EEG 수면 단계 분류를 위한 대역별 특징 학습 및 스택 앙상블 기법

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Bandwise Feature Learning and Stacked Ensembling for EEG Sleep Stage Classification

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Abstract

We propose a Bandwise CNN ensemble framework for EEG-based sleep stage classification. The EEG signals were first decomposed into five standard frequency bands (Delta, Theta, Alpha, Beta, Gamma). For each band, an individual CNN was trained to capture band-specific features. The softmax outputs from these CNNs were then combined using a multilayer perceptron (MLP) meta-learner, enabling the model to make final predictions based on all band-level information. Compared to conventional full-signal models such as LSTM, CNN-LSTM, and Transformer, our ensemble approach achieved superior performance, reaching 92.23% accuracy on the Sleep-EDF dataset. Notably, the method demonstrated improved generalization to minority classes. These results highlight that frequency-specific modeling with CNNs can be more effective than sequential models for EEG-based sleep stage analysis.

1. Introduction

EEG-based sleep stage classification is essential to the diagnosis of sleep disorders and the understanding of brain activity during rest.[1] The traditional method is to utilize the whole EEG signal, which comprises a wide range of frequency components.[5] EEG signals inherently comprise individual frequency bands — Delta, Theta, Alpha, Beta, and Gamma — containing different physiological information regarding sleep stages.[2] We propose here a band-specific modeling paradigm where separate 1D Convolutional Neural Networks (CNNs) are separately trained on each frequency band shown in figure.1 to learn specialized features appropriate for sleep stage classification. For fusing the best strengths of separate band-specific models, we employ a stacked ensemble architecture with a Multi-Layer Perceptron (MLP) meta-learner that takes the softmax output of each CNN as input. This approach leverages both the interpretability of frequency bands and the power of deep learning. Comprehensive experiments prove that our approach surpasses models trained on the whole EEG signal, and other architectures such as LSTM, CNN-LSTM, and Transformer. Our results highlight the effectiveness of processing EEG signals in a band-separated manner and show that different sleep stages are most accurately described in multiple frequency components.

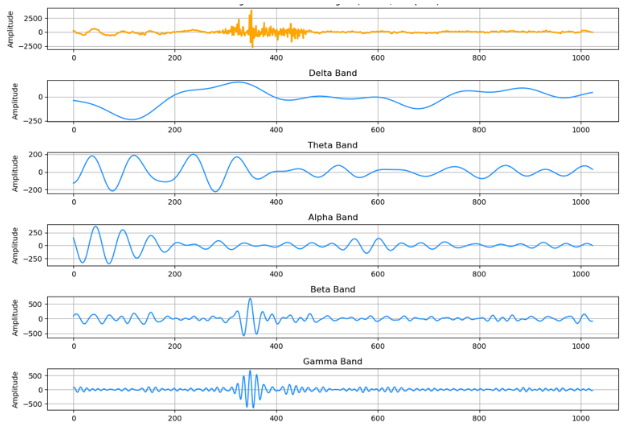

Figure 1. Visualization of an EEG signal segment (Fpz–Cz) and its decomposition into five canonical frequency bands: Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–80 Hz). Each band captures specific neural oscillations relevant to different sleep stages.

2. Related works

Recent studies in EEG-based automatic sleep stage classification have employed increasingly deeper learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, to automatically classify sleep stages based on raw or lightly preprocessed EEG signals.[3] Such approaches tend to use the full EEG time series as the input, seeking to learn temporal or spatial patterns from the whole frequency range.[7]

However, EEG signals have been discovered to consist of distinguishable frequency bands (I.e.,) (Delta, Theta, Alpha, Beta, Gamma), with each band corresponding to particular physiological states.[8] Despite this, majority of prior attempts overlook the natural separation and modeling of the bands, potentially omitting meaningful frequency-specific features that may cause transitions between sleep states

Some earlier effort used time-frequency transformations such as Short-Time Fourier Transform (STFT) or Wavelet Transform for visualization or augmentation of EEG inputs but still treated the EEG signal holistically.[4] Very little work has been done that systematically analyzed the contribution of individual bands or combined them with customized architectures.

In contrast, our method proposes a band-specific deep learning framework where separate CNNs are trained per frequency band, and their outputs are fused using a stacked ensemble meta-learner. This approach leverages both frequency specialization and model-level integration, resulting in performance improvements over standard full-signal models.

3. Proposed method: Stacked Ensemble with CNN Features

The EEG signal was transformed into the frequency domain using the Fast Fourier Transform (FFT), and five canonical bands (Delta: 0–4 Hz, Theta: 4–8 Hz, Alpha: 8–13 Hz, Beta: 13–30 Hz, Gamma: 30–80 Hz) were extracted via ideal bandpass filtering. After isolating the relevant frequency bins for each band, we applied the inverse Fast Fourier Transform (IFFT) to convert each band-limited signal back to the time domain. These frequency-specific components were treated as **independent feature representations**, analogous to having multiple input channels. Each band-specific signal was fed into a dedicated 1D CNN trained solely on that band, enabling extraction of unique temporal-spectral features. The softmax probability vectors (one per band) were then **concatenated (not averaged or voted)** into a unified feature vector of dimension 25 (5 bands × 5 sleep stages), which was passed to an MLP meta-learner. This structure shown in figure 2 allows the model to learn cross-band dependencies and make a **final decision by fusing band-specific knowledge**, rather than raw signal fusion or spatial channel combination.

Let $X \in \mathbb{R}^T$ denote an EEG segment $T = 1024$ time points. This signal decomposed into five standard EEG frequency Bands -Delta (δ) Theta (θ), Alpha (α), Beta (β), Gamma (γ) using Fourier-based bandpass filters:

$$X_b = \{Fourier\ transform\}_b(X), \{for\ \}b \in \{\delta, \theta, \alpha, \beta, \gamma\}$$

Each band-specific signal X_b is independently fed into a dedicated 1D CNN, yielding a softmax output vector:

$$P_b = Softmax(\{CNN\}_b(X_b)) \in \mathbb{R}^C$$

Where $C = 5$ is number of sleep stages (Wake, N1, N2, N3, REM). The output vector P_b represents the predicted class probabilities for the band b.

All five vectors are then concatenated to form a joint feature vector:

$$Z = [P_\delta; P_\theta; P_\alpha; P_\beta; P_\alpha] \in \mathbb{R}^5 = \mathbb{R}^{25}$$

This 25-dimensional vector Zserves as the input to a **meta-learner**, specifically a multilayer perceptron (MLP), defined as:

$$\hat{y} = Softmax(MLP(Z)) \in \mathbb{R}^C$$

The MLP is trained to learn a non-linear combination of the individual band predictions, effectively capturing cross-band dependencies and boosting the discriminative power, especially for underrepresented or confusable classes.

Empirical results show that this **stacked ensemble model** outperforms all baselines, including:

- individual band-specific CNNs,
- a single CNN trained on the full EEG signal,
- and deeper architectures such as CNN-LSTM and Transformers.

It achieved the **highest overall accuracy** and improved per-class precision, particularly in challenging sleep stages like N1 and REM.

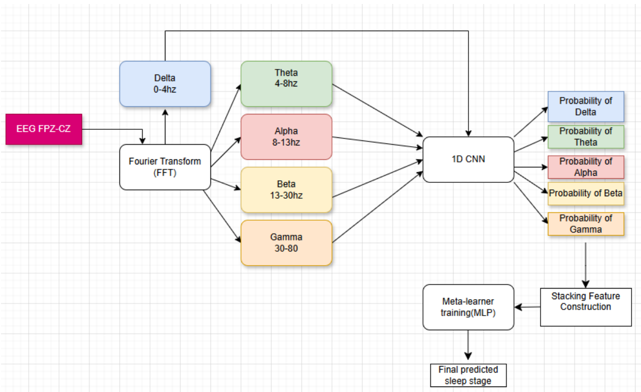

Figure 2. System Overview of the Proposed Bandwise CNN Ensemble Framework

4. Experiment and result

To validate our approach, we conducted extensive experiments on 13712 EEG epochs of the Sleep-EDF Expanded datasets first 20 patients data, each 30 seconds in length and sampled at 100Hz. Although the dataset includes only 20 patients, it provides 13,272 30-second EEG epochs, which is sufficient in quantity to train and evaluate deep learning models. Each epoch is treated as an independent training instance, allowing the models to learn robust temporal and spectral patterns across sleep stages. This segmentation increases data diversity and mitigates overfitting. However, we acknowledge that a larger and more diverse subject pool would further strengthen the generalizability of the model. Future work will focus on validating our method with cross-subject splitting and larger EEG datasets that include pathological sleep cases. We utilized a variety of model configurations: per-Band CNNs, a full-signal CNN baseline, and comparisons against LSTM, CNN-LSTM, and Transformer-based models. Each configuration was trained on 80% of the data and tested on the remaining 20%, with stratified splits to maintain class balance. Band-wise CNN models were trained separately for Delta, Theta, Alpha, Beta, and Gamma bands, and softmax outputs were stacked and passed through a meta-learner (MLP) to obtain the final prediction.

To evaluate model effectiveness, we compared various deep learning architectures on the full EEG signal, as well as our proposed stacked ensemble method. The table below summarizes the accuracy, macro-averaged F1 score, and weighted F1 score for each model:

Table 1. Quantitative Results

Model	Accuracy (%)	Macro F1	Weighted f1
1D CNN (Full EEG)	88.12	0.7360	0.9089
LSTM	81.30	0.4336	0.7776
CNN+LSTM	91.24	0.6921	0.9131
Transformer	81.92	0.5304	0.8085
Stacked CNN+Softmax	**92.23**	0.7273	**0.9150**

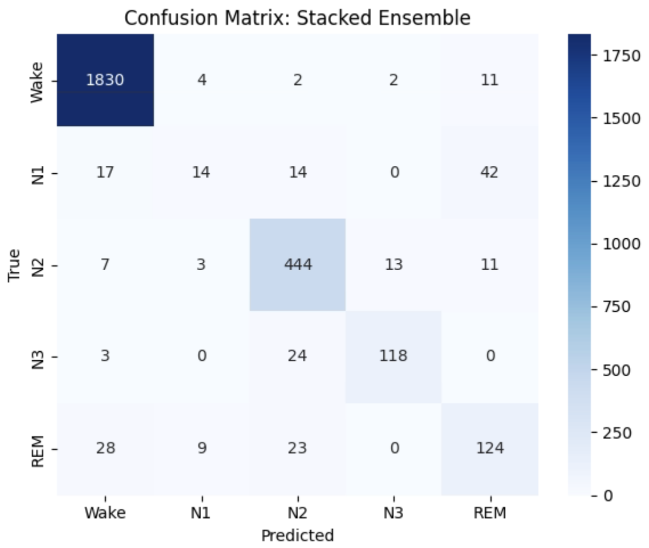

Figure 3. Confusion matrix of the proposed Stacked CNN+ Softmax ensemble model for sleep stage classification.

Our stacked ensemble method outperformed all individual models in terms of accuracy and weighted F1 score, demonstrating its robustness in handling class imbalance and extracting complementary features across EEG frequency bands. Although the CNN trained on the full signal achieved high performance on macro F1, the ensemble's integration of specialized band-wise models provided superior generalization in figure 3. Notably, the LSTM and Transformer models showed limited performance likely due to the challenge of capturing subtle frequency-based features from raw EEG.

5. Future work

In future work, we aim to enhance the ensemble mechanism by exploring attention-based or dynamic weighting strategies to better capture the importance of each frequency band. Expanding the model to support multi-channel EEG data could further improve performance by leveraging spatial information. Finally, we intend to validate our approach on larger and more diverse datasets, including pathological sleep cases, to assess generalizability and clinical applicability.

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