SleepMG: Multimodal Generalizable Sleep Staging with Inter-modal Balance of Classification and Domain Discrimination

Anonymous Authors

ABSTRACT

Sleep staging is crucial for sleep tracking and health assessment. Polysomnography (PSG), containing multiple modalities such as electroencephalography, electrooculography, electromyography, and electrocardiography, is the fundamental means of sleep staging. However, due to performance differences in both classification and domain discrimination across modalities in PSG, existing domain generalization methods face a dilemma of modal imbalance. To balance inter-modal differences and achieve highly accurate cross-domain sleep staging, we propose **SleepMG**, a **M**ultimodal **G**eneralizable **Sleep** staging method. SleepMG assesses the classification and domain discrimination performances of each modality and further defines the modal performance metrics by calculating the variance between the performance score and the average performance of each modality. Guided by these metrics, the gradients of the classifier and domain discriminator are adaptively adjusted, placing greater emphasis on poorly-balanced modalities while reducing emphasis on well-balanced modalities. Experimental results on public sleep staging datasets demonstrate that SleepMG outperforms state-of-the-art sleep staging methods, effectively balancing multiple modalities as evidenced by the visual experiment of modal imbalance degree. Our code will be released after formal publication.

CCS CONCEPTS

• **Information systems** → *Multimedia information systems*; • **Computing methodologies** → *Transfer learning*; • **Human-centered computing** → *HCI design and evaluation methods.*

KEYWORDS

Inter-modal balance, Polysomnography, Sleep staging, Domain generalization, Domain discrimination

1 INTRODUCTION

Sleep staging [54] is critical for health assessment and intervention, providing critical information on sleep quality of subjects and assisting in screening for brain and neurological health [5, 62, 12, 45]. Polysomnography (PSG) is multimodal physiological signals collected synchronously from different positions of the subject during sleep. PSG-based sleep staging [51, 25] can effectively monitor sleep progress and assist in diagnosing diseases such as Parkinson's and epilepsy. To ensure consistency, researchers mostly followed the American Academy of Sleep Medicine (AASM) [4] standard, classifying sleep into five stages for conducting studies. Initially, researchers manually staged sleep from the perspective of signal processing and medical knowledge based on the AASM standard. With the rise of deep learning, researchers began to employ automatic feature learning [51, 13, 46] to solve the time-consuming and labor-intensive problem in sleep staging. In sleep research, Convolutional Neural Networks (CNNs) were employed to automatically capture the spatial patterns in different sleep stages [48, 15] and distinctive features in different frequency bands [53], Recurrent Neural Networks (RNNs) [7, 49] and Long Short-Term Memory Networks (LSTMs) [63, 40] were employed to learn the dynamic patterns of signals [7, 49, 63] and capture the discriminative features at different time points [40]. Graph Convolutional Networks (GCNs) [20] were employed to model the association patterns between EEG channels. Sequence-to-sequence models [36, 38] were employed to capture the temporal dependencies between sequences and then learn distinguishing features in sleep staging tasks. Furthermore, the attention mechanism [42, 65, 10] was introduced to capture the differentiating features based on the relative importance of different sleep epochs.

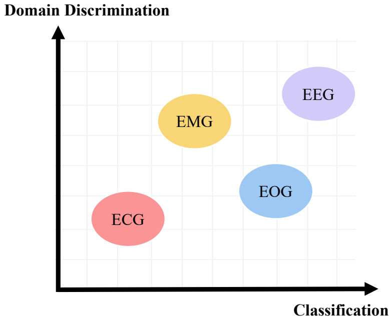


Figure 1: Varied classification and domain discrimination performances across different modalities of PSG.

However, as depicted in Figure 1, modal differences exist when multiple modalities of PSG jointly represent the sleep state. To explore the differences, modality-by-modality feature learning and fusion methods [17, 19, 60] have been designed to capture the differentiated features across modalities. Moreover, researchers have developed attention-based fusion techniques [60, 8] to enable multimodal models to focus on more important modalities. However, the attention mechanism amplifies the dominance of stronger modalities, exacerbating the inherent imbalance [35, 11] among them. This imbalance further hinders the model from fully utilizing the potential of all modalities. To balance modalities and make each modality as optimal as possible, Peng et al. [35] balanced two modality-specific feature extractors according to the classification performance of each modality. However, it is regrettable that they

ACM MM, 2024, Melbourne, Australia

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM
https://doi.org/XXXXXXX.XXXXXXX

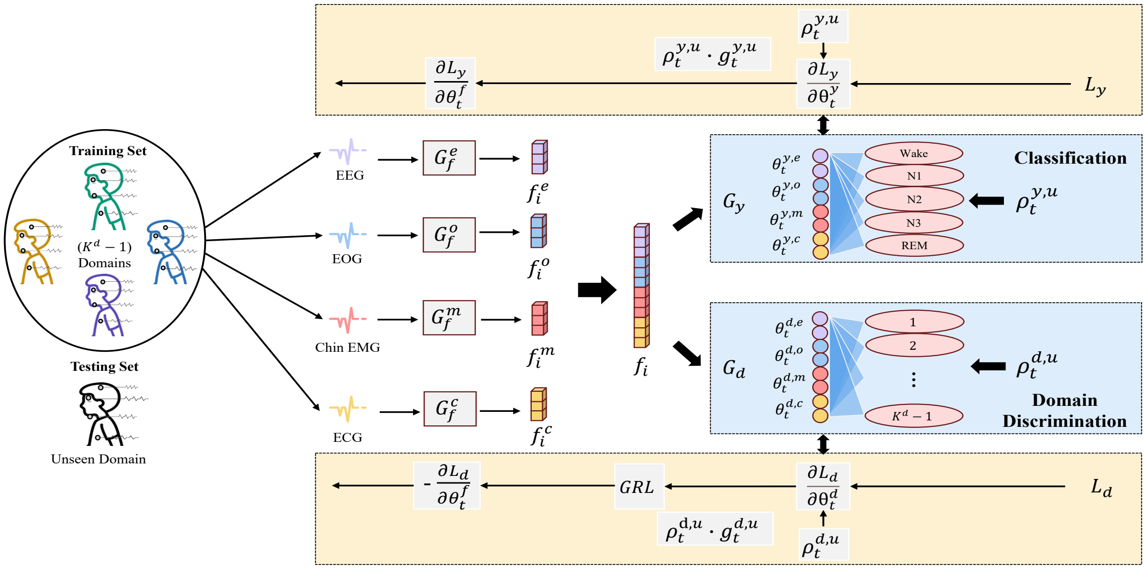


Figure 2: The pipeline of SleepMG. First, we perform modality-specific feature extraction, followed by the computation of modal performance metrics in classification and domain discrimination. These metrics are then utilized to adaptively influence the gradient backpropagation of the globally shared classifier and domain discriminator. SleepMG quantifies and balances inter-modal differences in two aspects, improving multimodal generalizable sleep staging.

compared the relative performance of two modalities, making it suitable only for balancing between two modalities. Additionally, balancing modality-specific feature extractors may interfere with the model to decouple and learn modality-related information, a more pronounced phenomenon in multimodal balancing scenarios.

Furthermore, PSG signals exhibit severe subject-dependency and existing generalizable sleep staging methods aim to enhance the cross-subject generalization capability of the model. The pre-training and fine-tuning method [37, 50] in transfer learning was introduced to do the subject personalized calibration. Unfortunately, the method requires significant data and some labeled data from the target subjects, posing inconvenience. As a result, the domain generalization method [57] was integrated. For example, domain adversarial methods [18, 29] were introduced to confuse the discrimination of the domain (i.e., the subject) by backpropagating the negative gradient of the domain discrimination loss, thereby allowing the model to learn domain-invariant information that is beneficial to unseen-domain generalization. Additionally, explicit feature alignment methods [39, 50] were introduced to learn shared feature representations across domains, improving the performance of the model on new fields or unseen data. However, as depicted in Figure 1, modal differences are not only reflected in classification performance, [6, 27], but also in domain discrimination performance [33, 24, 59]. The classification performance varies across different modalities [41], and it differs even more within different subject domains. The above methods enhance the cross-domain generalization of the model. However, none consider the inter-modal difference of domain generalization capability [33, 59], which is also crucial for sleep staging.

To tackle these challenges, we introduce SleepMG, a novel multimodal generalizable sleep staging method through classification and domain discrimination balancing. SleepMG first quantifies and balances the modal differences in classification and domain discrimination. SleepMG integrates domain adversarial learning into the multimodal feature learning framework and explicitly distinguishes the classification and domain discrimination performances of each modality through a globally shared classifier and discriminator separately. Guided by modal performance metrics, the gradients of model of the classifier and domain discriminator are adaptively adjusted, balancing the emphasis of the model on well and poorly-balanced modalities. SleepMG achieves modality-balanced and improves the multimodal generalizable sleep staging.

To summarize, our contributions are as follows:

- We construct a multimodal generalizable sleep staging model and first introduce metrics to assess the classification and domain discrimination performances of multiple modalities.
- By leveraging modal performance metrics, the gradients of the classifier and domain discriminator are adjusted adaptively, increasing greater emphasis on poorly-balanced modalities while reducing emphasis on well-balanced ones. This adaptive adjustment achieves balance across multiple modalities in two critical aspects.
- Extensive experiments on public datasets show that our proposed SleepMG achieves state-of-the-art sleep staging results, demonstrating its effectiveness in achieving multimodal balance and cross-domain generalization.

2 RELATED WORK

This section reviews the related work from two perspectives: sleep staging and generalizable sleep staging.

2.1 Automatic Sleep Staging

Sleep staging is crucial in assessing sleep quality and identifying potential neurological disorders [45]. Various methods have been developed to classify sleep stages based on PSG. Early studies relied on manual sleep staging, where experts manually classified sleep stages based on signal processing techniques and medical knowledge, following the AASM standard [3]. The AASM standard categorizes sleep into three main stages: the Wake stage, the Non-Rapid Eye Movement (NREM) stage, and the Rapid Eye Movement (REM) stage. The NREM stage is further divided into three sub-stages: N1, N2, and N3. These stages correspond to different degrees of sleep, resulting in five distinct categories. This manual approach is time-consuming and labor-intensive, prompting researchers to turn to deep learning techniques for automated sleep staging. Researchers utilized CNN [48, 15] to capture local spatial information in PSG data. Additionally, researchers have utilized RNNs [7, 63] and LSTM [48, 44] models to capture the sequential dependencies and temporal dynamics in PSG data. To model the correlations between different channels in PSG data, Jia et al. [20] introduced GCN-based GraphSleepNet, which represents PSG data as a graph to capture complex relationships. To handle the multi-level nature of PSG data, Phan et al. [36, 38] proposed sequence-to-sequence models to capture temporal dependencies across sleep epochs.

PSG includes multiple modalities collected from subjects, such as electroencephalography (EEG) [9, 14, 28, 22], electrooculography (EOG) [21], electromyography (EMG) [58], and electrocardiography (ECG) [32]. To explore the difference and consistency across modalities, researchers have designed modality-specific feature learning [52] modules and corresponding fusion modules [61]. Xiang et al. [58] designed a spatial encoder to capture the high-level shared semantic information between EEG and EMG. Considering the differences of importance across modalities, attention mechanisms have been incorporated into sleep staging models to help the model focus on more important modalities or parts. Zheng et al. [60] also used the attention mechanism to help learn the interdependencies across modalities. However, there are differences across modalities, and attention-based fusion can exacerbate the inter-modal imbalance, resulting in insufficient learning of each modal and limiting the classification capability of multimodal models.

2.2 Generalizable Sleep Staging

PSG, as a physiological signal, is highly subject-dependent [34], and the data distribution across subjects varies significantly. In this paper, we explore methods to enhance the out-of-distribution generalization of sleep staging models, aiming to construct a general automated sleep staging model that can be applied across subjects (i.e., domains). We refer to this model as a generalizable sleep staging model [30, 26, 43]. To achieve this, researchers have introduced transfer learning methods. A common approach is the pretraining-finetuning method [26, 56]. Wang et al. [56] trained on a large sleep dataset, MASS, to learn general sleep-related representations, and then fine-tuned on a smaller sleep dataset, sleep-edf sub-dataset. While this method has demonstrated effectiveness, it is not without its drawbacks. The pretraining phase requires a large dataset and substantial computational resources. The finetuning phase requires a small amount of labeled data, impractical in cross-domain application scenarios such as healthcare. Banluesombatkul et al. [1] used meta-learning for pretraining, which improved data dependency and task generalization to some extent. However, the method increased the computational cost during the pretraining phase. The finetuning phase still requires a small amount of labeled data, making cross-domain generalization unachievable. Tang et al. [50] addressed domain adaptation by explicitly aligning the feature distributions between the source and target domains, removing the reliance on labels in the target domain. However, it still requires data from the target domain and does not solve the cross-domain generalization problem.

To overcome these limitations, researchers integrated the domain generalization method. For example, some researchers incorporated domain adversarial learning [18, 29] into their model. The domain discriminator in domain adversarial played a crucial role in enhancing the cross-domain generalization performance of the model by intentionally confusing the capability of the model to identify different domains. The domain adversarial method has achieved considerable generalization performance. However, there is no specific domain adversarial technique for multimodal sleep staging. Moreover, differences exist across modalities, not only in terms of classification capability but also in domain generalization capability. Quantifying and balancing these two types of inter-modal differences is necessary.

3 PRELIMINARY

The training set is $\mathcal{D}_{train} = \{(x_i, y_i, d_i) | \; i \; \in \{1, \ldots, \; I\}\}$ and the testing set is $\mathcal{D}_{test} = \{x_j | j \; \in \{1, \ldots, \; J\}\}$. For generalizable sleep staging, the training data $\mathcal{D}_{train}$ and testing data $\mathcal{D}_{test}$ are from different subjects. $x_i = \left[x_i^e, \; x_i^o, \; x_i^m, \; x_i^c\right]$ and $x_j = \left[x_j^e, \; x_j^o, x_j^m, \; x_j^c\right]$ are PSG signals containing synchronized EEG, EOG, EMG, and ECG, and each epoch lasts 30 seconds. x_i and x_j are the i-th and j-th samples of training and testing set, respectively. $y_i \in \{1, 2, \ldots, K^y\}$ is the corresponding sleep category and K^y is the total number of categories. $d_i \in \{1, 2, \ldots, K^d - 1\}$ is the domain of x_i and $K^d - 1$ is the number of domain in training set. I and J are the sample sizes of the training and testing set, respectively. $C^U = C^e + C^o + C^m + C^c$ is the total number of PSG channels (containing EEG, EOG, EMG and ECG). U is the number of modalities, C^e, C^o, C^m and C^c are the channel numbers of different modalities.

Sleep staging problem is defined as $\hat{y}_i = \underset{k^y}{\operatorname{argmax}} \left[G_y(G_f(x_i))\right]_{k^y}$, where $G_f = [G_f^e, G_f^o, G_f^m, G_f^c]$ denote modality-specific feature extractors for EEG, EOG, EMG, ECG, respectively, and the parameter of G_f denoted as $\theta^f = \left[\theta^{f,e}, \theta^{f,o}, \theta^{f,m}, \theta^{f,c}\right]$, G_y denotes the label classifier. $\hat{y}_i$ denotes the predicted category and k^y denotes the index of category. $f_i = \left[f_i^e, \; f_i^o, \; f_i^m, \; f_i^c\right] = G_f(x_i) = \left[G_f^e(x_i^e), \; G_f^o(x_i^o), \; G_f^m(x_i^m), \; G_f^c(x_i^c)\right]$ denotes the multimodal fusion feature. f_i^e, f_i^o, f_i^m and f_i^c represent the features extracted from x_i^e, x_i^o, x_i^m and x_i^c, respectively. We combine the multimodal feature learning model with the domain adversarial method to create the naive multimodal generalizable sleep staging. The predicted domain in domain discrimination is $\hat{d}_i = \underset{k^d}{\operatorname{argmax}} \left[G_d(G_f(x_i))\right]_{k^d}$,

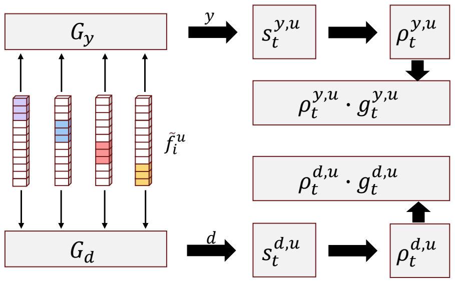


Figure 3: To calculate the classification and domain discrimination performance metrics for each modality, we employ zero-padding to align the features of each modality with the multimodal fusion feature and feed them to the globally shared classifier and domain discriminator.

where G_d denotes the domain discriminator and k^d denotes the index of domain.

To simplify the symbol expression, we use $a \in \{y,\ d\}$ to represent the symbol related to the category and domain. Specially, $K^a \in \{K^y, K^d\}$ denote the number of category and domain, $k^a \in \{k^y, k^d\}$ denote the label index of category and domain, $p_i^a \in \{y_i,\ d_i\}$ denote the truly label of category and domain, $\hat{p}_i^a \in \{\hat{y}_i,\ \hat{d}_i\}$ denote the predicted label of category and domain, $G_a \in \{G_y, G_d\}$ denote the classifier and domain discriminator and $\theta^a \in \{\theta^y,\ \theta^d\}$ denote their model parameters. Since the model structure of G_a is a simple fully connected layer, θ^a can be split into modality-specific $\theta^{a,u}$. In addition, $u \in \{e,\ o,\ m,\ c\}$ denotes the modality-related symbol. $\hat{p}_i^{a,u} \in \{\hat{p}_i^{a,e},\ \hat{p}_i^{a,o},\ \hat{p}_i^{a,m},\ \hat{p}_i^{a,c}\}$ denote the predicted category and domain labels of different modalities from the same x_i. f_i^u denotes the modality-specific feature. $\theta^{f,u}$ denotes the parameter of the modality-specific feature extractor G_f^u and $\theta^{a,u}$ denotes the parameter of the modality-specific part of G_a.

4 THE PROPOSED SLEEPMG

The pipeline of SleepMG is shown in Figure 2. We introduce SleepMG from three aspects: 1) Naive multimodal generalizable sleep staging (NaiveMG), the backbone of SleepMG. 2) Modal performance metrics of classification and domain discrimination. 3) Metric-guided adaptive modality balancing and generalizable sleep staging.

4.1 Naive Multimodal Generalizable Sleep Staging Method

To realize SleepMG, we first conduct the naive integration of modality-specific feature learning and domain adversarial methods, named the Naive Multimodal Generalizable method (NaiveMG). Specifically, NaiveMG employs FeatureNet [18], a dual-scale CNN model to establish each modality-specific feature extractor. These feature extractors capture the unique characteristics of each modality. In addition, NaiveMG fuses extracted features and classifies sleep stages using the simple fully connected classifier G_y. To further enhance cross-domain generalization, we set domain discriminator G_d with the same simple fully connected to confuse the identification of the model about domains by back-propagating negative gradients. By incorporating the above techniques, NaiveMG significantly enhances the cross-domain generalization capability of multimodal sleep staging models, enabling more accurate and reliable sleep stage classification across domains. The classification loss $\mathcal{L}_y$ and domain discrimination loss $\mathcal{L}_d$ are both calculated using the cross-entropy loss function. Details are as follows:

$$\mathcal{L}_a = -\frac{1}{I}\sum_{i=1}^{I}\sum_{k^a=1}^{K^a} 1_{p_i^a=k^a}\log([G_a(f_i)]_{k^a}) \tag{1}$$

where $G_a(f_i) = [G_a(f_i)\,[1], G_a(f_i)\,[2], \ldots, G_a(f_i)\,[K^a]]$ represents the list of softmax predicted output, $i \in \{1, 2, \ldots, I\}$ represents the total number of training samples, 1 represents an indicator function that returns 1 if the inputs are equal and returns 0 otherwise.

All model parameters are optimized by minimizing $\mathcal{L}$. Since $\mathcal{L}_d$ undergoes a gradient reversal in gradient backpropagation, the final optimization process is to minimize $\mathcal{L}_y$ and maximize $\mathcal{L}_d$. The sum of loss $\mathcal{L}$ is as follows:

$$\mathcal{L} = \mathcal{L}_y - \mathcal{L}_d \tag{2}$$

Utilizing NaiveMG as the backbone, SleepMG further quantifies inter-modal differences in classification and domain discrimination.

4.2 Multimodal Performance Metric

Figure 3 depicts the details of assessing the modal performance metrics of the classification and domain discrimination.

4.2.1 Evaluation of Multiple Modalities with Shared Model. To begin, we employ zero-padding on the modality-specific feature f_i^u to match the desired fused length, denoted as $\tilde{f}_i^u$. Subsequently, these padded features $\tilde{f}_i^u$ are fed into the globally shared classifier G_y and domain discriminator G_d, respectively, to obtain their modality-specific prediction results $\hat{p}_i^{a,u}$:

$$\hat{p}_i^{a,u} = \operatorname*{argmax}_{k^a} \left[G_a(\tilde{f}_i^u)\right]_{k^a} \tag{3}$$

where $G_a(\tilde{f}_i^u) = \left[G_a(\tilde{f}_i^u)\,[1], G_a(\tilde{f}_i^u)\,[2], \ldots, G_a(\tilde{f}_i^u)\,[K^a]\right]$ represents the list of softmax predicted output of the modality u, $\tilde{f}_i^u$ represents the feature of single modality u that has been zero-padded to match the length of multimodal fusion feature f_i.

4.2.2 Two Performance Values of Each Modality. Following [35], we calculate the sum of correctly predicted category probabilities from the softmax output as two performance values at the t time step of each modality. The classification and domain discrimination performance values of each modality are as follows:

$$v_t^{a,u} = \frac{1}{I}\sum_{i=1}^{I}\sum_{k^a=1}^{K^a} 1_{p_i^{a,u}=k^a}\left[G_a(\tilde{f}_i^u)\right]_{k^a} \tag{4}$$

where t is the time step, and 1 is the equality function that returns 1 if the inputs are equal and returns 0 otherwise.

4.2.3 Two Performance Metrics of Each Modality. According to two sets of performance values $v_t^{a,u} \in \{v_t^{y,u}, v_t^{d,u}\}$, we calculate the performance score $s_t^{a,u} \in \{s_t^{y,u}, s_t^{d,u}\}$ of each modality at t moment and finally define the modal performance metrics $\rho_t^{a,u} \in \{\rho_t^{y,u}, \rho_t^{d,u}\}$ based on the variance of the difference between $s_t^{a,u}$ and the average ratio $\frac{1}{U}$ of each modality. The smaller $\rho_t^{a,u}$ means the more balanced modality in classification or domain discrimination:

$$s_t^{a,u} = \frac{v_t^{a,u}}{\sum_{u=1}^{U} v_t^{a,u}} \tag{5}$$

$$\rho_t^{a,u} = tanh\left(\frac{(s_t^{a,u} - \frac{1}{U})^2}{\sum_{u=1}^{U}(s_t^{a,u} - \frac{1}{U})^2}\right) \tag{6}$$

where *tanh* is the active function for smooth, and the sum scaling method is employed for normalization.

4.3 Metric-Guided Modality-Balanced Model Construction

We backpropagate the gradients $g_t^{f,u}$ of the feature extractors normally, computed as $\frac{\partial \mathcal{L}_y}{\partial \theta_t^{f,u}} - \frac{\partial \mathcal{L}_d}{\partial \theta_t^{f,u}}$. While the gradients $g_t^{a,u}$, which are the modality-specific parts from $\frac{\partial \mathcal{L}_a}{\partial \theta_t^{a}}$, are guided by scalar $\rho_t^{a,u}$ to balance the classification and domain discrimination across modalities:

$$\tilde{g}_t^{a,u} = \rho_t^{a,u} \cdot g_t^{a,u} \tag{7}$$

We utilized the Adam optimizer for all models. Initially, we set the first-moment estimation $m_t^{a,u}$ and the second-moment estimation $v_t^{a,u}$ of the gradient to zero at time zero. Subsequently, we update $m_t^{a,u}$ and $v_t^{a,u}$ at time t based on estimation values of the previous time and the gradient $g_t^{a,u}$ of modality-specific parts of G_a:

$$m_t^{a,u} = \beta_1 \cdot m_{t-1}^{a,u} + (1-\beta_1)\cdot \tilde{g}_t^{a,u} \tag{8}$$

$$v_t^{a,u} = \beta_2 \cdot v_{t-1}^{a,u} + (1-\beta_2)\cdot (\tilde{g}_t^{a,u})^2 \tag{9}$$

where $g_t^{a,u}$ denote the gradient of modality-specific parts of θ_t^a. $m_t^{a,u}$, $v_t^{a,u}$ denote the first-moment and second-moment estimations of $\tilde{g}_t^{a,u}$, respectively. β_1 and β_2 denote the attenuation factors. $(\tilde{g}_t^{a,u})^2$ denotes the square of the gradient $\tilde{g}_t^{a,u}$.

Then further revise the first-moment and second-moment estimations to prevent them from being initially biased toward zero:

$$\hat{m}_t^{a,u} = \frac{m_t^{a,u}}{1-\beta_1} \tag{10}$$

$$\hat{v}_t^{a,u} = \frac{v_t^{a,u}}{1-\beta_2} \tag{11}$$

where $\hat{m}_t^{a,u}$ and $\hat{v}_t^{a,u}$ are revised $m_t^{a,u}$ and $v_t^{a,u}$.

The parameters $\theta_t^{a,u}$ of modality-specific parts of G_a are updated according to modal performance metrics $\rho_t^{a,u}$:

$$\theta_{t+1}^{a,u} = \theta_t^{a,u} - \left(\frac{\hat{m}_t^{a,u}}{\sqrt{\hat{v}_t^{a,u}} + \epsilon_1}\right)\cdot \eta \tag{12}$$

where t represents the time step, η represents the learning rate, ϵ_1 represents a small constant to prevent division by zero.

By setting a larger $\rho_t^{a,u}$ for the gradient $g_t^{a,u}$ of models $\theta_t^{a,u}$ with poorly-balanced modality in classification and domain discrimination performance and a smaller $\rho_t^{a,u}$ for the gradient $g_t^{a,u}$ with well-balanced modality, we achieve a multimodal generalizable sleep staging model that is modality-balanced. Notably, Since the gradients backpropagated through the domain discriminator undergo the same reversal, the balance degree of modalities remains unaffected.

4.4 Method Implement

The core of SleepMG is elucidated in Algorithm 1. SleepMG aims to calculate the performance of multiple modalities' classification and domain discrimination, ensuring the inter-modal balance in both classification and domain discrimination and achieving multimodal generalizable sleep staging. The backbone is naiveMG, which includes multimodal feature learning and domain adversarial methods. Multimodal PSG is first processed through modality-specific feature extractors G_f^u to extract features and fuse. Subsequently, domain adversarial methods are integrated to improve cross-domain generalization. The model is optimized by minimizing classification loss $\mathcal{L}_y$ and maximizing domain discrimination loss $\mathcal{L}_d$. By the early convergence stage, we assess the classification and domain discrimination capabilities of each modality by zero-padding their features and utilizing the shared classifier and discriminator. Additionally, the parameters $\theta_t^{f,u}$ of G_f^u are updated with minimizing $\mathcal{L}$ as usual. Furthermore, we calculate modal performance metrics of classification and domain discrimination, leveraging these metrics to influence the gradient update of parameters θ_t^a of G_a with minimizing $\mathcal{L}$. To achieve modality balance, the gradients backpropagated by modality-specific parts $\theta_t^{a,u}$ that correspond to the poorly-balanced modalities are relatively enhanced with large $\rho_t^{a,u}$, while those that correspond to the well-balanced modalities are relatively reduced with small $\rho_t^{a,u}$. The balanced multimodal generalizable sleep staging model is obtained when all the models converge.

Algorithm 1 The whole process of SleepMG method

```
Input: The training set $\mathcal{D}_{train} = \{(x_i, y_i, d_i)|i \in \{1,\dots, I\}\}$, the
    testing set $\mathcal{D}_{test} = \{x_j | j \in \{1,\dots, J\}\}$.
Output: The sleep staging result of testing data $\hat{y}_j$.
Initialize model parameters $\theta_{t=0}^{f,u}$ of the modality-specific feature extractor $G_f^u$ and $\theta_{t=0}^{a,u}$ of modality-specific parts of $G_a$(i.e., classifier and domain discriminator);
repeat
      % Metric Definition
    Extract the multimodal feature of $x_i$ with $G_f$: $f_i = G_f(x_i)$;
    Zero-pad $f_i^u$ to obtain $\tilde{f}_i^u$ and calculate two performance values of each modality $v_t^{a,u}$ with Eq. (4);
    Calculate two performance metrics $\rho_t^{a,u}$ of each modality based on $v_t^{a,u}$ with Eq. (5) and (6);
      % Model Training
    Calculate total loss $\mathcal{L}$ with Eq. (2);
    Update model parameters $\theta_t^{f,u}$ normally, while update $\theta_t^{a,u}$ under the guidance of $\rho_t^{a,u}$ using Eq. (12) to minimize $\mathcal{L}$;
until Iterate until model convergence
Sleep staging prediction: $y_j = G_y(f_j)$
```

5 EXPERIMENTS

All experiments are implemented with Python 3.8.5 and Pytorch 1.7.1. We conduct them on a computer server with 640GB RAM and two NVIDIA RTX A5000 GPUs with 24GB VRAM each.

5.1 Dataset and Data Processing

We evaluate SleepMG on two public datasets: ISRUC-S3 [23], and MASS-SS3 [31]. For a fair comparison, we remove the Movement and Unknown stages and merge the N3 and N4 stages into a single N3 stage, resulting in five categories of Wake, N1, N2, N3, and REM sleep stages according to the AASM standard. Each PSG recording is downsampled to 100 Hz and divided into 30-second epochs.

ISRUC-S3 collects PSG from 10 subjects (one male and nine female) over 8 hours in a single night, containing 8589 sleep epochs. We select ten of the 12 channels and remove the leg EMG far from the brain. It comprises four modalities: six-channel EEG, two-channel EOG, one-channel chin EMG, and ECG.

MASS-SS3 collects PSG from 62 subjects (28 male and 34 female) over 8 hours in a single night, containing 59304 sleep epochs. We select the same 10 channels with four modalities as ISRUC-S3.

5.2 Experiment Settings and Implementation

In the experiment, we utilize FeatureNet [16, 18] as the backbone of NaiveMG and SleepMG. We employ the leave-one-subject-out method to divide the dataset into five domains with different subjects and perform five-fold cross-validation to split the data into training and testing sets. From the training set, we further allocate 20% as a validation set. The best model based on the validation set is saved and evaluated on the cross-domain testing set. The final reported results represent the overall evaluation of the entire dataset. We employ the Adam optimizer for model optimization with a learning rate of 0.001, attenuation factors β_1 of 0.5 and β_2 of 0.999. The batch size for data processing is 256, and the training process is conducted over 50 epochs. The gradient reversal ratio employed in domain-adversarial training for the ISRUC-S3 and MASS-SS3 datasets is 0.1 and 1, respectively.

We employ *Accuracy*, *Macro F*1, *Kappa*, and *F*1 for each category as the evaluation metrics of the experimental results. *Accuracy* measures the proportion of correctly classified sleep epochs. The *F*1 score for each category evaluates precision and recall, comprehensively evaluating the performance of the model. *Macro F*1 score calculates the average F1 score across all sleep stage categories, providing insight into the capability of the model to perform well across categories without favoring a specific category. *Kappa* measures the agreement between the prediction of the model and the ground truth, accounting for chance. It assesses inter-rater agreement by considering both observed and expected accuracy.

5.3 Baseline Methods and Settings

We select eight classical and state-of-the-art sleep staging methods as baseline methods from four perspectives: four conventional sleep staging [18, 48, 64, 10] method, one generalizable sleep staging [50] method is based on transfer learning to improve cross-domain sleep staging, two multimodal sleep staging [17, 60] methods involve modality-specific feature extractors, and one balance method [35] is special-designed for multimodal fusion and balance.

- FeatureNet [18]: The conventional method uses a dual-scale CNN structure with varying kernel sizes and channel configurations. The first set of kernels consists of sizes {50, 8, 8, 8} and corresponding channels {32, 64, 64, 64}. The second set of kernels consists of sizes {64, 8, 6, 6, 4} and corresponding channels {64, 64, 64, 64}.
- DeepSleepNet [48]: The conventional method employs the CNN-BiLSTM model. CNNs captures local temporal patterns and spatial relationships, while the BiLSTM component captures long-term temporal dependencies.
- MaskSleepNet [64]: The conventional method combines dual-scale CNNs for feature extraction, squeeze and excitation block for optimizing feature weights, and multi-head attention for capturing temporal information.
- AttnSleep [10]: The conventional method integrates a multi-resolution CNN model, adaptive feature recalibration for learning interdependencies among features, and multi-head attention for capturing temporal dependencies.
- DAN [50]: The generalizable method is based on CNN-BiGRU and leverages the MMD alignment to learn domain-invariant representation.
- SleepPrintNet [17]: The multimodal method involves modality-specific feature learning based on the 1D convolutional model. In addition to learning temporal features across all PSG modalities, the EEG modality specifically focuses on spectral-spatial feature learning.
- MMASleepNet [60]: The multimodal method incorporates modality-specific feature learning through 1D convolutional models and squeeze-and-excitation, along with feature fusion utilizing transformer encoder models.
- OGM-GE [35]: The balance method was originally an audio-visual dual-modality balancing method, which improved the model by balancing the classification performance of two modalities and modulating the gradient of the feature extractor. To be fair, we employ FeatureNet as its backbone.

5.4 Comparative Experiment Results

To demonstrate the advantage of SleepMG in sleep staging, we compared SleepMG with a total of eight methods, including four conventional methods, one generalizable method, two multimodal methods, and one multimodal balance method. The experimental results in Table 1 show that SleepMG consistently outperforms other methods on both datasets. On the ISRUC-S3 dataset, the second-best *Accuracy* method is the NaiveGS method, DAN, and SleepMG achieves an *Accuracy* improvement of nearly two percentage points compared to it and approximately 3.6% *Accuracy* improvement compared to the backbone method, FeatureNet. These results indicate the effectiveness of transfer learning methods in enhancing cross-domain sleep staging performance, and SleepMG demonstrates superior performance by balancing modalities in classification and domain discrimination. On the MASS-SS3 dataset, the second-best method is the modal balancing method (OGM-GE), and SleepMG further improves by approximately 1.0% compared to it, highlighting the importance of modality balancing and the greater role of SleepMG in balancing the two performances of modalities.

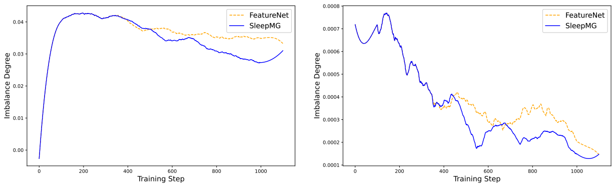
5.5 Imbalance Degrees Visualization Results

As illustrated in Figure 4, to further validate our progress in achieving modality balance, we visualized the changes of modal imbalance degree during training on the ISRUC-S3 dataset. The modal

Table 1: The performance comparison of state-of-the-art methods and SleepMG on two public datasets. The bold and underline items denote the best and second-best results, respectively.

Dataset	Method	Overall results			F1 for each category				
		Accuracy	Macro F1	Kappa	Wake	N1	N2	N3	REM
ISRUC-S3	FeatureNet [18]	0.7513	0.7275	0.6803	0.8456	0.4841	0.7409	0.8531	0.7136
	DeepSleepNet [48]	0.7456	0.7393	0.6758	0.8782	0.5306	0.7040	0.8277	0.7560
	MaskSleepNet [64]	0.6571	0.6297	0.5637	0.6516	0.4751	0.6903	0.8390	0.4925
	AttnSleep [10]	0.7611	0.7404	0.6932	0.8537	0.5041	0.7558	0.8649	0.7234
	DAN[50]	0.7687	0.7442	0.7008	0.8461	0.4484	**0.7711**	**0.8752**	0.7802
	SleepPrintNet [17]	0.7591	0.7435	0.6889	0.8305	0.5162	0.7565	0.8530	0.7614
	MMASleepNet [60]	0.7552	0.6847	0.6831	0.8588	0.2041	0.7573	0.8590	0.7442
	OGM-GE [35]	0.7610	0.7472	0.6947	0.8709	0.5415	0.7207	0.8386	0.7644
	SleepMG	**0.7868**	**0.7745**	**0.7264**	**0.8833**	**0.5691**	0.7613	0.8641	**0.7950**
MASS-SS3	FeatureNet [18]	0.8533	0.8019	0.7827	0.8968	0.5120	0.8964	0.8395	0.8649
	DeepSleepNet [48]	0.8531	0.7984	0.7807	0.8853	0.5083	0.9017	0.8380	0.8585
	MaskSleepNet [64]	0.8296	0.7679	0.7490	0.8573	0.4325	0.8818	0.8138	0.8541
	AttnSleep [10]	0.8510	0.7960	0.7796	0.8918	0.4836	0.8940	0.8488	0.8618
	DAN [50]	0.8231	0.7380	0.7326	0.8432	0.3323	0.8806	0.8150	0.8192
	SleepPrintNet [17]	0.8459	0.7871	0.7702	0.8816	0.4674	0.8859	0.8420	0.8584
	MMASleepNet [60]	0.8405	0.7820	0.7598	0.9001	0.5055	0.8822	0.7390	0.8831
	OGM-GE [35]	0.8570	0.8033	0.7881	0.8906	0.5131	0.9004	0.8407	0.8715
	SleepMG	**0.8660**	**0.8169**	**0.8015**	**0.9005**	**0.5462**	**0.9037**	**0.8493**	**0.8847**

imbalance degrees of classification and domain discrimination performances are measured with $\sum_{u=1}^{U}(s_t^{a,u} - \frac{1}{U})^2$, the sum of squared mean relative differences [2, 47]. The lower the modal imbalance degree, the more balanced each modality will be. It can be observed that the SleepMG method exhibits lower modal imbalance in both classification and domain discrimination, indicating a better balance. Additionally, we visualized the changes in test accuracy in Figure 5, revealing a significant improvement in cross-domain sleep staging on the test set when the modalities are more balanced.



(a) Classification (u=y) (b) Domain discrimination (u=d)

Figure 4: The change of the modal imbalance degrees of (a) Classification and (b) Domain discrimination during training on the ISRUC-S3 dataset.

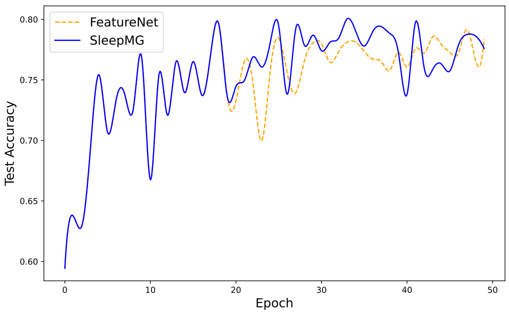


Figure 5: The change of the test accuracy per epoch on the ISRUC-S3 dataset with FeatureNet and SleepMG.

5.6 Ablation Experiment Results

As is shown in Table 2, to further demonstrate the contribution of each module in SleepMG, we compared the effects of multimodal and generalizable modules of NaiveMG (✓✓ in Table 2). We employ FeatureNet [18] as the backbone (×× in Table 2).The multimodal module performs modality-specific feature extraction followed by direct concatenation fusion. The generalizable module enhances model generalization by employing the domain adversarial learning method. The experimental results of sleep staging on two datasets show that the generalization method provides a little improvement, while the multimodal module exhibits a more noticeable effect compared to the generalizable module alone. Furthermore, the combination of multimodal and generalizable modules leads to a significant improvement.

To explore effective feature fusion methods for multimodal sleep staging, we employ FeatureNet to extract single-modal features and fuse them with direct concatenation, self-attention weighting, and modality balancing approaches, respectively. From the experimental results in Table 3, it can be seen that self-attention performed worse than direct concatenation. Conversely, the modality balancing method performed well on both datasets. This suggests self-attention focuses more on well-performing modalities, exacerbating modality imbalances and harming classification. Furthermore, contrary to the attention-based approach, the balancing method assigns greater weight to poorly performing modalities, positively contributing to classification accuracy.

Table 2: Ablation study of M(ultimodal) and G(eneralizable) modules of NaiveMG(✓✓) on two public datasets. The bold and underline items denote the best and second-best results, respectively.

Dataset	M	G	Overall results		
			Accuracy	Macro F1	Kappa
ISRUC-S3	×	×	0.7513	0.7275	0.6803
	×	✓	0.7545	0.7323	0.6844
	✓	×	0.7610	0.7487	0.6927
	✓	**✓**	**0.7711**	**0.7592**	**0.7067**
MASS-SS3	×	×	0.8533	0.8019	0.7827
	×	✓	0.8544	0.8017	0.7841
	✓	×	0.8570	0.8058	0.7869
	✓	**✓**	**0.8571**	**0.8068**	**0.7876**

Table 3: Ablation study of FeatureNet with different multimodal feature fusion methods on two public datasets. The bold and underline items denote the best and second-best results, respectively.

Dataset	Concat Method	Overall results		
		Accuracy	Macro F1	Kappa
ISRUC-S3	Direct-concat	0.7610	0.7487	0.6927
	Self-attention	0.7550	0.7490	0.6885
	Balance	**0.7738**	**0.7587**	**0.7089**
MASS-SS3	Direct-concat	0.8570	0.8058	0.7869
	Self-attention	0.8558	0.8060	0.7858
	Balance	**0.8603**	**0.8121**	**0.7936**

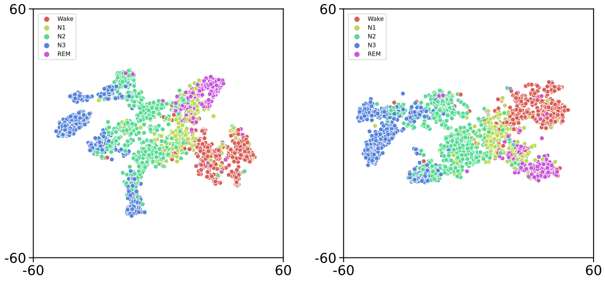
Table 4: Ablation study of NaiveMG(× × ×) with balancing different components on public datasets. The bold and underline items denote the best and second-best results, respectively.

Dataset	G_f^u	G_y^u	G_d^u	Overall results		
				Accuracy	Macro F1	Kappa
ISRUC-S3	×	×	×	0.7711	0.7592	0.7067
	✓	×	×	0.7680	0.7590	0.7034
	×	✓	×	0.7793	0.7647	0.7168
	×	×	✓	0.7728	0.7600	0.7085
	×	**✓**	**✓**	**0.7868**	**0.7745**	**0.7264**
MASS-SS3	×	×	×	0.8571	0.8068	0.7876
	✓	×	×	0.8582	0.8071	0.7890
	×	✓	×	0.8620	0.8117	0.7951
	×	×	✓	0.8634	0.8126	0.7975
	×	**✓**	**✓**	**0.8660**	**0.8169**	**0.8015**

As shown in Table 4, we compared the effects of balancing different components of NaiveMG (××× in Table 4). The results indicate that balancing the modality-specific feature extractor has minimal or no effect, while the fine-grained inter-modal balance of the modality-specific parts of classifier G_y and domain discriminator G_d has positive effects. In multimodal feature learning, focusing solely on achieving modality balance may significantly weaken the model's ability to extract modality-related information. In domain adversarial learning, classification capability and domain discrimination capability are often seen as opposing objectives. However, both imbalances across modalities can negatively affect the performance of the model. For example, if there is a significant difference in domain discrimination capability between different modalities, the model may learn irrelevant information about the participants that is modality-dependent or modality-specific, which can limit the capability of the model to generalize across domains. This intermodal imbalance can be detrimental to performance. In summary, these two inter-modal imbalances can negatively affect model performance. The fine-grained inter-modal balance of the classification and domain discrimination capabilities is crucial to mitigate these negative effects and improve overall performance in sleep staging.

5.7 Feature Visualization Analysis

For more interpretable analysis, we exploit the t-SNE [55] to visualize the feature embeddings of Feature and SleepMG methods. As shown in Figure 6, SleepMG exhibits more distinct classification boundaries than the FeatureNet method. For example, in SleepMG, the cluster representing the deep sleep stage N3 is fewer in number and more tightly grouped, while the cluster representing the N2 stage (indicated by green) clearly separates the blue N3 stage from other stages. The light sleep stage N1, which is the most challenging to differentiate, exhibits a tightly grouped yellow cluster in SleepMG, displaying clearer boundaries.



(a) FeatureNet

(b) SleepMG

Figure 6: The visualization of the t-SNE embeddings on the ISRUC-S3 dataset with (a) FeatureNet and (b) SleepMG.

6 CONCLUSION

This paper introduces SleepMG, a novel Multimodal Generalizable Sleep Staging method. Besides the naive integration of multimodal feature learning models and domain generalization methods, SleepMG quantitatively assesses and adaptively balances the classification and domain discrimination capabilities of multiple modalities, addressing the issues of inter-modal imbalances. Experimental results demonstrate that SleepMG outperforms state-of-the-art performance in cross-domain sleep staging and achieves inter-modal balances.

REFERENCES

[1] Nannapas Banluesombatkul et al. 2020. Metasleeplearner: a pilot study on fast adaptation of bio-signals-based sleep stage classifier to new individual subject using meta-learning. *IEEE Journal of Biomedical and Health Informatics*, 25, 6, 1949–1963.

[2] Brinnae Bent, Benjamin A Goldstein, Warren A Kibbe, and Jessilyn P Dunn. 2020. Investigating sources of inaccuracy in wearable optical heart rate sensors. *NPJ digital medicine*, 3, 1, 18.

[3] Richard B Berry, Rita Brooks, Charlene E Gamaldo, Susan M Harding, C Marcus, Bradley V Vaughn, et al. 2012. The aasm manual for the scoring of sleep and associated events. *Rules, Terminology and Technical Specifications, Darien, Illinois, American Academy of Sleep Medicine*, 176, 2012.

[4] Richard B Berry et al. 2012. Rules for scoring respiratory events in sleep: update of the 2007 aasm manual for the scoring of sleep and associated events: deliberations of the sleep apnea definitions task force of the american academy of sleep medicine. *Journal of clinical sleep medicine*, 8, 5, 597–619.

[5] Reza Boostani, Foroozan Karimzadeh, and Mohammad Nami. 2017. A comparative review on sleep stage classification methods in patients and healthy individuals. *Computer methods and programs in biomedicine*, 140, 77–91.

[6] Paula Branco, Luís Torgo, and Rita P Ribeiro. 2016. A survey of predictive modeling on imbalanced domains. *ACM computing surveys (CSUR)*, 49, 2, 1–50.

[7] Erik Bresch, Ulf Großekathöfer, and Gary Garcia-Molina. 2018. Recurrent deep neural networks for real-time sleep stage classification from single channel eeg. *Frontiers in computational neuroscience*, 12, 1–12.

[8] Lei Cao, Wenrong Wang, Yilin Dong, and Chunjiang Fan. 2024. Advancing classroom fatigue recognition: a multimodal fusion approach using self-attention mechanism. *Biomedical Signal Processing and Control (BSPC)*, 89, 105756.

[9] Xiangwen Deng, Junlin Zhu, and Shangming Yang. 2021. Sfe-net: eeg-based emotion recognition with symmetrical spatial feature extraction. In *Proceedings of the 29th ACM international conference on multimedia (ACM MM)*, 2391–2400.

[10] Emadeldeen Eldele, Zhenghua Chen, Chengyu Liu, Min Wu, Chee-Keong Kwoh, Xiaoli Li, and Cuntai Guan. 2021. An attention-based deep learning approach for sleep stage classification with single-channel eeg. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 29, 809–818.

[11] Yunfeng Fan, Wenchao Xu, Haozhao Wang, Junxiao Wang, and Song Guo. 2023. Pmr: prototypical modal rebalance for multimodal learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 20029–20038.

[12] Oliver Faust, Hajar Razaghi, Ragab Barika, Edward J Ciaccio, and U Rajendra Acharya. 2019. A review of automated sleep stage scoring based on physiological signals for the new millennia. *Computer methods and programs in biomedicine*, 176, 81–91.

[13] Luigi Fiorillo, Paolo Favaro, and Francesca Dalia Faraci. 2021. Deepsleepnet-lite: a simplified automatic sleep stage scoring model with uncertainty estimates. *IEEE transactions on neural systems and rehabilitation engineering*, 29, 2076–2085.

[14] Peiliang Gong, Ziyu Jia, Pengpai Wang, Yueying Zhou, and Daoqiang Zhang. 2023. Astdf-net: attention-based spatial-temporal dual-stream fusion network for eeg-based emotion recognition. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 883–892.

[15] Narjes Goshtasbi, Reza Boostani, and Saeid Sanei. 2022. Sleepfcn: a fully convolutional deep learning framework for sleep stage classification using single-channel electroencephalograms. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, 2088–2096.

[16] Xiaopeng Ji, Yan Li, and Peng Wen. 2022. Jumping knowledge based spatial-temporal graph convolutional networks for automatic sleep stage classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, 1464–1472.

[17] Ziyu Jia, Xiyang Cai, Gaoxing Zheng, Jing Wang, and Youfang Lin. 2020. Sleepprintnet: a multivariate multimodal neural network based on physiological time-series for automatic sleep staging. *IEEE Transactions on Artificial Intelligence*, 1, 3, 248–257.

[18] Ziyu Jia, Youfang Lin, Jing Wang, Xiaojun Ning, Yuanlai He, Ronghao Zhou, Yuhan Zhou, and H Lehman Li-wei. 2021. Multi-view spatial-temporal graph convolutional networks with domain generalization for sleep stage classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 29, 1977–1986.

[19] Ziyu Jia, Youfang Lin, Jing Wang, Xuehui Wang, Peiyi Xie, and Yingbin Zhang. 2021. Salientsleepnet: multimodal salient wave detection network for sleep staging. In *Proc. 29th Int. Joint Conf. Artif. Intell. (IJCAI)*, 2614–2620.

[20] Ziyu Jia, Youfang Lin, Jing Wang, Ronghao Zhou, Xiaojun Ning, Yuanlai He, and Yaoshuai Zhao. 2020. Graphsleepnet: adaptive spatial-temporal graph convolutional networks for sleep stage classification. In *Proc. 29th Int. Joint Conf. Artif. Intell. (IJCAI)*, 1324–1330.

[21] Wei-Bang Jiang, Xuan-Hao Liu, Wei-Long Zheng, and Bao-Liang Lu. 2023. Multimodal adaptive emotion transformer with flexible modality inputs on a novel dataset with continuous labels. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 5975–5984.

[22] Ming Jin and Jinpeng Li. 2023. Graph to grid: learning deep representations for multimodal emotion recognition. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 5985–5993.

[23] Sirvan Khalighi, Teresa Sousa, José Moutinho Santos, and Urbano Nunes. 2016. Isruc-sleep: a comprehensive public dataset for sleep researchers. *Computer methods and programs in biomedicine*, 124, 180–192.

[24] Jiachen Kuang, Guanghua Xu, Tangfei Tao, and Qingqiang Wu. 2021. Class-imbalance adversarial transfer learning network for cross-domain fault diagnosis with imbalanced data. *IEEE Transactions on Instrumentation and Measurement*, 71, 1–11.

[25] Shinjae Kwon, Hojoong Kim, and Woon-Hong Yeo. 2021. Recent advances in wearable sensors and portable electronics for sleep monitoring. *Iscience*, 24, 5.

[26] Joonnyong Lee, Hee Chan Kim, Yu Jin Lee, and Saram Lee. 2023. Development of generalizable automatic sleep staging using heart rate and movement based on large databases. *Biomedical Engineering Letters*, 13, 4, 649–658.

[27] Qing Li, Guanyuan Yu, Jun Wang, and Yuehao Liu. 2020. A deep multimodal generative and fusion framework for class-imbalanced multimodal data. *Multimedia Tools and Applications*, 79, 25023–25050.

[28] Yucheng Liu, Ziyu Jia, and Haichao Wang. 2023. Emotionkd: a cross-modal knowledge distillation framework for emotion recognition based on physiological signals. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 6122–6131.

[29] Shuo Ma, Yingwei Zhang, Yiqiang Chen, Tao Xie, Shuchao Song, and Ziyu Jia. 2023. Exploring structure incentive domain adversarial learning for generalizable sleep stage classification. *ACM Transactions on Intelligent Systems and Technology*.

[30] Samaneh Nasiri and Gari D Clifford. 2020. Attentive adversarial network for large-scale sleep staging. In *Machine Learning for Healthcare Conference*. PMLR, 457–478.

[31] Christian O'reilly, Nadia Gosselin, Julie Carrier, and Tore Nielsen. 2014. Montreal archive of sleep studies: an open-access resource for instrument benchmarking and exploratory research. *Journal of sleep research*, 23, 6, 628–635.

[32] Tongjie Pan, Yalan Ye, Hecheng Cai, Shudong Huang, Yang Yang, and Guoqing Wang. 2023. Multimodal physiological signals fusion for online emotion recognition. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 5879–5888.

[33] Or Patashnik, Dov Danon, Hao Zhang, and Daniel Cohen-Or. 2021. Balagan: cross-modal image translation between imbalanced domains. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2659–2667.

[34] Chanakya Reddy Patti, Thomas Penzel, and Dean Cvetkovic. 2018. Sleep spindle detection using multivariate gaussian mixture models. *Journal of sleep research*, 27, 4, e12614.

[35] Xiaokang Peng, Yake Wei, Andong Deng, Dong Wang, and Di Hu. 2022. Balanced multimodal learning via on-the-fly gradient modulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 8238–8247.

[36] Huy Phan, Fernando Andreotti, Navin Cooray, Oliver Y Chén, and Maarten De Vos. 2019. Seqsleepnet: end-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27, 3, 400–410.

[37] Huy Phan, Oliver Y Chén, Philipp Koch, Zongqing Lu, Ian McLoughlin, Alfred Mertins, and Maarten De Vos. 2020. Towards more accurate automatic sleep staging via deep transfer learning. *IEEE Transactions on Biomedical Engineering*, 68, 6, 1787–1798.

[38] Huy Phan, Kaare Mikkelsen, Oliver Y Chén, Philipp Koch, Alfred Mertins, and Maarten De Vos. 2022. Sleeptransformer: automatic sleep staging with interpretability and uncertainty quantification. *IEEE Transactions on Biomedical Engineering*, 69, 8, 2456–2467.

[39] Huy Phan, Kaare Mikkelsen, Oliver Y Chén, Philipp Koch, Alfred Mertins, Preben Kidmose, and Maarten De Vos. 2020. Personalized automatic sleep staging with single-night data: a pilot study with kullback–leibler divergence regularization. *Physiological measurement*, 41, 6, 064004.

[40] Jaeun Phyo, Wonjun Ko, Eunjin Jeon, and Heung-Il Suk. 2022. Transsleep: transitioning-aware attention-based deep neural network for sleep staging. *IEEE Transactions on Cybernetics*.

[41] Samira Pouyanfar, Tianyi Wang, and Shu-Ching Chen. 2019. A multi-label multimodal deep learning framework for imbalanced data classification. In *2019 IEEE conference on multimedia information processing and retrieval (MIPR)*, 199–204.

[42] Wei Qu, Zhiyong Wang, Hong Hong, Zheru Chi, David Dagan Feng, Ron Grunstein, and Christopher Gordon. 2020. A residual based attention model for eeg based sleep staging. *IEEE journal of biomedical and health informatics*, 24, 10, 2833–2843.

[43] Matias Rusanen et al. 2023. Generalizable deep learning-based sleep staging approach for ambulatory textile electrode headband recordings. *IEEE Journal of Biomedical and Health Informatics*, 27, 4, 1869–1880.

[44] Akane Sano, Weixuan Chen, Daniel Lopez-Martinez, Sara Taylor, and Rosalind W Picard. 2018. Multimodal ambulatory sleep detection using lstm recurrent neural networks. *IEEE journal of biomedical and health informatics*, 23, 4, 1607–1617.

[45] Hannah Scott, Bastien Lechat, Jack Manners, Nicole Lovato, Andrew Vakulin, Peter Catcheside, Danny J Eckert, and Amy C Reynolds. 2022. Emerging applications of objective sleep assessments towards the improved management of insomnia. *Sleep Medicine*.

[46] Rym Nihel Sekkal, Fethi Bereksi-Reguig, Daniel Ruiz-Fernandez, Nabil Dib, and Samira Sekkal. 2022. Automatic sleep stage classification: from classical machine learning methods to deep learning. *Biomedical Signal Processing and Control (BSPC)*, 77, 103751.

[47] Tessa Strain, Katrien Wijndaele, Leandro Garcia, Melanie Cowan, Regina Guthold, Soren Brage, and Fiona C Bull. 2020. Levels of domain-specific physical activity at work, in the household, for travel and for leisure among 327 789 adults from 104 countries. *British Journal of Sports Medicine*, 54, 24, 1488–1497.

[48] Akara Supratak, Hao Dong, Chao Wu, and Yike Guo. 2017. Deepsleepnet: a model for automatic sleep stage scoring based on raw single-channel eeg. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25, 11, 1998–2008.

[49] Akara Supratak and Yike Guo. 2020. Tinysleepnet: an efficient deep learning model for sleep stage scoring based on raw single-channel eeg. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 641–644.

[50] Minfang Tang et al. 2022. Deep adaptation network for subject-specific sleep stage classification based on a single-lead ecg. *Biomedical Signal Processing and Control (BSPC)*, 75, 1–13.

[51] Alexandra-Maria Tăutan, Alessandro C Rossi, Ruben De Francisco, and Bogdan Ionescu. 2020. Automatic sleep stage detection: a study on the influence of various psg input signals. In *2020 42nd annual international conference of the ieee engineering in medicine & biology society (EMBC)*. IEEE, 5330–5334.

[52] Carlos Torres, Jeffrey C Fried, Kenneth Rose, and Bangalore S Manjunath. 2018. A multiview multimodal system for monitoring patient sleep. *IEEE Transactions on Multimedia*, 20, 11, 3057–3068.

[53] Orestis Tsinalis, Paul M Matthews, and Yike Guo. 2016. Automatic sleep stage scoring using time-frequency analysis and stacked sparse autoencoders. *Annals of biomedical engineering*, 44, 5, 1587–1597.

[54] Enmei Tu, Nikola Kasabov, and Jie Yang. 2016. Mapping temporal variables into the neucube for improved pattern recognition, predictive modeling, and understanding of stream data. *IEEE transactions on neural networks and learning systems*, 28, 6, 1305–1317.

[55] Laurens Van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-sne. *Journal of machine learning research*, 9, 11.

[56] Hai Wang, Hongbo Guo, Kan Zhang, Ling Gao, and Jie Zheng. 2022. Automatic sleep staging method of eeg signal based on transfer learning and fusion network. *Neurocomputing*, 488, 183–193.

[57] Jindong Wang, Cuiling Lan, Chang Liu, Yidong Ouyang, Tao Qin, Wang Lu, Yiqiang Chen, Wenjun Zeng, and Philip Yu. 2022. Generalizing to unseen domains: a survey on domain generalization. *IEEE Transactions on Knowledge and Data Engineering*, 14, 8, 1–20.

[58] Tian-Yu Xiang et al. 2023. Learning shared semantic information from multimodal bio-signals for brain-muscle modulation analysis. In *Proceedings of the 31st ACM International Conference on Multimedia (ACM MM)*, 6016–6024.

[59] Yuzhe Yang, Hao Wang, and Dina Katabi. 2022. On multi-domain long-tailed recognition, imbalanced domain generalization and beyond. In *European Conference on Computer Vision (ECCV)*. Springer, 57–75.

[60] Zheng Yubo, Luo Yingying, Zou Bing, Zhang Lin, and Li Lei. 2022. Mmasleepnet: a multimodal attention network based on electrophysiological signals for automatic sleep staging. *Frontiers in Neuroscience*, 16, 973761.

[61] Bing Zhai, Yu Guan, Michael Catt, and Thomas Plötz. 2021. Ubi-sleepnet: advanced multimodal fusion techniques for three-stage sleep classification using ubiquitous sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5, 4, 1–33.

[62] Linda Zhang, Daniel Fabbri, Raghu Upender, and David Kent. 2019. Automated sleep stage scoring of the sleep heart health study using deep neural networks. *Sleep*, 42, 11, zsz159.

[63] Caihong Zhao, Jinbao Li, and Yahong Guo. 2022. Sleepcontextnet: a temporal context network for automatic sleep staging based single-channel eeg. *Computer Methods and Programs in Biomedicine*, 220, 1–12.

[64] Hangyu Zhu, Wei Zhou, Cong Fu, Yonglin Wu, Ning Shen, Feng Shu, Huan Yu, Chen Chen, and Wei Chen. 2023. Masksleepnet: a cross-modality adaptation neural network for heterogeneous signals processing in sleep staging. *IEEE Journal of Biomedical and Health Informatics*, 27, 2353–2364.

[65] Tianqi Zhu, Wei Luo, and Feng Yu. 2020. Convolution-and attention-based neural network for automated sleep stage classification. *International Journal of Environmental Research and Public Health*, 17, 11, 4152.