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Towards Interpretable Seizure Detection Using Wearables

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Pathology Dynamics

Importance of Interpretability in Healthcare

1. **Ethical considerations**: serious implications for patients' well-being so methods need to be understood and justified by healthcare professionals and patients themselves.
2. **Trust and accountability**: helps to build trust and accountability by providing transparency into the decision-making process
3. **Clinical decision-making**: provide clear and actionable insights that can be easily understood by healthcare professionals
4. **Regulatory compliance**: compliance with strict regulations by providing clear and transparent explanations of the decisions

[1] Andre Esteva, Alexandre Robicquet, Bharath Ramsundar, Volodymyr Kuleshov, Mark DePristo, Katherine Chou, Claire Cui, Greg Corrado, Sebastian Thrun, and Jeff Dean. A guide to deep learning in healthcare. *Nature medicine*, 25(1):24–29, 2019.
[2] Gregor Stiglic, Primoz Kocbek, Nino Fijacko, Marinka Zitnik, Katrien Verbert, and Leona Cilar. Interpretability of machine learning-based prediction models in healthcare. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(5):e1379, 2020.

Types of Interpretability

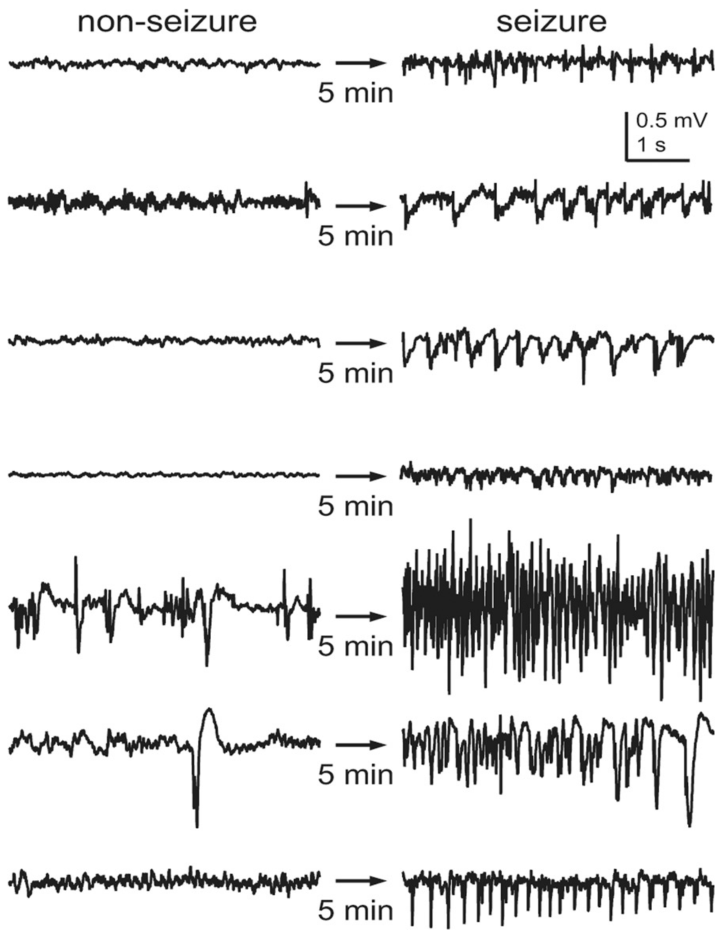
1. Intrinsic: by restricting the complexity of the machine learning model
2. Post hoc: applying methods that analyze the model after training

Result of the interpretation method:

- Feature summary statistic
- Feature summary visualization
- Model internals
- Data point
- Intrinsically interpretable model

[1] Molnar, C., 2020. *Interpretable machine learning*. Lulu. com.

Seizure vs Non-Seizure



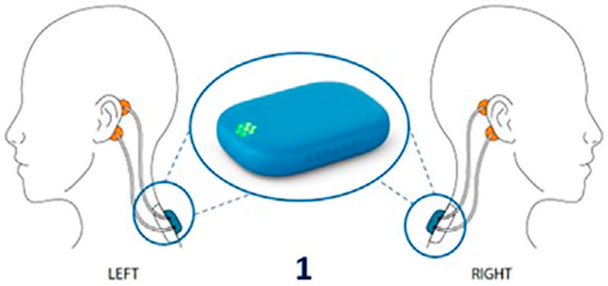
[2]

[1] Cho, KO., Jang, HJ. Comparison of different input modalities and network structures for deep learning-based seizure detection. *Sci Rep* **10**, 122 (2020). https://doi.org/10.1038/s41598-019-56958-y

Seizure Detection Challenge – Task 1 Overview

Task 1: Machine Learning Model Development

- Objective: Develop a machine learning model for detecting seizures in wearable SensorDot data from behind-the-ear EEG (bhe-EEG).
- Training set: SeizeIT1 dataset (vEEG, bhe-EEG, ECG) [1]
- Test set: Data from wearable SD device
  - Input: Wearable EEG data from the SD device and/or single-channel ECG data
  - Output: Seizure and non-seizure labels for each second of recording



Wearable behind the ear device [2]

[1] Chatzichristos, C., Swinnen, L., Macea, J., Bhagubai, M., Van Paesschen, W. and De Vos, M., 2022. Multimodal detection of typical absence seizures in home environment with wearable electrodes. Frontiers in Signal Processing, 2.

Seizure Detection Challenge

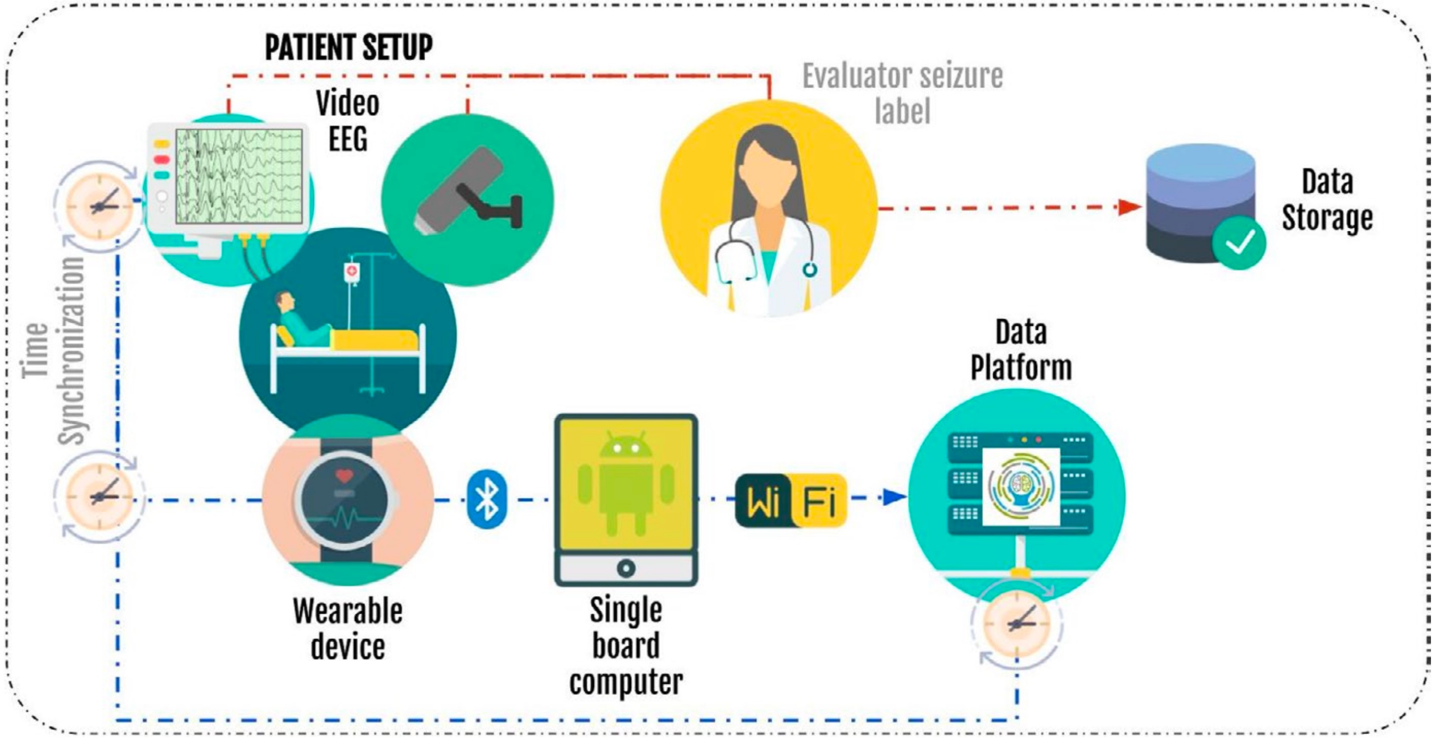
Task 2: Data-centric Seizure Detection

- Objective: Optimize data quality and representation for seizure detection.
  - Apply pre-processing techniques, data-augmentation, subsampling strategies etc.
  - Develop a training set to feed the model
- Training set: Same as Task 1, i.e., SeizeIT1 dataset (vEEG, bhe-EEG, ECG) [1]
- Provided Model: Adapted version of ChronoNet [2], a mixed convolutional and recurrent neural network.

[1] Chatzichristos, C., Swinnen, L., Macea, J., Bhagubai, M., Van Paesschen, W. and De Vos, M., 2022. Multimodal detection of typical absence seizures in home environment with wearable electrodes. Frontiers in Signal Processing, 2.

[2] Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Har- rer, "Chrononet: a deep recurrent neural network for abnormal eeg identification," in Artificial Intelligence in Medicine: 17th Conference on Artificial Intelligence in Medicine, AIME 2019, Poznan, Poland, June 26–29, 2019, Proceedings 17. Springer, 2019, pp. 47–56.

Wearable Seizure Detection Setup



Typical setup to acquire wearable data for seizure annotation [1]

[1] Bruno, E, Böttcher, S, Viana, PF, Amengual-Gual, M, Joseph, B, Epitashvili, N, et al. Wearable devices for seizure detection: Practical experiences and recommendations from the Wearables for Epilepsy And Research (WEAR) International Study Group. *Epilepsia*. 2021; 62: 2307–2321. https://doi.org/10.1111/epi.17044

SeizFt Method

Task 1

Augmentation using Fourier Transform (FT) Surrogates [1] → Feature Extraction → CatBoost Classifier

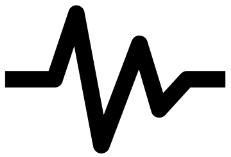
Task 2

Augmentation using Fourier Transform (FT) Surrogates [1] → Reweighting of each class → ChronoNet [2]

[1] Schwabedal, J.T., Snyder, J.C., Cakmak, A., Nemati, S. and Clifford, G.D., 2018. Addressing class imbalance in classification problems of noisy signals by using fourier transform surrogates. arXiv preprint arXiv:1806.08675.
[2] Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Har- rer, “Chrononet: a deep recurrent neural network for abnormal eeg identification,” in Artificial Intelligence in Medicine: 17th Conference on Artificial Intelligence in Medicine, AIME 2019, Poznan, Poland, June 26–29, 2019, Proceedings 17. Springer, 2019, pp. 47–56.

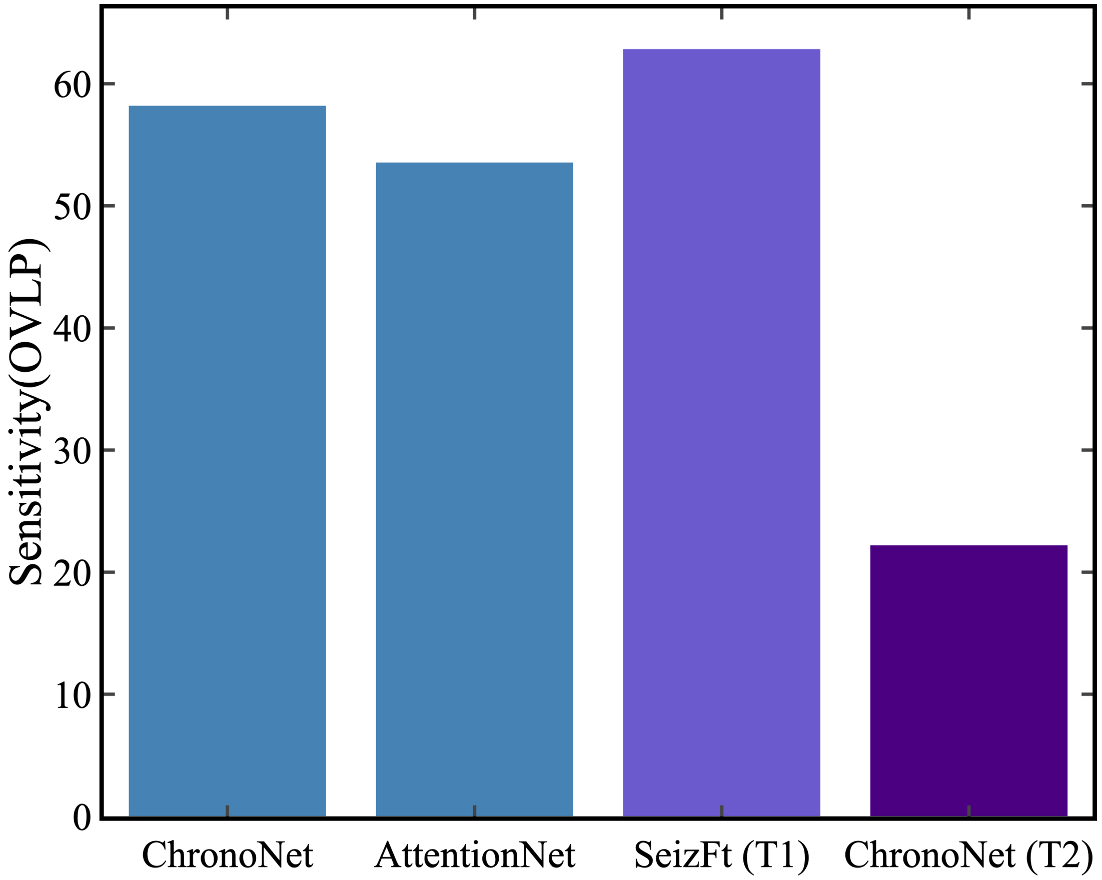
Features in SeizFt

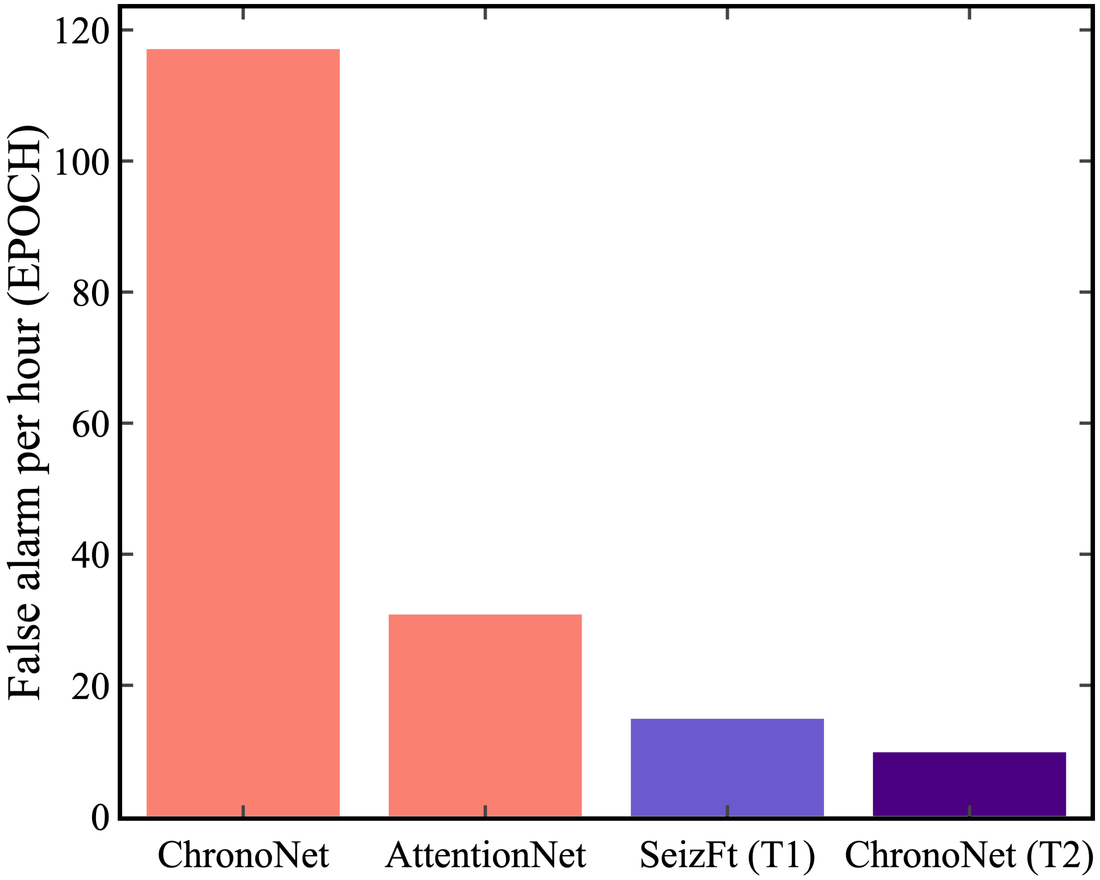
- Features inspired by prior work on sleep stage classification [1]
- Time domain features such as Kurtosis, Skewness, Hjorth Mobility, etc.
- Spectral Features such as Binned Fourier Entropy, Spectral Fourier Statistics, etc.



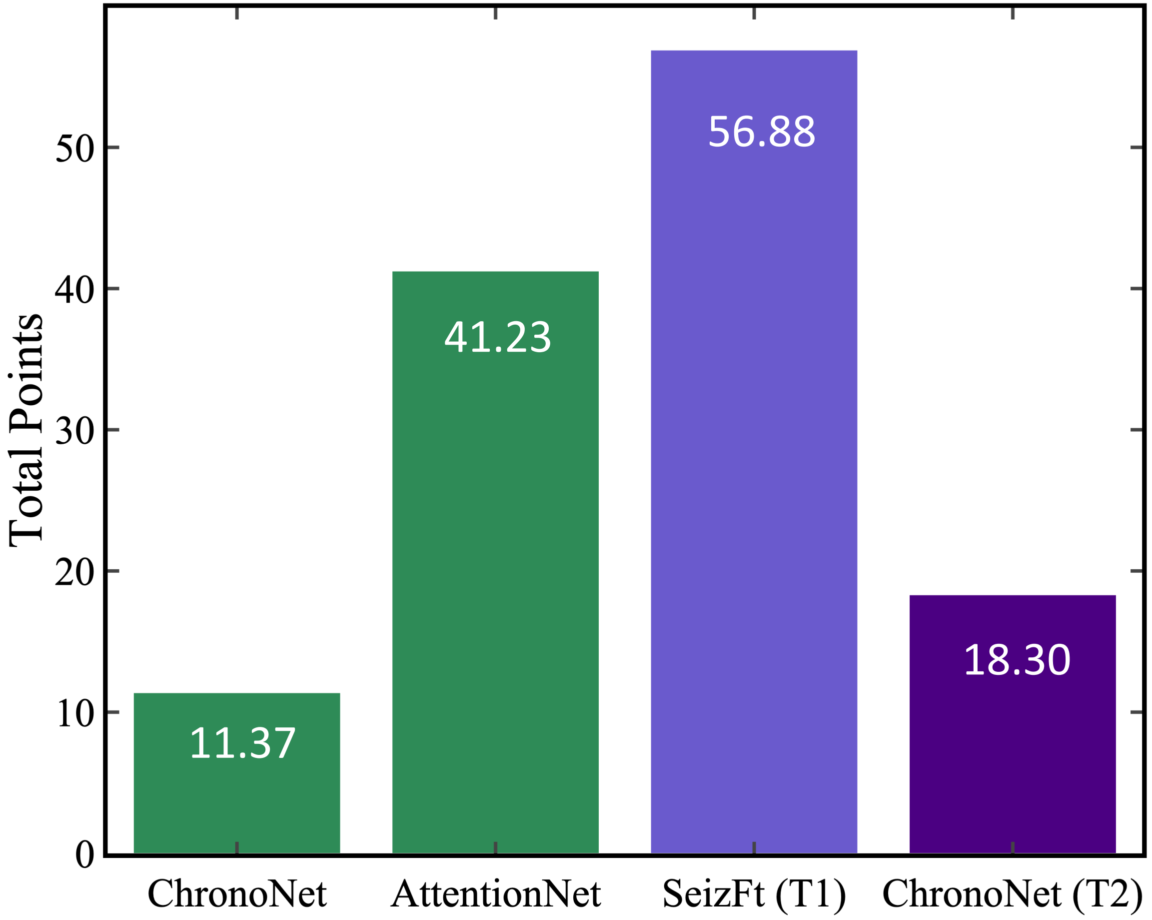
[1] Van Der Donckt, J., Van Der Donckt, J., Deprost, E., Vandenbussche, N., Rademaker, M., Vandewiele, G. and Van Hoecke, S., 2023. Do not sleep on traditional machine learning: Simple and interpretable techniques are competitive to deep learning for sleep scoring. *Biomedical Signal Processing and Control*, *81*, p.104429.

Sensitivity & False Alarm Per Hour

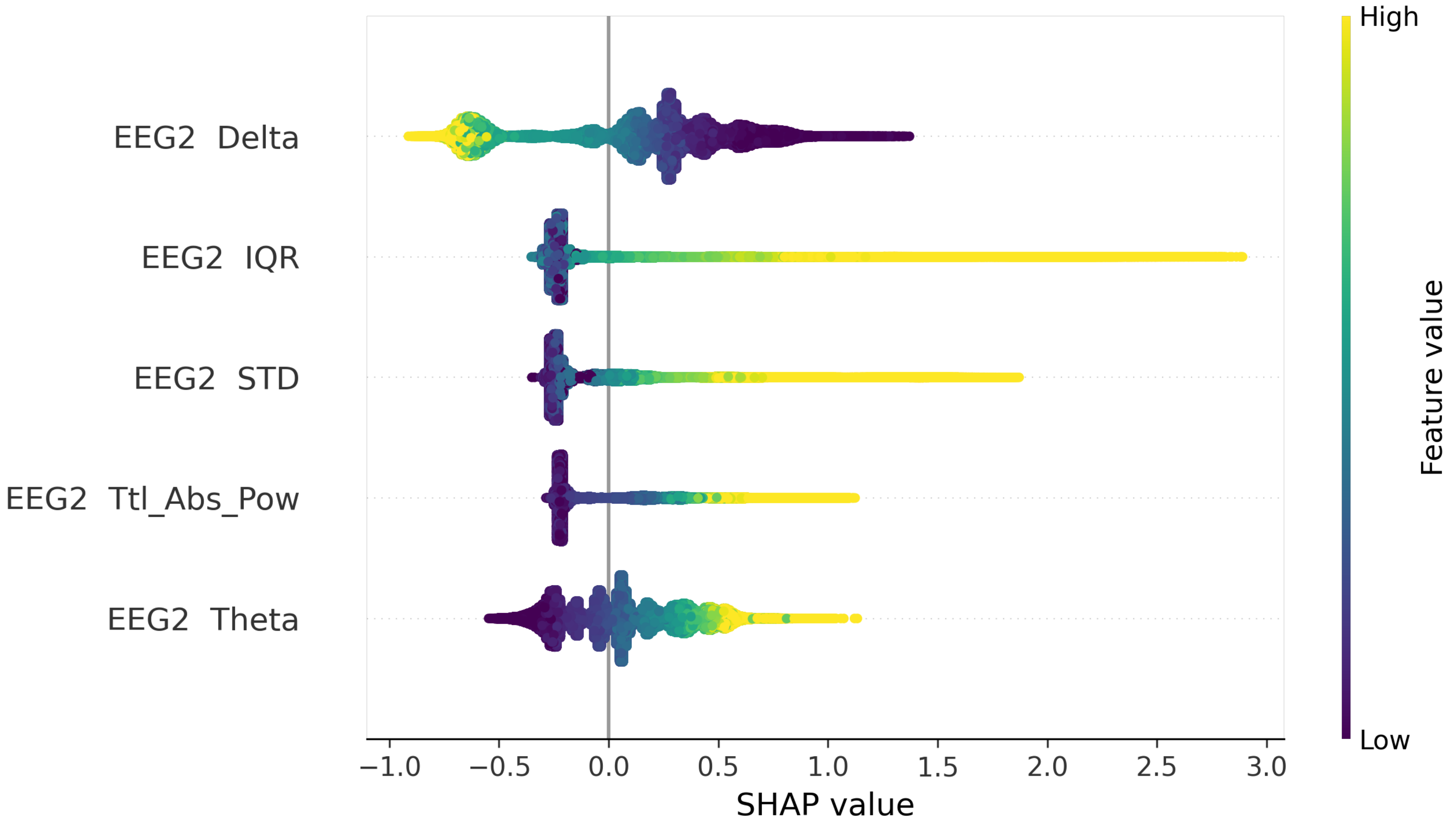




Total Points



SHAP values of 5 most important features



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Acknowledgment: