Towards Interpretable Seizure Detection Using Wearables

Irfan Al-Hussaini, Cassie S. Mitchell
Georgia Institute of Technology
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

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

Seizure vs Non-Seizure

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

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.


Wearable Seizure Detection Setup

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

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]


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.

Sensitivity & False Alarm Per Hour

**Sensitivity (OYLP):**
- ChronoNet
- AttentionNet
- SeizFt (T1)
- ChronoNet (T2)

**False alarm per hour (EPOCH):**
- ChronoNet
- AttentionNet
- SeizFt (T1)
- ChronoNet (T2)
Total Points

- ChronoNet: 11.37
- AttentionNet: 41.23
- SeizFt (T1): 56.88
- ChronoNet (T2): 18.30
SHAP values of 5 most important features

- EEG2 Delta
- EEG2 IQR
- EEG2 STD
- EEG2 Ttl_Abs_Pow
- EEG2 Theta
Towards Interpretable Seizure Detection Using Wearables

Irfan Al-Hussaini, Cassie S. Mitchell
Georgia Institute of Technology
alhussaini.irfan@gatech.edu, cassie.mitchell@bme.gatech.edu

Acknowledgment: