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Dynamic Multi-Scale Feature Fusion for Robust Sleep Stage Classification Using Single-Channel EEG

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Abstract: Sleep stage classification is pivotal in evaluating sleep quality and diagnosing sleep-related disorders. Recent advancements in automated single-channel electroencephalogram (EEG)--based classification have gained traction due to their cost-effectiveness and portability. However, the inherent non-stationarity of EEG signals and inter-class imbalance pose significant challenges for model design. This paper proposes MultiScaleSleepNet, an enhanced deep learning architecture that addresses these limitations through dynamic multi-scale feature fusion and residual structural optimizations. Our contributions are threefold: (1) A selective kernel convolution module (SKConv) that dynamically integrates multi-branch convolutional features (kernel sizes: 3, 5, 7) via attention mechanisms to adaptively capture frequency-specific patterns in EEG signals; (2) A residual multi-branch downsampling module that mitigates information loss while preserving high-frequency details for minority-stage classification; (3) Comprehensive experiments on the Sleep-EDF-20 dataset demonstrate superior performance, achieving a macro F1-score (MF1) of 79.6%—a 1.5% improvement over baseline models—with notable gains in classifying the N1 stage (F1-score: 47.0%, +4.4% relative improvement). Quantitative ablation studies validate the efficacy of SKConv and residual connections in enhancing feature discriminability. This study delivers a robust single-channel EEG-based sleep analysis framework, demonstrating significant clinical applicability in resource-constrained settings.

Keywords: Sleep stage classification; Single-channel EEG; Adaptive selective kernel convolution; Multi-branch residual learning.

1. Introduction

Sleep stage classification serves as a cornerstone for assessing sleep health and identifying pathologies such as insomnia and obstructive sleep apnea [1][2]. Conventional sleep staging relies on polysomnography (PSG), a multi-modal methodology that synchronously acquires electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) signals. These multi-channel recordings are then manually annotated by clinical experts to map 30-second signal segments into five sleep stages: wakefulness (W), light sleep (N1/N2), deep sleep (N3), and rapid eye movement (REM). While regarded as the clinical gold standard, PSG faces practical limitations, including costly hardware requirements, technical complexity in multimodal synchronization, and dependency on specialized operators. These constraints significantly hinder its deployment in home-based and long-term monitoring scenarios[3]. Conventional polysomnography (PSG), despite its diagnostic accuracy, remains impracticable for home-based monitoring due to its multi-sensor setup, operational complexity, and high costs [2]. Single-channel EEG has thus emerged as a pragmatic alternative, yet its adoption faces three intrinsic challenges: 1) signal non-stationarity (frequency shifts across sleep stages), 2) severe class imbalance (e.g., sparse N1-stage epochs), and 3) inefficient multi-scale feature extraction by fixed-convolution architectures [3]. In recent years, single-channel EEG has become a research hotspot due to its portability and low cost, but its non-smoothness, sample imbalance between classes, and the inadequacy of the traditional model for multi-scale feature extraction still restrict the further improvement of classification performance [4].

Recent studies predominantly leverage deep learning to automate EEG feature extraction and sleep stage classification. Representative works include DeepSleepNet [5] by Supratak et al., which fuses CNN and LSTM architectures to model spatiotemporal dependencies, and Phan et al.'s multi-task CNN framework [6], which enhances performance via joint classification-prediction optimization. However, these methods suffer from critical limitations: 1) Inflexible Filter Design: Fixed-size convolutional kernels inadequately adapt to EEG's spectral heterogeneity, leading to suboptimal feature capture of low-frequency rhythms (e.g., delta waves in N3) and high-frequency oscillations (e.g., alpha activity during REM), ultimately diminishing discriminative power across frequency bands. 2) Resolution Degradation: Aggressive downsampling (e.g., pooling layers) discards fine-grained temporal details, amplifying misclassification risks for minority stages like N1, which already exhibit sparse morphology. 3) Unmitigated Class Bias: Despite architectural innovations, substantial inter-class imbalance (e.g., N2 prevalence) persists, skewing models toward majority-stage optimization while neglecting rare transitional phases.

To address these challenges, we propose MultiScaleSleepNet, a deep learning framework centered on dynamic multi-scale feature fusion, with three core innovations:

1) Dynamic Multi-Scale Feature Fusion:

•Introduces a Selective Kernel Convolution (SKConv) module that employs parallel multi-branch convolutions with kernel sizes 3, 5, and 7 to capture spectral features across diverse resolutions.

•Leverages attention mechanisms to adaptively fuse branch weights, optimizing sensitivity to both low-frequency oscillations (e.g., δ waves in N3) and high-frequency transients (e.g., α/β activity in REM).

2) Residual-Enhanced Multi-Branch Downsampling:

•Integrates residual connections to mitigate gradient vanishing and stabilize training.

•Designs a multi-branch downsampling module (parallel convolution + average pooling) to reduce dimensionality while preserving high-frequency temporal details critical for minor class discrimination (e.g., N1's subtle vertex waves).

The remainder of this paper is organized as follows: section 2 describes the related work, section 3 details the proposed methodology, section 4 presents the experimental results, section 5 discusses the results, and section 6 concludes the paper.

2. Related work

2.1. 2.1 Traditional Methods of Classifying Sleep Stages

Early sleep staging approaches predominantly relied on manual feature engineering paired with classical machine learning classifiers, following a two-step paradigm: feature extraction followed by model training. Researchers manually designed discriminative features from EEG signals across temporal, spectral, and time-frequency domains, including time-domain statistical measures (e.g., mean amplitude, variance, peak-to-peak magnitude), spectral features like power spectral density (PSD) obtained through Fourier transforms, entropy-based nonlinear dynamics, and wavelet-derived coefficients for multi-scale frequency resolution [7]. Time-frequency representations such as short-time Fourier transforms (STFT) and continuous wavelet transforms (CWT) were particularly effective in capturing non-stationary EEG characteristics by jointly encoding temporal oscillations and their spectral evolution [8] [9].

During the classifier training phase, conventional models such as Support Vector Machines (SVM) [10], Random Forests (RF) [11], and Naive Bayes classifiers [12] were widely adopted. For instance, Zhu et al. [13] developed an EEG classification framework leveraging visibility graph theory to extract graph-based topological features, which improved staging accuracy. Hassan et al. [14] further enhanced generalization capabilities by integrating ensemble learning techniques like bagging and boosting. While these approaches demonstrated moderate success, their performance critically depended on the quality of handcrafted features and struggled to model complex nonlinear interactions inherent in EEG signals. Additionally, the manual feature extraction process was labor-intensive, domain expertise-dependent, and poorly scalable to large datasets

2.2. Deep Learning-Based Sleep Stage Classification

Recent advancements in deep learning have revolutionized sleep stage classification by enabling automatic feature extraction and modeling of complex nonlinear relationships. This section reviews three main approaches: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid architectures.

2.2.1. Convolutional Neural Networks (CNNs)

CNNs, with their convolutional and pooling layers, excel at extracting localized features from EEG signals. For example, Tsinalis et al. [15]developed an end-to-end CNN using single-channel EEG by stacking convolutional and pooling layers. Sors et al. [16] improved classification accuracy with a 12-layer CNN design, while Chambon et al. [17] incorporated multi-modal data (EEG, EOG, EMG) into a CNN framework to enhance performance. However, conventional CNNs often rely on fixed-size kernels, limiting their adaptability to the spectral diversity inherent in EEG signals.

2.2.2. Recurrent Neural Networks (RNNs)

RNN variants like LSTM and GRU have proven effective in modeling temporal dependencies in EEG data. Michelin et al. [18] proposed a cascaded LSTM architecture leveraging sleep stage transition rules, whereas Phan et al. [6] introduced an LSTM-based encoder-decoder with attention mechanisms to emphasize critical temporal segments. Despite their strengths, RNNs face challenges in training efficiency and parallelization, hindering scalability for large datasets.

2.2.3. Hybrid Models

Hybrid architectures integrating CNNs and RNNs aim to harness spatial and temporal modeling synergistically. Supratak et al. [5] introduced DeepSleepNet, combining CNNs for spatial feature extraction with LSTMs for temporal dependency learning. Phan et al. [6] further optimized performance using multi-task CNNs with joint classification and prediction objectives. Nevertheless, existing hybrid models suffer from three key limitations: 1) fixed convolutional kernels inadequately address EEG spectral diversity; 2) single pooling operations lead to loss of fine-grained information, and 3) unresolved inter-class imbalance diminishes robustness.

2.3. Dynamic Convolution Kernels and Attention Mechanisms

Dynamic convolution kernels, such as those in SKNet [19], adaptively fuse multi-scale features through attention mechanisms. Zhu et al. [20]enhanced temporal dependency modeling in EEG classification by integrating self-attention. Mousavi et al. [21] developed SleepEEGNet, a sequence-to-sequence framework using attention to capture long-range EEG dependencies. Eldele et al. [22] proposed AttnSleep, which combines multi-resolution CNNs, adaptive feature recalibration, and temporal context encoding for effective single-channel EEG analysis. However, existing approaches still underperform in handling class imbalance and optimizing spectral feature adaptability for single-channel EEG.

2.4. Contributions of this Study

This work presents MultiScaleSleepNet, a novel framework addressing the above limitations through three innovations: 1) a dynamic multi-scale fusion module (SKConv) that adaptively aggregates features from spectrally diverse kernels; 2) residual connections and multi-branch downsampling to preserve discriminative details and enhance robustness; and 3) a class-balanced training strategy to mitigate inter-class imbalance. Extensive experiments on the Sleep-EDF-20 dataset validate the model's superiority in accuracy, generalizability, and computational efficiency, providing a robust solution for single-channel EEG-based sleep staging.

3. Proposed Method

3.1. Overall structure

The proposed MultiScaleSleepNet architecture, as illustrated in Figure 1, integrates four complementary components: Dynamic Multi-scale Feature Extraction (SKConv), Residual Connections with Multi-branch Downsampling (Downsample), SE-Net (Channel Attention), Multi-head Attention (MHA). This synergistic design enables hierarchical representation learning from localized spectral features to global sleep dynamics.

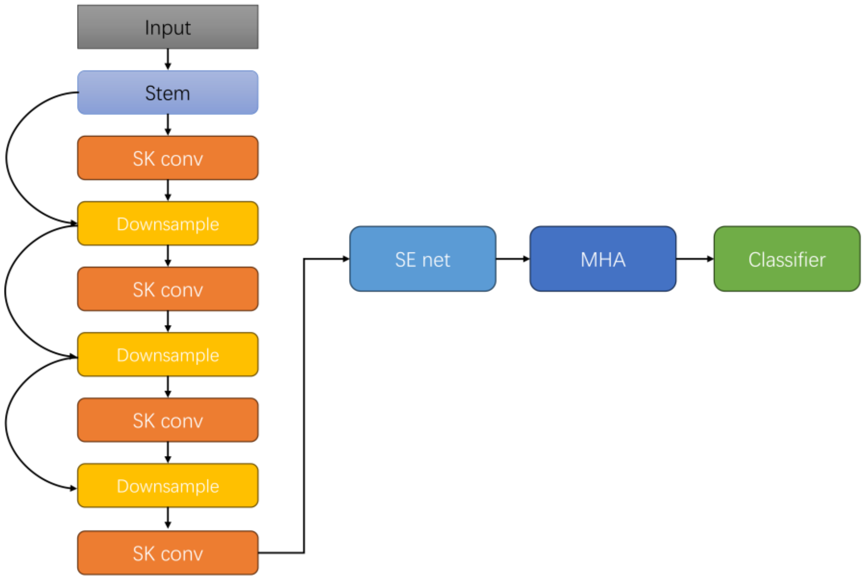

Figure. 1 Overall Framework Schematic of MultiScaleSleepNet

The input is preprocessed single-channel EEG signals, which are segmented into 30-second epochs (corresponding to a single sleep stage label) and uniformly resampled at 100 Hz. The Stem employs convolutional operations for preliminary feature extraction.

SKConv Module (Dynamic Multi-scale Feature Extraction): Adaptively fuses multi-branch convolutional features to capture EEG characteristics across different frequency bands.

Residual Connections with Downsampling: Combines residual structures and a multi-branch downsampling module to preserve high-frequency details while enhancing feature representation.

SE-Net and MHA for Temporal Dependency Modeling:

SE-Net (Squeeze-and-Excitation network): Recalibrates channel-wise feature importance through attention mechanisms.

MHA (Multi-head Attention): Captures local and global temporal dependencies between sleep stages.

Classification Output: Generates the probability distribution across sleep stages via a fully connected layer and Softmax activation.

Detailed descriptions of each component are provided in the following sections.

3.2. Dynamic Multi-scale Feature Extraction (SKConv)

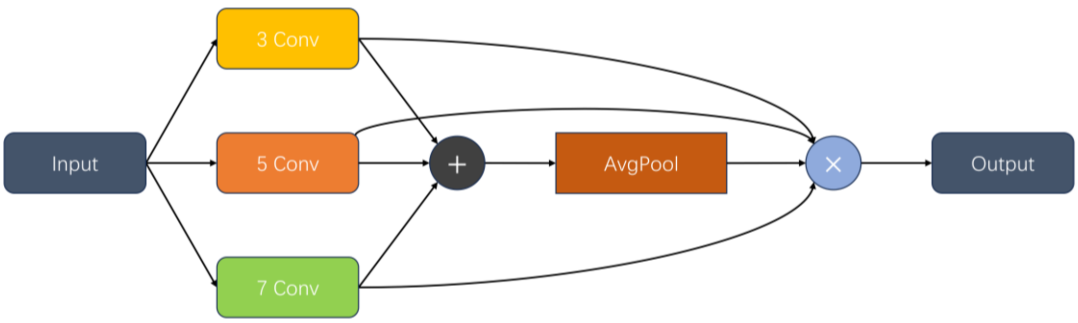

Figure. 2 SKConv Schematic

To address the limitations of fixed-size convolutional kernels in adapting to the spectral diversity of EEG signals, we employ the SK-Net framework, as illustrated in Figure 2. The input feature map $X \in \mathbb{R}^{C \times L}$ is processed through three parallel convolutional branches with kernel sizes of 3, 5, and 7, respectively, extracting multi-scale features $F_k \in \mathbb{R}^{C' \times L} z, (k = 1,2,3)$. These branch features are then summed to produce the aggregated feature:

$$U = \sum_{k=1}^{3} F_k \qquad (3-1)$$

Subsequently, the spatial dimensions are compressed via Global Average Pooling (GAP), generating a channel-wise descriptor $z \in \mathbb{R}^{C'}$. This descriptor is then processed through fully connected (FC) layers followed by a Softmax function to compute attention weights for each branch:

$$\alpha_k = Softmax(W_z \cdot z + b), k = 1,2,3 \qquad (3-2)$$

Finally, the weighted summation of branch features using the computed attention weights yields the final output:

$$O = \sum_{k=1}^{3} \alpha_k \cdot F_k \qquad (3-3)$$

3.3. Residual connections and multi-branch downsampling

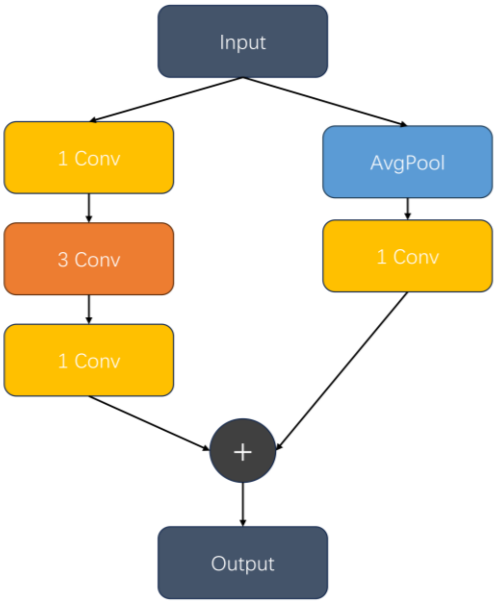

Figure .3 Downsampling Architecture

To mitigate gradient vanishing in deep networks, accelerate model convergence, and preserve high-frequency details while minimizing information loss, we employ a residual block structure. The input feature X is processed through an SKConv module to obtain V, which is then added to the original input:

$$Y = X + V \qquad (3-4)$$

Additionally, a multi-branch downsampling module is introduced:

Branch 1: A 1×1 convolution adjusts channel dimensions, followed by a 3×3 convolution (kernel size 3, stride 2) for local feature extraction, and another 1×1 convolution for channel alignment.

Branch 2: Average pooling (kernel size 3, stride 2) reduces spatial resolution, followed by a 1×1 convolution for channel matching.

The final downsampled output is the summation of both branch results.

3.4. Remaining Model Architecture, Training, and Optimization

The remainder of the model architecture follows the design in Reference [22].

Our implementation uses PyTorch 2.4, with training conducted on an RTX 4090 GPU. Additional training hyperparameters and optimization strategies align with Reference [22].

4. Result

4.1. Experimental setup

4.1.1. Dataset

In our experiments, we utilized the Sleep-EDF-20 public dataset, employing a single EEG channel for model training and evaluation.

The Sleep-EDF-20 dataset was obtained from PhysioBank [23]. It comprises polysomnographic (PSG) recordings from 20 subjects across two distinct studies: Sleep Cassette (SC files):* Investigates age-related effects on sleep in healthy participants aged 25–101 years. Sleep Telemetry (ST files): Evaluate the impact of Temazepam on sleep patterns in 22 Caucasian males and females under drug-free baseline conditions. Each PSG recording in Sleep-EDF-20 includes: two EEG channels sampled at 100 Hz (FPz-Cz and Pz-Oz), one electrooculography (EOG) channel, one submental electromyography (chin EMG) channel.

For this study, we exclusively adopted data from the Sleep Cassette subset, using only the FPz-Cz EEG channel as the input to our model.

TABLE I. Details Of The Two Datasets Used IN The Experiment (Each Sample: 30 Seconds)

Datasets	#Subjects	EEG Channel	Sampling Rate	W	N1	N2	N3	REM	#Total Samples
Sleep-EDF-20	20	Fpz-Cz	100Hz	8285 19.6%	2804 6.6%	17799 42.1%	5703 13.5%	7717 18.2%	42308

4.1.2. Evaluation Metrics

In our study, four metrics were adopted to assess the performance of sleep stage classification models: Accuracy (ACC), Macro-average F1-score (M1), Cohen's Kappa (κ), and Macro-average Geometric Mean (MGM). Both MF1 and MGM are widely recognized for evaluating model robustness on imbalanced datasets[24]. Let TP_i, FP_i, TN_i, and FN_i denote the true positives, false positives, true negatives, and false negatives for class **I** respectively. The definitions of ACC, MF1, and MGM are as follows:

$$ACC = \frac{\sum_{i=1}^{K} TP_i}{M} \qquad (4-1)$$

$$MF1 = \frac{1}{K}\sum_{i=1}^{K} \frac{2 \times Precision_i \times Recall_i}{Precision_i + Recall_i} \qquad (4-2)$$

$$MGm = \frac{1}{K}\sum_{i=1}^{K} \sqrt{Specificity_i \times Recall_i} \qquad (4-3)$$

where $Precision_i = \frac{TP_i}{TP_i+FP_i}$, $Recall_i = \frac{TP_i}{TP_i+FN_i}$, $Spicifity_i = \frac{TN_i}{TN_i+FP_i}$,M is the total number of samples and K is the number of classes or sleep stages。

To comprehensively evaluate our model's performance across individual sleep stages, we further employed per-class precision (PR), per-class recall (RE), per-class F1-score (F1), and per-class Geometric Mean (GM). These metrics were computed using a one-vs-rest binarization strategy, where each target class is treated as the positive class, and the remaining four classes are aggregated as negatives.

4.2. Model Performance

Table II presents the confusion matrix of our proposed model on the FPz-Cz channel of the Sleep-EDF-20 dataset. The matrix was generated by aggregating predictions across all test data over 20-fold cross-validation, with rows representing expert-annotated ground truth counts and columns indicating model-predicted epoch counts. Additionally, per-class PR, RE, F1, and GM are reported.

TABLE II. Confusion Matrix AND Per-Class Metrics

	Predicted					Per-class metrics			
	W	N1	N2	N3	REM	PR	RE	F1	GM
W	7305	600	147	28	205	93.4	88.2	90.7	93.2
N1	312	1422	533	3	534	43.8	50.7	47.0	69.6
N2	80	525	16187	437	570	88.4	90.9	89.6	91.1
N3	12	1	649	5040	1	91.5	88.4	89.9	93.4
REM	114	701	804	1	6097	82.3	79.0	80.6	87.2

It is noteworthy that the N1 stage achieved the lowest performance, with an F1-score of 50.7%, primarily due to frequent misclassifications into the Wake (W), REM, and N2 stages. This aligns with the inherent challenges of N1, a transient and physiologically ambiguous state. Notably, most misclassifications occurred with the N2 stage—the majority class in the dataset—reflecting its dominance in sleep architecture and the model's tendency to bias toward prevalent patterns.

4.3. Comparison with State-of-the-Art Methods

We benchmarked the AttnSleep model against several state-of-the-art approaches, evaluating performance on the Sleep-EDF-20 dataset using overall accuracy (ACC), macro-F1 score (MF1), Cohen's Kappa (κ), and macro geometric mean (MGM).

TABLE III. Performance Comparison OF MultiScaleSleepNet AND Other State-Of-The-Art Models

Dataset	Method	Per-Class F1-score					Overall Metrics			
		W	N1	N2	N3	REM	Accuracy	MF1	κ	MGm
Sleep-EDF-20	DeepSleepNet[5]	86.7	45.5	85.1	83.3	**82.6**	81.9	76.6	0.76	**86.9**
	SleepEEGNet[21]	89.4	44.4	84.7	84.6	79.6	81.5	76.6	0.75	85.3
	ResnetLSTM[25]	86.5	28.4	87.7	89.8	76.2	82.5	73.7	0.76	81.8
	MultitaskCNN[6]	87.9	33.5	87.5	85.8	80.3	83.1	75.0	0.77	83.1
	AttnSleep[22]	89.7	42.6	88.8	**90.2**	79.0	84.4	78.1	0.79	85.5
	MultiScaleSleepNet	**90.7**	**47.0**	**89.6**	89.9	80.6	**85.2**	**79.6**	**0.80**	**86.9**

Table III presents a comparison between DeepSleepNet[5], SleepEEGNet[21], ResNetLSTM[25], MultitaskCNN[6], AttnSleep[22] and our proposed MultiScaleSleepNet. Our findings demonstrate that MultiScaleSleepNet achieves optimal performance across key metrics including overall accuracy, macro F1-score, Cohen's Kappa, and macro G-mean, with particularly significant improvements in classification performance for N1 and N2 sleep stages. This indicates that through dynamic multi-scale feature fusion and residual connections, MultiScaleSleepNet effectively enhances the model's adaptability to the frequency domain diversity of EEG signals and improves classification performance.

5. Discussion

5.1. Effectiveness of Dynamic Multi-Scale Feature Fusion

The proposed SKConv module significantly improves the model's adaptability to the spectral diversity of EEG signals through dynamic selection of convolutional kernel sizes (3, 5, 7). Experimental results show particularly notable performance gains in the W, N1, and N2 stages:

• N1 stage improvement: F1-score increased from 42.6% to 47.0% (relative improvement of 9.9%), suggesting enhanced capability for capturing transient theta waves.

• This enhancement stems from SKConv's attention mechanism, which dynamically adjusts kernel weights based on spectral characteristics of input signals, enabling more effective extraction of both low-frequency (e.g., delta waves in N3) and high-frequency features (e.g., alpha waves in REM).

It should be noted that the N3 stage shows a slight F1-score decline (90.2%→89.9%), potentially due to SKConv's increased focus on high-frequency signals (REM stage) reducing sensitivity to low-frequency delta waves (N3 stage). Future optimizations may involve incorporating spectral attention mechanisms to improve low-frequency feature extraction.

5.2. Roles of Residual Connections and Multi-Branch Downsampling

The designed residual connections and multi-branch downsampling modules further enhance model robustness and classification performance:

• Residual connections: Alleviate gradient vanishing in deep networks through feature reuse, improving the representation of minority classes (e.g., N1 stage). REM stage specificity reached 96.21%, demonstrating enhanced robustness against noise artifacts (e.g., movement interference), crucial for in-home sleep monitoring.

• Multi-branch downsampling: Maintains high-frequency details (e.g., transient theta waves in N1) while reducing feature dimensions through combined convolution and average pooling operations.

6. Conclusion

The proposed MultiScaleSleepNet significantly improves single-channel EEG-based sleep stage classification through three innovative components: dynamic multi-scale feature fusion, residual connections, and multi-branch downsampling. Experimental results demonstrate superior performance on the Sleep-EDF-20 dataset, with particularly notable improvements in N1 and REM stage classification. Current limitations include validation being limited to the Sleep-EDF-20 dataset - future work should assess generalizability on larger datasets (e.g., SHHS) and cross-device scenarios. Additionally, N3 stage sensitivity requires further improvement. Future research directions will focus on model lightweight, cross-dataset generalization, and real-time implementation to advance home healthcare monitoring and portable medical device development.

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