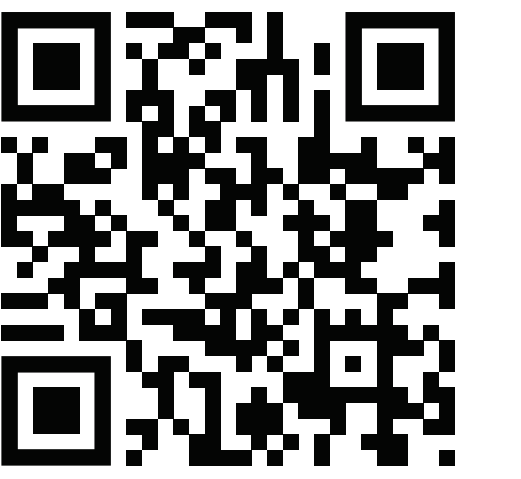# U-Time: A Fully Convolutional Network for Time Series Segmentation Applied to Sleep Staging

Mathias Perslev[1], Michael Hejselbak Jensen[1], Sune Darkner[1], Poul Jørgen Jennum[2] & Christian Igel[1]

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Paper

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Overview

- Most deep learning systems for physiological time-series analysis combine convolutional and recurrent layers. These are difficult to tune and optimize and they often require task-specific modifications.

- We suggest *U-Time*; a fully feed-forward model for time-series segmentation based on the U-Net architecture[6, 7]. Evaluated on the problem of 'sleep staging', we find that *U-Time* offers:

  - Higher segmentation accuracy compared to CNN-LSTM type models
  - High robustness in its hyperparameters across datasets
  - Very fast inference (full patient scoring in seconds on laptop CPUs)
  - Ability to output segmentations of higher-than-labels temporal resolution through in-built multiple instance learning mechanism.

Method

- *U-Time* is a fully convolutional encoder-decoder network. It maps 1D time-series to contiguous segments of labels at a chosen temporal scale.

- Let $\mathbf{x} \in \mathbb{R}^{\tau S \times C}$ be a signal of C channels sampled at rate S for τ seconds. Let e be the frequency at which we want to segment $\mathbf{x}$. Our goal is to map $\mathbf{x}$ to $\lfloor \tau e \rfloor$ labels where each label represents $i = S/e$ connected samples.

- The input x to *U-Time* are T fixed-length connected segments of signal each of length i. The model $f(x; \theta) : \mathbb{R}^{T \times i \times C} \to \mathbb{R}^{T \times K}$ with parameters θ maps x to K class confidence scores for all T segments. It consists of three submodules; an **encoder**, **decoder** and **segment classifier**.

  - The **encoder** and **decoder** map x to an intermediate, high frequency segmentation in $\mathbb{R}^{T \times i \times K}$. The **segment classifier** performs average pooling over segments of length i to project the segmentation down in frequency to match the labels in $\mathbb{R}^{T \times K}$.
  - The **segment classifier** serves as a trainable link to the intermediate, high frequency segmentation.
  - The segmentation frequency, e, may be increased at inference time.

Experiments

- We evaluated *U-Time* for 'sleep-stage' segmentation of raw EEG data.

- *U-Time* was trained to segment an EEG into sleep stages in the label set {wake, N1, N2, N3, REM} with frequency $e = 1/30$ Hz.

- We evaluated *U-Time* across 7 different datasets *without hyperparameter modifications*. The datasets cover both healthy and diseased populations.

- We compared to single- and multi-channel EEG methods from literature as well as our single-channel re-implementation of the state-of-the-art sleep staging CNN-LSTM described in [1] trained on the *U-Time* pipeline.

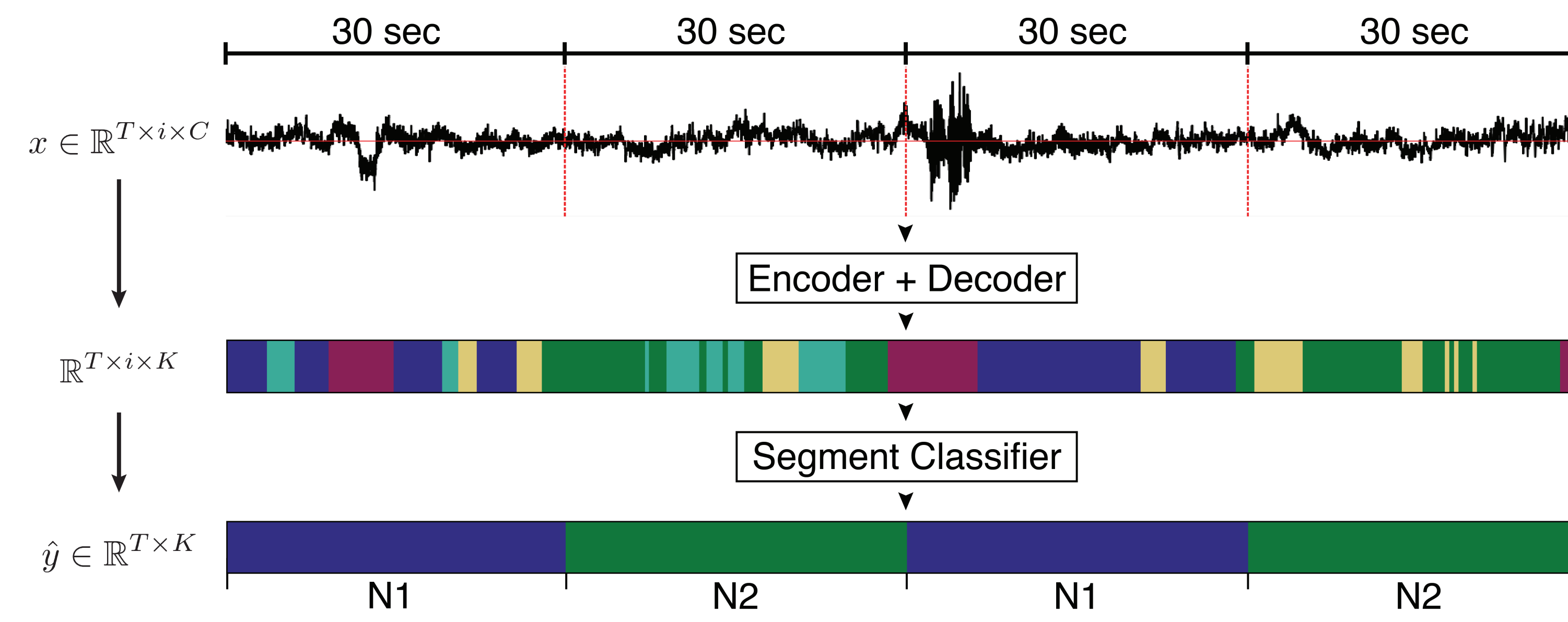- We conducted a large number of baseline hyperparameter experiments on the S-EDF-39 and DCSM datasets.

Figure 1: Illustration of how *U-Time* maps potentially very long input sequence to segmentations at a chosen temporal scale (here 1/30 Hz) by first segmenting the signal at every data-point and then aggregating these scores to form final predictions.
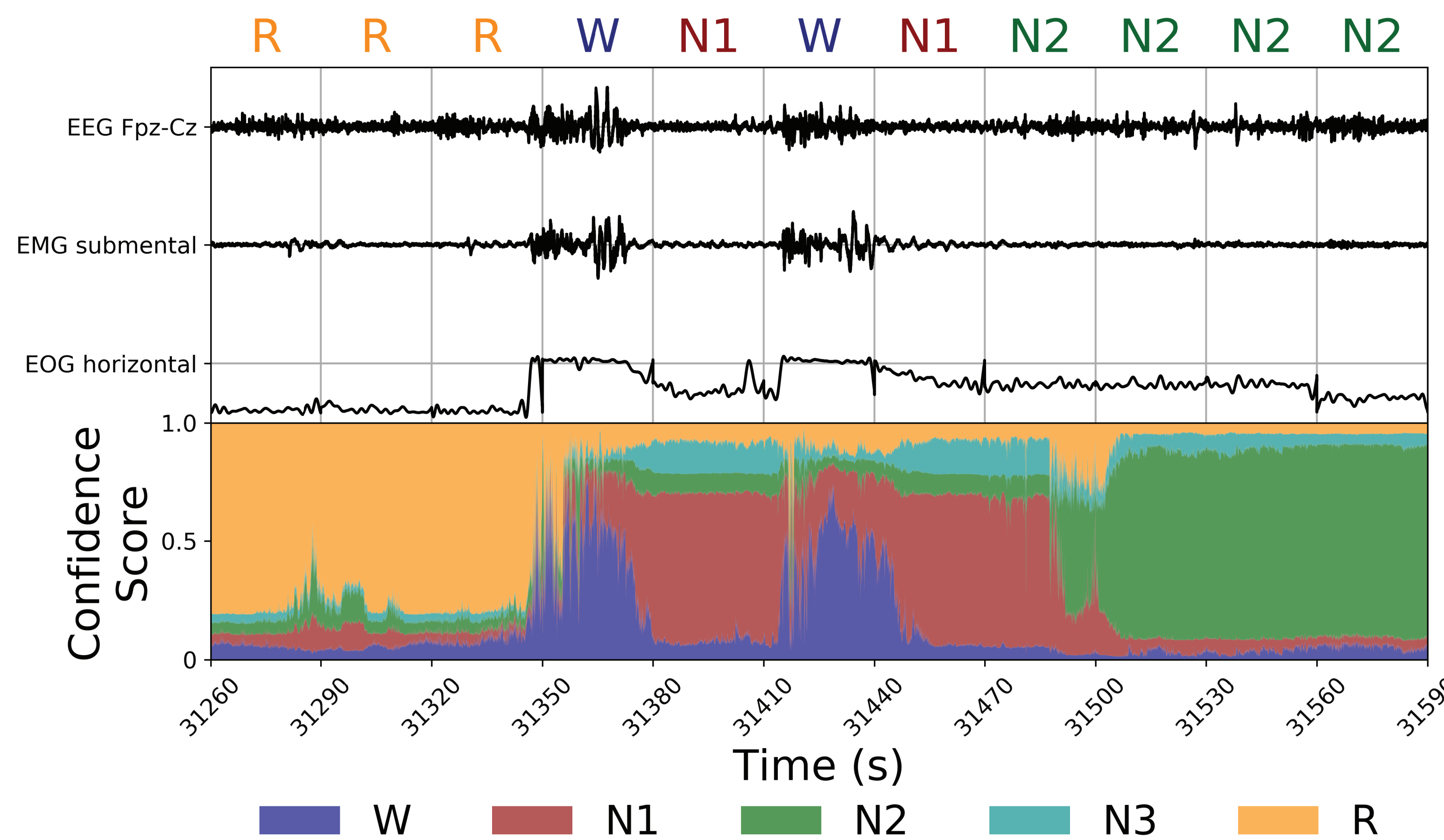

Figure 2: Visualization of the class confidence scores of *U-Time* on three input channels of a test subject from the Sleep-EDF-153 dataset. The segmentation frequency is set to match the input signal frequency of 100 Hz. I.e. *U-Time* outputs 100 sleep stage scorings per second.

Dataset	Size	Sample Rate	Channel	Scoring	Disorders
S-EDF-39	39	100	Fpz-Cz	R&K	None
S-EDF-153	153	100	Fpz-Cz	R&K	None
Physio-2018	994	200	C3-A2	AASM	Non-specific sleep disorders
DCSM	255	256	C3-A2	AASM	Non-specific sleep disorders
ISRUC	99	200	C3-A2	AASM	Non-specific sleep disorders
CAP	101	100-512	C4-A1/C3-A2	R&K	7 types of sleep disorders
SVUH-UCD	25	128	C3-A2	R&K	Sleep apnea, primary snoring

Table 1: Datasets overview. The 'Size' column gives the number of subjects included in our study, 'Sample Rate' lists the original rate in Hz, and 'Scoring' reports the annotation protocol (R&K = Rechtschaffen and Kales, AASM = American Academy of Sleep Medicine).

Results

Dataset	Model	Eval		Global F1 scores					
		Records	CV	W	N1	N2	N3	REM	mean
S-EDF-39	*U-Time*	39	20	0.87	0.52	0.86	0.84	0.84	0.79
	CNN-LSTM[1]	39	20	0.85	0.47	0.86	0.85	0.82	0.77
	VGGNet[2]	39	20	0.81	0.47	0.85	0.83	0.82	0.76
	CNN[3]	39	20	0.77	0.41	0.87	0.86	0.82	0.75
	Autoenc.[4]	39	20	0.72	0.47	0.85	0.84	0.81	0.74
S-EDF-153	*U-Time*	153	10	0.92	0.51	0.84	0.75	0.80	0.76
	CNN-LSTM	153	10	0.91	0.47	0.81	0.69	0.79	0.73
Physio-18	*U-Time*	994	5	0.83	0.59	0.83	0.79	0.84	0.77
	CNN-LSTM	994	5	0.82	0.58	0.83	0.78	0.85	0.77
DCSM	*U-Time*	255	5	0.97	0.49	0.84	0.83	0.82	0.79
	CNN-LSTM	255	5	0.96	0.39	0.82	0.80	0.82	0.76
ISRUC	*U-Time*	99	10	0.87	0.55	0.79	0.87	0.78	0.77
	CNN-LSTM	99	10	0.84	0.46	0.70	0.83	0.72	0.71
	Human obs.	99	-	0.92	0.54	0.80	0.85	0.90	0.80
CAP	*U-Time*	101	5	0.78	0.29	0.76	0.80	0.76	0.68
	CNN[5]	104	5	0.77	0.35	0.76	0.78	0.76	0.68
	CNN-LSTM	101	5	0.77	0.28	0.69	0.77	0.75	0.65
SVUH-UCD	*U-Time*	25	25	0.75	0.51	0.79	0.86	0.73	0.73

Table 2: *U-Time* results across 7 datasets. *U-Time* and our CNN-LSTM baseline process single-channel EEG data. Referenced models process single- or multi-channel EEG data. F1 scores are computed across all subjects. Please refer to the supplementary material for per-subject summary metrics.

- Without hyperparameter tuning, *U-Time* performs at least at the level of methods from literature as well as the CNN-LSTM baseline.

- *U-Time* performs at near human (expert) level performance.

- (Supplementary) We were not able to improve the CNN-LSTM baseline on neither S-EDF-153 nor DCSM across 13 architectural modifications.

- (Supplementary) *U-Time* might benefit from accepting multiple input channels. Expectedly, including an EOG (eye-movement) channel improves performance on the REM sleep stage.

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