LightSleepNet: Design of a Personalized Portable Sleep Staging System Based on Single-Channel EEG

Yiqiao Liao[†], Chao Zhang^{*}, Milin Zhang^{*}, Zhihua Wang[†], Xiang Xie[†]

Abstract—This paper proposed LightSleepNet - a light-weight, 1-d Convolutional Neural Network (CNN) based personalized architecture for real-time sleep staging, which can be implemented on various mobile platforms with limited hardware resources. The proposed architecture only requires an input of 30s singlechannel EEG signal for the classification. Two residual blocks consisting of group 1-d convolution are used instead of the traditional convolution layers to remove the redundancy in the CNN. Channel shuffles are inserted into each convolution layer to improve the accuracy. In order to avoid over-fitting to the training set, a Global Average Pooling (GAP) layer is used to replace the fully connected layer, which further reduces the total number of the model parameters significantly. A personalized algorithm combining Adaptive Batch Normalization (AdaBN) and gradient re-weighting is proposed for unsupervised domain adaptation. A higher priority is given to examples that are easy to transfer to the new subject, and the algorithm could be personalized for new subjects without re-training. Experimental results show a state-of-the-art overall accuracy of 83.8% with only 45.76 Million Floating-point Operations per Second (MFLOPs) computation and 43.08 K parameters.

Index Terms—Sleep staging, Light-weight architecture, Channel shuffle, CNN, Personalized healthy equipment

I. INTRODUCTION

Sleep is important for humans to keep the nervous system functioning well. Unfortunately, more than 20 percent of the adult population are suffering from various sleep disorders [1]. Sleep staging can be applied for the diagnosis and treatment of sleep disorders [2]. Polysomnography (PSG) based sleep staging is widely used in clinical practice. It is the golden standard as experts label the sleep stages according to the recorded Electroencephalography (EEG), Electrooculography (EOG), Electromyography (EMG) and Electrocardiogram (ECG). However, it is difficult to apply at home due to the complex operation process of sleep staging. In addition, the requirement for real-time sleep staging is emerging while exploring effective methods to improve the sleep quality, such as sounds, lights and electrical stimulation [3]. As a result of the development of the wearable personal health monitoring

Chao Zhang and Milin Zhang are with the Department of Electronic Engineering, Tsinghua University, Beijing, China, 100084. Corresponding author e-mail: zhangmilin@tsinghua.edu.cn

This work is supported in part by the National Key Research and Development Program of China (No.2018YFB220200*), in part by the Beijing Innovation Center for Future Chip, in part by the Beijing National Research Center for Information Science and Technology.

Digital Object Identifier

devices in recent years, a long-term, real-time, high-precision sleep staging algorithm is required for implementation in various portable devices [4].

Hardware-friendly algorithms with low computational complexity have been explored to fit sleep staging process in wearable devices. Traditional machine learning based methods [5–7], such as decision tree [6] or support vector machine [7] based classifiers, can be implemented in wearable or mobile devices, but suffer from low accuracy, usually lower than 80% [6]. Deep learning based algorithms have been widely applied to improve the performance of biomedical signals (e.g. EEG) processing in recent years [8, 9]. A considerable amount of literature [10–18] has been published on automatic sleep staging based on deep learning. The SeqSleepNet [11] achieved an accuracy of near 90%. However, it suffers from a difficult compromise between observation latency and computational complexity, since it requires ten raw EEG epochs together as the input. Time-Distributed Deep CNN has been applied to fit the requirement of real-time processing [17], showing a promising result but the computational complexity is high.

The individual differences raise another challenge for automatic sleep staging system. Features extracted from the EEG signals distribute differently between the training set and test set, which makes the algorithms mentioned above unreliable for new subjects. Traditional solutions require fine-tuning using labeled data from the target subject for personalization [19]. However, professional knowledge is required for raw data labeling, which is unavailable at home. [12] proposed to solve this problem with adversarial training, but there was sleep information lost in the training process, which resulted in a low accuracy. [20] proposed to apply weighted kernel logistic regression for handcrafted feature extraction. However, a retraining of the network is required for most domain adaptation methods, which is both hardware hungry and power hungry.

This paper proposes a light-weight personalized sleep staging algorithm, which is denoted as LightSleepNet. The proposed architecture is suitable for implementation on various mobile platforms for real-time processing. To reduce the negative influence of individual differences, unlabeled data can be used to personalize for new subject without re-training. A 1-d CNN is designed for the feature extraction from 30s singlechannel EEG epochs. In order to remove the redundancy in the CNN, residual blocks consisting of group 1-d convolution bring a dramatic reduction on the complexity of the network. Channel shuffles are inserted into each convolution layer to improve the accuracy. In order to avoid over-fitting to the

Yiqiao Liao, Zhihua Wang and Xiang Xie are with the Institute of Microelectronics, Tsinghua University, Beijing, China, 100084.

training set, a Global Average Pooling (GAP) layer is used to replace the fully connected layer, which further reduces the total number of the model parameters by 12 times.

In order to further improve the algorithm robustness to individual differences without a significant increase of the complexity, a personalized unsupervised domain adaptation algorithm is proposed. Inspired by [21], the gradient contribution of different samples could be re-weighted to improve the generalization. In our proposed work, a higher priority will be given to those examples that are easier to transfer to new subjects based on the gradient re-weighting in training. The proposed Adaptive Batch Normalization (AdaBN) [22] based method is designed for subject-specific adaptation, which normalizes the intermediate output of CNN from training set and the data from the new subject to a similar distribution.

The rest of the paper is organized as follows. Section II introduces the proposed light-weight architecture and details of the proposed low complexity solution to improve the algorithm robustness to individual differences. Section III illustrates the experimental results, while Section IV concludes the work.

II. ARCHITECTURE OF THE PROPOSED LIGHTSLEEPNET

A. The Process of the LightSleepNet

Fig.1A illustrates the proposed LightSleepNet. It consists of five 1-d convolutional layers (as illustrated in the orange blocks) and one GAP layer to lower the dimension of the feature map as well as to reduce the workload for classification.

The input is a 30s single-channel EEG epoch, which is denoted as X_i . The 1-d CNN is built with residual blocks consisting of 1-d group convolution. As illustrated in Fig.1B, there are three steps in each 1-d convolutional layer:

1) 1-D group convolution with its filters:

As the step 1 of Fig.1B shows, the j-th channel output feature for the i-th sample can be calculated as follow:

$$out_n(i,j) = bias_n(j) + \sum_u weight_n(j,u) * in_n(i,u)$$
(1)

where $j = [1, ..., C_{out}]$. * is the convolution operation and u is the corresponding index of input channel belonging to the same group with the j-th output channel. n = [1, 2, ..., 5] is the index of this convolution layer.

2) adaptive batch normalization:

BN layers transform the features x_j into y_j as

$$y_{j} = \gamma_{j} \frac{x_{j} - E(X_{j})}{\sqrt{Var(X_{j})}} + \beta_{j}$$
⁽²⁾

where x_j and y_j are the input and output scalars of the BN, respectively, with j = [1, ..., U]. U is the feature dimension. $X_j \in \Re^N$ is the j-th column of the input feature. N is the size of a batch, chosen as 40 in this paper. γ_j and β_j are the training parameters.

3) rectified linear unit (ReLU) activations: relu(x)=max(0,x)

A channel shuffle is inserted after each 1-d convolutional layer to improve the information independence introduced by group convolution. The channel dimension of the output from group convolution is reshaped into $(g, \frac{C_{in}}{q})$. It is then

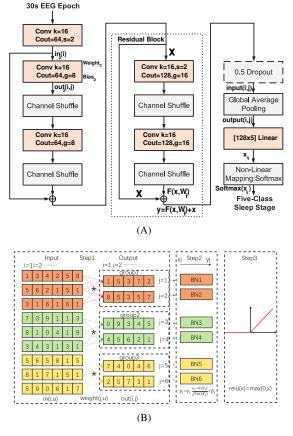


Fig. 1. (A) The overall architecture of LightSleepNet. C_{out} and C_{in} are the numbers of feature channels in output and input respectively. k is the kernel size of convolution. g is the number of group for convolution. s is the stride with a default value of 1. (B) Three steps in 1-d convolutional layer (the orange blocks in (A)). The vectors in step 1 example the input and output of the 1-d group convolution.

transposed to $(\frac{C_{in}}{g}, g)$, before flattened as the input of next layer. In order to assist the network training with multi-scale information, residual connection is inserted between every two convolution layers to form a residual block. The input x is mapped by the residual block through the function $\mathscr{F}(*)$ as

$$y = \mathscr{F}(x, W_i) + x \tag{3}$$

where W_i are the parameters of the residual block.

A Dropout layer is applied after the residual blocks for regularization with a 50% probability randomly setting some of the input tensor as zero. A GAP layer is inserted after the Dropout layer. A smaller fully connected layer with a dimension of 128×5 is applied to the output of the GAP layer. A Softmax layer is applied to the output of the fully connected layer for classification. There are five optional outputs, Wake, N1, N2, N3 and REM, according to the sleep staging definition by the American Academy of Sleep Medicine (AASM).

B. Training Process Design

The traditional cross entropy loss imposes equal importance for different samples, whereas every sample does not contribute the same for the generalization. There are samples hard to learn, which is usually a noise in the EEG signal and has lesser contribution to the generalization with uncertain predictions (i.e. large gradients). Those samples may deteriorate the training process. There are also samples easy to learn, which is easy to transfer to new subject with confident predictions (i.e. small gradients), contributing more to the generalization. We quantify the difficulty of samples by the norm of gradient and suppress those gradients from noise samples with lower weight, while giving high priority to those gradients from easyto-transfer samples. Fig.2A illustrates the gradient distribution for sleep staging. Gradient density is used to represent the number of samples within a specific gradient range. It is noted that there is a high gradient density in easy-to-transfer samples and low density in noise samples. We could give high priority to those samples with high gradient density. We propose to replace the CrossEntropy loss in our model with a modified version to apply the re-weighting:

$$L_{weighted} = \frac{1}{N} \sum_{i=1}^{N} \beta_i L_{CE}^i \tag{4}$$

where L_{CE}^{i} is the Cross-Entropy loss for the i-th sample. N is the number of samples in one batch. β_i is the weight of gradient for the i-th sample.

$$\beta_i = \frac{GD(g_i)}{N} \tag{5}$$

where g_i is the gradient of the i-th sample and $GD(g_i)$ is the gradient density of gradient g_i .

After the re-weighting, the gradient distribution is illustrated in Fig.2B, in which those samples easy-to-transfer initially focused on low gradient move right whereas those noise samples move left, which increases the number of samples with moderate gradient in the center region of the distribution. As the gradients are amplified for almost sixty times, a learning rate scheduler is applied for the adaptive learning rate adjustment.

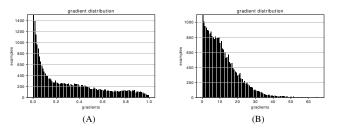


Fig. 2. (A) Gradient Distributed Before Weighting (B) Gradient Distributed After Weighting.

C. The AdaBN based Personalized Adaptation

In order to improve the personalized adaptation, domain adaptation with unlabeled data from the new subject was applied. In the proposed work, AdaBN was used for subjectspecific adaptation. AdaBN normalized features from training set and from the new subject to a similar distribution with zero bias and one variance without additional training cost. The AdaBN is applied after every convolution layer.

The implementation of BN improves the similarity of the input distribution of each layer. The efficiency and robustness 3

of the training process are improved as well. However, the data distribution and statistic values are different between the training and the test set when there is a significant domain shift. The normalization process is unable to normalize these two datasets into a similar distribution since the statistic values in the target domain are not used. Compared to BN, it is better to use AdaBN when there are different statistic values between training stage and test stage, since the data distribution of the target domain is taken into consideration by the AdaBN. With unlabeled data from a new subject, the batch statistic values are calculated offline or online based on forward propagation. With those statistic values, the feature distribution in new subjects would also be normalized to a similar distribution with zero bias and one variance. Each layer receives a similar input distribution for both data originated from the training set and a new subject. As a result, the domain shift between different subjects is alleviated with personalized adaptation. The process of training and testing with personalized adaptation is described in Algorithm 1.

Algorithm 1 The process of training and testing with personalized adaptation.

- **Input:** The set of input EEG epochs of source domain, X_n^s ; The corresponding sleep stages labels of source domain, Y_n^s ; The set of unlabeled EEG epochs of target domain, X_n^t ;
- **Output:** The corresponding sleep stages labels of target domain, Y_n^t ; 1: Training:
- 2: for epoch < 100 do
- Forward Propagation to get prediction \hat{Y}_n^s for the EEG input 3: X_n^s from source domain;
- 4:
- Calculating the CrossEntropy Loss with function $L_{CE} = -\frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{5} Y_{ji}^{s} log(\hat{Y}_{ji}^{s});$ Calculating the reweighting loss with weights corresponding to samples $L_{weighted} = \sum_{i=1}^{N} \frac{GD(g_i)}{N^2} L_{CE}^{i};$ 5:
- 6: Backward Propagation to update the model;

- 8: Testing:
- 9: for all neuron j in DNN do
- Calculating neuron responses x_j on all EEG signals X_n^t of 10: target domain;
- Update the mean and variance of the target domain for that 11: neuron using online algorithm: $\mu_j^t = E(x_j^t), \sigma_j^t = \sqrt{Var(x_j^t)}$
- 12: end for
- for all neuron j in DNN do 13:
- Calculating BN output on all EEG signals X_n^t of target domain for neuron j: $y_j = \gamma_j \frac{x_j E(X_j)}{\sqrt{Var(X_j)}} + \beta_j$ 14:
- 15: end for
- 16: Forward Propagation to get prediction Y_n^t for the EEG input X_n^t
 - from target domain using the BN output calculating above;
- 17: return Y_n^t ;

D. The Computational Complexity of the LightSleepNet

Figure 3 shows that there is a trade-off between the accuracy (ACC) and the complexity of the network. The best performance is achieved with a residual block number of 2.

Table I compares the ACC and computational complexity between different cases. It shows the improvement by applying group convolution, GAP layer, residual blocks and channel

^{7:} end for

shuffles. In the proposed work, the number of parameters of one group convolution layer can be calculated as:

$$\left(k * \frac{C_{in}}{g} * C_{out} + C_{out}\right) \propto \frac{1}{g} \tag{6}$$

As a result, the number of parameters could be reduced by g times, where g is the number of groups. The FLOPs of that layer can be calculated as:

$$\left(k * \frac{C_{in}}{g} * C_{out} + C_{out}\right) * \frac{L_{out}}{s} \propto \frac{1}{g * s} \tag{7}$$

where L_{out} is the length of the output feature. s is the stride size and k is the kernel size. According to eq.(7), the FLOPs could also be reduced by g times. As a result, the group convolution brings a 12 times reduction with a higher accuracy.

For the fully connected layer, the number of parameters and FLOPs can be calculated as:

$$N_{in} * N_{out} + N_{out} \tag{8}$$

where N_{in} and N_{out} are the counts of the input and output features, respectively. An $N_{out} = 5$ is used for the sleep staging in the proposed work. The using of the GAP layer reduced the value of N_{in} from 96256 to 128. As a result, a number of 480k parameters reduction and an improve of 3.24% accuracy improvement are achieved. The introduce of channel shuffle features a 1.25% improvement of the accuracy.

 TABLE I

 Comparison of the ACC and number of parameters between the proposed work under different cases

·			
Methods	Parameters	FLOPs	ACC
LightSleepNet	43.08K	45.76M	77.42%
Group Residual Block*1+GAP	17.93K	26.88M	76.17%
Group Residual Block*2+GAP	43.08K	45.76M	77.42%
Group Residual Block*3+GAP	76.10K	70.80M	77.09%
Group Residual Block*4+GAP	126.41K	89.69M	77.11%
Traditional Residual Block*2+GAP	526.4K	496.45M	75.84%
Group Residual Block*2	523.72K	46.24M	71.14%
Group Block*2+GAP	43.08K	45.76M	74.35%
LightSleepNet Without Shuffle	43.08K	45.76M	76.17%

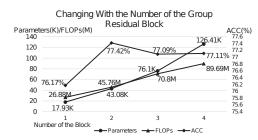


Fig. 3. Performance Changing With The Number Of Block

It is noted that in Fig.3, the accuracy first increases with the model depth and then decreases due to over-fitting. In order to deal with the over-fitting issue, dropout layer, regularization term and unlabeled data are used. In addition, a group convolution and GAP layer based lightweight network is used to control the model complexity. It integrates fewer model parameters and features higher parameter efficiency.

III. EXPERIMENTAL RESULTS

The proposed model was evaluated using Sleep-EDF dataset [23], which contains 20 healthy patients with overnight 100Hzsampled EEG records and corresponding sleep patterns based on AASM. Only the Fpz-Cz channel was used for training and testing. The single-channel Fpz-Cz with 20 fold crossvalidation was used for evaluation, where both nights from each subject were used. In the test stage, there will be no subjects who have already appeared in the training set.

There are 43.08K parameters in the proposed model. The proposed light-weight model prevents the algorithm from over-fitting. In addition, the model can be stored in on-chip SRAM, which greatly reduces the power consumption in reading/writing the memory. The calculation complexity is 45.76 MFLOPs. The proposed work is implemented on the snapdragon 810 platform. It features a less than 1% occupation of the CPU resources.

Table II illustrates the comparison between the proposed LightSleepNet and highly-efficient convolution blocks in computer vision in the terms of accuracy, the number of parameters, and the computational complexity. The block proposed in IGCV1 [24], super separable convolution [25] and Time-Distributed Deep CNN [17] was re-implemented for comparison purposes. The experimental results show that the proposed work achieves the best in accuracy with a good trade-off in the number of parameters. As the first and fourth rows in Table II show, the proposed personalized adaptation methodology contributes a 1.44% improvement for the task without additional parameter and computation cost in inference. [10] proposed a classical deep CNN architecture in sleep staging. However, the accuracy performance is worse than most of the light-weight architectures listed in Table II due to the over-fitting with the Sleep-EDF dataset.

The proposed work is also compared with state-of-the-art designs in Table III. [5] features a higher accuracy than the proposed work, but it belongs to the non-independent dataset splitting, in which, data of all subjects has been occurred in the training set, which is equivalent to remove the influence of individual differences and it is not suitable for new subjects who have never seen before. [13] achieves the best performance in single-channel sleep staging. However, it is power hungry while the computational complexity of the proposed work is much lower, which makes the proposed work a better solution for wearable devices. Furthermore, the proposed scheme could be easily applied to EEG signal processing tasks where there is no sufficient data for pre-training.

IV. CONCLUSION

This paper proposed LightSleepNet - a single-channel EEG based, high accuracy personalized sleep staging architecture with high parameter efficiency and low computational complexity. The proposed framework can be implemented on various mobile platforms with limited hardware resources. It achieves a state-of-the-art overall accuracy of 83.8% with only 45.76 MFLOPs computation and 43.08 K parameters. The latency of the proposed framework is less than 30s for sleep staging with an input of one 30s single-channel EEG

	TABLE II	
COMPARISON OF THE ACC ,NUMBER	OF PARAMETERS AND	OMPUTATION COMPLEXITY

Methods	Parameters	FLOPs	ACC Test D		W		N1		N2		N3		REM	
wethous	1 arameters	TLOIS	ACC	Test Data	TP	FN	TP	FN	TP	FN	TP	FN	TP	FN
The proposed Method	43.08K	45.76M	78.86%	11012	1938	316	198	488	3495	821	1755	175	1278	549
LightSleepNet+AdaBN	43.08K	45.76M	78.05%	11012	1915	339	185	501	3495	821	1755	174	1242	585
LightSleepNet+Gradient Weighting	43.08K	45.76M	77.59%	11012	1915	339	205	481	3539	777	1639	290	1260	567
LightSleepNet	43.08K	45.76M	77.42%	11012	1848	406	164	522	3539	777	1716	213	1242	585
DeepCNN[10]	614.02K	22.07M	73.36%	11012	1645	609	89	597	3150	1166	1736	193	1443	384
IGCV1 big[24]	234.95K	208.02M	75.70%	11012	2028	226	178	508	3237	1079	1736	193	1151	676
IGCV1 small	40.13K	34.98M	74.42%	11012	1848	406	240	446	3150	1166	1678	251	1260	567
Super Separable Convolution[25]	8.26K	8.66M	74.90%	11012	1983	271	150	536	3323	993	1504	425	1278	549
Time-Distributed Deep CNN[17]	226.53K	654.72M	73.27%	11012	1938	316	253	433	2891	1425	1736	193	1268	559

 TABLE III

 COMPARISON WITH THE STATE OF THE ART USING EEG FPZ-CZ CHANNEL

Methods	Dataset	Test Data	Overall Metrics			Per-class F1-Score				
			ACC	MF1	kappa	W	N1	N2	N3	REM
Proposed Method	Sleep-EDF	42308	83.8	75.3	0.78	90	31	88	89	78
LightSleepNet Without Personalized Adaptation	Sleep-EDF	42308	83.3	75.3	0.77	90	33	88	89	76
IEEE TNSRE17[10]	Sleep-EDF	41950	82.0	76.9	0.76	85	47	86	85	82
ISCAS20[12]	Sleep-EDF	41950	82.9	75.6	0.77 -	90	24	87	95	82
Arxiv19 [13]	Sleep-EDF	41950	85.2	79.6	0.79	-	-	-	-	-
NCA17 [5]	Sleep-EDF	15136	91.3	77.0	0.86	98	30	89	86	83
IEEE TNSRE18[14]	Sleep-EDF	37022	81.44	72.2	-	81	40	85	76	79
EMBC18[15]	Sleep-EDF	37022	82.6	74.2	0.76	90	33	87	86	75
IEEE TBE 18[16]	Sleep-EDF	37022	81.9	73.8	0.74	76	32	87	87	91
BSN 19[17]	Sleep-EDF	41950	83.5	-	-	89	44	85	86	77

 TABLE IV

 Per-class Metrics For the LightSleepNet

Class	TP	FN	Sensitivity	Specificity
W	7456	829	0.90	0.98
N1	644	2160	0.23	0.98
N2	15663	2136	0.88	0.91
N3	5075	628	0.89	0.98
REM	6559	1158	0.85	0.93

epoch. The proposed framework could be personalized for new subject using unlabeled data without re-training, in which the accuracy of LightSleepNet is improved without additional training and computation cost.

REFERENCES

- [1] Pasic et al., "Incidence and types of sleep disorders in patients with stroke," *Medical Archives*, vol. 65, no. 4, p. 225, 2011.
- [2] Pachori et al., "Biomedical engineering fundamentals," Intelligent Internet of Things, pp. 547–605, 2020.
- [3] Leminen et al., "Enhanced memory consolidation via automatic sound stimulation during non-rem sleep," *Sleep*, 2017.
- [4] Younes et al., "Performance of a new portable wireless sleep monitor," *Journal of clinical sleep medicine*, 2017.
- [5] Sharma et al., "Automatic sleep stages classification based on iterative filtering of electroencephalogram signals," *Neural Computing and Applications*, vol. 28, no. 10, 2017.
- [6] Imtiaz et al., "An ultralow power system on chip for automatic sleep staging," *IEEE JSSC*, vol. 52, no. 3, pp. 822–833, 2017.
- [7] Bajaj et al., "Automatic classification of sleep stages based on the time-frequency image of eeg signals," *Computer methods and programs in biomedicine*, vol. 112, no. 3, 2013.
- [8] Srirangan et al., "Time-frequency domain deep convolutional neural network for the classification of focal and non-focal eeg signals," *IEEE Sensors Journal*, 2019.

- [9] Sisodia et al., "Handbook of research on advancements of artificial intelligence in healthcare engineering," 2020.
- [10] Supratak et al., "Deepsleepnet: a model for automatic sleep stage scoring based on raw single-channel eeg," *IEEE TNSRE*, vol. 25, no. 11, pp. 1998–2008, 2017.
- [11] Phan et al., "SeqSleepNet: end-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging," *IEEE TNSRE*, vol. 27, no. 3, pp. 400–410, 2019.
- [12] Yiqiao et al., "Tri-featurenet:an adversarial learning-based invariant feature extraction for sleep staging using single-channel eeg," *ISCAS*, 2020.
- [13] Phan et al., "Towards more accurate automatic sleep staging via deep transfer learning," *arXiv*, 2019.
- [14] Chambon et al., "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series," *IEEE TNSRE*, 2018.
- [15] Phan et al., "Dnn filter bank improves 1-max pooling cnn for single-channel eeg automatic sleep stage classification," *EMBC*, pp. 453–456, 2018.
- [16] Phan et al., "Joint classification and prediction cnn framework for automatic sleep stage classification," arXiv, 2018.
- [17] Koushik et al., "Real-time smartphone-based sleep staging using 1-channel eeg," *BSN*, pp. 1–4, 2019.
 [18] Chang et al., "An ultra-low-power dual-mode automatic sleep
- [18] Chang et al., "An ultra-low-power dual-mode automatic sleep staging processor using neural-network-based decision tree," *IEEE TCAS II*, vol. 66, no. 9, pp. 3504–3516, 2019.
- [19] Attaran et al., "Embedded low-power processor for personalized stress detection," *IEEE TCAS II*, vol. 65, no. 12, 2018.
- [20] Khalighi et al., "Adaptive automatic sleep stage classification under covariate shift," *EMBC*, pp. 2259–2262, 2012.
- [21] Li et al., "Gradient harmonized single-stage detector," AAAI, 2019.
- [22] Li et al., "Adaptive batch normalization for practical domain adaptation," *Pattern Recognition*, vol. 80, pp. 109–117, 2018.
- [23] Kemp et al., "Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the eeg," *IEEE TBE*, vol. 47, no. 9, pp. 1185–1194, 2000.

- [24] Zhang et al., "Interleaved group convolutions," in *ICCV*, pp. 4373–4382, 2017.
 [25] Kaiser et al., "Depthwise separable convolutions for neural machine translation," *arXiv*, 2017.