Deep-Learning-Based Classification of Cyclic Alternating Pattern Sleep Phases

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M.Sc. Final Exam

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Outline

- Background and Motivation
- Current and Proposed Solutions
- Proposed Method in Depth
- Results and Discussion
- Summary and Conclusion

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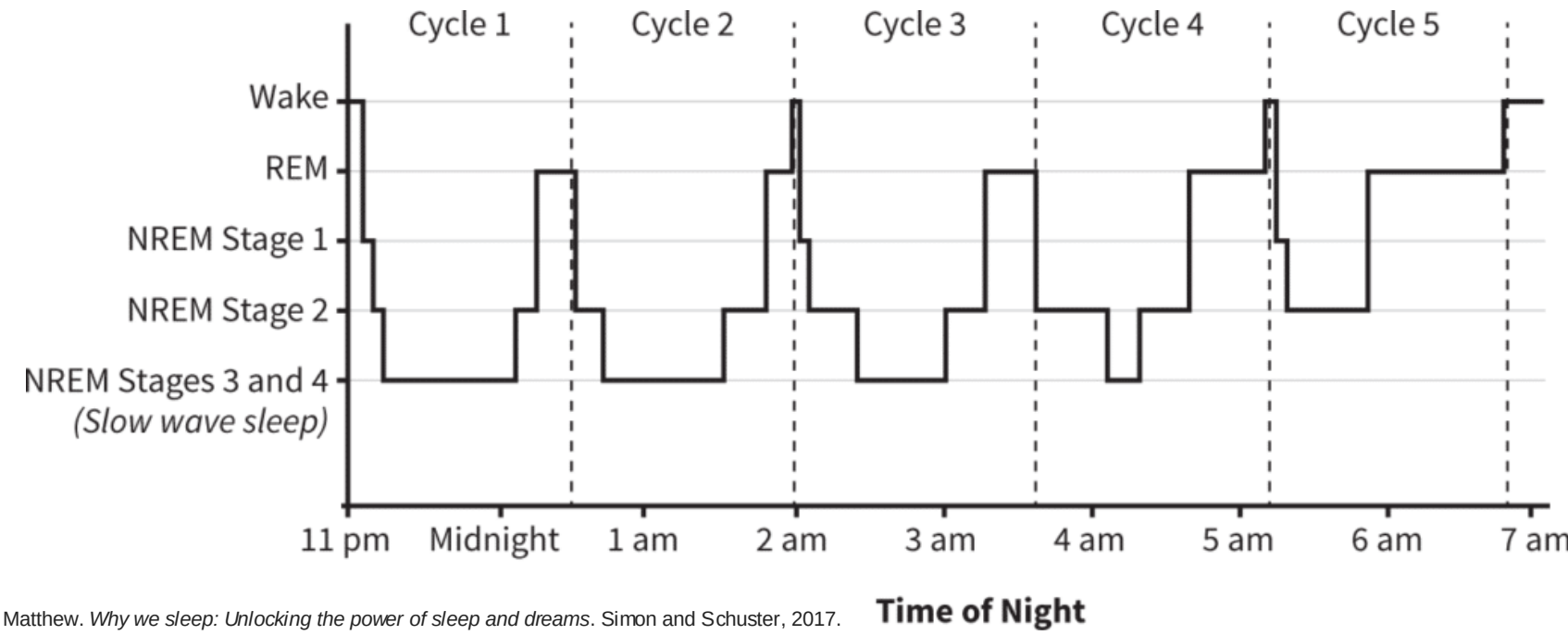
Sleep

- Essential for all mammals, especially humans.
- Crucial for maintaining health, improving focus, mood, immunity, and supporting learning and growth.
- Complex process which is constantly being researched.



Sleep Stages

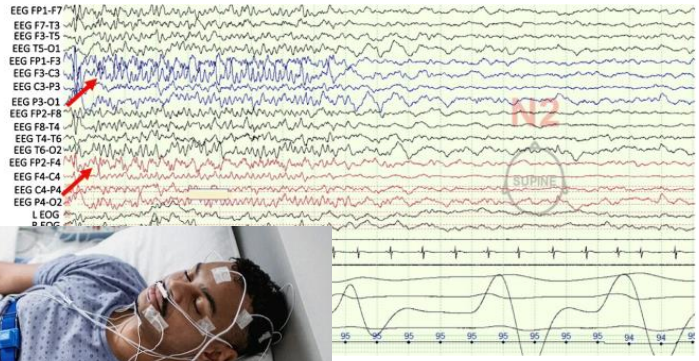
- Sleep is **not** homogenic.
- Our body alternates between two distinct modes: REM (rapid eye movement) and non-REM sleep.
- This division defines the **macro-structure** of sleep.

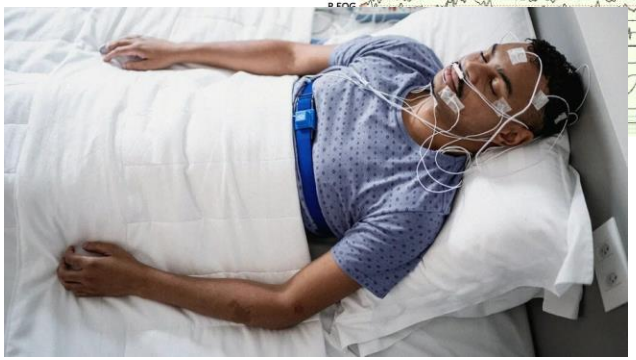


Walker, Matthew. *Why we sleep: Unlocking the power of sleep and dreams*. Simon and Schuster, 2017.

Sleep Measuring

- **Polysomnography** (PSG) is a detailed sleep study that diagnoses sleep disorders and assesses sleep quality by monitoring:
  - brain activity (EEG)
  - eye movements (EOG)
  - muscle activity (EMG)
  - heart rate (ECG)
  - breathing patterns





- Basic sleep analysis can also be performed in other different ways:

Comparison of Measuring Methods

	Polysomnography (PSG)	Home Sleep Test	Smartwatch	Phone App
What is measured?	EEG, EOG, EMG ECG, breathing, oxygen levels	Heart rate, airflow, oxygen saturation	Motion, heart rate	Sound
How it works?	Lab-based, multiple sensors	Portable device, worn at home	Worn on wrist, built-in sensors	Phone placed by the bed
What is it used for?	Diagnosing sleep disorders, evaluating sleep quality	Sleep apnea detection	Tracking sleep duration and stages	
Pros and Cons	Most accurate and comprehensive Expensive, inconvenient	Conducted at home Limited to apnea	Convenient, everyday use Limited to wellness tracking	
How it looks?				

The Cyclic Alternating Pattern

- **This thesis focuses on cyclic alternating pattern (CAP)**.
  - Occurs during the Non-REM sleep.
  - A periodic EEG activity with sequences of short cerebral activation (A-phase) followed by longer periods of deactivation (B-phase).
  - Defines the **micro-structure** of sleep.

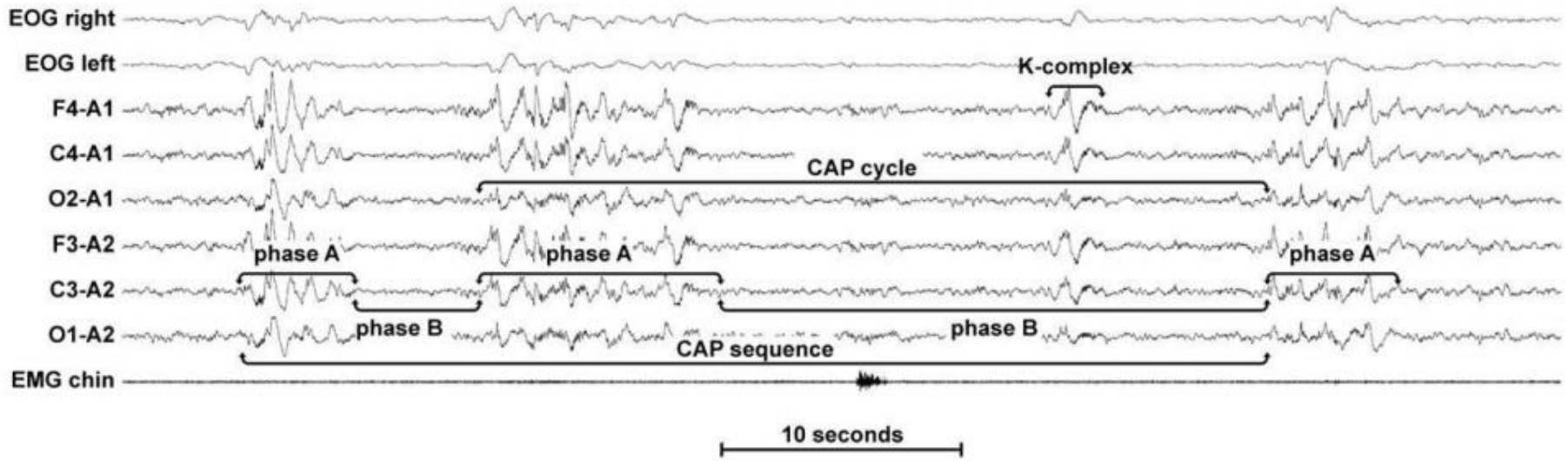
"The cyclic alternating pattern (CAP) is a long-lasting periodic activity consisting of two alternate electroencephalogram (EEG) patterns. This variation in EEG is closely related to fluctuations in the level of arousal that characterize two different functional states in the arousal control mechanism."

MG Terzano – "Father of CAP"

Terzano, Mario Giovanni, et al. "The cyclic alternating pattern as a physiologic component of normal NREM sleep." *Sleep* 8.2 (1985): 137-145.

CAP – Definitions

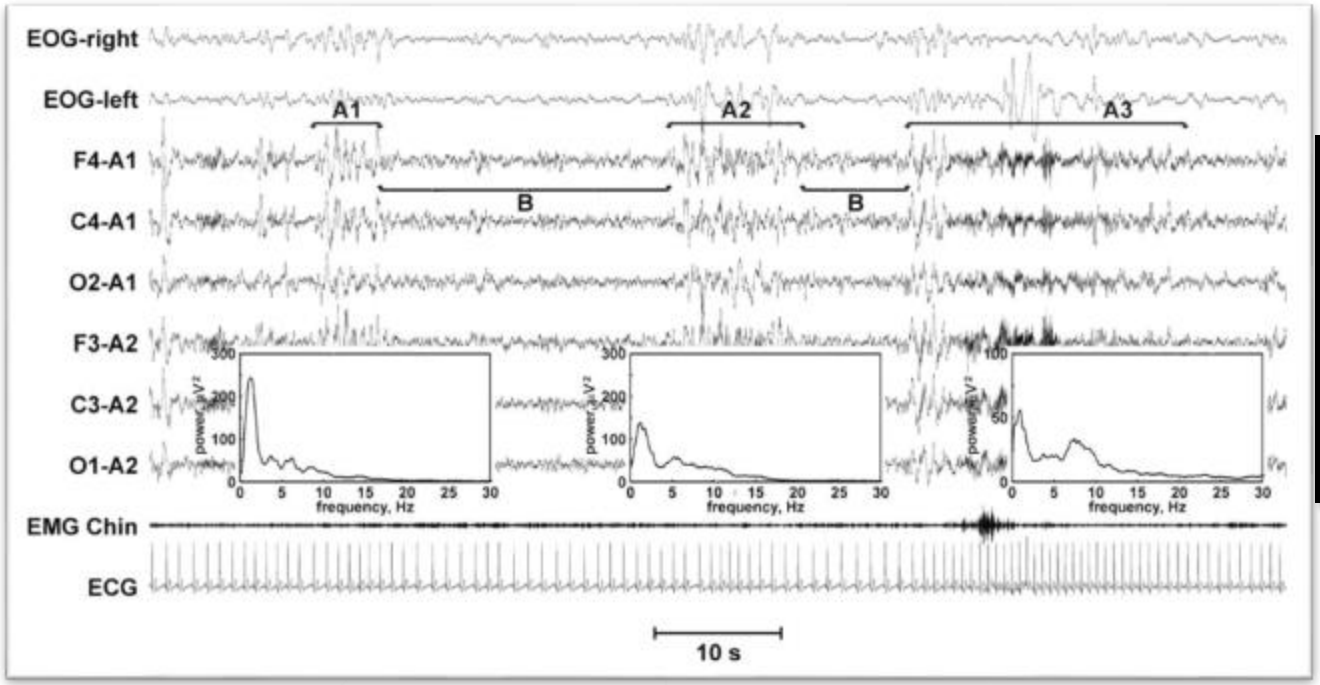
- **A-phase:** "Greater arousal“ events, lasts 8-12 seconds
- **B-phase:** "Lesser arousal“ events (background), lasts 16-25 seconds (up to 60)
- **CAP cycle:** An A-phase followed by a B-phase
- **CAP sequence:** At least 2 CAP cycles in succession
- **Non-CAP**: The absence of CAP for more than 60 seconds



Parrino, Liborio, et al. "Cyclic alternating pattern (CAP): the marker of sleep instability." *Sleep medicine reviews* 16.1 (2012): 27-45.

A-Phase Subtypes

- A-phase is divided into three subtypes:
  - *A1:* Slow waves (0.5-4Hz) with high amplitude
  - *A3:* Higher frequency (8-12Hz) with lower amplitude
  - *A2:* Combination of both *A1* and *A3*



Age	CAP rate%	A1%	A2%	A3%
1–4 months	12.9	85.2	10.3	4.4
Pre-school-age	25.9	63.2	21.5	15.3
School-age	33.4	84.4	6.4	9.1
Peripubertal	62.1	85.5	9.1	3.2
Adolescence	43.4	71.3	19.7	9.0
Young adults	31.9	61.4	27.9	10.7
Middle age	37.5	62.0	26.2	11.8
Elderly	55.3	46.6	35.3	18.1

Parrino, Liborio, et al. "Cyclic alternating pattern (CAP): the marker of sleep instability." *Sleep medicine reviews* 16.1 (2012): 27-45.

CAP and Sleep Quality

- CAP has a pivotal role in assessing sleep quality:
- The ***CAP Rate*** serves as **an indicator for sleep instability**
  - Linked to various sleep disorders
  - Higher CAP rates suggest poorer sleep quality

$$\textbf{CAP RATE} = \frac{total\ CAP\ time\ [s]}{total\ Non\ REM\ time\ [s]}$$

Changes of the main CAP parameters (vs. age-matched normal controls) in the different pathologies studied in adults.

	CAP rate%	A1%	A2%	A3%
Noise	↑	↑	↑	↑
Narcolepsy	↓	↓	↑	=
OSAS	↑	↓	=	↑
UARS	↑			
Insomnia	↑	↑	↑	↑
Hypnotics (vs. placebo)	↓	↓	↓	=/↓
First night effect[162]	↑	↓	↑	↑
PLM	↑	↓	↑	↑
Bruxism	=	↓	↑	↑
NFLE	↑	↑	↑	↑
PGE	↑	↑	↑	↓
Depression	↑	↑	↑	↑
Eating disorders	↑	–	–	–
MSA	↓	–	–	–

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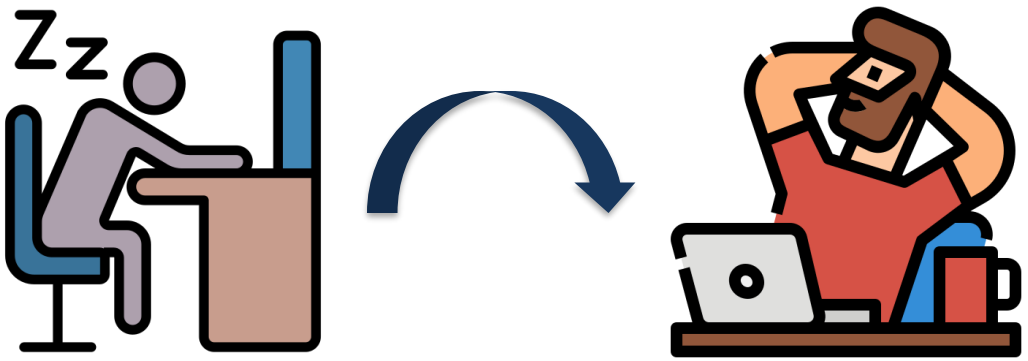
Current Analysis of CAP

- Accurate CAP analysis is crucial for diagnosing sleep disorders. Yet, visual scoring by human experts remains the gold standard.
- Manual assessment is inefficient and has many drawbacks.
- **Automated tools are essential** to improve reliability and streamline clinical workflows.

Deep-Learning-Based Classification of Cyclic Alternating Pattern Sleep Phases



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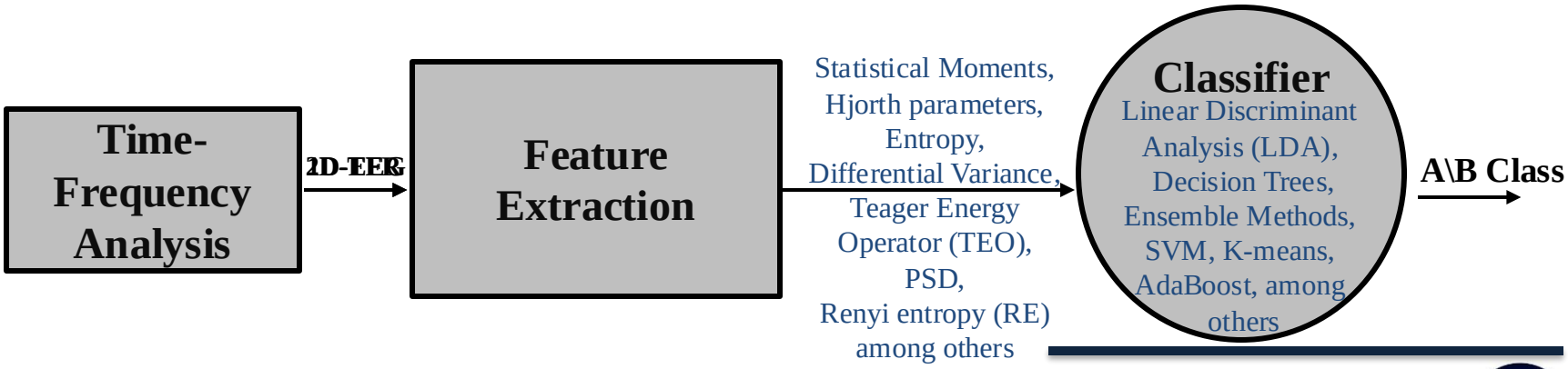
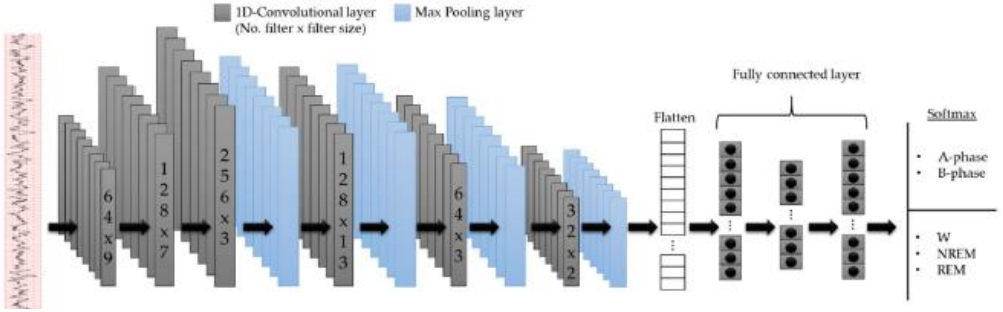
Machine Learning Approaches

- Previous studies mainly rely on 1) **feature extraction** and 2) a **(ML) classifier.**
  - Various features and classifiers were tested
  - Features often derived from the five EEG frequency bands
  - supervised learning with k-fold cross-validation
- Sometimes time-frequency analysis is used
  - Still reduced to feature vectors



Deep Learning Approaches

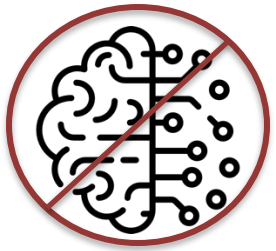
- **1D-CNN**
  - Classification using a 1D-CNN architecture
  - 2-second segments raw EEG
  - Training on a balanced dataset
  - Performance dropped on unbalanced datasets



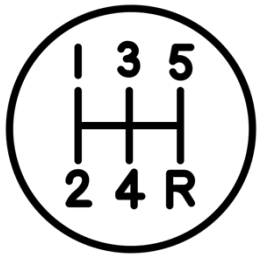
- **LSTM**
  - Handcrafted feature extraction are fed into an LSTM neural network
  - Post-processing the outcomes (to align with the CAP scoring Atlas)

Loh, Hui Wen, et al. "Automated detection of cyclic alternating pattern and classification of sleep stages using deep neural network." *Applied Intelligence* 52.3 (2022): 2903-2917.

Gaps in Current Methods



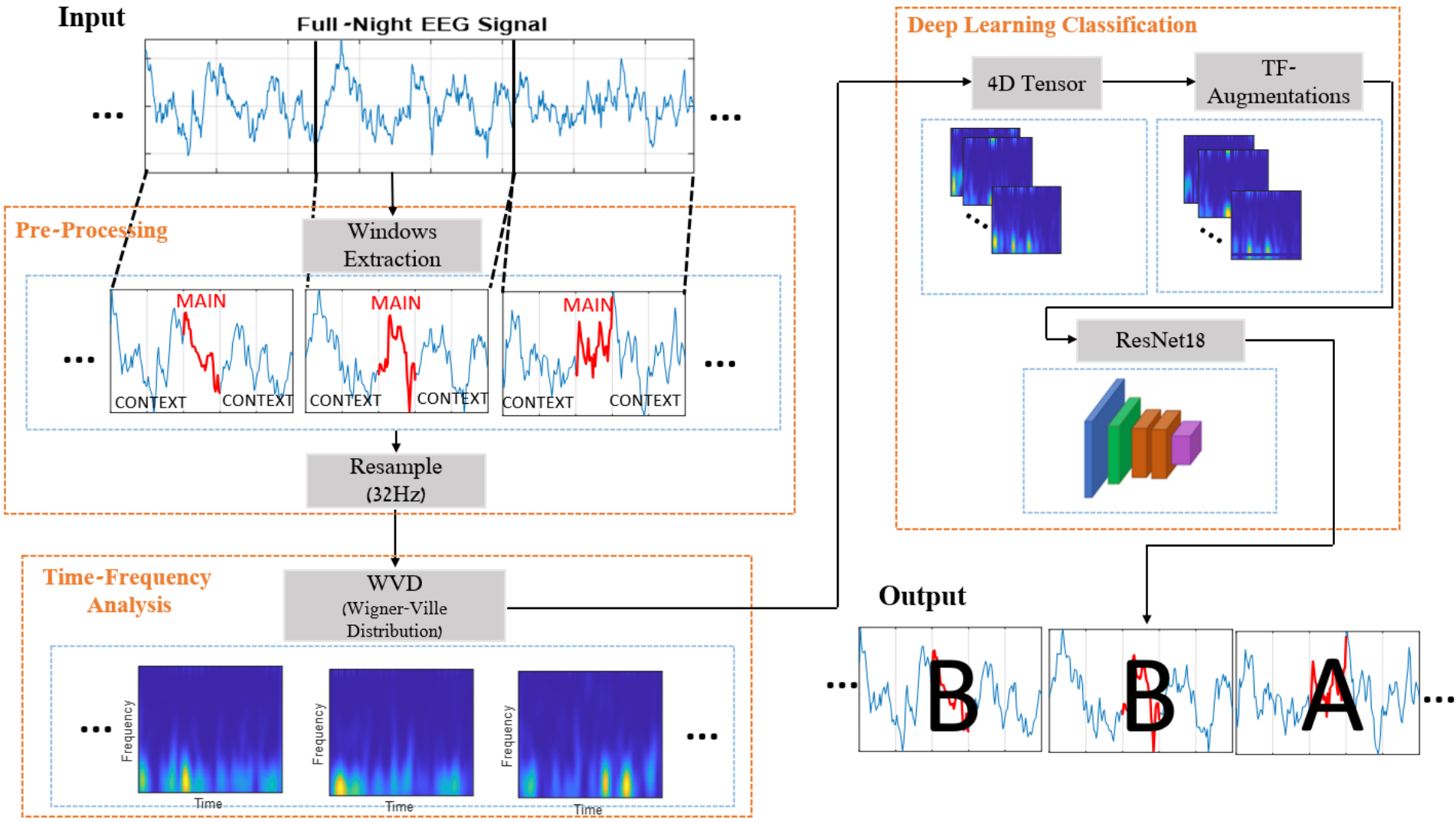
Limited application of deep learning techniques



Reliance on handcrafted features

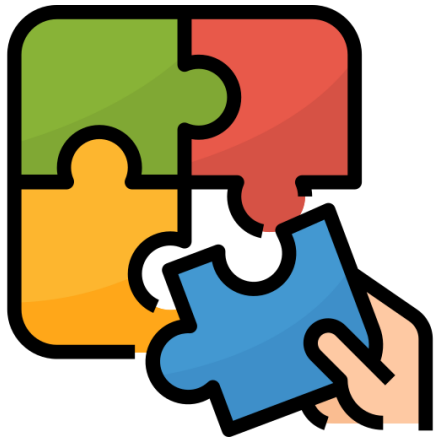
Discrepancy in performance between balanced and unbalanced datasets

Proposed Method



Main Contributions

- Bridging the gap between deep learning and CAP research
- Using an efficient CNN to classify TFR “images”
  - On-device implementation
- Leveraging the sequential nature of EEG signals
- State-of-the-art performance
- Ablation study to evaluate the impact of key components



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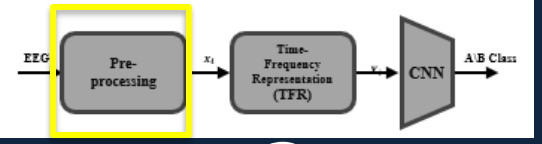
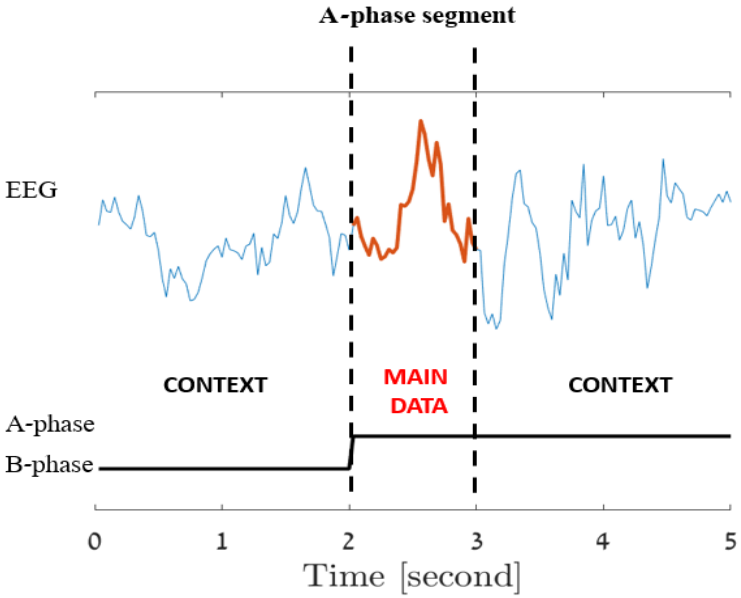
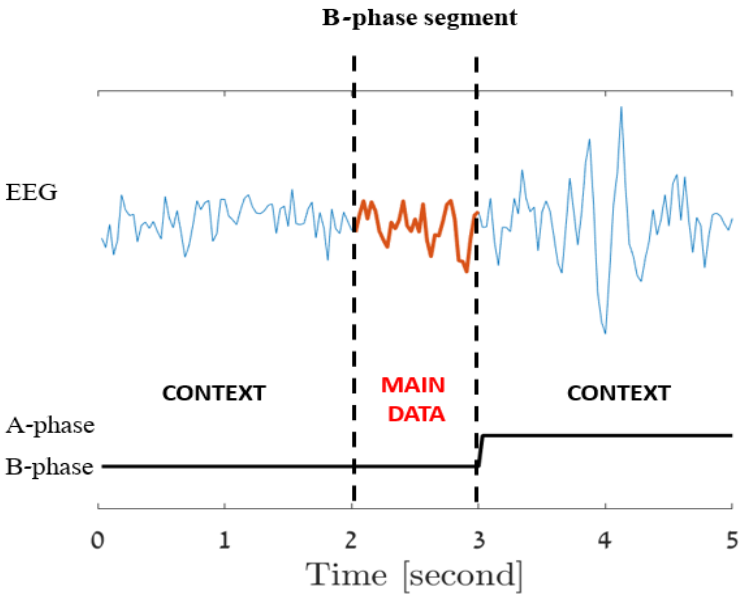
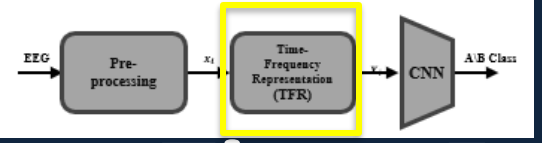


Context-Aware Segmentation

- The data's annotations are 1-second resolution
- Enlarged windows were taken (up to 11 sec) to involve the **contextual information of the sequential data**
- Determining the label by the **central** second – one label per segment
- Re-sampling all signals to 32Hz

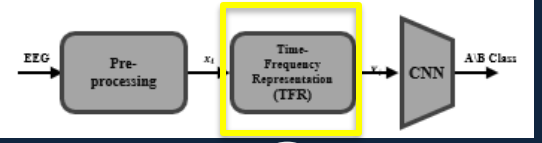






Time-Frequency Representations

- 1D-EEG segments are transformed into 2D time-frequency representations (TFR)
  - EEG signals are **non-stationary**
  - Highlighting **spectral differences between A-phase and B-phase**
  - Preparing the data for **input into the convolutional neural network**



Spectrogram vs. Wigner Dist.

Spectrogram

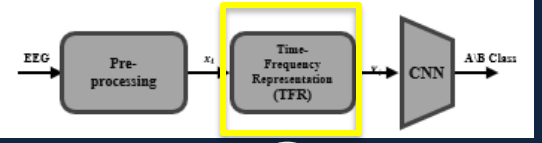
$$S_x(t,f) = |\int_{-\infty}^{\infty} x(\tau)h^*(\tau - t)e^{-j2\pi f\tau}\, d\tau|^2$$

- The squared-magnitude of the short-time Fourier transform (STFT)
- Widely acknowledged as a prevalent method for analyzing non-stationary signals
- Time-frequency resolution is inherently limited

Wigner-Ville Distribution

$$W_x(t,f) = \int_{-\infty}^{\infty} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j2\pi f\tau}d\tau$$

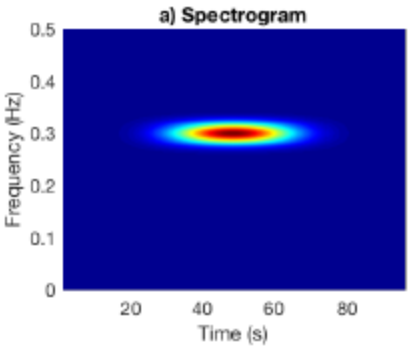
- High-resolution time-frequency analysis. In some cases, best possible concentration in the TF domain
- Neither parameters nor a window function are required
- Suffers from cross-terms (non-linearity)



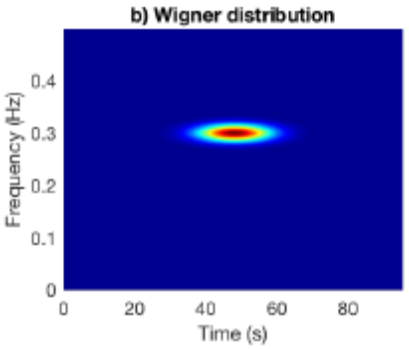
Spectrogram vs. Wigner Dist.

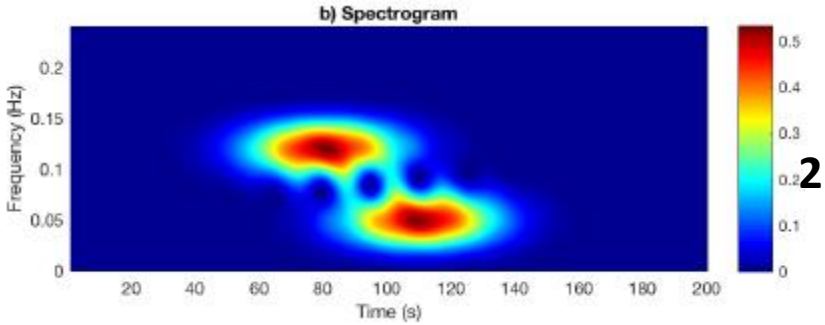
Spectrogram

Wigner-Ville Distribution

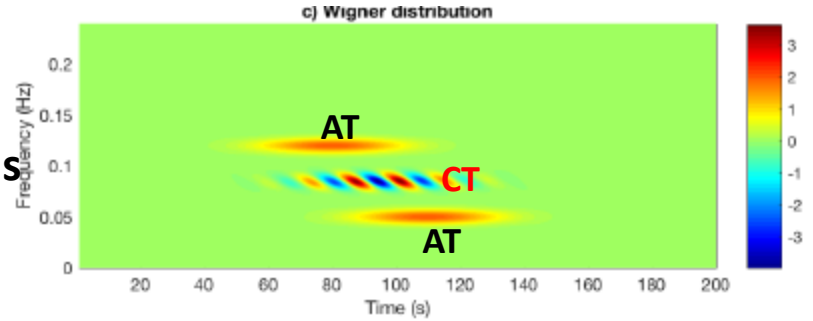


1 Gaussian

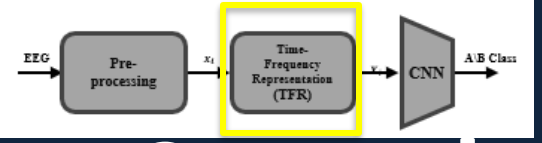




2 Gaussians



Sandsten, M. (2016). Time-frequency analysis of time-varying signals and non-stationary processes. *Lund University*.



Smooth-Pseudo Wigner-Ville Dist.

- An effective method to deal with the WVD cross-terms is the SPWVD, which is a "filtered version" of WVD. It is given by:

$$W_x^{sp}(t,f) = W_x(t,f) * *\Phi(t,f)$$

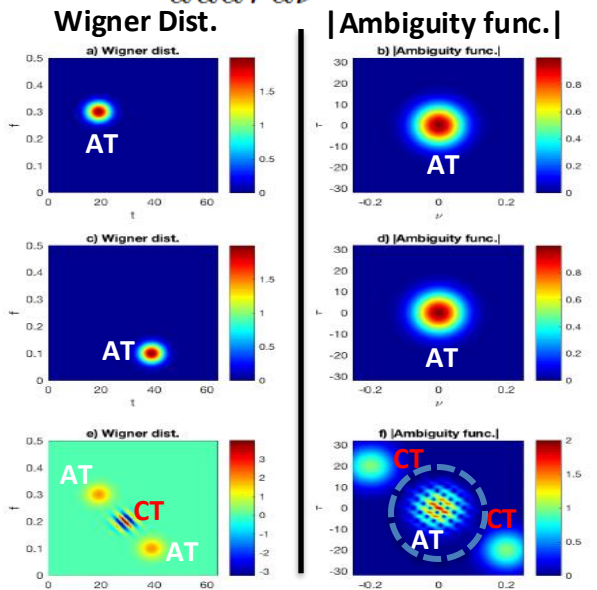
$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x(u+\frac{\tau}{2})x^*(u-\frac{\tau}{2})\Phi(\nu,\tau)e^{j2\pi(\nu t - f\tau - \nu u)}dud\tau d\nu$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x(u+\frac{\tau}{2})x^*(u-\frac{\tau}{2})e^{-j2\pi\nu u}\Phi(\nu,\tau)e^{j2\pi(f\tau-\nu t)}dud\tau d\nu$$

Ambiguity function

$$A_x(\nu,\tau) = \int_{-\infty}^{\infty} x(u+\frac{\tau}{2})x^*(u-\frac{\tau}{2})e^{-j2\pi\nu u}du$$

$$W_x^{sp}(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} A_x(\nu,\tau)\Phi(\nu,\tau)e^{-j2\pi(f\tau-\nu t)}d\tau d\nu,$$



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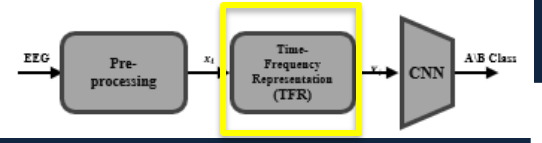
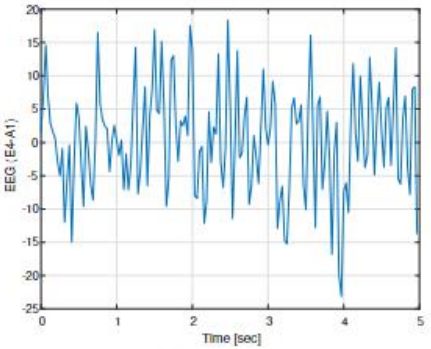
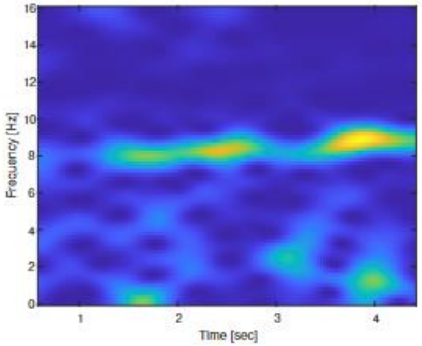


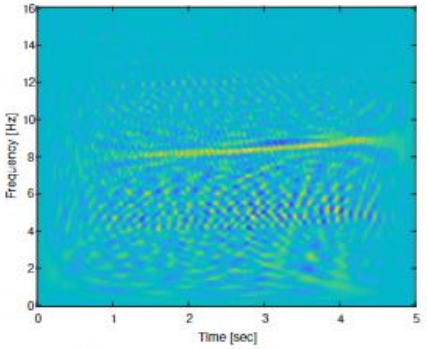
Back to Real-World: TFRs of EEG Segment



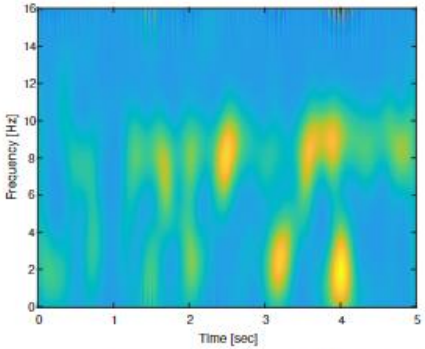
(a) 1D-EEG signal



(b) Spectrogram



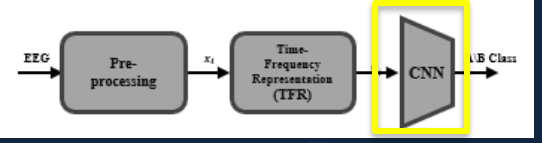
(c) Wigner-Ville distribution



(d) Smoothed pseudo-Wigner-Ville distribution

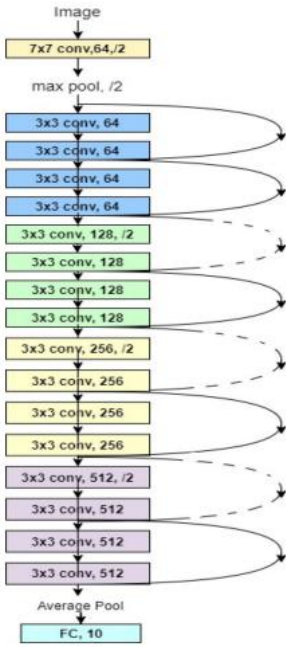
Figure 3.3: Example of (a) 5 s 1D-EEG segment from channel E4-A1 and its corresponding time-frequency representations (TFRs): (b) spectrogram (SPEC), (c) Wigner–Ville distribution (WVD), and (d) smoothed pseudo-Wigner–Ville distribution (SPWVD). The WVD exhibits a distinct energy concentration when compared to SPEC, albeit with the tradeoff of noticeable cross-term patterns.

Kahana, Y., Aberdam, A., Amar, A., & Cohen, I. (2023). Deep-Learning-Based Classification of Cyclic-Alternating-Pattern Sleep Phases. *Entropy*, *25*(10), 1395.



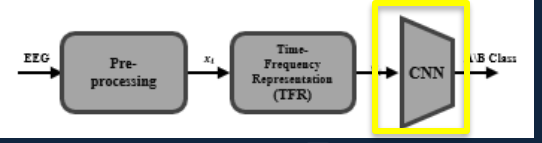
Deep learning classification

- TFRs are interpreted as images and classified using a CNN
- The **ResNet18 architecture was chosen** for its efficiency and robustness
- The model was trained **from scratch** due to significant differences between current data and ImageNet images



Hyperparameters	Value
Batch size	256
Loss functions	cross entropy
Optimizer	SGD
Learning rate	0.001
Momentum	0.9
Epochs	40
Dropout	No

Table 3.1: Hyperparameters used in the proposed framework.



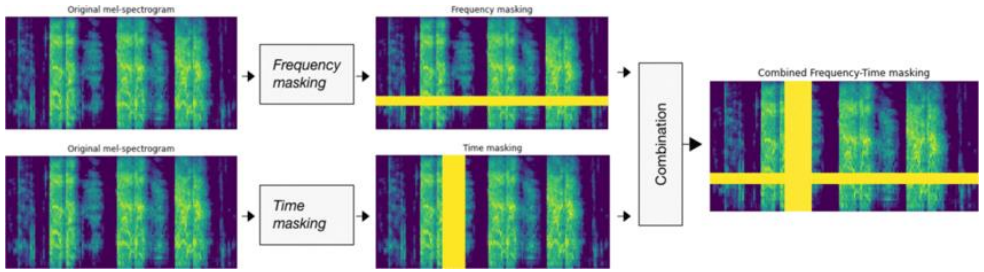
Deep learning classification

- **Normalization:** To preserve the energy level differences between A and B phases, each input sample was divided ***constantly*** by the *mean* standard deviation of the ***entire*** training set

$$\tilde{x_i} = \frac{x_i - \bar{x_i}}{\sigma_i} \quad \Big| \quad \tilde{x_i} = \frac{x_i - \bar{x_i}}{\bar{\sigma}}, \bar{\sigma} = \frac{1}{N} \sum_{i \in X_N} \sigma_i$$

- **Augmentation:** we *randomly employed a series of augmentations*:

TF-Aug.
  - Noise
  - Gaussian blur
  - Crop and Resize (slight)
  - SpecAugment
  - Random Time-shifts



Park, Daniel S., et al. "Specaugment: A simple data augmentation method for automatic speech recognition." *arXiv preprint arXiv:1904.08779* (2019).

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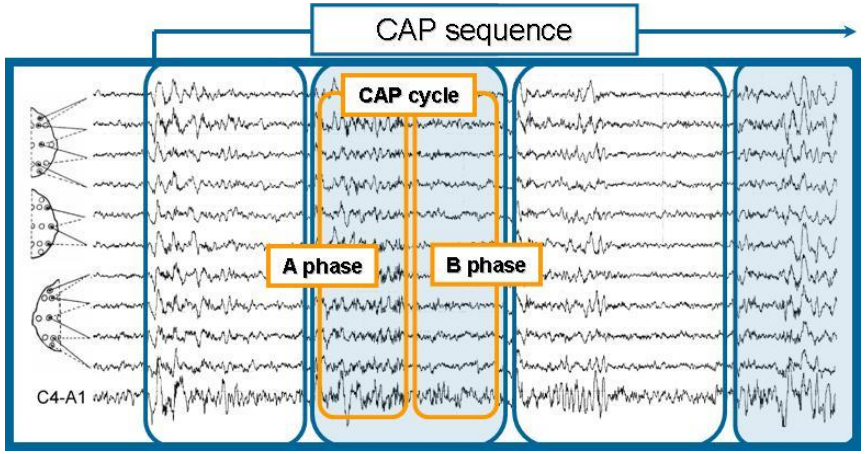
PhysioNet CAP Sleep Database

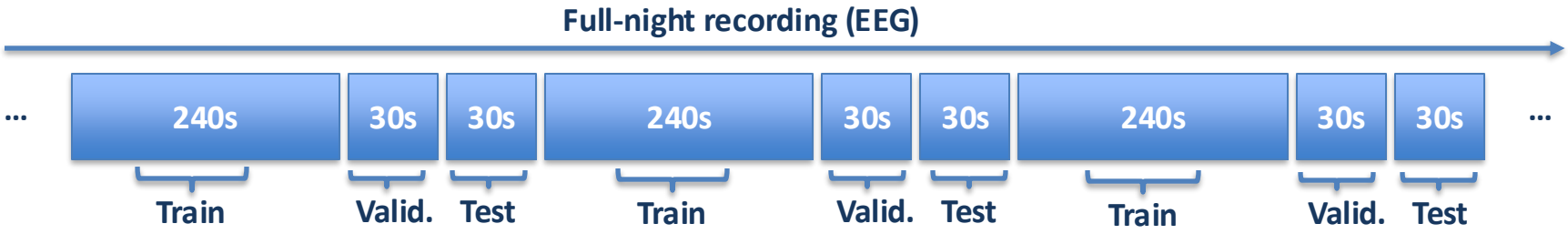
- A comprehensive collection of **polysomnographic recordings includes 108 recordings** from both healthy and disordered subjects.
  - Includes EEG (3+ channels), EOG, EMG, breathing signals, and ECG
  - Expert annotations for sleep stages and CAP phases (1-sec resolution), along with patient details (age, gender, disorders).
- Serves as **a benchmark in CAP research.**



Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

Dataset Creation

- To evaluate our method, we used:
  - **16 normal** (healthy) subjects
  - **Single EEG channel** per participant (C4-A1 or C3-A2 channel)
- The database was split into **train, validation, and test sets**
- The full-night EEG signals were divided into non-overlapping 300-second segments, assigned periodically into the train, validation, and test sets (80:10:10)



- Finally, the data set was **balanced** to represent A-phase and B-phase equally

CAPSLPDB and Our Dataset

Subject name	CAPSLPDB (Unbalanced) A_1	A_2	A_3	Total A	B	Our Dataset (Balanced) A_1	A_2	A_3	Total A	B
n1	2217	747	1122	**4086**	**21804**	2063	703	1046	**3812**	**3812**
n2	1115	590	783	**2488**	**12122**	1036	552	693	**2281**	**2281**
n3	611	597	891	**2099**	**15451**	550	556	830	**2281**	**2281**
n4	986	356	848	**2190**	**15030**	928	323	797	**2048**	**2048**
n5	2854	328	620	**3802**	**18158**	2673	314	586	**3573**	**3573**
n6	1871	970	1401	**4242**	**17268**	1723	905	1280	**3908**	**3908**
n7	1616	564	479	**2659**	**17501**	1508	525	438	**2471**	**2471**
n8	949	465	1868	**3282**	**17028**	914	421	1752	**3087**	**3087**
n9	1036	377	676	**2089**	**18341**	959	363	641	**1963**	**1963**
n10	1484	326	829	**2639**	**13351**	1385	282	785	**2452**	**2452**
n11	1724	583	796	**3103**	**15377**	1640	539	734	**2913**	**2913**
n12	1064	153	573	**1790**	**18040**	986	139	515	**1640**	**1640**
n13	1628	1037	1017	**3682**	**14078**	1532	985	955	**3472**	**3472**
n14	1035	1234	1209	**3478**	**15902**	950	1118	1126	**3194**	**3194**
n15	1449	1046	1244	**3739**	**18461**	1345	967	1159	**3471**	**3471**
n16	2247	1125	837	**4209**	**17841**	2110	1041	786	**3937**	**3937**
Total of samples:				**49577**	**265753**				**46503**	**46503**

B-phase events are much more common

A1 is the most common subtype

Kahana, Y., Aberdam, A., Amar, A., & Cohen, I. (2023). Deep-Learning-Based Classification of Cyclic-Alternating-Pattern Sleep Phases. *Entropy*, *25*(10), 1395.

Performance Appraisal

- To evaluate classification performance, we employed standard metrics:

  accuracy (ACC), precision (PRE), recall (REC), specificity (SPE) and F1-score (F1)

$$ACC = \frac{t_p + t_n}{t_p + t_n + f_p + f_n}, PRE = \frac{t_p}{t_p + f_p}.$$

$$REC = \frac{t_p}{t_p + f_n}, SPE = \frac{t_n}{t_n + f_p}.$$

$$F1 = \frac{2 \cdot t_p}{2 \cdot t_p + f_p + f_n}.$$

  - *tp* (true positives) - number of correctly identified A-phase events
  - *tn* (true negatives) - number of correctly recognized B-phase samples
  - *fp* (false positive) - count of samples incorrectly classified as A-phase
  - *fn* (false negative) - count of samples incorrectly classified as B-phase

Method Evaluation Overview

- An **ablation study** was carried out to evaluate our method and to explore the following aspects:
  - Influence of incorporating contextual EEG information
  - Comparison of different time-frequency methods
  - Effective data augmentation strategy
- Each experiment involved training various CNNs with specific configurations
- Training ranged from several hours up to 20 hours per session

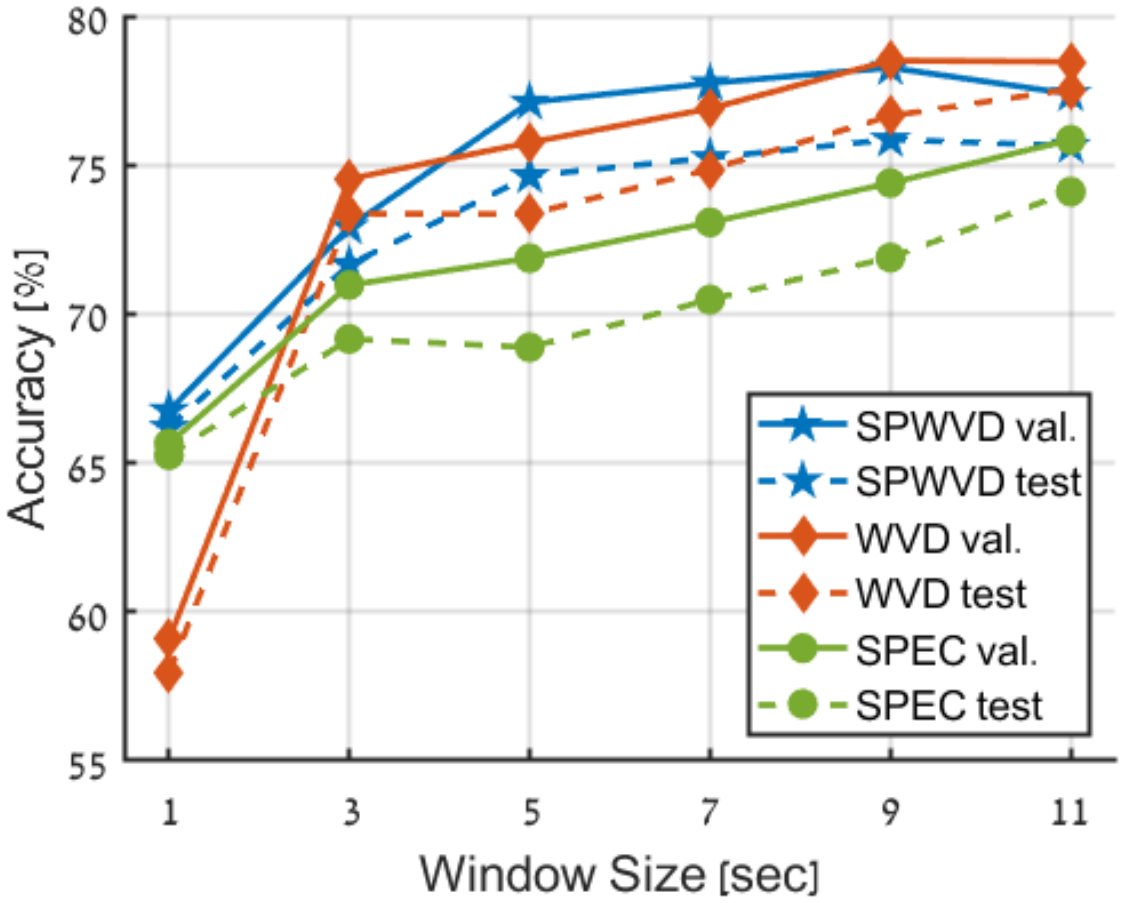
Google Colaboratory

Experiment #1

Contextual information boosts performance

- 10%-20% improvement in accuracy
- Trend plateaus at 9-second segment

Wigner-based transforms outperform Fourier-based spectrograms

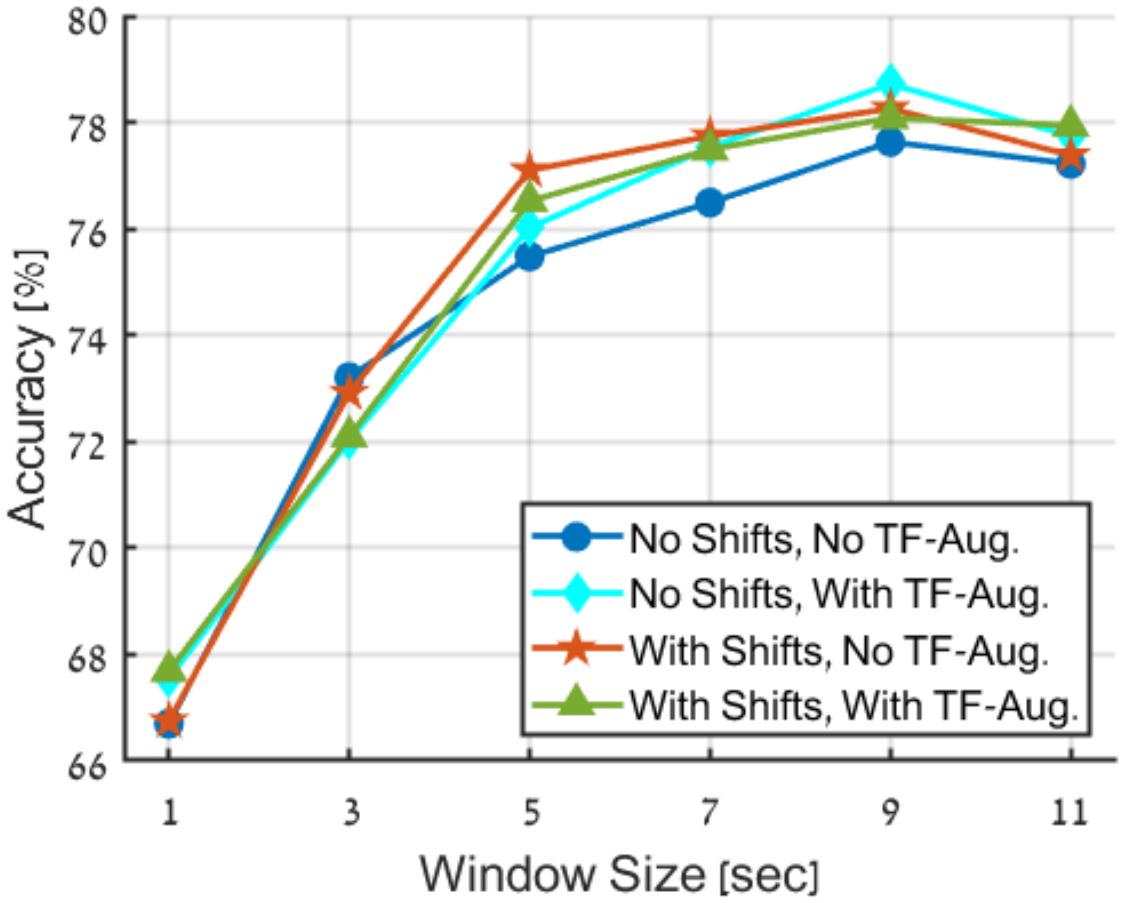


Kahana, Y., Aberdam, A., Amar, A., & Cohen, I. (2023). Deep-Learning-Based Classification of Cyclic-Alternating-Pattern Sleep Phases. *Entropy*, *25*(10), 1395.

Experiment #2

Augmenting the dataset has a positive effect

TF-aug. is most effective method



Kahana, Y., Aberdam, A., Amar, A., & Cohen, I. (2023). Deep-Learning-Based Classification of Cyclic-Alternating-Pattern Sleep Phases. *Entropy*, *25*(10), 1395.

Analysis of Detection by Class

The true-positive-rate (TPR) is **consistent** across the A-phase and B-phase

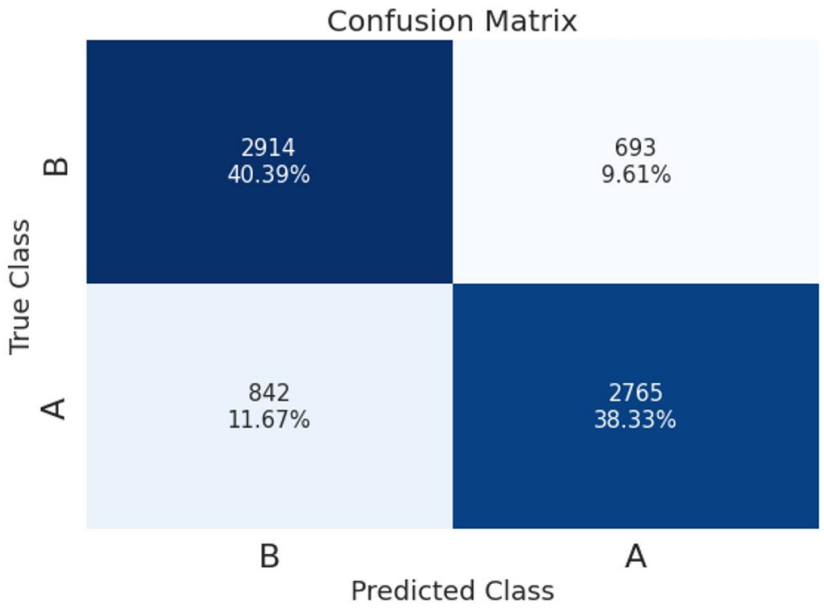


Table 4.3: True-positive rate (%) per A-phase sub-types and B-phase.

Predicted	True			
	A1	A2	A3	B
A	1422	561	782	2914
B	343	99	400	693
TPR [%]	**80.6**	**85**	**66.2**	**80.8**

The TPR *A1* and *A2* subtypes is significantly higher than *A3*.

Identification is driven more by power intensity than spectral content level.

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Comparative Analysis of Methods

Author	Method	Segment Length [Sec]	Number of Subjects	Performance Parameter [%] on Validation Set	Performance Parameter [%] on Test Set	Accuracy [%] Evaluated on Unbalanced Test Set
Dhok et al. (2020)	Wigner-Ville distribution (WVD), Renyi entropy (RE), support vector machine (SVM)	2	6 patients	ACC=72.3 PRE=64.1 REC=76.8 SPE=69.2 F1=69.9	-	-
Sharma et al. (2021)	Wavelet-based features, SVM	2	16 patients	ACC=75.7 PRE=75.0 REC=77.7 F1=76.0	-	-
Sharma et al. (2022)	Biorthogonal wavelet filter bank (BOWFB), ensemble bagged tree -	2 -	6 patients	ACC=74.4 REC=67.53 SPE=81.3		
Hartmann et al. (2019)	Hand–crafted features, long-short term memory (LSTM)	1-3	16 patients	ACC=82.4± 7.1 REC=75.3± 12 SPE= 83.9 ± 8.9 F1=57.4 ± 9.6	-	-
Loh et al. (2021)	1D-CNN	2	6 patients	ACC=74.4	ACC=73.6 PRE=71.0 REC=80.3 SPE= 67.0 F1=75.3	53.0
Murarka et al. (2022)	1D-CNN	2	6 patients	ACC=76.7	ACC=78.8 PRE=82.5 REC=73.4 SPE=84.3 F1=77.7	60.6
Our method	**Spectrogram, Wigner-based represen-tations, ResNet18**	**1-11**	**16 patients**	**ACC=78.5 PRE=78.9 REC=77.8 SPE= 79.3 F1=78.4**	**ACC=77.5 PRE=78.4 REC=75.9 SPE= 79.1 F1=77.1**	**81.8**

Inter-observer reliability is up to 77%

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Outline

- Background and Motivation
- Current and Proposed Solutions
- Proposed Method in Depth
- Results and Discussion
- Summary and Conclusion

Summary and Conclusions

- Cyclic alternating pattern is a key factor in sleep quality assessment, and automating its classification is vital
- **An innovative algorithm has been developed:**
  - CNN-based classification of time-frequency representations
  - leverages the sequential nature of EEG signals
  - Achieves high performance both on balanced and unbalanced data
  - Ablation study conducted to evaluate the key components
- **Limitations:**
  - Accuracy hovers around 80% with potential for improvement
  - Algorithm tested exclusively on healthy subjects

Future Directions for Research

- **Advanced DL Architecture:**
  - Utilize contrastive learning to enhance the model
  - Explore transformer-based architectures (fit to sequential data)
- **Classification Noise:**
  - Investigate methods to mitigate random classification noise to enhance model robustness
- **Data Fusion:**
  - Include multi-modal data to leverage the information of the PSG measurements (multi-channel EEG, ECG, EOG, etc.)

Thank You!
Any Questions?