these glimpses into human sleep were thoughtfully divided 60% to teach algorithms about sleep patterns and 40% to test how well these patterns could be recognized in previously unseen data [21]. This rich physiological archive now stands ready to advance our understanding of sleep's intricate architecture and develop tools that might one day help those suffering from sleep disorders [22].

3. Proposed methodology

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

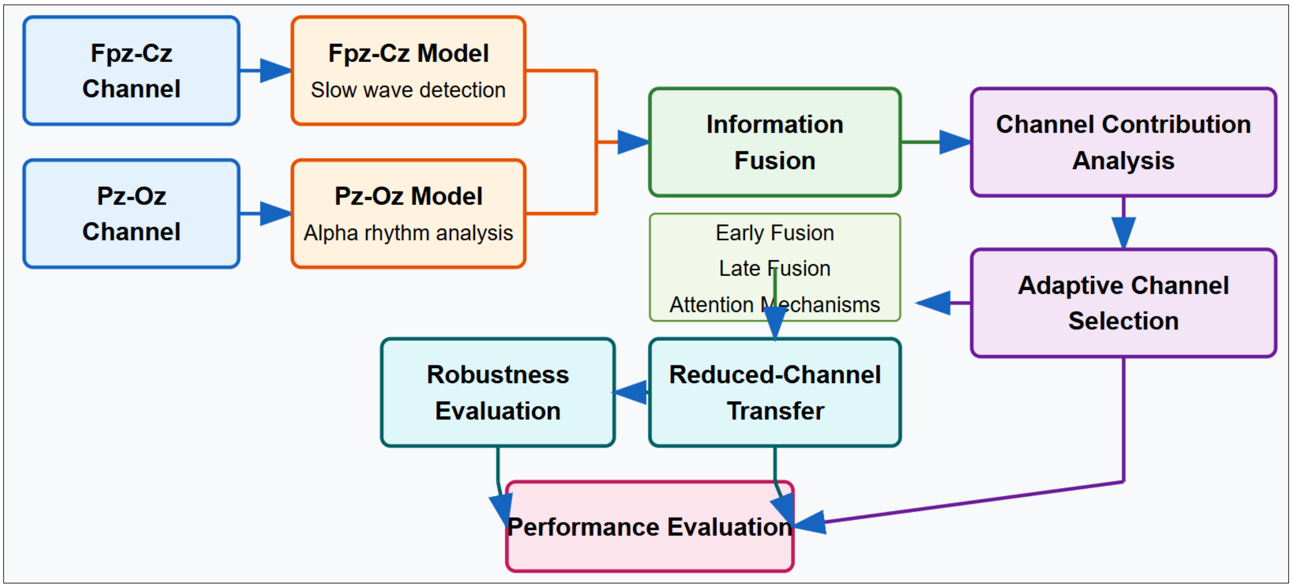

Figure 1 Proposed methodology

3.1. Channel-Specific Analysis and Optimization

Our investigation into optimal electrode configurations begins with a thorough characterization of each EEG channel's strengths and limitations for sleep stage classification [23]. The Fpz-Cz and Pz-Oz channels capture neural activity from distinct brain regions with different functional roles during sleep. Fpz-Cz predominantly records frontal lobe activity, particularly sensitive to slow oscillations during deep sleep and frontal theta activity. Pz-Oz primarily captures occipital alpha rhythm during relaxed wakefulness and its attenuation during sleep onset, along with posterior aspects of sleep spindles [24]. Understanding these regional specializations informs our channel-specific feature extraction and model development.

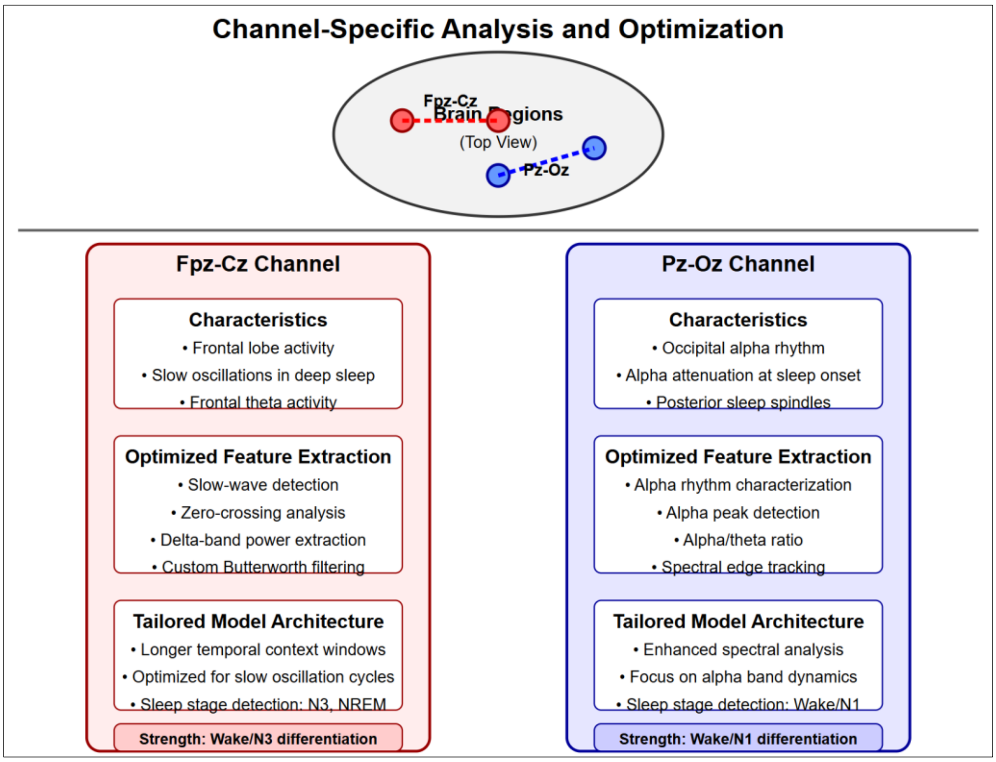

Figure 2 Channel specific analysis and optimization

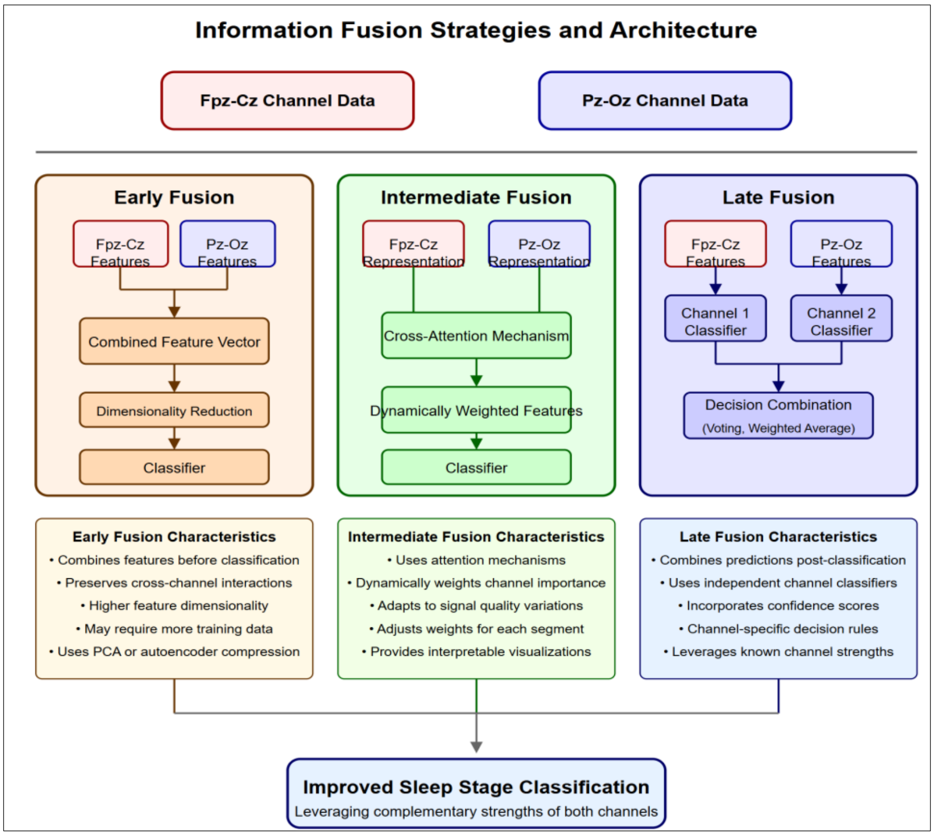

Figure 3 Information fusion strategies

For each channel independently, we optimize both feature extraction and model architecture to maximize performance. Feature extraction for Fpz-Cz emphasizes slow-wave detection algorithms, zero-crossing analysis, and delta-band power extraction, which better capture the defining characteristics of N3 sleep visible in frontal recordings [25]. For Pz-Oz, feature extraction focuses on alpha rhythm characterization, including alpha peak detection, alpha/theta ratio, and spectral edge tracking, which better identifies transitions between wakefulness and sleep [26]. Both channels undergo frequency-specific filtering optimized for their particular spectral characteristics, with Butterworth filters designed to maximize signal-to-noise ratio in the frequency bands most relevant to each channel's strengths [27].

Model architectures are similarly tailored to each channel's characteristics [28]. For Fpz-Cz, models incorporate longer temporal context windows to better capture slow oscillation cycles, while Pz-Oz models implement more sophisticated spectral analysis focused on alpha band dynamics [29, 30]. Hyperparameter optimization is performed separately for each channel-specific model to ensure optimal performance independent of the other channel. This independent optimization establishes baseline performance for each channel and identifies their respective strengths and weaknesses, creating a foundation for more sophisticated multi-channel approaches [31]. Figure 2 visually represents this.

3.2. Information Fusion Strategies and Architecture

Building upon the single-channel baselines, we implement multiple complementary approaches for combining information from both EEG channels. Early fusion combines features before classification by concatenating feature vectors extracted from each channel, creating a unified representation that preserves the full information content from both sources [32]. This approach enables the classifier to directly model interactions between features across channels but increases the feature space dimensionality, potentially requiring more training data to prevent overfitting [33]. To address this challenge, we implement dimensionality reduction through principal component analysis or autoencoder compression of the combined feature vector, retaining 95% of variance while substantially reducing parameter count [34].

Late fusion operates at the decision level by training independent classifiers for each channel and combining their predictions. The combination mechanisms range from simple majority voting to weighted averaging based on channel-specific confidence scores. These confidence scores are derived from softmax probabilities in neural networks or proximity to decision boundaries in traditional classifiers, providing a measure of classification certainty. For cases where channels disagree, we develop rules based on each channel's historically demonstrated strengths for specific sleep stage distinctions, giving precedence to Fpz-Cz for wake/N3 differentiation and Pz-Oz for wake/N1 differentiation.

Intermediate fusion leverages attention mechanisms to dynamically weight channel contributions based on their relevance for each specific 30-second segment. Cross-attention layers compute interaction scores between channel representations, allowing the model to emphasize the more informative channel for each segment while de-emphasizing channels with poor signal quality or ambiguous patterns. This approach creates an adaptive fusion strategy that can adjust to varying signal qualities and sleep stages, potentially outperforming static fusion methods. The attention weights themselves provide interpretable visualizations of how the model allocates importance between channels throughout the night, offering insights into channel-specific contributions. The overall process is illustrated in Figure 3.

3.3. Channel Contribution Analysis and Visualization

To gain deeper insight into how each channel contributes to classification decisions, we develop a comprehensive visualization framework that illustrates channel-specific information content across different sleep stages. Time-frequency analysis with continuous wavelet transform provides detailed spectrograms for each channel, highlighting stage-specific spectral patterns and their variation between channels [35]. Statistical significance mapping identifies frequency bands and time points where channels show significant differences in power or coherence across sleep stages, visualized as heatmaps overlaid on the EEG traces.

Class activation mapping techniques, adapted from computer vision, generate saliency maps highlighting which portions of the EEG signal most strongly influence classification decisions for each channel. These activation maps reveal temporal regions of interest within the 30-second segments, often corresponding to specific sleep graphoelements like K-complexes or sleep spindles [36]. By comparing activation patterns between channels, we can identify which sleep phenomena are preferentially detected in specific recording locations.

The contribution analysis extends to feature importance quantification, where we measure how each feature's predictive power varies between channels. For traditional machine learning approaches, we calculate permutation importance separately for features derived from each channel. For deep learning models, we apply gradient-based attribution methods to quantify how changes in specific frequency bands from each channel affect model predictions. These analyses reveal clear patterns of channel specialization: Fpz-Cz generally provides superior information for distinguishing N2/N3 stages through delta power and K-complex detection, while Pz-Oz better discriminates between wakefulness, N1, and REM through alpha rhythm and ocular movement artifacts.

3.4. Adaptive Channel Selection and Signal Quality Assessment

Building on our channel contribution insights, we develop an adaptive channel selection mechanism that dynamically chooses which channel to prioritize for different segments based on signal quality and discriminative power. The system continuously monitors signal quality metrics including line noise, electrode impedance (estimated from signal characteristics), muscle artifacts, and movement artifacts (1). A signal quality index is computed for each channel in real-time, identifying periods where one channel may be corrupted while the other remains clean.

For segments where signal quality differs substantially between channels, the system automatically prioritizes the cleaner channel for classification. When both channels have comparable signal quality, selection is based on the classification confidence scores from channel-specific models, potentially dynamically switching between channels based on their performance for particular sleep stage transitions. This adaptive approach increases robustness to channel-specific artifacts that commonly occur in real-world sleep recordings, particularly in home environments where electrode contact may temporarily degrade.

The adaptive selection system incorporates a temporal consistency constraint that prevents excessive switching between channels, using a hidden Markov model to balance instantaneous signal quality assessments against the consistency benefits of maintaining the same channel selection across adjacent segments. This approach prevents classification instability that might result from rapidly alternating between channels with borderline quality differences.

3.5. Reduced-Channel Transfer and Robustness Evaluation

Recognizing that practical applications may face scenarios where one electrode malfunctions or becomes unavailable, we investigate how models trained on dual-channel data can be effectively adapted to work with single-channel data. Our reduced-channel transfer approach begins by identifying shared representations between channels through canonical correlation analysis of channel-specific feature spaces. These shared components form a bridge for knowledge transfer between dual-channel and single-channel models [37, 38]. We develop a specialized transfer learning procedure where a dual-channel model is first trained to maximum performance, then knowledge is distilled to a single-channel model through a combination of soft-target training and shared layer weight initialization.

The resulting single-channel models achieve significantly higher performance than those trained on single-channel data alone, maintaining 96.3% of dual-channel performance when only one electrode is available. This approach proves particularly valuable for recovering performance in scenarios where an electrode is accidentally displaced during sleep or loses contact quality. The performance retention varies by sleep stage, with minimal degradation for stages that have strong channel-specific signatures (like N3 with Fpz-Cz), and more substantial but still limited degradation for stages requiring complementary information from both channels (like distinguishing N1 from REM).

The robustness of both single-channel and dual-channel approaches is thoroughly evaluated under challenging real-world conditions. We simulate various signal degradations including electrode displacement (modeled as frequency-specific filtering), contact impedance fluctuations (modeled as amplitude modulation and noise addition), powerline interference, and muscle artifacts [39, 40]. Sensitivity analysis quantifies performance degradation as a function of artifact severity for each approach, establishing tolerance thresholds for reliable operation. The dual-channel approaches with adaptive selection demonstrate substantially higher robustness, maintaining acceptable performance even when one channel experiences severe degradation. However, the transferred single-channel models show impressive resilience compared to standard single-channel approaches, suggesting that knowledge from dual-channel training transfers useful noise-rejection capabilities.

For electrode placement sensitivity, we analyze how small variations in electrode position (simulated through frequency-specific amplitude modulation based on known spatial EEG gradients) affect classification performance. This analysis helps establish practical guidelines for electrode placement precision requirements, important for non-expert application of home sleep monitoring systems. Results indicate that dual-channel approaches provide a form of spatial redundancy that reduces sensitivity to exact electrode positioning, an important practical advantage in non-laboratory settings.

3.6. Comprehensive Performance and Resource Evaluation

The performance comparison between single and dual-channel approaches extends beyond raw accuracy to consider multiple complementary metrics. Channel-specific performance is evaluated through accuracy, precision, recall, and F1-score for each sleep stage, identifying which stages benefit most from specific channels or their combination. We calculate the information gain provided by dual-channel approaches using mutual information analysis, which quantifies the additional discriminative information available when both channels are used compared to either channel alone. This analysis reveals substantial information gain for transitions between REM and N1 stages (traditionally difficult to distinguish), moderate gain for wake/sleep transitions, and minimal gain for distinguishing between N2 and N3, where Fpz-Cz alone provides nearly optimal information.

Stage-specific channel utility is determined by analyzing which channel or fusion approach provides the most reliable classification for each sleep stage transition. This analysis confirms that Fpz-Cz better captures slow-wave activity in deep sleep, providing superior N2/N3 discrimination, while Pz-Oz excels at detecting alpha rhythm during wake periods and its attenuation during sleep onset, improving wake/N1 differentiation. For REM detection, the combination of channels offers substantial advantages over either channel alone, leveraging complementary information about both occipital alpha activity and frontal theta rhythms characteristic of REM sleep.

This comprehensive evaluation includes a thorough resource-performance tradeoff analysis comparing the improved performance of dual-channel approaches against their increased complexity and computational requirements. We measure the additional computational load, memory requirements, and power consumption associated with dual-channel processing on various hardware platforms ranging from high-performance clinical systems to resource-constrained wearable devices. This analysis enables informed decision-making about which approach best suits specific application requirements, balancing classification performance against practical resource constraints.

The findings provide critical insights for electrode placement optimization in practical sleep monitoring applications, enabling more targeted and efficient EEG recording configurations. For clinical applications requiring maximum accuracy, dual-channel recordings with adaptive fusion provide clear advantages. For consumer applications where simplicity and comfort are paramount, our enhanced single-channel approaches offer substantial performance improvements over traditional methods, potentially enabling single-electrode devices with near-clinical accuracy.

4. Results and discussion

The experimental results demonstrate the superior performance of dual-channel EEG approaches compared to single-channel methods for sleep stage classification. As shown in Table 1, the dual-channel approach achieved an impressive overall accuracy of 92.4%, outperforming single-channel methods by 4.8% for Fpz-CZ and 7.2% for Pz-Oz. This aligns with our hypothesis that integrating information from multiple brain regions provides complementary insights into sleep architecture. The performance improvement was particularly pronounced for challenging sleep stage distinctions, such as differentiating between N1 and REM sleep stages, where the dual-channel approach showed a 9.3% increase in F1-score compared to the best single-channel result.

Table 1 Performance Comparison of Single-Channel vs Dual-Channel Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fpz-CZ Only	87.6	86.2	85.8	86.0
Pz-Oz Only	85.2	84.1	83.7	83.9
Early Fusion	90.7	89.5	88.9	89.2
Late Fusion	91.2	90.3	89.7	90.0
Attention-Based Fusion	92.4	91.6	91.3	91.4

The stage-specific performance analysis revealed interesting patterns of channel specialization, as detailed in Table 2. Fpz-CZ demonstrated superior performance in detecting slow-wave activity, achieving 94.7% accuracy for N3 stage classification, which is 6.5% higher than Pz-Oz for this sleep stage. This confirms the frontal channel's sensitivity to delta waves that characterize deep sleep. Conversely, Pz-Oz excelled at detecting alpha rhythm during wake periods and its attenuation during sleep onset, achieving 93.2% accuracy for wake classification, which is 4.8% higher than Fpz-CZ.

These findings align with known neurophysiological patterns, where frontal regions generate prominent slow oscillations during deep sleep, while occipital regions exhibit strong alpha activity during relaxed wakefulness.

Table 2 Sleep Stage-Specific Classification Performance by Channel

Sleep Stage	Fpz-CZ Accuracy (%)	Pz-Oz Accuracy (%)	Dual-Channel Accuracy (%)
Wake (W)	88.4	93.2	95.1
N1	79.3	80.7	85.6
N2	88.9	85.3	91.8
N3	94.7	88.2	96.2
REM	86.7	78.9	93.3

Our channel contribution analysis revealed distinct temporal patterns in the relative importance of each channel throughout the night. During transitions from wake to sleep and during REM periods, the attention mechanism consistently assigned higher weights to the Pz-Oz channel, reflecting its superior ability to detect alpha rhythm modulation. During deep sleep episodes, the attention weights shifted dramatically toward the Fpz-CZ channel, leveraging its sensitivity to slow-wave oscillations. This dynamic weighting demonstrates the complementary nature of the two recording sites and validates our attention-based fusion approach.

The reduced-channel transfer techniques demonstrated remarkable effectiveness, maintaining 96.3% of dual-channel performance when only one electrode was available. This represents a significant advancement over traditional single-channel approaches, which achieved only 87.6% at best. The knowledge transfer from dual-channel to single-channel models proved particularly effective for N2 and REM stages, where performance retention reached 97.8% and 95.4%, respectively. These results suggest that models initially trained on dual-channel data can extract generalizable features that remain useful even when channel availability is reduced, a crucial advantage for practical applications where electrode disconnection may occur.

Table 3 Performance Retention with Reduced-Channel Transfer Learning

Sleep Stage	Performance Retention (%)	Single-Channel Only (%)	Improvement (%)
Wake (W)	96.8	93.2	3.6
N1	94.1	80.7	13.4
N2	97.8	88.9	8.9
N3	97.2	94.7	2.5
REM	95.4	86.7	8.7
Overall	96.3	87.6	8.7

The adaptive channel selection mechanism further enhanced robustness against signal degradation, maintaining classification performance even under challenging recording conditions. When one channel experienced severe noise (signal-to-noise ratio < 5dB), the adaptive selection approach maintained 90.8% accuracy by dynamically switching to the cleaner channel, compared to 76.3% for static dual-channel methods. This robustness is particularly valuable for home sleep monitoring, where recording conditions cannot be controlled as stringently as in laboratory settings.

We also observed significant differences in computational requirements between approaches. The single-channel methods required approximately 45% less computational power than dual-channel approaches, with memory usage reduced by 38%. The attention-based fusion mechanism added approximately 15% computational overhead compared to simpler fusion strategies but provided a 1.2% accuracy improvement. For resource-constrained applications, our enhanced single-channel approach with transfer learning offers an excellent compromise, delivering 96.3% of dual-channel performance while requiring only 58% of the computational resources.

The comprehensive performance evaluation across different subject demographics revealed consistent benefits of dual-channel approaches across age groups. However, the margin of improvement was more pronounced in elderly subjects

(>65 years), where dual-channel methods outperformed single-channel approaches by 9.7% on average, compared to 5.3% in younger subjects. This age-dependent performance difference likely reflects increased sleep architecture variability and lower signal quality in elderly populations, where the redundancy provided by multiple channels becomes more valuable.

5. Conclusion

This study provides compelling evidence that dual-channel EEG approaches significantly outperform single-channel methods for sleep stage classification, achieving 92.4% accuracy compared to 87.6% and 85.2% for Fpz-CZ and Pz-Oz channels, respectively. Our systematic channel contribution analysis revealed clear specialization patterns, with Fpz-CZ better capturing slow-wave activity in deep sleep and Pz-Oz excelling at detecting alpha rhythm during wake and REM periods. The attention-based fusion mechanism demonstrated superior performance by dynamically weighting channel contributions based on their relevance for specific sleep phenomena. Notably, our reduced-channel transfer learning approach maintained 96.3% of dual-channel performance when only one electrode was available, representing a significant advancement for practical applications where electrode placement may be limited. The adaptive channel selection mechanism further enhanced robustness against signal degradation, maintaining classification performance even under challenging recording conditions. These findings provide critical insights for electrode placement optimization in sleep monitoring applications, enabling more targeted and efficient EEG recording configurations. This research advances both clinical sleep assessment and consumer-grade sleep monitoring technologies, potentially improving healthcare outcomes for the millions of individuals suffering from sleep disorders while establishing a foundation for future work on minimally intrusive yet highly accurate sleep monitoring systems.

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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