

# Convolutional Neural Network Based Sleep Stage Classification with Class Imbalance

Authors:

Qi Xu<sup>a,1,\*</sup>, **Dongdong Zhou<sup>b,1</sup>**, Jian Wang<sup>b</sup>, Jiangrong Shen<sup>c</sup>, Lauri Kettunen<sup>d</sup>, Fengyu Cong<sup>a,b,d</sup>

**a School of Artificial Intelligence, Dalian University of Technology**

**b School of Biomedical Engineering, Dalian University of Technology**

**c College of Computer Science and Technology, Zhejiang University**

**d Faculty of Information Technology, University of Jyväskylä**



# Contents

## 1. Introduction

## 2. Materials and methodologies

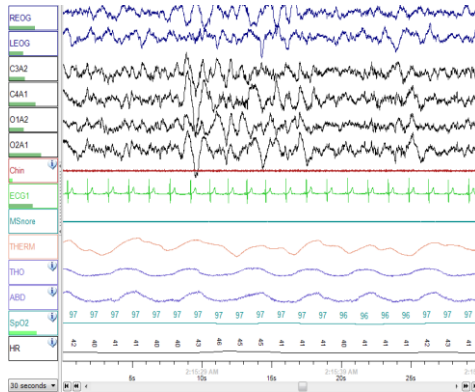
## 3. Experimental results



Figure 1. Sleep  
(<https://wblog.wiki/uk/Sleeping>)

# 1. Introduction

## 1.1 Manual labeling



Polysomnography (PSG)

Visual inspection  
→

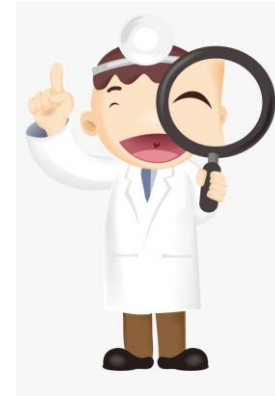


Figure 2. The process of manual labeling of PSG recordings

**Drawbacks: Time-consuming, Subjective error**

# 1. Introduction

## 1.2 Two gold rules

- ❑ R&K manual (Rechtschaffen, 1968): Wake, N-REM (N1, N2, N3, N4), and REM.
- ❑ AASM rule (C. Iber et al., 2007) : Wake, N-REM (N1 ,N2, N3) and REM.

REM: Rapid eye movement; N-REM: Non-REM.

The biggest change in AASM standard is that stages N3 and N4 are merged into N3 with the abolition of stage “movement time”. (C. Iber et al., 2007)

# 1. Introduction

## 1.3 Automatic sleep scoring methods

- ❑ Conventional classifier: SVM, KNN, Random forest, etc.
- ❑ Artificial neural networks: CNN, RNN, Transformer, etc.

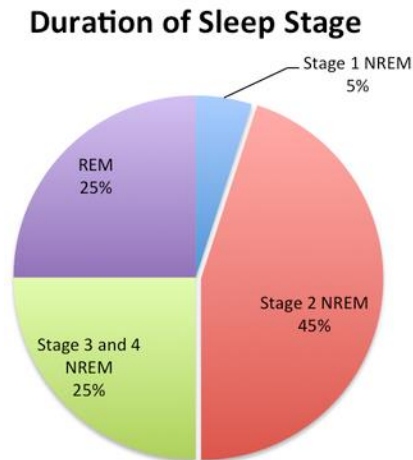


Figure 3. The percentage of each sleep stage in a typical overnight sleep

### **Class imbalance problem (CIP):**

The number of each category is severely unequal. N1 is a representative of minority group.

# 1. Introduction

## 1.4 Main contributions

- ❑ We systematically analyze the class imbalance problem in PSG datasets and propose the class imbalance factor to quantify it.
- ❑ We introduce two balancing methods with the Gaussian white noise, termed signal-driven and image-driven, to balance the dataset samples.
- ❑ We propose a novel CNN-based model, implementing the multi-convolution (MC) block, for learning multi-scale feature presentations from the time-frequency image.

## 2. Materials and methodologies

### 2.1 Experimental datasets

- ❑ Sleep-EDF Database (Sleep-EDF-V1, 2013): 20 subjects (25-34 years), EEG Fpz-Cz
- ❑ Sleep-EDF Database Expanded (Sleep-EDF, 2018): 78 subjects (25-101 years), EEG Fpz-Cz
- ❑ Cleveland Children's Sleep and Health Study (CCSHS): (16-19 years), 515 subjects, EEG C4/A1

Table I. The data distribution of the experimental datasets

Stage	Sleep-EDF-V1	Sleep-EDF	CCSHS
W	10197 (23.1%)	69518(34.9%)	211030 (30.6%)
N1	<b>2804 (6.3%)</b>	21522 (10.8%)	<b>19211 (2.8%)</b>
N2	17799 (40.3%)	69132 (34.7%)	249681 (36.2%)
N3	5703 (13.0%)	<b>13039 (6.6%)</b>	110188 (16.0%)
REM	7717 (17.5%)	25835 (13.0%)	100252 (14.5%)

## 2. Materials and methodologies

### 2.2 Proposed class imbalance factor (*CIF*)

$$CIF = \frac{N}{2 \cdot c \cdot \min\{N_i\}} \quad i \in \{1, 2, \dots, c\} \quad (1)$$

$N$ : total samples.  $c$ : number of stages.  $N_i$ : the number of stage  $i$ .

***CIF***

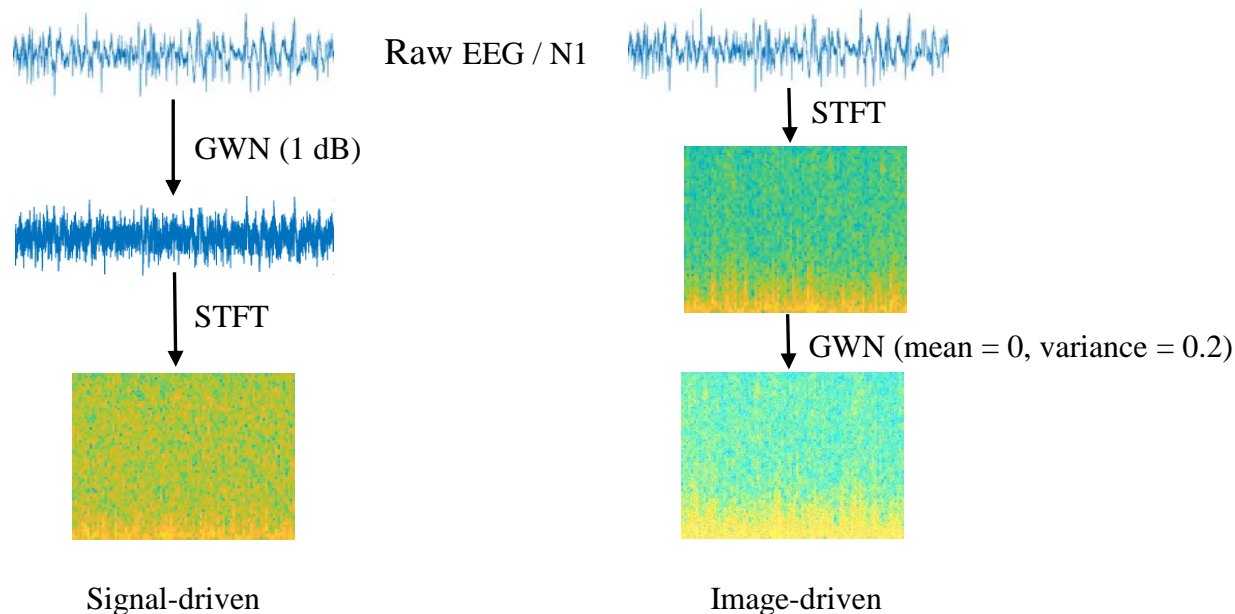
**Sleep-EDF-V1: 3.6 Sleep-EDF: 1.5 CCSHS: 1.6**



## 2. Materials and methodologies

### 2.3 Balancing Method

Subjective: Increasing the number of minority class (i.e., N1)



GWN: Gaussian white noise

## 2. Materials and methodologies

### 2.3 Balancing Method

Table II. The scheme of signal-driven and image-driven approaches

Intensity	signal-driven	image-driven
low	10 dB	mean = 0, variance = 0.05
moderate	5 dB	mean = 0, variance = 0.1
high	1 dB	mean = 0, variance = 0.2

**Different intensities: low → moderate → high**

## 2. Materials and methodologies

### 2.4 Evaluation model

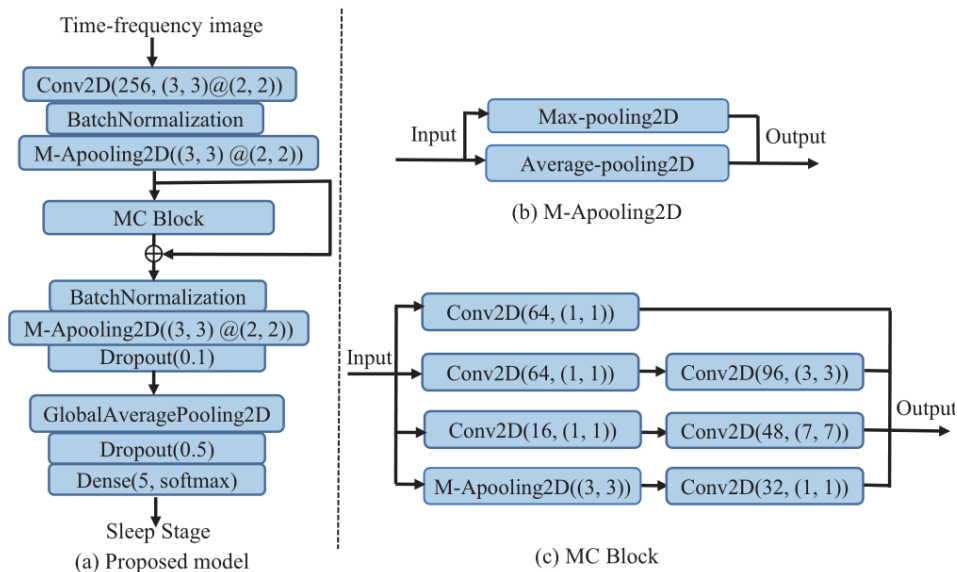


Figure 4. The overall construct of the evaluation model.

**MC Block:**

Large kernel: (7, 7), Small kernel: (3, 3)

# 3. Experimental results

## 3.1 Evaluation metrics

$$RE = \frac{TP}{TP + FN}. \quad (2)$$

$$ACC = \frac{\sum_{i=1}^n x_{ii}}{N} \quad (3)$$

$$K = \frac{\frac{\sum_{i=1}^n x_{ii}}{N} - \frac{\sum_{i=1}^n (\sum_{j=1}^n x_{ij} \sum_{j=1}^n x_{ji})}{N^2}}{1 - \frac{\sum_{i=1}^n (\sum_{j=1}^n x_{ij} \sum_{j=1}^n x_{ji})}{N^2}}. \quad (4)$$

*RE*: recall

*ACC*: accuracy

*K*: Cohen's kappa coefficient

*TP*: true positive

*FN*: false negative

*N*: total samples

*n*: number of stages

$x_{ii}$ : diagonal value of the confusion matrix

# 3. Experimental results

## 3.2 Results

Table III. Performance comparison of different intensities of the Gaussian noise addition (signal-driven and image-driven ways) in this work

	Sleep-EDF-V1			Sleep-EDF			CCSHS		
	<i>ACC</i> (%)	<i>K</i> (%)	<i>RE_N1</i> (%)	<i>ACC</i> (%)	<i>K</i> (%)	<i>RE_N1</i> (%)	<i>ACC</i> (%)	<i>K</i> (%)	<i>RE_N1</i> (%)
Without DA	86.3	81.1	38.9	84.5	79.0	24.6	87.0	82.0	22.9
DA (signal-driven, 10 dB)	85.4	80.0	35.2	84.5	79.0	26.1	87.3	82.4	25.7
DA (signal-driven, 5 dB)	86.8	81.1	42.7	84.3	78.6	18.7	87.2	82.3	24.1
DA (signal-driven, 1 dB)	87.1	82.3	34.8	84.7	79.3	24.0	87.5	82.5	27.3
DA (image-driven, $V = 0.05$ )	87.0	82.1	30.8	84.6	79.0	15.6	87.1	82.1	21.9
DA (image-driven, $V = 0.1$ )	87.0	82.2	34.5	84.6	79.1	21.1	87.3	82.3	22.2
DA (image-driven, $V = 0.2$ )	86.1	80.7	30.3	84.6	79.1	25.9	87.3	82.3	23.0
DA (Combination, 1 dB & $V = 0.1$ )	87.2	82.4	28.5	84.9	79.4	19.1	87.9	82.9	20.7

# 3. Experimental results

## 3.2 Results

Table IV. Performance comparison between the proposed methods and previous methods on the CCSHS dataset

Study	Method	Input channel	Input type	Subjects	$ACC(\%)$	$K(\%)$	RE_N1
Nakamura <i>et al.</i> [22]	HMM	C4/A1 + C3/A2	Spectrogram	515	-	73.0	-
Li <i>et al.</i> [23]	Random Forest	C4/A1	Features	116	86.0	80.5	7.3
<b>Baseline</b>	<b>CNN</b>	<b>C4/A1</b>	<b>Time-frequency image</b>	<b>515</b>	<b>87.0</b>	<b>82.0</b>	<b>22.9</b>
<b>DA (signal-driven, 1 dB)</b>	<b>CNN</b>	<b>C4/A1</b>	<b>Time-frequency image</b>	<b>515</b>	<b>87.5</b>	<b>82.5</b>	<b>27.3</b>
<b>DA (image-driven, <math>V = 0.1</math>)</b>	<b>CNN</b>	<b>C4/A1</b>	<b>Time-frequency image</b>	<b>515</b>	<b>87.3</b>	<b>82.3</b>	<b>23.0</b>

# 3. Experimental results

## 3.2 Results

Table V. Performance comparison between the proposed methods and previous methods on the Sleep-EDF-V1 and Sleep-EDF datasets

Study	Database	Method	Input type	Subjects	$ACC(\%)$	$K(\%)$	RE_N1
Fan <i>et al.</i> [14]	Sleep-EDF-V1	Deep CNN	Time series	20	74.8	66.0	-
Phan <i>et al.</i> [21]	Sleep-EDF-V1	1-max CNN	Time-frequency image	20	82.6	76	29.9
Zhou <i>et al.</i> [15]	Sleep-EDF-V1	CNN	Spectrogram	20	86.1	81.0	-
<b>Baseline</b>	<b>Sleep-EDF-V1</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>20</b>	<b>86.3</b>	<b>81.1</b>	<b>38.9</b>
<b>DA (signal-driven, 5 dB)</b>	<b>Sleep-EDF-V1</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>20</b>	<b>86.8</b>	<b>81.1</b>	<b>42.7</b>
<b>DA (image-driven, <math>V = 0.1</math>)</b>	<b>Sleep-EDF-V1</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>20</b>	<b>87.0</b>	<b>82.2</b>	<b>34.5</b>
Mousavi <i>et al.</i> [26]	Sleep-EDF	CNN + LSTM	Time series	78	80.0	73	-
Supratak <i>et al.</i> [27]	Sleep-EDF	CNN + LSTM	Time series	78	83.1	77	-
Phan <i>et al.</i> [11]	Sleep-EDF	RNN	Time series	78	84.0	77.8	-
<b>Baseline</b>	<b>Sleep-EDF</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>78</b>	<b>84.5</b>	<b>79.0</b>	<b>24.6</b>
<b>DA (signal-driven, 10 dB)</b>	<b>Sleep-EDF</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>78</b>	<b>84.5</b>	<b>79.0</b>	<b>26.1</b>
<b>DA (image-driven, <math>V = 0.2</math>)</b>	<b>Sleep-EDF</b>	<b>CNN</b>	<b>Time-frequency image</b>	<b>78</b>	<b>84.6</b>	<b>79.1</b>	<b>25.9</b>



**Q & A**

**Further information: [dongdongzhou1017@foxmail.com](mailto:dongdongzhou1017@foxmail.com)**

**Corresponding author: [xuqi@dlut.edu.cn](mailto:xuqi@dlut.edu.cn)**

