

# EEG Artifact Detection via Time series Segmentation (EAD)

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# EAD – Introduction



- Electroencephalography (**EEG**) is an invaluable tool in medicine and research.
- **EEG data** is highly susceptible to disturbances (**artifacts**).
- Removing artifacts enables better diagnosis and sharper analysis.

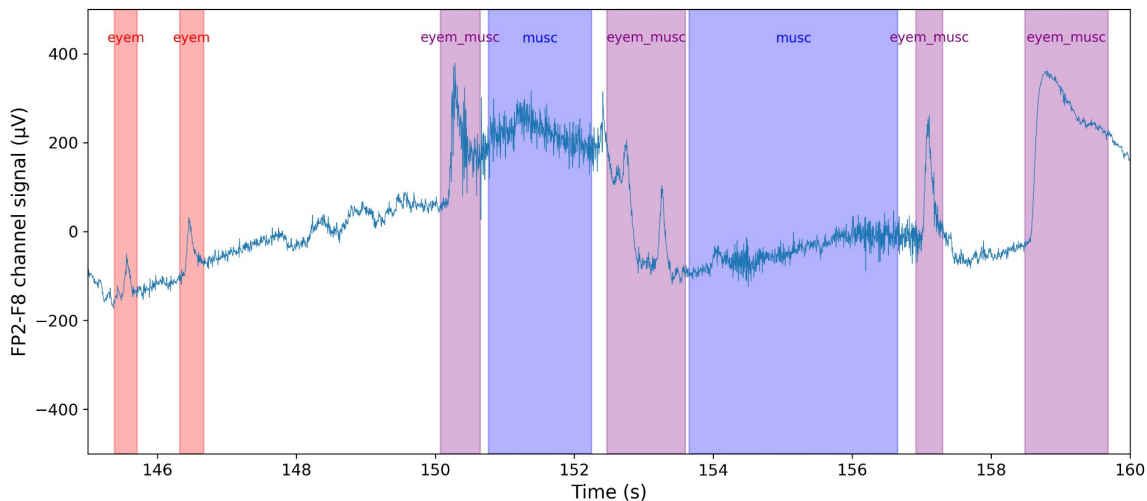
[1]

# EAD – Overview of EEG recordings

Key technical characteristics of EEG recordings include:

- **Montage** used while recording (which **determines** the **channels**).
- Duration.
- Recording **frequency** (e.g. 250 Hz).

[1]



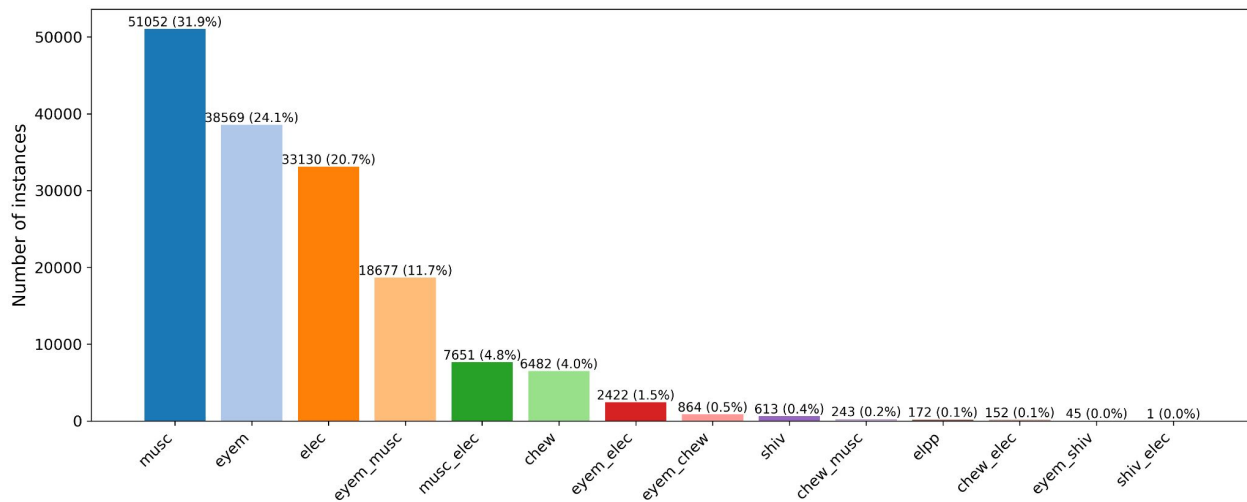
An example that showcases a snippet of EEG data with artifacts. Here, for clarity purposes, only a single channel, namely the FP2-F8 channel, is shown.

# EAD – Methods – TUAR Dataset

Relevant information about the TUAR dataset:

- **310 EEG recordings** (~100 hours total).
- **213 patients** (54% F., 46% M.).
- **160073 artifact instances.**
- **1901 hours of data \*.**

[1]



The number of EEG artifacts in TUAR by kind (class)

Label	musc	eyem	elec	chew	shiv	elpp
Significance	stands for and represents muscle movement	stands for and represents eye movement	represents all kinds of electrical related events	stands for and represents chewing	stands for and represents shivering	un-specified

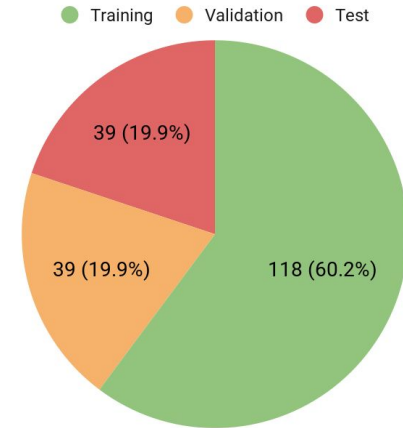
The different artifact classes' labels and what they represent.  
Compound labels signify both events happening at the same time.

\* 1901 hours of data after removing seizure recordings.

# EAD – Methods – Preprocessing

The preprocessing steps that were taken:

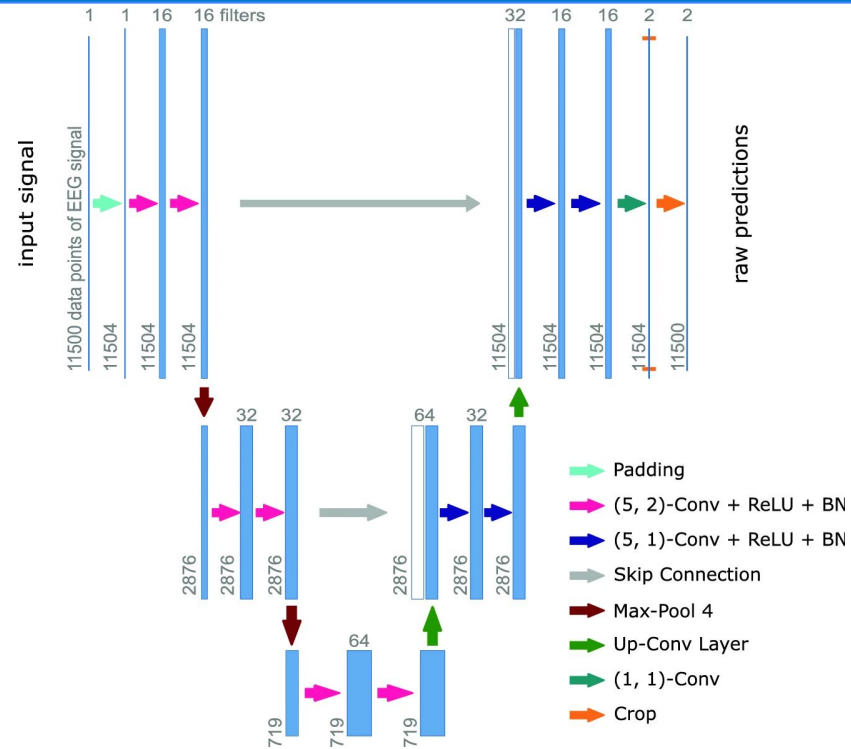
1. **Removing seizure** recordings. → ~~310~~ **268 EEG recordings** from ~~213~~ **196 patients**
2. **Recomputing** the EEG data in the **TCP montage**.
3. **Splitting data** into training, validation, and test sets. →
4. **Filtering** channels' **signals** with a 5th-order **Butterworth** band-pass filter (**0.5-80 Hz**)
5. Applying a **60 Hz Notch filter** (quality factor 15)
6. **Downsampling** signals to **170 Hz**.
7. **Clipping** values **outside** the **-500 to 500  $\mu$ V** range.
8. **Segmenting** data into **10-second** segments.



Number of patients per split

# EAD – Methods – SUMOv2 Model

We use **SUMOv2** [1], a **U-Net** [2]  
**based model** with two decoder  
and two encoder blocks.



SUMOv2 architecture. This architecture diagram has been copied from the original SUMO paper. More information and details about SUMO can be found in said paper too [3].

[1]: Grieger N, Mehrkanoon S *et al.* From Sleep Staging to Spindle Detection: Evaluating End-to-End Automated Sleep Analysis.

[2]: Ronneberger O, Fischer P, and Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation.

[3]: Kaulen L, Schwabedal JTC, Schneider J *et al.* Advanced sleep spindle identification with neural networks.

# EAD – Methods – Metrics: F1-Score

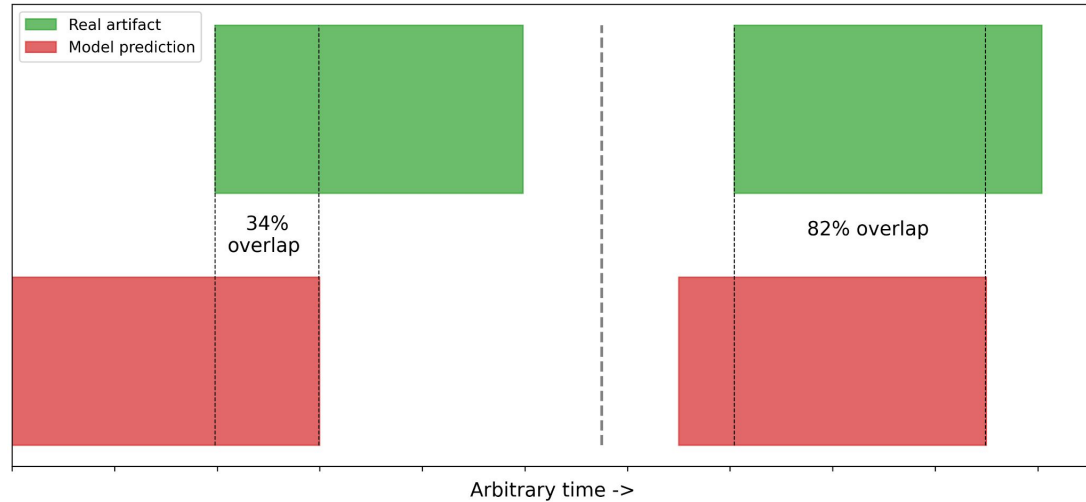
$$F1 = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

Where **TP**, **FP**, and **FN** stand for **True Positive**, **False Positive**, and **False Negative**, respectively.

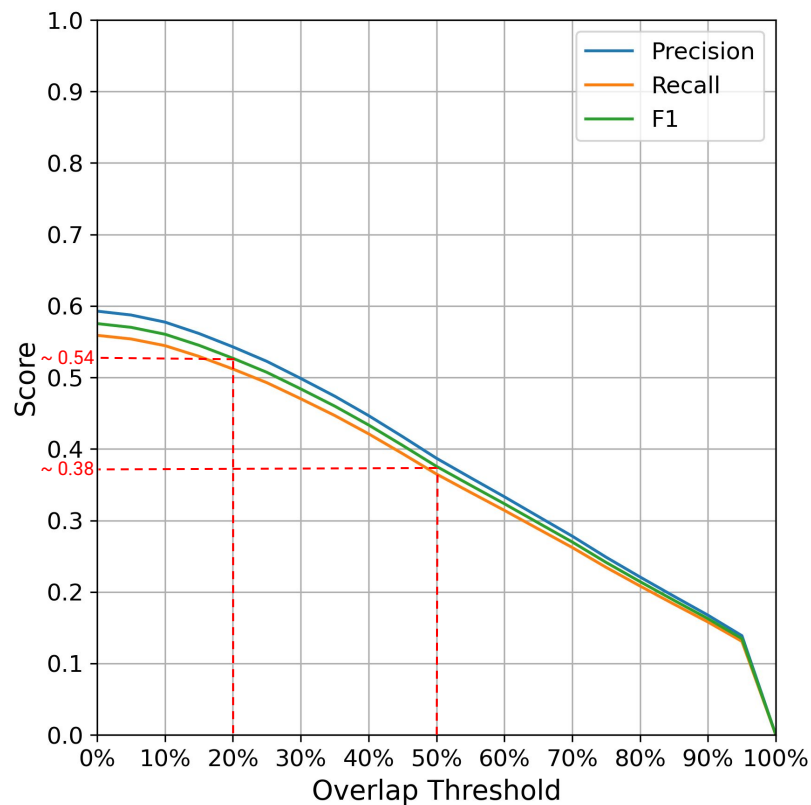
[1]



An illustrative example to help the explanation of the overlap threshold of TP, FP, and FN.

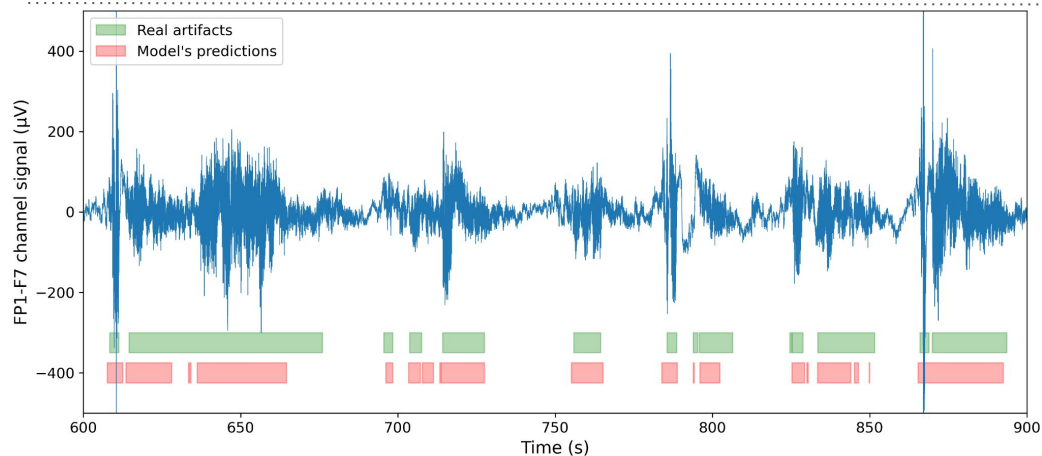
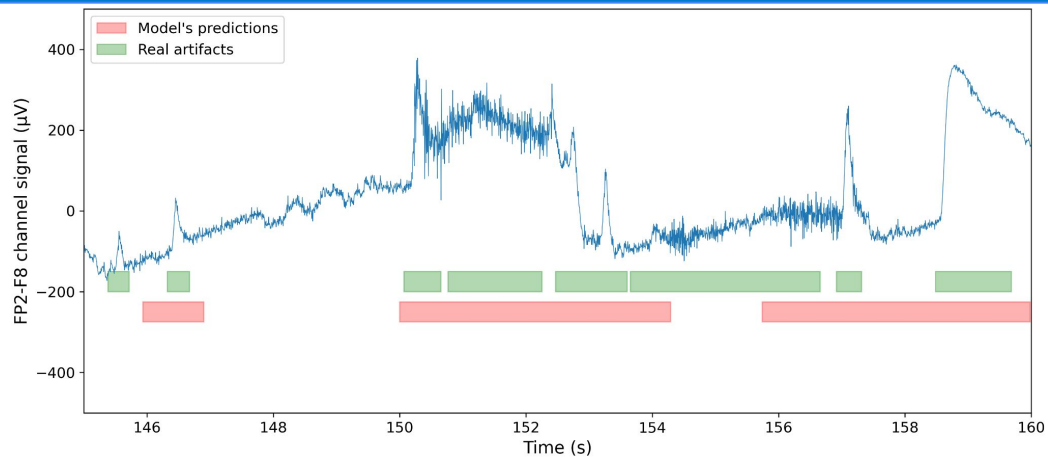


# EAD – Results



The model's F1 score over different overlap thresholds

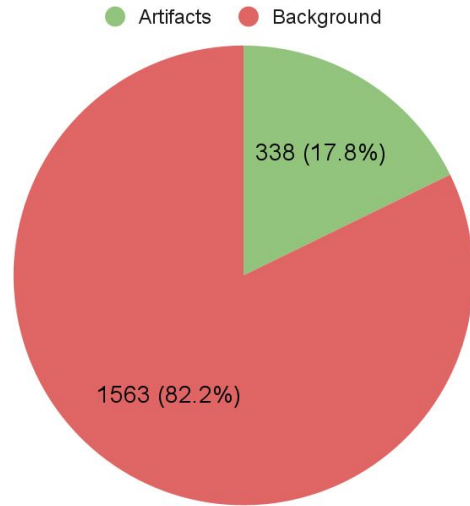
# EAD – Results – Predictions examples



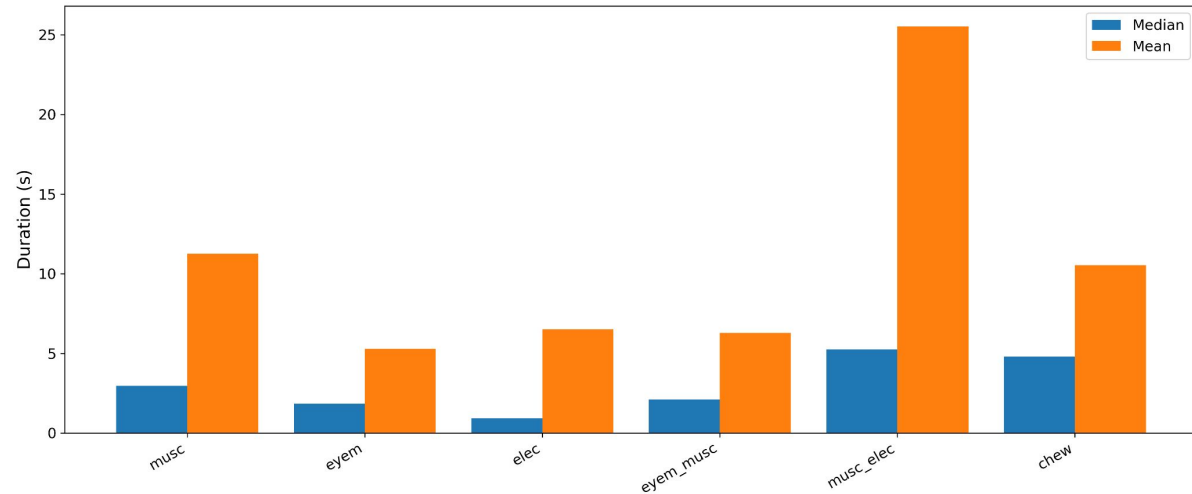
Two examples of the model's predictions of where the artifacts are

# EAD – Discussion

Hypotheses that could explain the achieved results:



The amount of artifacts and background data in hours.  
(After removing seizure recordings.)



The median vs. the mean of the duration of the 6 most common artifact classes

# EAD – Summary

In this presentation, we covered:

- what **EEG recordings** are,
- relevant information about the **TUAR dataset**,
- the U-Net based model **SUM0v2** that we used,
- the **F1-Score** metric used for evaluation,
- the **results** we achieved,
- and, finally, potential reasons for the model's performance and ways in which the results could be improved.

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Thank you for your attention!

Please feel free to ask any questions!