ICPR 2026 | International Conference on Pattern Recognition

Improving N1-Sleep Stage detection using CQT-based CNN-LSTM

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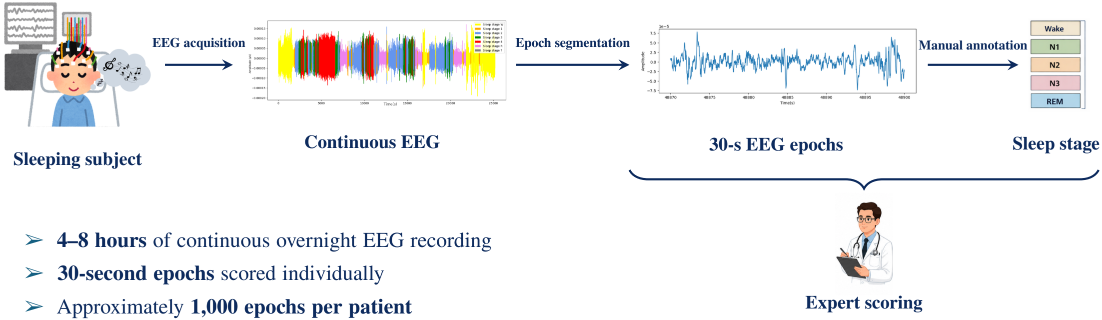
Cité des Congrés, Lyon - France | 20th August, 2026

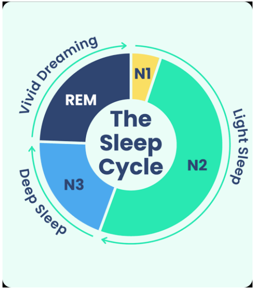
Introduction



- **4–8 hours** of continuous overnight EEG recording
- **30-second epochs** scored individually
- Approximately **1,000 epochs per patient**
- Manual scoring performed by **trained sleep specialists**

Why automatic sleep stage classification?

Sleep staging is the gold standard for diagnosing sleep disorders, but manual scoring is a long and demanding process.
Current AI-based sleep staging systems still struggle to achieve reliable performance.
$\Longrightarrow$ Almost complete correction of sleep stage annotations by clinicians.



Main challenges

- Time-consuming analysis
- Inter-expert variability
- Difficult detection of the **N1** stage

Motivation

Develop an automatic sleep stage classifier to assist clinicians.

State of the Art

Deep Learning Architectures

- CNN-based models
- CNN–LSTM / CNN–BiLSTM
- Graph Convolutional Networks (GCNs)
- Transformer-based models

Signal Representations

- Raw EEG
- Multi-modal signals (EEG, EOG, EMG)
- Fractional Fourier Transform (FrFT)
- Wavelet Transform

Proposed Approach

CQT + **CNN-LSTM**

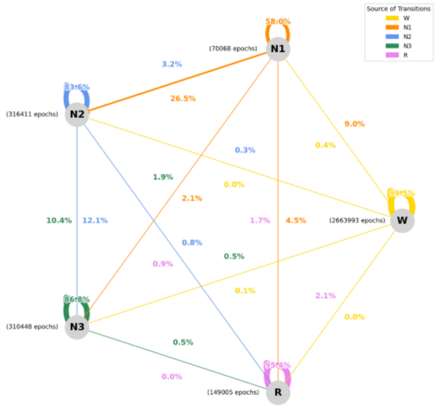
CQT provides an adaptive time-frequency representation, while the CNN-LSTM architecture jointly exploits spatial and temporal information for improved sleep stage classification.

Dataset

Sleep-EDF Expanded

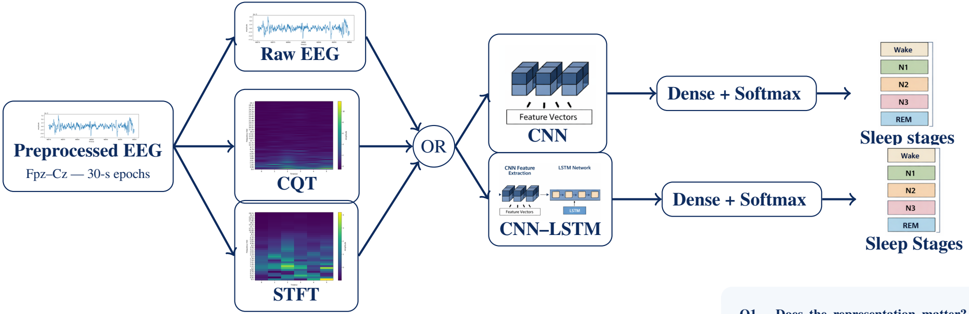
- **78 healthy subjects**
- **153 overnight recordings**
- EEG channel: **Fpz–Cz**
- Sampling frequency: **100 Hz**
- Epoch duration: **30 s**
- Sleep stages:
  - Wake (W)
  - N1
  - N2
  - N3
  - REM

Characteristics of N1



Sleep stage transitions

Methodology Overview



Q1 – Does the representation matter?

Q2 – Does temporal modeling help?

Q3 – Which combination is most effective for N1?

Methodology

❶ Why CQT?

- Logarithmic frequency scale.
- Constant quality factor Q.
- Adaptive time-frequency resolution.
- Higher frequency resolution at low frequencies.

❷ CQT for Sleep EEG

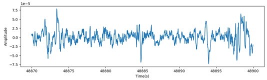
- Sleep EEG is dominated by low-frequency activity.
- Captures δ, θ, α activity.
- Represents transient events such as sleep spindles.
- Potentially beneficial for the challenging **N1** stage.

❸ Configuration

- Epoch duration: **30 s**
- Frequency range: **0.5–32 Hz**
- Frequency bins: **36**
- Bins per octave: **6**
- Hop length: **512**
- Z-score normalization

Sleeping subject

→



30-s EEG epoch

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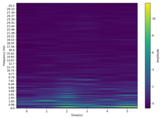


CQT representation

→ …

Methodology

❶ CNN Feature Extraction

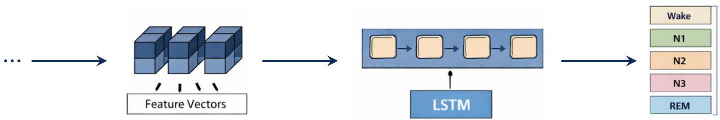
- CQT representations are fed into a lightweight CNN.
- The CNN extracts feature representations from each epoch.

❷ Temporal Modeling

- CNN features are grouped into temporal sequences.
- Sequence length: $S = 10$ **epochs**.
- 10 consecutive epochs $\approx$ **5 min**.
- LSTM models temporal dependencies across epochs.

❸ Classification

- LSTM output $\longrightarrow$ fully connected layer.
- Softmax for 5 sleep stages.
- Classes: W, N1, N2, N3, REM.
- Weighted cross-entropy loss.



CNN LSTM Sleep Stage Classification

Results and Discussion

Model	Stage	Raw signal Precision	Raw signal Recall	Raw signal F1	CQT 36-6-512 Precision	CQT 36-6-512 Recall	CQT 36-6-512 F1	STFT 1024-512 Precision	STFT 1024-512 Recall	STFT 1024-512 F1
CNN	W	0.977	0.882	0.927	0.994	**0.923**	**0.957**	**0.985**	0.891	0.936
	N1	0.222	0.320	0.262	**0.295**	**0.526**	**0.378**	0.257	0.494	0.338
	N2	0.708	0.631	0.667	**0.839**	**0.741**	**0.787**	0.792	0.694	0.74
	N3	0.456	0.859	0.596	**0.717**	0.875	**0.788**	0.545	**0.832**	0.659
	REM	0.283	0.441	0.345	**0.678**	**0.843**	**0.751**	0.562	0.758	0.646
CNN-LSTM	W	**0.994**	**0.944**	**0.968**	0.992	0.909	0.948	0.983	0.93	0.956
	N1	0.291	0.537	0.377	0.321	**0.671**	**0.434**	**0.337**	0.608	**0.434**
	N2	0.869	**0.775**	**0.819**	**0.873**	0.762	0.813	0.855	0.735	0.79
	N3	0.639	**0.9**	0.748	**0.795**	0.878	**0.834**	0.617	0.836	0.71
	REM	0.629	0.753	0.685	**0.682**	**0.843**	**0.754**	0.673	0.758	0.713

Table 1. Performance comparison of models across different signal representations and sleep stages with 20-CV

Ref.	Input	epochs (BS)	Sleep-EDFX-N	n-cv	Accuracy	N1 Recall
[6]	Fpz-Cz EEG	100 (40)	20	20-cv	0.838	0.31
[2]	Fpz-Cz EEG	100 (10)	20	20-cv	0.816	0.397
[5]	Fpz-Cz EEG	150 (5)	20	LOSO-cv	0.868	0.466
[3]	Fpz-Cz EEG	30 (128)	20	20-cv	0.876	0.494
[7]	Fpz-Cz EEG	100 (8)	20	LOSO-cv	0.886	0.478
[4]	Fpz-Cz EEG	u (64)	77	5-cv	0.795	0.31
[1]	2 EEG+EOG	u>5 (64)	**78**	20-cv	0.853	0.461
[3]	Fpz-Cz EEG	30 (128)	**78**	20-cv	0.843	0.49
[5]	Fpz-Cz EEG	150 (5)	**78**	20-cv	0.830	0.453
CQT*	Fpz-Cz EEG	10 (32)	**78**	20-cv	0.836	**0.526**
CQT**	Fpz-Cz EEG	10 (32)	**78**	20-cv	**0.865**	**0.671**

Table 2. Comparison with the state-of-the-art on the Sleep-EDF-X database

Conclusions

Main Results

Significant improvement over the state of the art

N1 Recall

0.675 ↑ **18.1**%

Improved detection of the challenging N1 stage

Overall Accuracy

0.865 ↑ **2.2**%

Improvement over the state-of-the-art baseline

CQT + CNN-LSTM provides an effective combination of time-frequency representation and temporal modeling for sleep stage classification.

Future Work

- **Explainable AI :** identify and visualize the EEG patterns contributing to sleep-stage predictions.
- Extend the proposed framework to multimodal sleep recordings (EEG, EOG, EMG) and evaluate its generalization on additional public sleep datasets the model's decisions.

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Thank You

Acknowledgements

Experiments presented were carried out using the CALCULCO computing platform, supported by DSI/ULCO and funded by CPER CornelIA, Co-construction responsable et durable d'une Intelligence Artificielle (2021-2027).

The authors would like to warmly thank the Sleep Unit of the Dunkerque Hospital Center, Alexandra Lepève for their precious domain expertise. This unit specializes in the diagnosis and management of sleep and wakefulness disorders.