Investigating the Need for Pediatric-Specific Machine Learning Approaches for Seizure Detection in EEG

Lan Wei
FutureNeuro SFI Research Centre
School of Computer Science
University College Dublin
Dublin, Ireland
lan.wei@ucd.ie

Catherine Mooney*
FutureNeuro SFI Research Centre
School of Computer Science
University College Dublin
Dublin, Ireland
catherine.mooney@ucd.ie

***Abstract*—Approximately 1 in every 150 children is diagnosed with epilepsy during the first ten years of life. These children experience seizures, which disrupt their lives and directly harm the developing brain. EEG is a key tool for the non-invasive recording of brain activity and the diagnosis of epilepsy. However, the interpretation of EEGs requires time-consuming expert analysis. Automated seizure detection can help to reduce the time required to annotate EEGs. Research on seizure detection methods mainly focuses on adult EEG; automated seizure detection methods in paediatric EEG has been limited. Research has shown that brain events in EEG change with ageing. Therefore, adult-based seizure detection methods maybe not be suitable for children. In this study, we present a random forest-based seizure detection method developed using TUH adult EEG. 4,449 adult EEG recordings were used to train the method, and 490 adult EEG recordings were used to validate the method. An additional 509 TUH adult EEG and 192 TUH pediatric EEG were used for independent testing of the method. The CHB-MIT pediatric EEG Database (N=668) was used as an external independent test set. Ten channels were selected, and twenty-two features were estimated from each channel to develop the method. The random forest-based method achieved 69.3% balanced accuracy on the independent test set of TUH adult EEG and 70.9% on the independent test set of TUH pediatric EEG. However, balanced accuracy on the paediatric CHB-MIT independent test set was only 50.8%. Additionally, specificity was very low on both the TUH pediatric and CHB-MIT independent test sets (49.8% and 10.3% respectively). These result shows that the adult-based seizure detection method is unsuitable for children. There is a need to develop seizure detection methods specifically for paediatric EEG.**

***Index Terms*—TUH-EEGs, CHB-MIT, Adult seizure detection, Pediatric seizure detection, Machine learning**

I. Introduction

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. Epilepsy is caused by disruption of the fine-tuned inhibitory and excitatory balance in brain networks, manifesting clinically as seizures [2]. The diagnosis of epilepsy is particularly challenging in children, and misdiagnosis is common [3].

A diagnosis of epilepsy often carries restrictions on childhood activities and potentially lower educational expectations and career prospects [1]. There is an urgent need for biomarkers to guide epilepsy diagnosis and classification in children, as research has shown that up to 30% of children may be misdiagnosed as having epilepsy [1].

Objective methods that could differentiate between children with and without seizures would allow those with epilepsy to be treated promptly with antiepileptic drugs, and delays could be reduced before other therapies were explored for children without an epilepsy diagnosis [4], [5]. Electroencephalography (EEG) is the main tool used clinically to diagnose seizures and epilepsy. However, the interpretation of EEGs requires time-consuming expert analysis [6]. Moreover, reproducibility between observers is low and complicated by different types of seizures [2].

Automated detection systems are a powerful tool that can help address these issues by reducing expert annotation time and making annotations more reproducible [7]. Research on the automated detection of seizures in pediatric EEG has been limited. A number of pediatric seizure detection methods have been developed [8]–[10] using the CHB-MIT Scalp EEG Database (https://physionet.org/content/chbmit/1.0.0/) [11]. However, the CHB-MIT database is relatively small with only 22 subjects (5 males, ages 3–22; and 17 females, ages 1.5–19). Whether these methods generalise well to other pediatric patients is uncertain. Most seizure detection methods have been developed and tested using larger numbers of adult EEG [12]–[14]. However, research has shown that brain events in EEG change with ageing [15]. Therefore, adult-based method maybe not be suitable for children. There is a need to develop a pediatric-specific seizure detection method, which could dramatically improve the quality of life of children suspected of having epilepsy.

To the best of our knowledge, there is no research to date where a seizure detection method which has been developed for adults has been tested on pediatric EEG, directly comparing differences in seizure events between adults and

children. Here we explore why adult-based seizure detection methods are not suitable for children, the underlying reasons, and potential solutions.

II. Data

A. TUH EEG dataset

The open-source EEG database from Temple University Hospital's (TUH) Department of Neurology is the world's largest publicly available database of clinical EEG data [16]. The TUH seizure corpus v 1.5.1 was used in this study (https://isip.piconepress.com/projects/tuh_eeg/). 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) [17]. This dataset consists of EEG recordings from 642 subjects (ages 1-90 years).

In order to evaluate whether an adult seizure detection method is suitable for children, we divided the TUH seizure corpus v 1.5.1 with 5,610 EEG recordings into two different age groups, adults (ages: 21 - 90, with 5,418 EEG recordings) and children (ages: 1 - 20, with 192 EEG recordings). In this study, 4,449 adult EEG recordings were used to train the method, and 490 adult EEG recordings were used to validate the method. An additional 509 adult EEG and 192 pediatric EEG were used for independent testing of the method. Figure 2 shows examples of the TUH adult and TUH children's focal non-specific seizures in channel C4-P4.

B. CHB-MIT EEG dataset

The CHB-MIT Scalp EEG Database is an open-source EEG database collected at the Children's Hospital Boston (https://physionet.org/content/chbmit/1.0.0/) [11]. CHB-MIT EEG recordings are provided by the Massachusetts Institute of Technology (MIT, USA). Most CHB-MIT EEG contains 18 channels, FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FZ-CZ, CZ-PZ, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8 and P8-O2, collected from 22 subjects (ages 1-22 years). CHB-MIT pediatric EEG recordings (N = 668) were used as an external independent test set for the our method. The detail of the dataset used in this study is shown in Table I and Table II.

TABLE I
TABLE SHOWING THE NUMBER AND DURATION OF SEIZURES AND NON-SEIZURES IN TUH AND CHB-MIT EEG RECORDINGS USED IN THIS STUDY.

	TUH EEG files	CHB-MIT EEG files
Total file number	5,610	668
EEG files with seizure events	1,147	139
Total seizure numbers	3,043	198
Number of seizures/file	2.7	1.4
Average duration/seizure (s)	74.5	58.3
Total seizure duration(s)	226,584	11,550
Total non-seizure duration(s)	3,094,932	3,457,534
Patient number	642	22
Age range	1-90	1-22

III. Methodology

A. Channel Selection

EEG recording is an extremely complex process that requires adaptation to the unique channel configuration of each EEG or clinical site [13]. In order to be able to independently test our method on the CHB-MIT EEG, we chose overlapping channels between the TUH EEG recordings and the CHB-MIT EEG recordings. The ten channels used to train and test the method are FP1-F7, FP2-F8, FP1-F3, FP2-F4, P3-O1, P4-O2, C3-P3, C4-P4, F3-C3, and F4-C4. Figure 1 shows the selected channels used in this study.

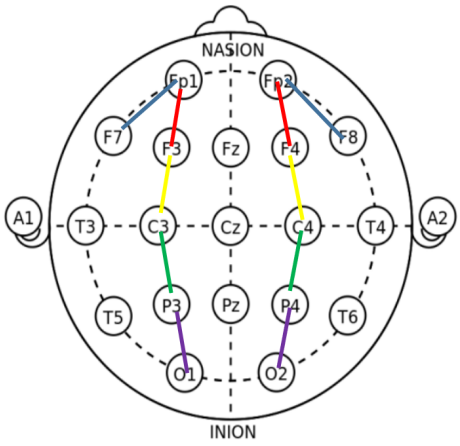

Fig. 1. Figure showing the overlapping channels between the TUH EEG and the CHB-MIT EEG. These channels are FP1-F7, FP2-F8, FP1-F3, FP2-F4, P3-O1, P4-O2, C3-P3, C4-P4, F3-C3, and F4-C4.

B. Data Pre-processing

The CHB-MIT EEG dataset was sampled at 256 Hz, and TUH EEG data were sampled at different sampling frequencies (250Hz, 256Hz, 400Hz, and 1000Hz). Therefore, the TUH EEG signal was resampled to 256Hz in this study. A notch filter (60Hz) was used to remove power line interference, and DC offset was removed from EEG in both data sets. EEG signals were divided into 1s epoch (256 time points) with 0.5s overlap. Each epoch corresponds to a seizure event or non-seizure event.

C. Feature Estimation

Features from time and frequency domain were estimated. A Teager-Kaiser energy operator (TKEO) was applied to distinguish the seizure from the non-seizure EEG signal. Due to the simplicity and ease of implementation of TKEO, it has been shown to be powerful in identifying changes in signal properties in applications such as seizure detection [18]. Butterworth filters (6th order) were used to filter the signals within the frequency bands of interest to reduce the interference of other waves: delta (0.1-4Hz), theta (4-8Hz), alpha (8–16 Hz), beta (16-32 Hz) and gamma (32-64 Hz). 1s epochs with 0.5s overlap were used to estimate 22 features in each channel. We used ten channels to train our models

TABLE II

TABLE SHOWING THE NUMBER AND DURATION OF SEIZURES AND NON-SEIZURES IN TUH AND CHB-MIT EEG RECORDINGS USED IN THIS STUDY.

	Dataset	Files	Number of Seizures	Total Seizure duration (s)	Total Non-seizure duration (s)
TUH	Train (adult)	4,449	2,220	158849.5	2450949.0
	Validation (adult)	460	254	18242.0	250154.0
	Test (adult)	509	355	39396.5	273739.0
	Test (pediatric)	192	214	10096.0	120090.0
CHB-MIT	Test (pediatric)	668	198	11,550.0	3,457,534.0

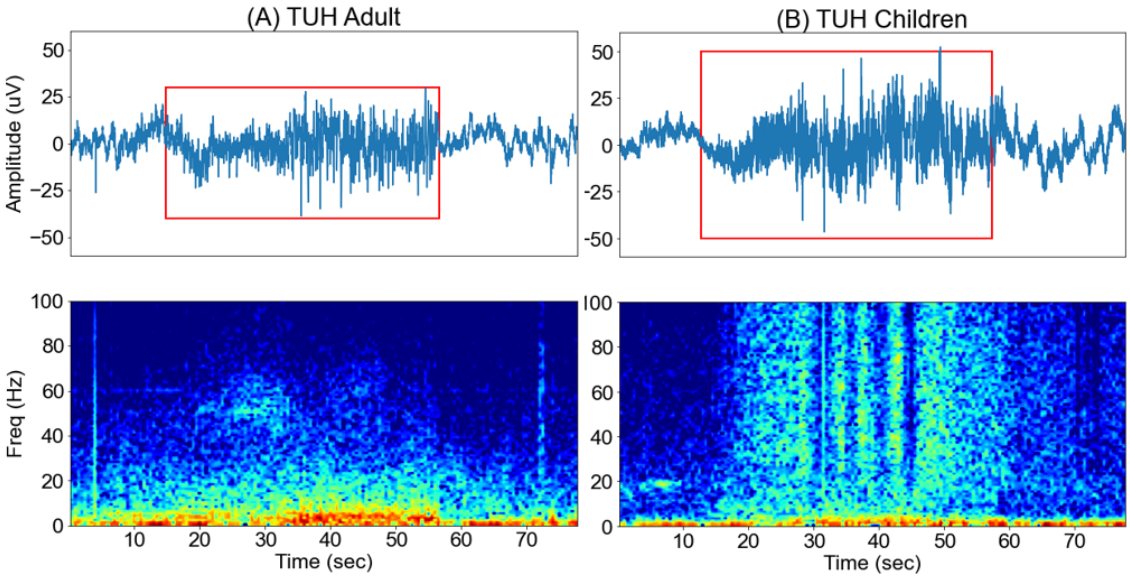

Fig. 2. Figure A and B show examples of the TUH adult and TUH children Focal Non-Specific Seizure in channel C4-P4 (each example with 80 seconds EEG recordings) and corresponding spectrogram; the signal in the red block indicates the presence of seizure.

(220 features in total). The features from each channel are as follows:

Time domain (10): The mean, standard deviation, signal envelope, kurtosis, skewness, complexity, mobility, TKEO, variance and fractal dimension of the pre-processed absolute amplitude of EEG recordings.

$$\text{TKEO[n]} = x[n]^2 - x[n-1]x[n+1] \tag{1}$$

$$FD = \frac{log_{10}^{N}}{log_{10}^{N} + log_{10}^{N/(N+0.4\delta)}} \tag{2}$$

$$\text{Mobility} = \sqrt{\frac{\text{Var}(\dot{x})}{\text{Var}(x)}} \tag{3}$$

Where: N is the number of samples in each epoch; δ is the number of sign changes in the signal derivative in that epoch; $\dot{x}$ is the time derivative of the pre-processed EEG signal x. x[n] is the nth sample, x[n-1] is the (n-1)th sample and x[n+1] is the (n+1)th sample of the pre-processed EEG signal in the epoch. Var (x) is the variance of x estimated for that epoch.

Frequency domain (12): Relative and absolute band power of delta, theta, alpha, beta, gamma, 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 method.

D. Classification Algorithms

Several classification algorithms have been used for seizure detection including neural networks [17], [19], XGboost [20] and support vector machines [21]. Although these methods have been successful in many classification problems, the random forest classifier performed best in this study. The Scikit-learn library "RandomForest" package [22] was used to develop the seizure detection method within the Python 3.6 environment. Figure 3 presents the overview of the developed method.

Four parameters were optimized: n-estimators (the number of trees in the forest), min-samples-split (the minimum number of samples required to split an internal node), min-samples-leaf (the minimum number of samples required to be at a leaf node), and max-depth (the maximum depth of the tree). These parameters were optimized based on the performance of the validation set to improve the performance of the method for the detection of seizures in TUH adult EEG recordings. The n-estimators values were tested from 100 to 500, min-samples-split were tested from 5 to 15, min-samples-leaf were tested from 10 to 30, and max-depth from 2 to 10. The

best performance on the validation set was achieved when n-estimators = 300, min-samples-split = 10, min-samples-leaf = 20 and max-depth = 8.

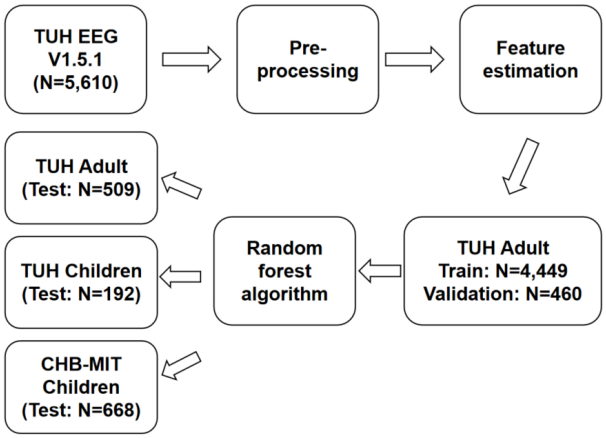

Fig. 3. Overview of the random forest-based adults' seizure detection method. The TUH adult EEG data was used to train the random forest algorithm. TUH adult EEG, TUH pediatric EEG and CHB-MIT pediatric EEG were used for independently testing the method.

E. Performance Evaluation

Automatic seizure detection is a binary classification task, and we used the following metrics to evaluate the performance of our model: sensitivity (Sens), specificity (Spec), accuracy (Acc) and balanced accuracy (BAcc).

$$\begin{aligned} Sens &= \frac{TP}{TP+FN} \\ Spec &= \frac{TN}{TN+FP} \\ Acc &= \frac{TP+TN}{TP+TN+FP+FN} \\ BAcc &= \frac{Sens+Spec}{2} \end{aligned} \tag{4}$$

where: True Positives (TP): the number of seizures predicted as seizures; False Positives (FP): the number of non-seizures predicted as seizures; True Negatives (TN): the number of non-seizures predicted as non-seizures; False Negatives (FN): the number of seizures predicted as non-seizures.

IV. Results

A. Comparison of seizure events in EEG recordings of adults and children

Table V shows the mean absolute amplitude of the seizure events in each selected channel. Comparing the TUH adult EEG and TUH pediatric EEG, it is clear that the mean absolute amplitude of the seizure events in pediatric EEG is much higher than the adult EEG.

B. Feature importance

Figure 4 shows the random forest-based feature importance plot (top 10) in the training set. These top 10 features are 1) C3-P3 variance, 2) C3-P3 standard deviation, 3) P4-O2 variance, 4) P2-O2 TKEO, 5) P3-O1 variance, 6) P4-O2 standard deviation, 7) C3-P3 TKEO, 8) P3-O1 standard deviation, 9) C4-P4 standard deviation, and 10) C4-P4 variance.

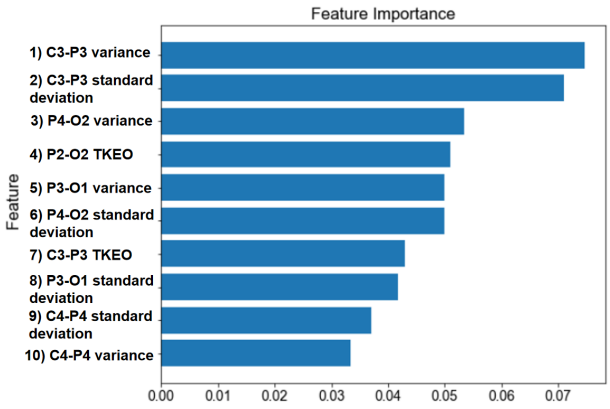

Fig. 4. Top 10 random forest-based important features in the training set.

TABLE III
COMPARISON OF SEIZURE DETECTION METHODS DEVELOPED USING THE TUH EEG DATASET (TUH V 1.5.1)

Ref	Subjects	Sens (%)	Spec (%)	BAcc (%)
[23]	TUH (all)	29.2	85.1	57.2
[17]	TUH (all)	39.2	90.4	64.8
[24]	TUH (all)	17.3	66.0	41.7
[25]	TUH (all)	30.8	97.1	64.0
[13]	TUH (all)	20.0	-	-
[26]	TUH (all)	23.3	-	-
[19]	TUH (all)	12.4	-	-
[27]	TUH (all)	37.2	96.9	67.1
This work	TUH (adult)	67.5	71.1	69.3
(Test set)	TUH (children)	91.9	49.8	70.9

C. Performance on TUH and CHB-MIT EEG

Table IV presents the results of the random forest-based seizure detection method on the training set, validation set, and independently test set. The proposed method 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 of adult TUH EEG data on training, validation and independent test set were 79.7%, 72.3% and 71.1%, respectively. For the pediatric EEG data set, the method achieved a higher sensitivity (91.9% for TUH pediatric EEG test set, 91.2% for CHB-MIT pediatric EEG test set), and a lower specificity (49.8% for TUH pediatric EEG test set, 10.3% for CHB-MIT pediatric EEG test set) than the adult EEG data.

D. Benchmarking

Table III shows previously published TUH-based seizure detection methods (TUH V 1.5.1). Compared with previous

TABLE IV
PERFORMANCE OF THE RANDOM FOREST-BASED SEIZURE DETECTION METHOD ON THE TRAINING, VALIDATION AND INDEPENDENT TEST SET (TUH ADULT, TUH PEDIATRIC AND CHB-MIT PEDIATRIC EEG).

	Dataset	Files	Sens (%)	Spec (%)	Acc (%)	BAcc (%)
TUH	Train (adult)	4,449	82.7	79.7	79.9	81.2
	Validation (adult)	460	69.3	72.3	72.1	70.8
	Test (adult)	509	67.5	71.1	70.6	69.3
	Test (pediatric)	192	91.9	49.8	53.1	70.9
CHB-MIT	Test (pediatric)	668	91.2	10.3	10.5	50.8

work, the method developed in this study achieved higher sensitivity and balanced accuracy (i.e. a better balance between sensitivity and specificity).

V. DISCUSSION

In this study, we explore the suitability of a random forest-based seizure detection method trained on adult TUH EEG for the detection of seizures in children. The random forest algorithm can return a measure of feature importance, which is essential to understanding the decision making of the algorithm [15]. The top 10 important features in the training set are presented in Figure 4. These are the TKEO, variance and standard deviation of different channels, which means TKEO, variance, and standard deviation are essential to predict the target.

The method developed in this study was trained on TUH adult EEG data and tested on the EEG recordings of TUH adult, TUH pediatric and CHB-MIT pediatric EEG. Table IV shows that the method performs well on TUH adult EEG. However, when tested on pediatric EEG, both the TUH pediatric and CHB-MIT pediatric EEG achieved high sensitivity, low specificity and low accuracy, and low balanced accuracy on the CHB-MIT EEG.

Table III presents the bench-marking of our seizure detection method with other work. Most of these methods were developed on TUH V 1.5.1, and used the same dataset as this study. He et al. [23] developed a rectifier neural networks-based seizure detection method which achieved specificity of 85.1%, but only sensitivity and balanced accuracy of 29.2% and 57.2%. Shah [17] used CNN combined with a bidirectional LSTM to detect seizure events in TUH EEGs, with specificity, sensitivity and balance accuracy of 90.4%, 39.2% and 64.8%, respectively. A Hidden Markov model was presented by Ziyabari [24] to detect seizures with balance accuracy of 41.7%. Gated recurrent networks used by Golmohammadi [25], obtained specificity, sensitivity and balance accuracy of 97.1%, 30.8% and 64.0%, respectively. Results show that our method achieved higher sensitivity, with 67.5% for TUH adult EEG and 91.9% for TUH paediatric EEG, and higher balanced accuracy (i.e. a better balance between sensitivity and specificity), with 69.3% for TUH adult EEG and 70.9% for TUH paediatric EEG.

Table V shows the mean absolute amplitude (MAA) of the seizure events in each selected channel. The average MAA from ten selected channels of seizure events for TUH EEG is 22.37 μV. The average MAA of non-seizure events for TUH EEG from ten selected channels is 18.69 μV. The average MAA from ten selected channels of CHB-MIT is 17.60 μV and 9.17 μV for seizure and non-seizure events, respectively. The seizure events have higher MAA than non-seizure events. However, the MAA of TUH EEG is higher than CHB-MIT EEG. The TUH EEG recordings and CHB-MIT EEG recordings were recorded in different systems and methods, which may cause the difference in the amplitude of the signals. Therefore, this study only analyses the MAA of the seizure events in TUH adult and TUH pediatric EEG. The average MAA from ten selected channels of the seizure events in TUH adult EEG is 17.22 μV. However, the average MAA from ten selected channels of the seizure events in TUH children's EEG data is almost twice that of adults, 37.82 μV, indicating a difference between the seizure events in adults and children. Figure 2 shows examples of the TUH adult and TUH pediatric focal non-specific seizures in channel C4-P4. The amplitude of TUH pediatric seizure events is higher than the seizure event in TUH adults. The difference may be why our method performs well on the adult independent test set but poorly on the pediatric EEG. The adult-based seizure detection method is prone to predict most of the events in pediatric EEG as "positive" (seizure) events, which results in high sensitivity, low specificity and balanced accuracy for pediatric EEG. In addition, from the spectrogram in Figure 2, it is clear to see that the rhythm activities in adults and children are also different. The focal non-specific seizure in channel C4-P4 shows higher power in the 0–10 Hz frequency range and lower power above 20 Hz frequency range in adults compared to children. These differences between seizure events in adults and children show that adult-based seizure detection methods are not suitable for children. Therefore, there is a need to develop seizure detection methods specifically for pediatric EEG.

Overall, research on automatic seizure detection methods mainly focuses on adults and research on pediatric EEG is limited. We find that a seizure detection method 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 [28]. Explainable AI (XAI) can be

TABLE V
MEAN ABSOLUTE AMPLITUDE OF THE SEIZURE EVENTS IN SELECTED CHANNELS IN TUH EEG DATA AND CHB-MIT EEG DATA.

	Dataset (μV)	FP1-F7	FP1-F3	F3-C3	FP2-F8	FP2-F4	P3-O1	P4-O2	C3-P3	C4-P4	F4-C4
TUH	Train (adult)	21.38	21.10	13.34	20.07	20.79	14.72	18.83	11.38	16.48	17.02
	Validation (adult)	14.33	14.08	8.24	14.71	18.04	8.58	9.75	7.46	8.57	11.33
	Test (adult)	31.58	25.86	11.20	32.57	25.86	33.44	30.86	11.11	13.26	10.63
	Test (pediatric)	37.14	39.13	39.11	42.02	35.21	36.15	39.06	25.24	37.88	47.26
CHB-MIT	Test (pediatric)	18.09	17.71	14.10	18.83	17.92	12.32	12.36	10.41	10.93	13.36

described as aiming to make machine learning algorithms more understandable to humans [29]. We will use XAI in future work to gain clinicians' trust in automatic seizure detection methods and assist experts' analysis of EEG.

VI. CONCLUSIONS

Research on automated seizure detection methods mainly focuses on adults and research on seizure detection methods in pediatric EEG is limited. In addition, most automated seizure detection methods do not consider changes in EEG with ageing, potentially leading clinicians to unknowingly use automated detection methods which may make errors in different age groups. In this study, we present an automated seizure detection method for adult EEG. We find that this adult-based seizure detection method is not suitable for children. Therefore, there is a need to develop a pediatric-specific seizure detection method and to consider age as a feature in developing automated seizure detection algorithms.

ACKNOWLEDGMENTS

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.

REFERENCES

[1] K. M. Aaberg, N. Gunnes, I. J. Bakken, C. Lund Søraas, A. Berntsen, P. Magnus, M. I. Lossius, C. Stoltenberg, R. Chin, and P. Surén, "Incidence and prevalence of childhood epilepsy: a nationwide cohort study," *Pediatrics*, vol. 139, no. 5, 2017.

[2] L. Wei, H. Boutouil, R. R. Gerbatin, O. Mamad, M. Heiland, C. R. Reschke, F. Del Gallo, P. F. Fabene, D. C. Henshall, M. Lowery *et al.*, "Detection of spontaneous seizures in EEGs in multiple experimental mouse models of epilepsy," *Journal of Neural Engineering*, vol. 18, no. 5, p. 056060, 2021.

[3] Y. Xu, D. Nguyen, A. Mohamed, C. Carcel, Q. Li, M. A. Kutlubaev, C. S. Anderson, and M. L. Hackett, "Frequency of a false positive diagnosis of epilepsy: a systematic review of observational studies," *Seizure*, vol. 41, pp. 167–174, 2016.

[4] W. T. Kerr, E. A. Janio, C. T. Braesch, J. M. Le, J. M. Hori, A. B. Patel, N. L. Gallardo, J. Bauirjan, A. M. Chau, E. S. Hwang *et al.*, "An objective score to identify psychogenic seizures based on age of onset and history," *Epilepsy & Behavior*, vol. 80, pp. 75–83, 2018.

[5] S. Dwajani, E. Adarsh, K. Nirmala, and H. Sahajananda, "Sociodemographic, rationale drug use of antiepileptic drugs among pediatric patients with epilepsy: a prospective study at a tertiary care hospital," *Journal of Neurosciences in Rural Practice*, vol. 10, no. 03, pp. 474–478, 2019.

[6] L. Wei, S. Ventura, M. Lowery, M. A. Ryan, S. Mathieson, G. B. Boylan, and C. Mooney, "Random forest-based algorithm for sleep spindle detection in infant EEG," *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 58–61.

[7] L. Wei, S. Ventura, M. A. Ryan, S. Mathieson, G. B. Boylan, M. Lowery, and C. Mooney, "Deep-spindle: An automated sleep spindle detection system for analysis of infant sleep spindles," *Computers in Biology and Medicine*, vol. 150, p. 106096, 2022.

[8] S.-K. Lin, L.-C. Wang, C.-Y. Lin, H. Chiueh *et al.*, "An ultra-low power smart headband for real-time epileptic seizure detection," *IEEE journal of translational engineering in health and medicine*, vol. 6, pp. 1–10, 2018.

[9] C.-L. Liu, B. Xiao, W.-H. Hsaio, and V. S. Tseng, "Epileptic seizure prediction with multi-view convolutional neural networks," *IEEE access*, vol. 7, pp. 170 352–170 361, 2019.

[10] J. Xiang, C. Li, H. Li, R. Cao, B. Wang, X. Han, and J. Chen, "The detection of epileptic seizure signals based on fuzzy entropy," *Journal of neuroscience methods*, vol. 243, pp. 18–25, 2015.

[11] A. H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, Massachusetts Institute of Technology, 2009.

[12] V. Shah, E. Von Weltin, S. Lopez, J. R. McHugh, L. Veloso, M. Golmohammadi, I. Obeid, and J. Picone, "The temple university hospital seizure detection corpus," *Frontiers in neuroinformatics*, vol. 12, p. 83, 2018.

[13] L. Wei and C. Mooney, "Epileptic seizure detection in clinical EEGs using an XGBoost-based method," *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2020, pp. 1–6.

[14] E. Amorim, C. A. Williamson, L. M. Moura, M. M. Shafi, N. Gaspard, E. S. Rosenthal, M. M. Guanci, V. Rajajee, and M. B. Westover, "Performance of spectrogram-based seizure identification of adult EEGs by critical care nurses and neurophysiologists," *Journal of clinical neurophysiology: official publication of the American Electroencephalographic Society*, vol. 34, no. 4, p. 359, 2017.

[15] L. Wei, S. Ventura, S. Mathieson, G. B. Boylan, M. Lowery, and C. Mooney, "Spindle-AI: sleep spindle number and duration estimation in infant EEG," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 1, pp. 465–474, 2021.

[16] A. Harati, S. Lopez, I. Obeid, J. Picone, M. Jacobson, and S. Tobochnik, "The TUH EEG CORPUS: A big data resource for automated EEG interpretation," *2014 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2014, pp. 1–5.

[17] V. Shah, M. Golmohammadi, S. Ziyabari, E. Von Weltin, I. Obeid, and J. Picone, "Optimizing channel selection for seizure detection," *2017 IEEE signal processing in medicine and biology symposium (SPMB)*. IEEE, 2017, pp. 1–5.

[18] L. Wei, "Automatic detection and characterization of seizures and sleep spindles in electroencephalograms using machine learning," 2022.

[19] C. Chatzichristos, J. Dan, A. M. Narayanan, N. Seeuws, K. Vandecasteele, M. De Vos, A. Bertrand, and S. Van Huffel, "Epileptic seizure detection in EEG via fusion of multi-view attention-gated U-net deep neural networks," *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2020, pp. 1–7.

[20] L. Wei, R. Gerbatin, O. Mamad, H. Boutouil, C. Reschke, M. Lowery, D. Henshall, G. Morris, and C. Mooney, "XGboost-based Method for Seizure Detection in Mouse Models of Epilepsy," *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*.

[21] T. De Cooman, K. Vandecasteele, C. Varon, B. Hunyadi, E. Cleeren, W. Van Paesschen, and S. Van Huffel, "Personalizing heart rate-based seizure detection using supervised SVM transfer learning," *Frontiers in neurology*, vol. 11, p. 145, 2020.

[22] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg *et al.*, "Scikit-learn: Machine learning in Python," *Journal of machine learning research*, vol. 12, no. Oct, pp. 2825–2830, 2011.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 1026–1034.

[24] S. Ziyabari, V. Shah, M. Golmohammadi, I. Obeid, and J. Picone, "Objective evaluation metrics for automatic classification of EEG events," *arXiv preprint arXiv:1712.10107*, 2017.

[25] M. Golmohammadi, S. Ziyabari, V. Shah, E. Von Weltin, C. Campbell, I. Obeid, and J. Picone, "Gated recurrent networks for seizure detection," *2017 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2017, pp. 1–5.

[26] A. Thyagachandran, M. Kumar, M. Sur, R. Aghoram, and H. Murthy, "Seizure Detection Using Time Delay Neural Networks and LSTMs," *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2020, pp. 1–5.

[27] V. Shah, I. Obeid, J. Picone, G. Ekladious, R. Iskander, and Y. Roy, "Validation of temporal scoring metrics for automatic seizure detection," *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2020, pp. 1–5.

[28] Y. Du, A. R. Rafferty, F. M. McAuliffe, L. Wei, and C. Mooney, "An explainable machine learning-based clinical decision support system for prediction of gestational diabetes mellitus," *Scientific Reports*, vol. 12, no. 1, pp. 1–14, 2022.

[29] A. M. Antoniadi, Y. Du, Y. Guendouz, L. Wei, C. Mazo, B. A. Becker, and C. Mooney, "Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: a systematic review," *Applied Sciences*, vol. 11, no. 11, p. 5088, 2021.