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A comparative study of AI systems for epileptic seizure recognition based on EEG or ECG

Yikai Yang[1], Nhan Duy Truong[1], Christina Maher[1], Armin Nikpour[2] and Omid Kavehei[1,*]

Abstract— **The majority of studies for automatic epileptic seizure (ictal) detection are based on electroencephalogram (EEG) data, but electrocardiogram (ECG) presents a simpler and more wearable alternative for long-term ambulatory monitoring. To assess the performance of EEG and ECG signals, AI systems offer a promising way forward for developing high performing models in securing both a reasonable sensitivity and specificity. There are crucial needs for these AI systems to be developed with more clinical relevance and inference generalization. In this work, we implement an ECG-specific convolutional neural network (CNN) model with residual layers and an EEG-specific convolutional long short-term memory (ConvLSTM) model. We trained, validated, and tested these models on a publicly accessible Temple University Hospital (TUH) dataset for reproducibility and performed a non-patient-specific inference-only test on patient EEG and ECG data of The Royal Prince Alfred Hospital (RPAH) in Sydney, Australia. We selected 31 adult patients to balance groups with the following seizure types: generalized, frontal, frontotemporal, temporal, parietal, and unspecific focal epilepsy. Our tests on both EEG and ECG of these patients achieve an AUC score of 0.75. Our results show ECG outperforms EEG with an average improvement of 0.21 and 0.11 AUC score in patients with frontal and parietal focal seizures, respectively.**

Clinical relevance— **Prior research has demonstrated the value of using ECG for seizure documentation. It is believed that specific epileptic foci (seizure origin) may involve network inputs to the autonomic nervous system. Our result indicates that ECG could outperform EEG for individuals with specific seizure origin, particularly in the frontal and parietal lobes.**

I. Introduction

Epilepsy affects about 1% people globally [1], and it entails some severe psychiatric comorbidities and psychosocial disorders, such as social exclusion and unemployment [2], [3]. Electroencephalogram (EEG) has been the golden standard in epilepsy diagnosis and monitoring the brain's electrical activity. Over the past two decades, there has been widespread use of EEG signals for seizure documentation and research into seizure forecasting [4]–[6]. Recently, several deep learning techniques achieved excellent results using EEG for non-patient-based seizure detection on the Temple University Hospital (TUH) EEG dataset [7]. The disadvantage of EEG-based methods is their limited applicability beyond clinics (in- and out-patients) due to their wearability and comfort. There have been attempts to reduce the number of EEG channels involved in signal processing. One recent one is the Neureka 2020 Epilepsy Challenge that considered channel numbers in their scoring formula. The winner of this Challenge used a multi-view attention-gated U-Net algorithm and achieved 12.46% sensitivity and one false alarm per 24 hrs, using 16-channel of EEG poor in sensitivity [8]. These results show challenges associated with developing a high-performance EEG-based seizure detection system with a small number of electrodes.

The authors in [9] leveraged the abundance of weak annotations that were primarily analyzed by a mixed group of technicians, fellows, students, and epileptologists to train their convolutional neural network and achieved an area under the receiver operating characteristic curve (AUC) score of 0.78. In our recent work [10], our comprehensive solution reached an AUC score of 0.84 using a convolutional long short-term memory network (ConvLSTM) tested in a non-patient-specific inference-only mode. Our EEG results in this paper are based on the same AI system.

Compared with EEG, electrocardiography (ECG) is less complicated, more portable and recording of ECG is routinely used in clinical settings [11]. However, algorithms using ECG signals for non-patient-based seizure detection are limited. Heart-rate variability (HRV) might aid the identification of seizure onset, for instance, reported for children with temporal-lobe epilepsy [12]–[15]. Such studies reflect the influence of seizures on the brain network inputs to the autonomic nervous system [16].

The most promising works using ECG have focused on seizure prediction (early seizure detection) [17], [18]. However, there has been little focus on using the ECG signal for seizure detection, and the performance is not comparable with using multiple EEG channels. The support vector machine (SVM) method was recently applied to ECG to detect temporal seizures, achieving a 70% sensitivity and an average of 2.11 false alarms per hour. This study focused on seizures originating from the temporal lobe yet tested only on a small group (11) of patients.

In this paper, we perform generalized non-patient-specific inference-only tests on 31 adult patients to investigate the performance of our seizure detection models developed separately for EEG and ECG analysis. The main contributions of this paper are in the following:

- Introduce a residual convolutional neural network

* Corresponding author
[1] Y. Yang, N.D. Truong, C. Maher, and O. Kavehei are with the School of Biomedical Engineering, and the Australian Research Council Training Centre for Innovative BioEngineering, Faculty of Engineering, The University of Sydney, NSW 2006, Australia.{yikai.yang, duy.truong, christina.maher, omid.kavehei}@sydney.edu.au
[2] A. Nikpour is with the Comprehensive Epilepsy Services, Department of Neurology, The Royal Prince Alfred Hospital, NSW 2050. He is also with the Faculty of Medicine and Health, The University of Sydney, NSW 2006, Australia. armin@sydneyneurology.com.au

(CNN) model, inspired by [19], for seizure detection using ECG data and achieve a promising result relative to a full set of 19 EEG electrodes. Note that the ECG data is collected alongside the EEG.
- A generalized and non-patient-specific inference-only test using both EEG and ECG modalities. In this study, we train, validate and test two separate deep learning models on a publicly available US-based TUH dataset and run it in inference-only mode on an Australia-based RPAH dataset.
- We have also explained our results on ECG and demonstrate a potential influence of specific epileptic foci (seizure origin) on the autonomic nervous system (ANS).

To the best of our knowledge, this is the first inference-only study using ECG designed for clinical utility which explore the potentials influence of seizure origin on the ECG outcome.

We organize the remainder of the paper as follows. The next section discusses the features of the datasets used in the models. Section III introduces the proposed method for automatic seizure detection. Lastly, we discuss the results and conclude the paper.

II. Dataset

Tables I and II summarize the two datasets used in this work. The world's largest open database Temple University Hospital (TUH) seizure corpus [7] was used for training the deep learning models. The TUH dataset consists of both EEG and ECG data information, which we separately used. There are 1,095 sessions with 540 patients (174 participants with seizures) in the training set, and 228 sessions with 46 patients (36 patient with seizures) in the development set. During training, we randomly split the TUH training dataset into 80%, 20% for training and validation, respectively, and test on the TUH development dataset. To examine our clinical utility, we limit the test of our models to inference-only mode on the the Royal Prince Alfred Hospital (RPAH) dataset.

We selected 31 adults with epilepsy from a local large dataset that we have access to, from the RPAH. We reported a comprehensive use of this dataset in an internationally generalized inference-only test using EEG sets in [10]. No training was performed on the sets we conducted our inference tests (in this case RPAH EEG and ECG sets). The positive (seizure) samples are extracted from ictal period (from onset to end) into 12-second windows and the remainder of ictal period that is less than 12 seconds long is discarded. A similar process is applied to negative samples that are extracted from non-seizure periods.

The interaction between seizures and the autonomic nervous system (ANS) is complex one. We selected six most common seizure types, namely generalized, frontal, frontotemporal, temporal, parietal and unspecified focal epilepsy. To explore the potential connection between the seizure foci and the ANS, we included participants with specific seizure types. As shown in Table II, the total recording length and mean seizure duration are 2495.7 hours and 97.2 seconds, respectively.

TABLE I: Summary of the TUH datasets with ECG

TUH dataset attribute	**Train**	**Dev**
Files	4141	953
Sessions	1095	228
Patients	540	46
Files with seizures	746	258
Sessions with seizures	301	94
Patients with seizures	174	36
Number of seizures	2129	650
Background duration (hours)	669.3	149.2
Seizure duration (hours)	43.0	14.6
Total duration (hours)	712.3	163.8

III. Method

A. Pre-processing

Heart rate variability (HRV) [20] is one of the most common features extracted from ECG for seizure detection. However, for deep learning techniques, HRV is unsuitable as it is itself a method to engineer features from ECG and could leave out helpful information in the process. We aim to leverage a convolutional neural network (CNN) capability to inherently extract relevant information from ECG signals without any feature engineering. Although raw ECG signals can be directly fed into the neural network, the lack of explicit frequency information makes it difficult for the network to extract essential features. In this work, we used the short-time Fourier transform (STFT) to translate 12 second segments of raw ECG signals into spectrum's as input to the neural network. To address differences in the recording sample rates, we re-sampled all ECG signals to 250 Hz, therefore, a 12-s ECG signal has a 3,000 samples. We used a window length of 250 (or 1 s) and 50% overlapping when doing the STFT so that the data shape would become $(23 \times 1 \times 126)$. The DC component in the spectrogram was removed before feeding to the neural network so that the final data shape would become $(23 \times 1 \times 125)$.

B. Machine learning

The network was trained with the Training set of the TUH dataset only and tested on the Development set of the TUH dataset. Then we used the trained network to test on 31 participants from the RPAH dataset directly.

CNN-residual network is a widely used method for computer vision [21]. Recently, a deep network based on CNN-residual blocks achieved excellent performance on cardiovascular disease classification problems using 12-lead ECG channels [19]. In this work, we fine-tune the CNN-residual network to efficiently and accurately use ECG signals for the seizure detection task. As shown in Fig. 2, the input was first fed into a batch normalization layer which ensures the input data has zero mean and unit variance to reduce the internal covariate shift [22]. The ReLu activation function was used inside the network [23], and the kernel size for all blocks was

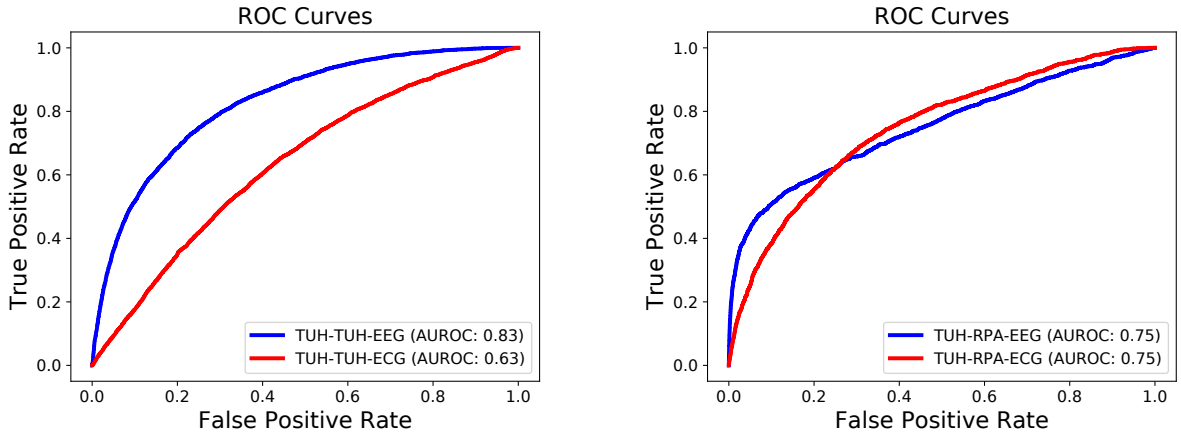

Fig. 1: Receiver operating characteristic (ROC) curves for the seizure detection task. TUH-TUH-EEG and TUH-TUH-ECG represent the model trained on the training set of the TUH dataset and tested on the development set of the TUH dataset (that contains ECG data) using 19 EEG electrodes and 1 ECG electrode, respectively; TUH-RPA-EEG and TUH-RPA-ECG represent the model trained on the training set of the TUH dataset and tested on the 31 participants from the RPAH dataset using 19 EEG electrodes and 1 ECG electrode, respectively.

TABLE II: Summary of the 31 participants' information from the RPAH dataset and post test results (inference only)

Patient	Gender	Age	SN	Origin	Severity of motor activity	RD (h)	Mean SD (s)	Range SD (s)	EEG AUC	ECG AUC
1	M	20	10	Generalised	Moderate	86.9	13	[7.2, 17.6]	0.32	0.95
2	M	33	4	Generalised	Minor	93.6	91.9	[51.2, 117.1]	0.91	0.88
3	M	22	9	Generalised	Moderate	8.0	76.4	[26.2, 191.0]	0.84	0.83
4	F	41	1	Generalised	Severe	57.8	47.5	[47.5, 47.5]	0.96	0.70
5	M	21	7	Generalised	Moderate	71.9	423.1	[21.9, 1324.4]	0.75	0.78
6	F	22	6	Frontal	Moderate	97.7	74.5	[57.1, 95.3]	0.71	0.80
7	M	39	11	Frontal	Moderate	47.8	72.5	[32.1, 132.3]	0.38	0.82
8	M	38	2	Frontal	Minor	16.4	43.5	[40.2, 46.7]	0.26	0.58
9	M	62	7	Frontal	Severe	73.2	98.4	[40.1, 158.6]	0.33	0.48
10	M	31	7	Frontal	Moderate	34.7	63	[17.4, 102.0]	0.61	0.65
11	F	51	11	Frontotemporal	Severe	93.4	161.2	[92.5, 175.4]	0.89	0.84
12	M	25	8	Frontotemporal	Moderate	93.0	77.5	[42.4, 154.6]	0.91	0.59
13	F	43	8	Frontotemporal	Minor	90.1	178.7	[28.0, 1095.9]	0.94	0.81
14	F	22	5	Frontotemporal	Minor	138.2	79.4	[62.5, 105.2]	0.83	0.92
15	M	31	11	Frontotemporal	Severe	82.4	73.1	[50.8, 202.7]	0.88	0.84
16	F	58	14	Frontotemporal	Moderate	68.3	102.2	[17.0, 237.7]	0.97	0.63
17	M	41	8	Temporal	Minor	97.0	44	[29.9, 69.6]	0.81	0.63
18	M	39	9	Temporal	Minor	91.3	67.5	[45.0, 78.1]	0.97	0.89
19	M	51	7	Temporal	Minor	162.4	69.9	[13.9, 147.5]	0.83	0.84
20	F	41	14	Temporal	Minor	90.2	126.5	[45.1, 719.7]	0.61	0.59
21	F	32	9	Temporal	Minor	45.8	74.7	[10.9, 118.1]	0.90	0.75
22	M	32	8	Temporal	Minor	92.2	67.3	[41.9, 135.0]	0.92	0.93
23	M	33	8	Temporal	Minor	87.4	59.8	[41.3, 113.1]	0.65	0.77
24	M	32	9	Temporal	Minor	64.4	71.4	[17.4, 138.3]	0.77	0.59
25	M	41	8	Temporal	Minor	72.4	57.1	[31.4, 112.7]	0.65	0.46
26	F	25	11	Parietal	Moderate	92.5	134.7	[10.5, 1074.6]	0.73	0.77
27	F	48	2	Parietal	Minor	91.8	401.9	[320.7, 483.1]	0.55	0.68
28	M	28	4	Parietal	Minor	65.8	213.4	[58.3, 485.8]	0.73	0.90
29	F	24	6	Focal vertex	Moderate	113.0	24.8	[3.5, 95.7]	0.98	0.79
30	M	21	3	Left hemisphere focal	Moderate	87.9	98.7	[88.7, 107.7]	0.92	0.62
31	F	45	11	Left insula	Minor	88.2	38.3	[9.7, 46.4]	0.39	0.38
Total	–	–	238	–	–	2495.7	97.2	[3.5, 1324.4]	0.75	0.75

M: Male, F: Female, SN: Number of seizures, RD: Recording length, Mean SD: Mean of seizure duration, Range SD: Seizure duration range

3×1. The residual block was designed with a skip connection combined with two branches, and the down-sampling value in the max-pooling layer was selected to make the sample outsize as expected. The output feature size was halved block by block, from 64 to 8, while the number of filters was doubled block by block, from 32 to 256. The four residual blocks were the flatten layer and one fully connected layer with sigmoid activation and output dimension of 2. Both the flatten layer and fully connected layer had a 0.5 dropout rate.

During the training, we use batch size as 32 and learning rate of 5e-4 with the adam optimizer. To avoid the over-fitting issue, we used the dropout and applied the early-stopping technique. The early-stopping considers both training loss and valuation loss, stopping the training when the combined loss has not decreased for 20 epochs. We implemented our model in Python 3.6 with the use of Keras 2.0 with a

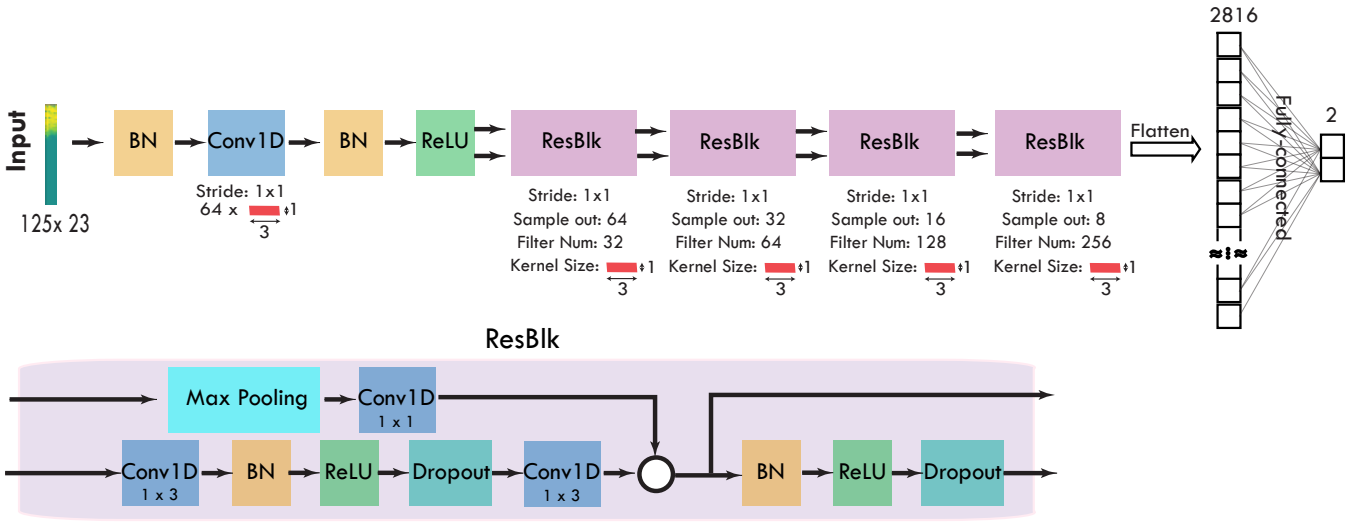

Fig. 2: Architecture of the CNN-residual network.

Tensorflow 1.4.0 backend.

C. Performance metrics

To evaluate the performance of the proposed method for the seizure detection task, we used the metric named the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve is the recall plot versus the false-positive rate (FPR), and the score is calculated based on the size of the area under the ROC curve (AUC). Definitions of the recall and the false-positive rate are shown in the below equations.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{1}$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN+FP}} \tag{2}$$

where TP, TN, FP, and FN represent true positives (correct seizure detection), true negatives (correct non-seizure detection), false positives (incorrect seizure detection), and false negatives (incorrect non-seizure detection), respectively.

IV. Results

This section tests our approach on the Development set of the TUH dataset and performs a prospective study on the selected 31 participants from the RPAH dataset. We investigate the system performance in four scenarios: (1) the overall AUC score on the Development set of the TUH dataset, (2) the overall AUC score on the RPAH dataset, (3) the seizure origin location-based AUC score on the selected participants from the RPAH dataset. Using ECG is compared with our previous work of using EEG [10].

The compassion between EEG and ECG performance can help us better understand the impact of the autonomic nervous system on individuals with different seizure origins. As shown in Fig 1, for the test on the Development set of the TUH dataset, using EEG signals from 19 electrodes achieves an AUC higher by 0.2 than using the single ECG signal, whereas, for the prospective test on the 31 RPA selected patients, the performance is comparable between the two types of signals. Table II and Fig 4 show the detection result with patient information on the RPAH dataset. It can be seen that EEG and ECG perform differently on different patients, and the average result for EEG and ECG are tied at 0.75. From Fig 3, it appears that, apart from the outliers, ECG performs best for participants with parietal focal seizures, whereas EEG performs the best for participants with frontotemporal focal seizures. For participants with frontal and parietal focal seizures, ECG achieves higher performance than EEG; for frontotemporal, temporal, and unspecific focal seizures, EEG outperforms ECG. For participants with generalized seizures, interestingly, ECG outperforms EEG when considering the outliers.

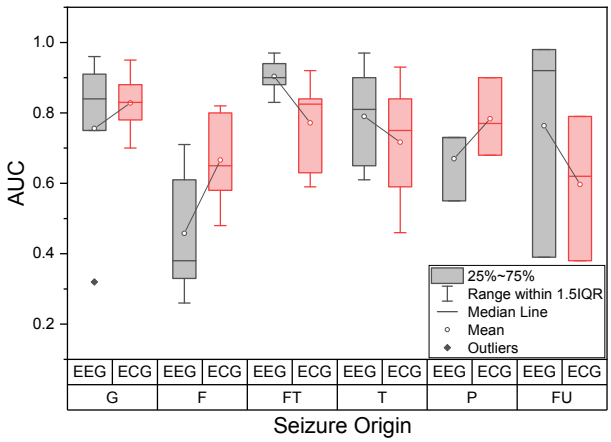

Fig. 3: G: Generalized, F: Frontal, FT: Frontotemporal, T: Temporal, P: Parietal, FU: Focal unspecific

Our results illustrate that our proposed model is generalizable across datasets collected in different countries by different hardware. Using a single ECG electrode, the results are comparable with 19 EEG electrodes in our prospective test on the RPAH dataset. The ECG signal achieves higher performance than EEG for participants with frontal and parietal focal seizures. This result is in agreement with research

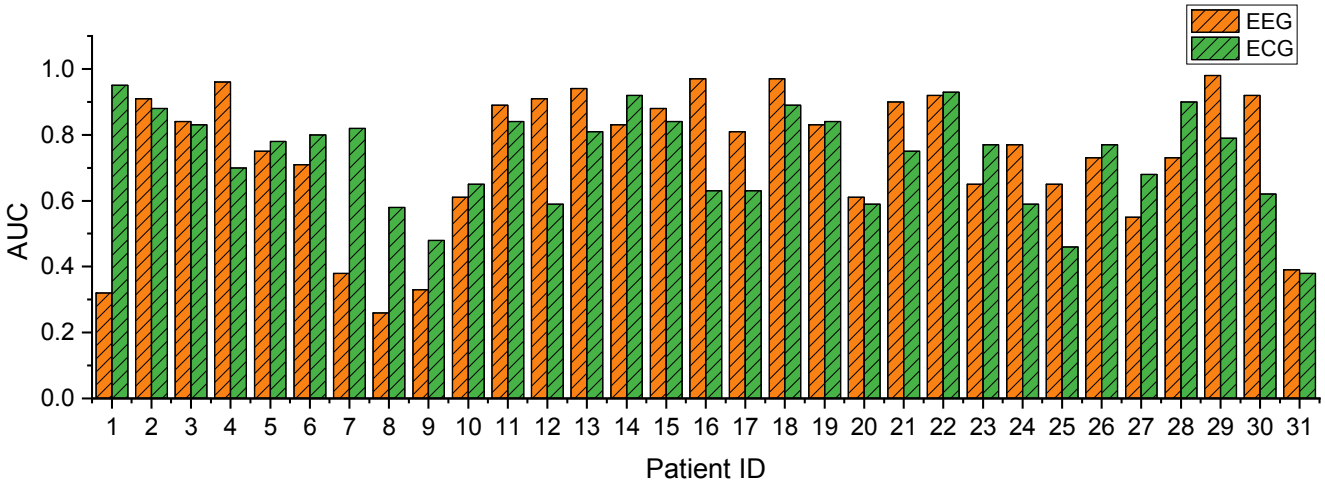

Fig. 4: Seizure detection performance from inference-only studies on a selected 31 participants from the RPAH dataset.

showing that epileptic attacks may influence brain network inputs to the ANS. The insula is involved in autonomic functions such as heartbeat [24], [25]. The parietal and frontal lobes are very connected to the insula [26]. This may be the reason for achieving superior performance in detecting parietal and frontal seizures using the addition of ECG, though further work is needed. However, our results from the standalone ECG seizure detection suggest that for adult patients with frontal focal seizures, ECG provides additional information for seizure detection. Therefore the use of ECG-based detection in addition to EEG-based detection may produce a superior solution to seizure detection based on EEG alone.

V. Conclusion

Using EEG for seizure detection has been studied and improved over the last four decades. However, limited research has been done with ECG signals, as the performance is not on par with EEG-based approaches. Our proposed model suggests that for prospective study ECG can achieve a comparable result with EEG, and even higher on the frontal and parietal focal seizures (adult patients), with an improvement of 0.21 and 0.11 AUC scores, respectively. This is the first study using deep learning to demonstrate a comparable performance between two separate and generalized inference-only EEG and ECG tests.

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Ethics declarations

Ethics X19-0323-2019/STE16040: Validating epileptic seizure detection, prediction and classification algorithms approved on 19 September 2019 by the NSW Local Health District (LHD), for implementation in the Comprehensive Epilepsy Services, Department of Neurology, The Royal Prince Alfred Hospital.

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