Classification of Epileptic and Psychogenic Non-Epileptic Seizures Using Electroencephalography and Electrocardiography

Wenjuan Xiong, Ewan S. Nurse, Elisabeth Lambert, Mark J. Cook, and Tatiana Kameneva

***Abstract*— Patients with psychogenic non-epileptic seizures (PNES) may exhibit similar clinical features to patients with epileptic seizures (ES). Misdiagnosis of PNES and ES can lead to inappropriate treatment and significant morbidity. This study investigates the use of machine learning techniques for classification of PNES and ES based on electroencephalography (EEG) and electrocardiography (ECG) data. Video-EEG-ECG of 150 ES events from 16 patients and 96 PNES from 10 patients were analysed. Four preictal periods (time before event onset) in EEG and ECG data were selected for each PNES and ES event (60-45 min, 45-30 min, 30-15 min, 15-0 min). Time-domain features were extracted from each preictal data segment in 17 EEG channels and 1 ECG channel. The classification performance using k-nearest neighbour, decision tree, random forest, naive Bayes, and support vector machine classifiers were evaluated. The results showed the highest classification accuracy was 87.83% using the random forest on 15-0 min preictal period of EEG and ECG data. The performance was significantly higher using 15-0 min preictal period data than 30-15 min, 45-30 min, and 60-45 min preictal periods ($p<0.001$). The classification accuracy was improved from 86.37% to 87.83% by combining ECG data with EEG data ($p<0.001$). The study provided an automated classification algorithm for PNES and ES events using machine learning techniques on preictal EEG and ECG data.**

***Index Terms*— Classification, epileptic seizures (ES), electroencephalography (EEG), electrocardiography (ECG), machine learning, psychogenic non-epileptic seizures (PNES).**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the St Vincent Hospital Melbourne Human Research Ethics Committee under application HREC Low Risk Research 165/19.

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I. Introduction

PATIENTS with psychogenic non-epileptic seizures (PNES) are often misdiagnosed as having epilepsy; with 10-20% of patients referred to epilepsy centers are found to have PNES [1]. Epileptic seizures (ES) are occasionally misdiagnosed and inappropriately treated as PNES [2]. Differentiation between PNES and ES symptoms can be challenging since clinical features such as convulsions and alterations in behavior and consciousness occur in both PNES and ES [2]. Misdiagnosis of PNES can lead to inappropriate treatment such as prescriptions of anti-seizure medicine with adverse effects [3].

Electroencephalography (EEG) and electrocardiography (ECG) analysis is common in ES studies [4], [5], [6]. Ictal, interictal, and preictal states refer to the periods during a seizure, between seizures, and the transition during which the brain dynamics evolve into a seizure [7]. Preictal EEG data has been used to detect and predict ES with varying success [8], [9]. ECG-based research is a complementary approach to improving ES detection and prediction [9], [10].

Since EEG data can be difficult to collect and not widely available, there has been an increasing interest analysing ECG data for patients with PNES. Studies have demonstrated that before the onset of PNES, sympathetic activity increases, while a rise in parasympathetic activity occurs during the event [11]. These changes in autonomic nervous system activity have hence been used to detect and predict PNES events [11], [12].

Previous works have attempted to classify PNES and ES using EEG data mostly focusing on ictal states

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TABLE I
PNES AND ES CLASSIFICATION STUDIES BASED ON EEG AND ECG DATA

Author	Data	Features	Patients	Seizures	Method	Results	Notes
Dos Santos et al., 2022	Ictal EEG	Wavelet coefficients	12 21	42 PNES 117 ES	Support vector machine	Accuracy 95-100%	Seizure types are not provided.
Pippa et al., 2017	Ictal EEG	Temporal and spectral features	5 4	19 PNES 105 ES	Bayesian network, random committee, random forest	Accuracy 95% (Bayesian network) 89% (random committee) 87% (random forest)	A small number of PNES events.
Seneviratne et al., 2016	Ictal EEG	Ictal duration	62 73	341 PNES 441 ES	Youden's index	Sensitivity 65% Specificity 93%	An ictal duration $>$ 5min is a marker.
Vinton et al., 2014	Ictal EEG	Frequency	15 15	15 PNES 15 ES	Fast Fourier transform	The dominant frequency remained stable during PNES and increased during ES.	Convulsive ES and PNES.
Ahmadi et al., 2018	Interictal EEG	Entropy and fractal dimension features	20 20		Desion tree, random forest, support vector machine	Accuracy 95% (support vector machine) 87% (decision tree) 89% (random forest)	High computational cost; Seizure counts are not provided.
Xu et al., 2014	Interictal EEG	Coherence, clustering coefficients, and shortest path length	15 10	15 PNES 10 ES	Support vector machine	Accuracy 92% Sensitivity 100% Specificity 80%	A small number of ES events.
Yong et al., 2020	Ictal ECG	Heart rate	62 68	265 PNES 341 ES	Younden's index	AUC 0.84	Tonic-clonic ES.
Zsom et al., 2019	Ictal heart rate	Heart rate, electrodermal activity	8 10	12 PNES 23 ES	Tree-based classification and regression algorithm	Accuracy 76.5-79.5 %	Low performance.
Ponnusamy et al., 2012	Ictal ECG	Heart rate variability	24 26		Binary logistic regression	Classifies 88% and 73% of patients with ES and PNES.	Focal ES; Seizure counts are not provided.
Opherk et al., 2002	Ictal ECG	Heart rate	23 35	38 PNES 67 ES	Threshold	Sensitivity 83% Specificity 96%	Non-convulsive seizures.

[13], [14], [15], [16]. Vinton et al. performed fast Fourier transform on ictal EEG and observed the dominant frequency was more stable during PNES compared to ES [13]. Seneviratne et al. compared the ictal EEG duration between PNES and ES, and the presented classification method achieved a sensitivity of 65% [14]. A small study involving 5 patients with 19 PNES used ictal EEG to develop Bayesian network and random forest classifiers, presenting the highest accuracy of 95% [15]. Another small study involving 6 PNES and 16 ES events used ictal EEG and achieved the highest accuracy of 95.8% [17]. Santos et al. applied wavelet coefficients from ictal intracranial EEG data using a support vector machine classifier [16]. The proposed algorithm achieved accuracy above 95%.

A few studies used interictal EEG recordings for classification. Xu et al. studied the coherence, clustering coefficients, and shortest path length of interictal EEG data, presenting an accuracy of 92% for 10 focal ES and 15 PNES [18]. Ahmadi et al. tested decision tree, random forest, and support vector machine classifiers using complexity features of interictal EEG data [19]. The result showed that the support vector machine achieved the best performance with an accuracy of 95%. A recent study used deep learning technology to classify 42 ES and PNES events, achieving an accuracy of 85.7% [20].

There has been increased interest to use ictal heart rate extracted from ECG data to differentiate PNES from ES [21], [22], [23], [24], [25]. Opherk and Hirsch compared ictal heart rate to distinguish PNES from ES [21]. A sensitivity of 83% was obtained. Zsom et al. developed a tree-based and regression algorithm using ictal heart rate to achieve the highest accuracy of 79.5% [22]. Ponnusamy et al. developed a logistic regression model based on ictal heart rate variability to classify 88% and 73% of patients with ES and PNES [23]. Yon et al. investigated ictal heart rate of PNES and bilateral tonic-clonic ES, achieving an average area under the receiver-operating characteristic curve (AUC) of 0.84 [24]. However, some studies had reported conflicting results showing that ictal heart rate data was not helpful in the classification of PNES and ES [24], [25]. Studies that used EEG and ECG data to classify PNES and ES are summarised in Table I.

Ictal data are often contaminated with artifacts which are associated with clinical symptoms such as muscular activity [26] or rhythmic movement [13]. The artifacts are difficult to remove due to their broad distribution in frequency bands [26]. Classification of PNES and ES is possible only when muscle activity is not prominent in PNES [13], [27]. These artifacts are found at the onset rather than before seizures; therefore, recent studies have indicated that preictal data may be an alternative to classify PNES and ES [25], [28], [29]. Patients with PNES showed a decrease of beta power in preictal EEG data which was not observed before ES events [28]. In addition, there was a significant difference in preictal heart rate between PNES and ES [25], [29].

Currently, no classification study has systematically investigated the differences in PNES and ES using features extracted from preictal EEG and ECG data. While critical slowing cycles

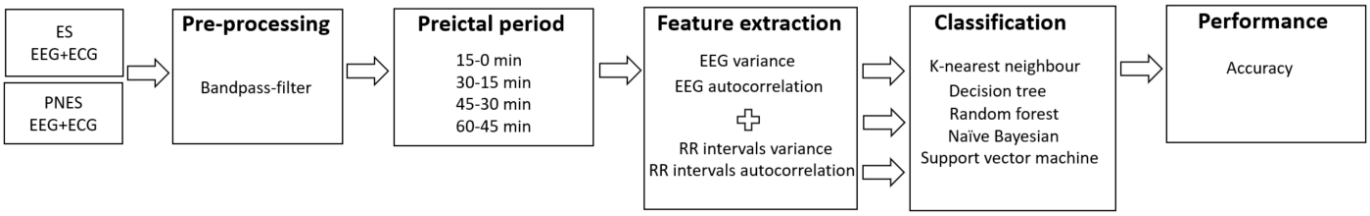

Fig. 1. Schematic of the study design. ES: epileptic seizure, PNES: psychogenic non-epileptic seizures, RRI: RR interval, the time elapsed between two successive R-waves on the ECG.

to forecast seizures were considered previously [9], [30], the classification between ES and PNES has not been addressed. Classification between ES and PNES using data during a preictal period is the focus of this study.

Critical slowing is a characteristic of a dynamical system that is nearing a critical transition [31], [32]. It is hypothesized that brain and heart activity change from an interictal to an ictal state in an ES is a such critical transition [31], [33]. Thus, critical slowing is a phenomenon only observed in preictal periods. Critical slowing is measured by increases in features (variance and autocorrelation) of the system's state during a preictal period [31], [34]. Critical slowing features extracted from preictal EEG and ECG data have been used to forecast the ES onset in recent studies [8], [9], [32]. There are no published studies investigating critical slowing phenomenon in classification between ES and PNES events.

In this study, we hypothesize that critical slowing in neural and cardiovascular systems would be different in patients with PNES and ES, therefore, critical slowing features from preictal EEG and ECG data may be potential markers to differentiate the two conditions. We developed classification algorithms using machine learning techniques and tested the performances of different classifiers.

II. Materials and Methods

A. Participants

This study was approved by the St Vincent's Hospital Melbourne Human Research Ethics Committee (HREC Low Risk Research 165/19). All patients provided written informed consent.

Video-EEG-ECG data of 150 ES events from 16 patients and 96 PNES events from 10 patients were analysed. Patients diagnosed with PNES have a similar semiology with patients with epilepsy but no background of epilepsy. All events were verified by an epileptologist (author MC). The median period of EEG and ECG recordings was 162.7 hours for ES and 163.4 hours for PNES. The median number of events per patient during the monitoring period was 9 for ES and 8 for PNES. The details of patients with PNES and ES are listed in Table II.

TABLE II
Patients Characteristics

ID	Age (years)	Sex	Recording (hours)	No.events	Types
1	29	F	163.5	17	F, Left T
2	25	M	158.9	8	F, Left T
3	30	M	163.7	5	F, Right T
4	51	F	227.5	13	G, Right T
5	19	F	185.9	7	G, Left T
6	27	M	115.1	13	F, Unknown
7	19	F	151.5	8	G, Bilateral
8	34	F	211.5	12	F, Left T
9	18	M	102.1	6	F, Right T
10	51	M	164.5	9	F, Right T
11	50	F	163.3	12	G, Bilateral
12	42	M	160.2	11	F, Right T
13	32	M	136.1	6	F, Unknown
14	45	M	162	6	G, Bilateral
15	42	M	160.9	6	G, Bilateral
16	28	M	164.2	11	G, Bilateral
Median	Female: 31.5 Male: 31		162.7	9	
1	56	F	162.5	9	PNES
2	46	F	167.3	14	PNES
3	43	M	147.4	7	PNES
4	47	M	158	6	PNES
5	46	F	164.4	15	PNES
6	27	M	165.8	7	PNES
7	40	F	164.4	19	PNES
8	50	F	66	8	PNES
9	20	F	164.3	6	PNES
10	23	F	137.7	5	PNES
Median	Female: 46 Male:43		163.4	8	

In types, F: focal seizure, G: generalised seizure, T: temporal lobe, PNES: psychogenic non-epileptic seizure.

B. Classification Model Design

The schematic diagram of the study design is shown in Figure 1. There are five steps: pre-processing, preictal period selection, feature extraction, classification, and performance evaluation.

1) Pre-Processing: The EEG and ECG data of patients with PNES and ES were pre-processed using an approach previously described [9]. EEG data were recorded from 17 channels (Fz, C4, Pz, C3, F3, F4, P4, P3, T4, T3, O2, O1, F7, F8, T6, T5, Cz). Fp1, Fp2, A1, and A2 channels were excluded due to ocular and muscular artifacts [35]. The EEG data were filtered using a 5^{th}-order, zero-phase bandpass Butterworth filter with a cutoff frequency of 1-30 Hz. The data was collected in patient's home without interrupting their daily activity, which leads to larger noise and unpredictable artefacts. To reduce high-frequency noise and artefacts, we implement a cut-off frequency at 30 Hz. ECG data were recorded from the channel placed in the 5^{th} intercostal space in the axillary line. The ECG data were filtered using a 5^{th}-order, zero-phase bandpass Butterworth filter with a cutoff frequency of 3-45 Hz. RR intervals (RRI: the time elapsed between two successive R-waves on the ECG) were extracted from ECG data using an adaptive threshold algorithm [36].

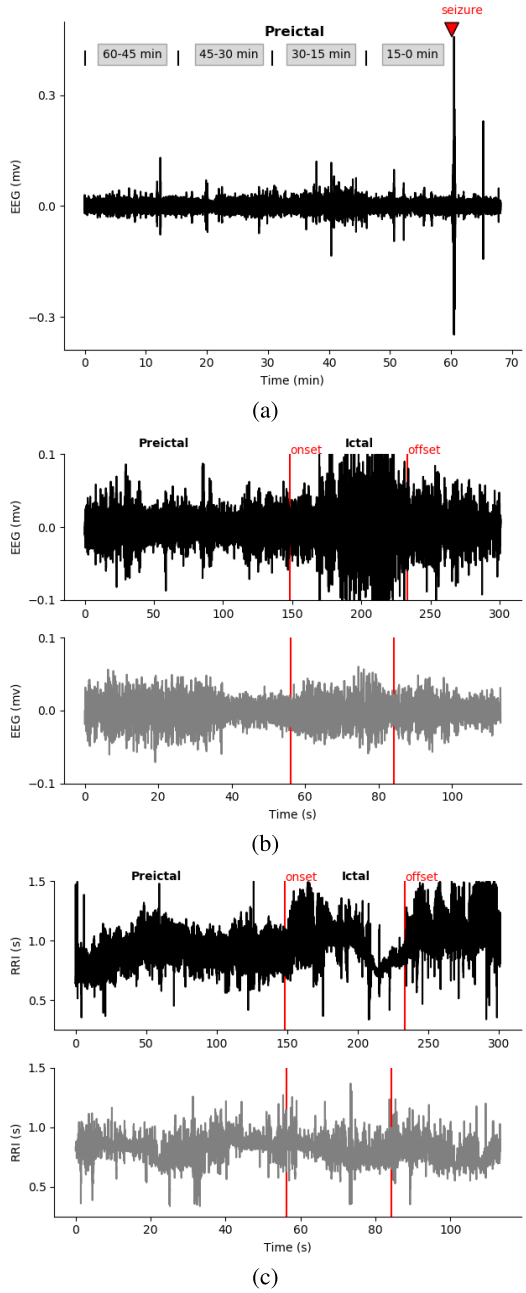

Fig. 2. Examples of EEG and RRI recordings with PNES and ES events. (a) Four periods of preictal EEG data with an ES event; the red triangle represents the onset of the seizure; (b) EEG data with an ES (black, top trace) and an PNES event (grey, bottom trace); (c) RRI data with an ES (black, top trace) and an PNES event (grey, bottom trace); red lines in each subplot represent the onset and offset of the event.

2) Preictal Period Selection: Since there is no clear definition of a preictal duration [37], we explored classification performance using four preictal periods: 15-0 min; 30-15 min; 45-30 min; and 60-45 min. Figure 2a shows different preictal periods of EEG data with an ES event. Figures 2b and 2c represent EEG and RRI data with one ES (black) and one PNES (grey) event, respectively. Figure 2b shows significant discharges in the EEG data of ES (black), which are not found during the PNES (grey).

3) Feature Extraction: Critical slowing features (variance and autocorrelation) of each preictal period of EEG and RRI data were calculated as previously described [9]. Critical slowing features were calculated in every 15-s. The number of preictal data points for each event was equal to 15min/15s = 60 data points. The total number of the data segments was 9000 (150*60) for ES and 5760 (96*60) for PNES, respectively. At each data point, we derived 36 features (17 EEG variance, 17 EEG autocorrelation, 1 RRI variance, and 1 RRI autocorrelation). The variance (Eq. (1)) and autocorrelation (Eq. (2)) were computed using following formulas:

$$V_x = \frac{1}{N}\sum_{n=1}^{N}(x_n - \overline{x})(x_n - \overline{x}) \tag{1}$$

$$C_x = \frac{1}{N}\frac{\sum_{n=1}^{N-\lambda}(x_n - \overline{x})(x_{n+\lambda} - \overline{x})}{V_x} \tag{2}$$

where, V_x and C_x represent variance and autocorrelation function of a signal x in each segment respectively, N is the number of samples in each segment, $\overline{x}$ is the signal mean, λ is the lag value in an autocorrelation function. The autocorrelation was calculated as describe in [8], which equals the width at half the maximum of the autocorrelation function.

4) Classification: Classification of the preictal data of PNES and ES was carried out using five classifiers: k-nearest neighbors (KNN), decision tree (DT), random forest (RF), naive Bayes (NB), and support vector machine (SVM). PNES data was assigned label 0, whereas ES data was assigned label 1. The data set was divided into two parts: a training set (80%) and a testing set (20%). The training set was unbalanced in the number of samples per class. To alleviate this effect, we undersampled the ES data set by random selection [38]. The number of neighbors used in the KNN classifier was 5. The number of trees in the RF classifier was set to 100. The radial basis Gaussian function (rbf) was used as the kernel for the SVM classifier.

5) Performance Evaluation: Accuracy was used to evaluate classification performance. We defined PNES events as true positives and ES events as false positives in this study. For each classifier, we split the training and the testing data randomly and repeat the split process 100 times. Performances using EEG features (34), ECG features (2), and a combination of EEG and ECG-based features (36) were computed.

C. Statistical Analysis

The t-test (two-sided) was used to assess the statistical significance of accuracy for different classifiers and different preictal data. A p-value < 0.05 was considered statistically significant.

III. Results

A. Classification Using EEG Data

The classification performance using different preictal intervals for EEG data across classifiers is shown in Figure 3a and Table III. The highest mean accuracy for each classifier was 86.37% (RF), 80.23% (KNN), 76.16% (DT), 73.65% (SVM), and 52.92% (NB), respectively. On average, the RF

TABLE III
CLASSIFICATION PERFORMANCES USING EEG DATA

		KNN	DT	RF	NB	SVM
15-0 min	Acc	80.13 (0.61)	**76.16 (0.88)**	**86.37 (0.60)**	52.56 (0.23)	**73.65 (0.43)**
	Sen	80.13 (0.61)	**76.16 (0.88)**	**86.37 (0.60)**	52.56 (0.23)	**73.65 (0.43)**
	Spec	79.29 (0.69)	**76.42 (1.10)**	**86.13 (0.46)**	6.41 (0.08)	**53.03 (0.55)**
30-15 min	Acc	79.83 (0.60)	75.74 (0.73)	85.41 (0.55)	52.29 (0.26)	72.95 (0.39)
	Sen	79.83 (0.60)	75.74 (0.73)	85.41 (0.55)	52.29 (0.26)	72.95 (0.39)
	Spec	79.86 (0.56)	75.54 (1.12)	84.29 (0.50)	6.61 (0.16)	51.77 (0.59)
45-30 min	Acc	**80.23 (0.62)**	75.79 (0.93)	85.57 (0.51)	52.88 (2.24)	73.48 (0.42)
	Sen	**80.23 (0.62)**	75.79 (0.93)	85.57 (0.51)	52.88 (2.24)	73.48 (0.42)
	Spec	**79.93 (0.61)**	76.17 (1.09)	84.53 (0.49)	48.04 (41.43)	53.13 (0.61)
60-45 min	Acc	79.08 (0.66)	75.05 (0.95)	85.48 (0.57)	**52.92 (0.47)**	73.57 (0.42)
	Sen	79.08 (0.66)	75.05 (0.95)	85.48 (0.57)	**52.92 (0.47)**	73.57 (0.42)
	Spec	79.16 (0.58)	75.79 (1.05)	84.48 (0.49)	**13.91 (25.1)**	54.32 (0.58)

Acc: accuracy, Sen: sensitivity; Spec: specificity. PNES and ES events represent true positives and false positives respectively. The values outside brackets represent the mean classifier performances, the values in the brackets are standard deviations. The unit is %.

TABLE IV
CLASSIFICATION PERFORMANCES USING ECG DATA

		KNN	DT	RF	NB	SVM
15-0 min	Acc	52.66 (0.85)	51.88 (0.79)	51.66 (0.86)	49.62 (0.79)	50.84 (0.72)
	Sen	52.66 (0.85)	51.88 (0.79)	51.66 (0.86)	49.62 (0.79)	50.84 (0.72)
	Spec	52.13 (0.98)	53.47 (0.89)	51.14 (0.92)	88.14 (11.47)	47.63 (6.55)
30-15 min	Acc	51.49 (0.74)	53.52 (0.78)	53.38 (0.76)	48.84 (0.36)	50.98 (0.76)
	Sen	51.49 (0.74)	53.52 (0.78)	53.38 (0.76)	48.84 (0.36)	50.98 (0.76)
	Spec	49.66 (0.88)	56.76 (0.78)	54.53 (0.82)	91.47 (0.94)	57.99 (21.36)
45-30 min	Acc	52.16 (0.76)	51.65 (0.77)	51.65 (0.75)	49.08 (0.87)	**51.79 (0.72)**
	Sen	52.16 (0.76)	51.65 (0.77)	51.65 (0.75)	49.08 (0.87)	**51.79 (0.72)**
	Spec	51.01 (0.95)	53.49 (1.06)	51.26 (0.98)	87.75 (14.6)	**49.62 (4.59)**
60-45 min	Acc	**54.13 (0.84)**	**53.98 (0.76)**	**53.89 (0.79)**	**49.76 (0.39)**	51.20 (0.65)
	Sen	**54.13 (0.84)**	**53.98 (0.76)**	**53.89 (0.79)**	**49.76 (0.39)**	51.20 (0.65)
	Spec	**54.48 (1.04)**	**57.77 (0.92)**	**55.48 (0.88)**	**90.53 (8.72)**	46.76 (6.32)

Acc: accuracy, Sen: sensitivity; Spec: specificity. PNES and ES events represent true positives and false positives respectively. The values outside brackets represent the mean classifier performances, the values in the brackets are standard deviations. The unit is %.

TABLE V
CLASSIFICATION PERFORMANCES USING COMBINED EEG AND ECG DATA

		KNN	DT	RF	NB	SVM
15-0 min	Acc	**80.83 (0.59)**	76.97 (0.85)	**87.83 (0.45)**	52.60 (0.22)	73.58 (0.46)
	Sen	**80.83 (0.59)**	76.97 (0.85)	**87.83 (0.45)**	52.60 (0.22)	73.58 (0.46)
	Spec	**80.10 (0.57)**	77.01 (1.11)	**87.40 (0.49)**	6.41(0.08)	52.88 (0.63)
30-15 min	Acc	80.40 (0.67)	**77.22 (0.73)**	86.81 (0.46)	52.29 (0.28)	73.04 (0.42)
	Sen	80.40 (0.67)	**77.22 (0.73)**	86.81 (0.46)	52.29 (0.28)	73.04 (0.42)
	Spec	80.51 (0.55)	**77.45 (1.10)**	85.77 (0.47)	6.60 (0.17)	51.95 (0.64)
45-30 min	Acc	80.38 (0.55)	76.52 (0.95)	86.94 (0.50)	**53.32 (2.28)**	73.45 (0.48)
	Sen	80.38 (0.55)	76.52 (0.95)	86.94 (0.50)	**53.32 (2.28)**	73.45 (0.48)
	Spec	80.21 (0.55)	76.39 (1.15)	86.31 (0.51)	**43.76 (38.3)**	53.17 (0.64)
60-45 min	Acc	79.44 (0.63)	75.93 (0.85)	87.21 (0.49)	53.06 (0.53)	**73.80 (0.48)**
	Sen	79.44 (0.63)	75.93 (0.85)	87.21 (0.49)	53.06 (0.53)	**73.80 (0.48)**
	Spec	79.48 (0.57)	76.04 (1.10)	86.91 (0.50)	15.18 (25.7)	**54.48 (0.76)**

Acc: accuracy, Sen: sensitivity; Spec: specificity. PNES and ES events represent true positives and false positives respectively. The values outside brackets represent the mean classifier performances, the values in the brackets are standard deviations. The unit is %.

classifier was the best classifier resulting in a significantly higher accuracy compared to other classifiers (t-test, p-value $<$ 0.001). The accuracy using 15-0 min interval for EEG data for the RF classifier was the highest (mean: 86.37%), which was significantly higher than those using 30-15 min interval (mean: 85.41%, p-value=2.3e-24), 45-30 min interval (mean: 85.57%, p-value=2.0e-19), and 60-45 min interval (mean: 85.48%, p-value=1.3e-21), although the effect size is small.

For the best performing algorithm, RF, we compared the classification performance when ES are divided into focal and generalised seizures. The accuracy using 15-0 min interval for the RF classifier to classify generalised ES and PNES events (mean: 90.22%) was significantly higher than classifications between focal ES and PNES events (mean: 86.92%, p-value = 1.17e-95).

B. Classification Using ECG Data

The classification performance using different preictal intervals for ECG data across classifiers is shown in Figure 3b and Table IV. The highest mean accuracy for each classifier was 54.13% (KNN), 53.98% (DT), 53.89% (RF), 51.79% (SVM), and 49.76% (NB), respectively. On average, the KNN classifier was the best classifier. The accuracy using 60-45 min interval for ECG data for the KNN classifier was the highest (mean: 54.13%), which was significantly higher than those using 15-0 min interval (mean: 52.66%, p-value = 8.3e-26), 30-15 min interval (mean: 51.49%, p-value = 6.8e-59), and 45-30 min interval (mean: 52.16%, p-value = 4.9e-41).

For the best performing algorithm, KNN, we compared the classification performance when ES seizures are divided into focal and generalised seizures. The accuracy using 60-45 min interval for the KNN classifier to classify generalised ES and PNES events (mean: 53.76%) was significantly lower than classification performance between focal ES and PNES events (mean: 56.26%, p-value = 8.73e-54).

C. Classification Using Combined EEG and ECG Data

The classification performance using different preictal intervals for EEG and ECG data across classifiers is shown in Figure 3c and Table V. The highest mean accuracy for each classifier was 87.83% (RF), 80.83% (KNN), 77.22% (DT), 73.80% (SVM), and 53.32% (NB), respectively. On average, the RF classifier achieved the highest performance (p-value $<$ 0.001). The accuracy using 15-0 min interval for EEG and ECG data for the RF classifier was the highest (mean: 87.83%), which was significantly higher than those using 30-15 min interval (mean: 86.81%, p-value = 2.4e-17), 45-30 min interval (mean: 86.94%, p-value = 1.9e-08), and 60-45 min interval (mean: 87.21%, p-value = 2.4e-4).

For the best performing algorithm, RF, we compared the classification performance when ES seizures are divided into focal and generalised seizures. The accuracy using 15-0 min interval for the RF classifier to classify generalised ES and PNES events (mean: 91.07%) was significantly higher than classification between focal ES and PNES events (mean: 89.06%, p-value = 1.06e-67).

The classification performance was significantly improved by combining ECG data with EEG data for the RF classifier for 15-0 min interval (p-value = 1.6e-47), 30-15 min interval (p-value = 1.5e-47), 45-30 min interval (p-value = 1.6e-46), and 60-45 min interval (p-value = 1.5e-57); the KNN classifier for 15-0 min interval (p-value = 2.5e-14), 30-15 min interval (p-value = 3.1e-09), and 60-45 min interval (p-value = 1.4e-04); and the DT classifier for 15-0 min interval (p-value = 4.0e-10), 30-15 min interval (p-value = 3.2e-32), 45-30 min interval (p-value = 1.1e-07), and 60-45 min interval

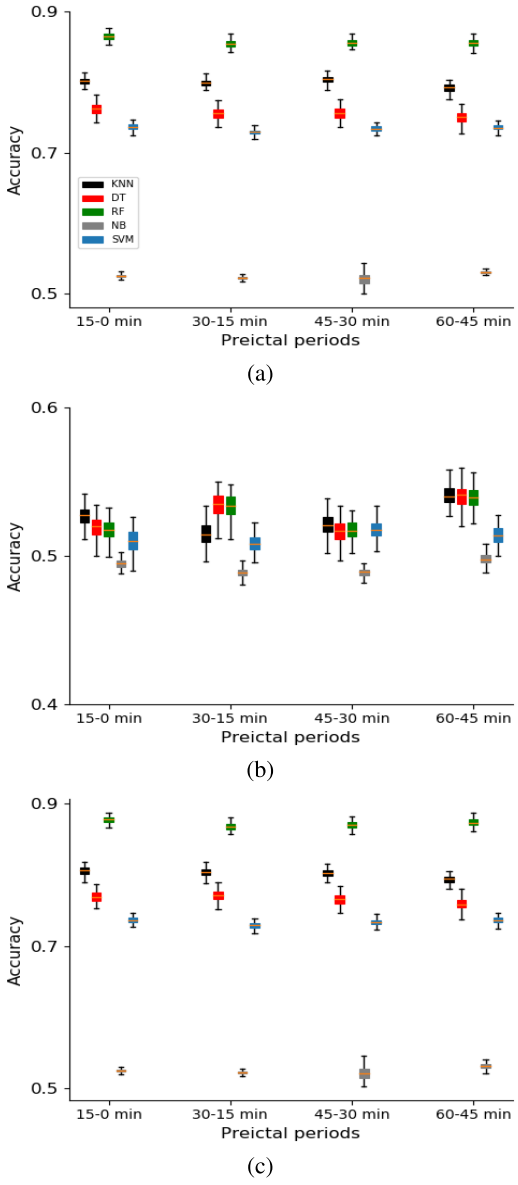

Fig. 3. Classification performances using different classifiers based on (a) EEG data, (b) ECG data, (c) EEG and ECG data. KNN: k-nearest neighbors, DT: decision tree, RF: random forest, NB: naive Bayes, SVM: support vector machine.

(p-value = 1.0e-10). For the NB and SVM classifiers, the accuracy was not significantly different compared to using EEG data for four intervals (t-test, p-value > 0.05).

D. Comparison With Existing Algorithms

To compare our results using existing algorithms for biological data classification, we run an experiment using the methodology proposed in [16]. In short, the wavelet coefficients were derived from ictal EEG data and fed into various classifiers. The results are presented in Table VI. The results indicate that the accuracy using wavelet classification is around 56%, which is significantly lower than classification based on critical slowing features with EEG data 88%.

TABLE VI
CLASSIFICATION PERFORMANCES USING WAVELET COEFFICIENTS FROM EEG DATA

	KNN	DT	RF	NB	SVM
Acc	51.80 (0.07)	52.56 (0.078)	56.17 (0.061)	47.80 (0.037)	49.27 (0.029)
Sen	51.80 (0.07)	52.56 (0.078)	56.17 (0.061)	47.80 (0.037)	49.27 (0.029)
Spec	56.21 (0.09)	50.42 (0.121)	55.58 (0.079)	66.37 (0.299)	92.68 (0.167)

Acc: accuracy, Sen: sensitivity; Spec: specificity. PNES and ES events represent true positives and false positives respectively. The values outside brackets represent the mean classifier performances, the values in the brackets are standard deviations. The unit is %.

IV. DISCUSSION

The study investigated the use of machine learning techniques for automatic classification of PNES and ES. Critical slowing features extracted from preictal EEG and ECG data were used either independently or in combination to develop classification models. The results showed that the RF classifier achieved the highest accuracy of 87.83% using EEG and ECG data. The performance was significantly improved by combining ECG data with EEG data using RF, DT and KNN classifiers. The accuracy was significantly higher using 15-0 min preictal EEG data or a combination of EEG and ECG data compared to 30-15 min, 45-30 min, and 60-45 min preictal periods.

The present study demonstrated that a combination of preictal EEG and ECG data can classify ES and PNES events. As it is difficult to differentiate PNES from ES without highly specialized clinical assessment, misdiagnosis and delayed diagnosis of PNES can lead to high morbidity [19] and considerable healthcare costs [39]. Clinicians commonly utilize semiologic features such as eye closure, side-to-side head movement, and event duration (longer than 2 min) to differentiate PNES from ES. However, these clinical signs had been shown to not always be reliable [14], [39]. The present study yielded a classification accuracy of 87.83%, indicating that the preictal EEG and ECG data is a promising tool to distinguish between PNES and ES. This finding can aid early recognition of PNES, appropriate treatment delivery, and unnecessary health costs reduction.

The high classification accuracy using EEG critical slowing features (Table III) suggested that critical slowing in the neural system was different in patients with PNES and ES. Previous studies had investigated critical slowing in ES [8], [9], which suggested that brain activity changed from an interictal to an ictal state in an ES is a critical transition [31], [33]. When the neural system approaches a critical point at a state transition [32], it returns more slowly to its steady-state after perturbations than at other states [32], [34]. This phenomenon is called critical slowing. The previously published results suggested that critical slowing is detectable in ES events. Table III showed that the classification model using EEG critical slowing features achieved a high performance, which means EEG critical slowing features were different during the transition state to PNES and ES events in the neural system and hence may be used for classification. The accuracy using ECG critical slowing features was low (Table IV), which indicated that critical slowing may not be significantly different during the transition state to PNES and ES events in

the cardiovascular system. However, the presented study did not provide evidence of whether PNES demonstrates critical slowing in the neural or cardiovascular systems. The results only indicated the differences during the transition state to PNES and ES events.

The performance was improved by combining information from both EEG and ECG data. As opposed to previous research that utilized only ECG or EEG data, we proposed a classification algorithm using both EEG and ECG data. The performance changed from 86.37% to 87.83% when ECG data was combined with EEG data using the RF classifier (Table V). Although the accuracy when using combined EEG and ECG data, compared to only EEG data, increased only slightly, it highlighted a possibility of using multi-modal data [40], such as ECG or data from wearable devices such as holter monitoring, to improve the classification performance.

It was found that the features from the 15-0 min preictal interval achieved the best performance using EEG data and a combination of EEG and ECG data. However, we noted the performance dropped only slightly from 86.37% to 85.48% using EEG data (Table III), 87.83% to 87.21% using EEG and ECG data (Table V) when selected data from 15-0 min to 60-45 min periods before events. This result showed that critical slowing phenomenon could be happening up to 1 hour prior to events. Currently, there is no clear definition of timescale of critical slowing in epilepsy studies, which could range from 90 seconds [32] to 4 hours [41]. Future work could be translating this method to intervals more than 1 hour before events.

Previous studies analyzed either focal or generalised seizures [13], [15], [18], [21], [24]. In this work, we analysed both focal and generalised seizures (Table II). Our results showed that the classification performance between generalised seizures and PNES was higher than that between focal seizures and PNES. A similar approach using a mix of seizure types have been reported in the literature [22], which showed an accuracy of 76.5-79.5%. The present study achieved higher performance. Therefore, the proposed algorithms could be applied to patients with variable seizure types.

Machine learning techniques were applied to classify patients with PNES from ES. Previous studies have employed KNN [27], DT [19], [27], RF [19], [27], [42], NB [42], and SVM [18], [19] classifiers to achieve various quality of performance. Our study achieved a comparable accuracy, which was higher than the accuracy of 81% and 87% previously reported [27], [42]. The previous results showed that the best classifier was the SVM with an accuracy of 95% [19], higher than our performance. However, it should be noted that hundreds of EEG features were used in the previous study which required a high computational cost. Moreover, whilst the previous study analysed 20 patients with ES and 20 patients with PNES, the number of seizures were not provided. We generated the classification results based on the method presented in [16] using our EEG data. The accuracy was around 56% which was much lower than 87.83% in the present study.

In a preliminary analysis, we tested different parameters in classifiers. The results showed that different parameters in KNN and RF classifiers had a trivial effect on classification performance. The accuracy remained stable when the number of neighbors in KNN was set to 3, 5, and 10, and the number of trees in RF was set to 50, 100, and 200 using 15-0 min intervals for EEG and ECG data. However, the SVM classifier with linear and sigmoid kernels generated unsatisfactory results. The current parameters used generated the best classification performance.

Our study has some limitations. The number of patients and seizures was relatively small compared to previous studies [14], [39]. Thereby the proposed approach needs to increase the number of patients and seizure events. The current results did not provide insight into the differences in underlying pathophysiology between PNES and ES. Future work will focus on investigating the underlying mechanisms of PNES and ES events such as generation mechanism and evidence of critical slowing in PNES. Moreover, the study did not investigate channel selection. The reduced channels may be more practical for use in an emergency situation, and a step towards application of a wearable device. Future work will look at using reduced number of channels and further improving the performance. We analysed 15 min duration data to avoid computational complexity. Future work will investigate if different duration of data affects the classification performance. Furthermore, as deep learning has been used to classify PNES and ES [43], this approach may allow widespread deployment in the clinical environment.

V. Conclusion

In this paper we reported the results using machine learning techniques on critical slowing features of EEG and ECG data to classify PNES and ES. We tested different preictal data and found the features from a 15-0 min preictal period could achieve the best performance, although performance only dropped slightly when looking up to one hour before the event. The results showed that the classification performance of the RF classifier was the best. The study indicated that the performance can be improved by a combination of EEG and ECG data compared to EEG data only. The reported algorithm showed the highest accuracy of 87.83%.

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