Investigating the Need for Pediatric-Specific Automatic Seizure Detection

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Approximately 1 in every 150 children is diagnosed with epilepsy during the first ten years of life [1]. These children experience seizures, which disrupt their lives and directly harm the developing brain. Electroencephalography (EEG) is the main tool used clinically to diagnose seizures and epilepsy. However, the interpretation of EEGs requires time-consuming expert analysis [2]. Automated detection systems are a powerful tool that can help address the issue by reducing expert annotation time. Research on the automatic detection of seizures in pediatric EEG has been limited. Most seizure detection methods have been developed and tested using larger numbers of adult EEG [3, 4]. However, research has shown that brain events in EEG change with ageing [5, 6]. Therefore, model trained on EEGs from adults may not be be suitable for children. To test this hypothesis, we trained a seizure detection model on adult EEG and tested on adult and pediatric EEG recordings.

The TUH seizure corpus v 1.5.1 from Temple University Hospital's (TUH) Department of Neurology, the world's largest publicly available database of clinical EEG data [7], was used in this study. The EEG recordings are sampled at different sampling frequencies of 250Hz, 256Hz, 400Hz, and 1000Hz, therefore, we resampled the data to 256Hz. Power line interference was removed by a notch filter (60Hz), and DC offset was also removed. A combination of vertical and horizontal bipolar skin for TUH-EEG data was applied to create 22 different channels (channels F7-T3, F8-T4, FP1-F7, FP2-F8, FP1-F3, FP2-F4, T5-O1, T6-O2, T3-T5, T4-T6, A1-T3, T4-A2, C3-CZ, CZ-C4, T3-C3, C4-T4, P3-O1, P4-O2, C3-P3, C4-P4, F3-C3 and F4-C4) [8].

In order to evaluate whether models trained on adult EEGs are suitable for children, we divided the TUH seizure corpus v 1.5.1 (5,610 EEG recordings) into two different age groups: adults aged 21 - 90 years (5,418 EEG recordings) and children aged 1 - 20 years (192 EEG recordings). 4,449 adult EEG recordings were used to train the model, and 490 were used for validation. An additional 509 adult and 192 pediatric EEGs were used for independent testing of the model.

A random forest classifier (Scikit-learn library "RandomForest" package) was used to develop the seizure detection model within the Python 3.6 environment. We used ten channels to train our model: FP1-F7, FP2-F8, FP1-F3, FP2-F4, P3-O1, P4-O2, C3-P3, C4-P4, F3-C3, and F4-C4 (220 features in total). 1s epochs with 0.5s overlap were used to estimate twenty-two features in each channel, and each epoch corresponds to a seizure event or non-seizure event. The features from each channel are: the mean, standard deviation, signal envelope, kurtosis, skewness, complexity, mobility, Teager-Kaiser energy operator (TKEO), variance and fractal dimension of the pre-processed absolute amplitude of EEG recordings. Relative and absolute band power of delta (0-4 Hz), theta (4-8 Hz), alpha (8–16 Hz), beta (16-32 Hz), gamma (32-64 Hz), the absolute band power of the EEG amplitude and the sum of relative beta and gamma were also estimated as features for developing the seizure detection model.

Our model achieved a sensitivity of 82.7%, 69.3% and 67.5% on the training, validation and independent test set for adult TUH EEG recordings, respectively. The specificity for adult TUH EEG data on the training, validation and independent test sets was 79.7%, 72.3% and 71.1%, respectively. The model achieved 91.9% sensitivity on the TUH pediatric EEG test set, with only 49.8% specificity, demonstrating that this model is unsuitable for pediatric seizure detection.

In summary, research on automatic seizure detection methods mainly focuses on adults and research on pediatric EEG is limited. We find that a seizure detection model trained on adult EEGs is not suitable for children. Therefore, there is a need to develop a pediatric-specific method. In future work, we will develop a pediatric-specific automatic seizure detection method on a large number of pediatric EEG recordings to assist clinicians in analysing seizure events in children. The limitation of the work is that as machine learning is a "black box" method, clinicians may have difficulty trusting machine learning-based methods. Explainable AI (XAI) can be described as aiming to make machine learning algorithms more understandable to humans [9]. We will use XAI in future work to gain users' trust in automatic seizure detection methods and assist experts' analysis of EEG.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 Research and Innovation Programme under the NeuroInsight Marie Skłodowska-Curie grant agreement No. 101034252. We acknowledge the Research IT HPC Service at University College Dublin for providing computational facilities and support that contributed to the research results reported in this paper.

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Introduction

- EEG is the main tool used clinically to diagnose seizures and epilepsy.
- The interpretation of EEGs requires time-consuming expert analysis.
- Automated detection systems are a powerful tool that can help address the issue by reducing expert annotation time.
- Approximately 1 in every 150 children is diagnosed with epilepsy during the first ten years of life.
- Research on the automatic detection of seizures in pediatric EEG has been limited.
- Brain events in EEG change with ageing, model trained on EEGs from adults may not be be suitable for children.

Data

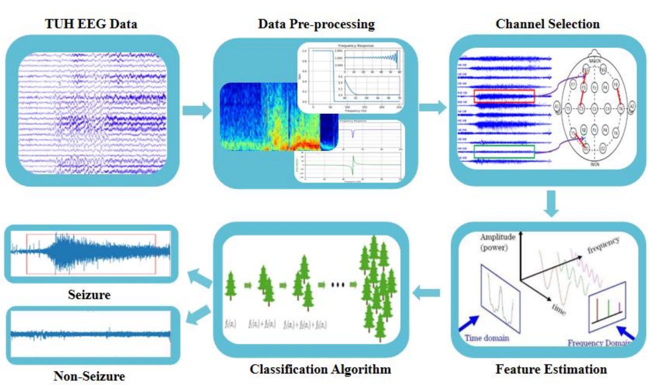
The TUH seizure corpus v 1.5.1 from Temple University Hospital's (TUH) Department of Neurology.

Two different age groups:

- ❑ Adults: aged 21 - 90 years (5,418 EEG recordings)
  - Train: 4,449 adult EEGs
  - Validation: 490 adult EEGs
  - Test: 509 adult EEGs
- ❑ Children: aged 1 - 20 years (192 EEG recordings)
  - Test: 192 pediatric EEGs

Method

- **Remove artefacts:** Powerline interface; DC offset
- **Select channels:** FP1-F7, FP2-F8, FP1-F3, FP2-F4, P3-O1, P4-O2, C3-P3, C4-P4, F3-C3, and F4-C4
- **Feature estimation:** 1s epochs with 0.5s overlap were used to estimate twenty-two features in each channel (each epoch: seizure or non-seizure).
- **Classification:** Random forest classifier

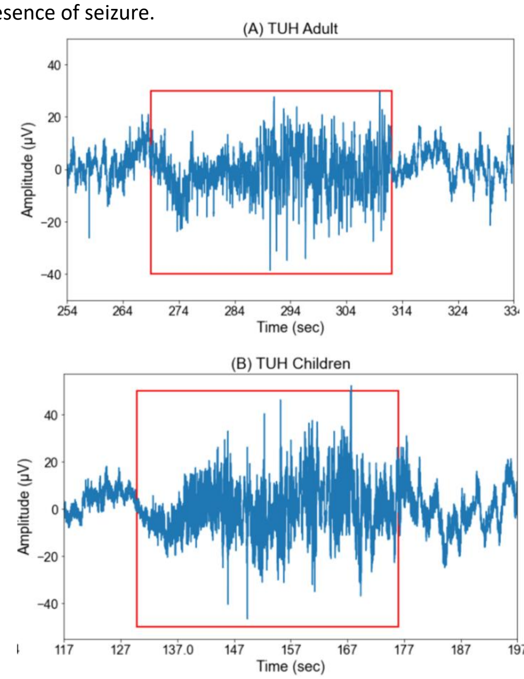


Results

Performance of the random forest-based seizure detection method on the training, validation and independent test set.

	Sens (%)	Spec (%)	Acc (%)	BAcc (%)
Train (adult)	82.7	79.7	79.9	81.2
Validation (adult)	69.3	72.3	72.1	70.8
Test (adult)	67.5	71.1	70.6	69.3
Test (pediatric)	91.9	49.8	53.1	70.9

Figure A and B show examples of the TUH adult and TUH children Focal Non-Specific Seizure in channel C4-P4 (each example with 80 seconds EEG recordings); the signal in the red block indicates the presence of seizure.



Conclusion and Future work

❑ In summary, research on automatic seizure detection methods mainly focuses on adults and research on pediatric EEG is limited. We find that a seizure detection model trained on adult EEGs is not suitable for children. Therefore, there is a need to develop a pediatric-specific method.

❑ In future work, we will develop a pediatric-specific automatic seizure detection method on a large number of pediatric EEG recordings to assist clinicians in analysing seizure events in children.

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This publication has emanated from research supported in part by a research grant from Service Foundation Ireland (SFI) under Grant Number 16/RC/3948 and co-funded under the European Regional Development Fund and by FutureNeuro industry partners.