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Comprehensive Analysis of EEG Datasets for Epileptic Seizure Prediction

Rihat Rahman[1*], Shiva Maleki Varnosfaderani[2*], Omar Makke[2], Nabil J. Sarhan[2], Eishi Asano[3], Aimee Luat[3], Mohammad Alhawari[2]

[1]Department of Computer Science, Wayne State University, Detroit, USA

[2]Department of Electrical and Computer Engineering, Wayne State University, Detroit, USA

[3]Department of Pediatrics and Neurology, Wayne State University, Detroit, USA

***Abstract*—This paper provides a comprehensive analysis of the available EEG datasets that are used for epilepsy prediction systems, including Melbourne, CHB-MIT, American Epilepsy Society, Bonn, and European Epilepsy datasets. These datasets are compared in terms of the sampling rate, number of patients, recording time, number of channels, artifacts, and types of EEG signals. We also provide details on the challenges of using one dataset over the others in predicting epilepsy. Subsequently, we compare the performance of various machine learning models that use these datasets for epileptic seizure prediction. This is the first work that provides a comprehensive analysis of various EEG datasets and should be of great importance for researchers in EEG-based hardware and systems for epileptic seizure prediction.**

***Index Terms*—Epilepsy, epilepsy prediction system, Electroencephalography (EEG), EEG datasets, machine learning.**

I. Introduction

Epilepsy is one of the most common seizure disorders that is caused by abnormal brain activities and result in blank stares, unusual physical movements, and unconsciousness to patients [1]. According to the Centers for Disease Control and Prevention (CDC), 3.4 million people in the United States suffer from epileptic seizures, where 30% of them suffer from refractory epilepsy, which is uncontrollable by medications [2], [3]. Half of the refractory epileptic patients might experience sudden unexplained death in epilepsy (SUDEP) [4], a leading cause of death in people with uncontrolled seizures.

Epileptic seizures can be classified into various types based on the location of the seizure in the brain, the physical symptoms, and the occurrence rate [5]. These types include focal onset seizures which is limited to one hemisphere, generalized onset seizures, which start from various locations, and rapidly engaging, and unknown onset seizures [6].

Epileptic patients might suffer from constant depression caused by not knowing when the next seizure will occur, leading to suicidal thoughts in some cases. The development of machine learning algorithms, as well as the availability of large EEG datasets, have enabled predicting seizures before they occur, and thus patients can take precautions, stop certain activities (such as driving, swimming alone, or climbing ladders), and/or reduce their effects.

Epileptic seizures can be detected using EEG signals by identifying certain abnormal brain activities associated with epileptic seizures, such as sharp spikes. As shown in Figure 1, the EEG signal can be classified into four main categories: *preictal*, *seizure or ictal*, *postictal*, and *interictal*. Preictal is the time before seizure occurrence which lasts around fifty minutes to one hour, whereas postictal is the time right after a seizure, and interictal is the time between preictal and postictal stages. Ictal refers to the phase when a seizure takes place [7].

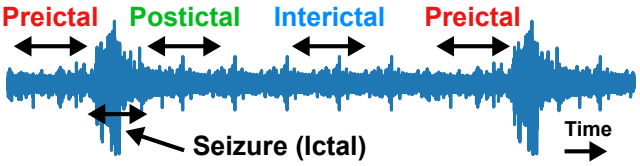

Fig. 1. Various stages of EEG signal in epileptic patients.

This paper provides a comprehensive analysis of various EEG datasets, which can be used for epilepsy prediction, including *Melbourne*, *CHB-MIT*, *American Epilepsy Society*, *Bonn*, and *European Epilepsy*. All are public and free to access, except for the European Epilepsy dataset, which is the largest. To the best of the authors' knowledge, this is the first work that analyzes and compares the most popular datasets used for epilepsy prediction. The analyzed parameters include the number of patients, number and types of electrodes used for recording, sampling rate, recording time for each patient, and general artifacts in the datasets. Besides, the paper compares the performance of various machine learning models that use these datasets for epileptic seizure prediction.

The remainder of the paper is organized as follows. The details of EEG signals are presented in Section II. The information on available public and private datasets are detailed in Section III, including comparative analysis. Dataset usage in prediction systems is discussed in Section IV, including main challenges and insights. Finally, conclusions are drawn.

II. EEG Signals

There are two types of EEG signals: *Scalp EEG* (sEEG) and *intracranial EEG* (iEEG). sEEG is recorded using electrodes that are placed on the scalp of the subject, as shown in Figure 2a. sEEG is noninvasive and easy to place; however, it cannot be used to record data for a long time. sEEG can be contaminated with different types of artifacts, including motion artifacts. Besides, sEEG uses a low number of electrodes compared to iEEG but covers a larger brain surface.

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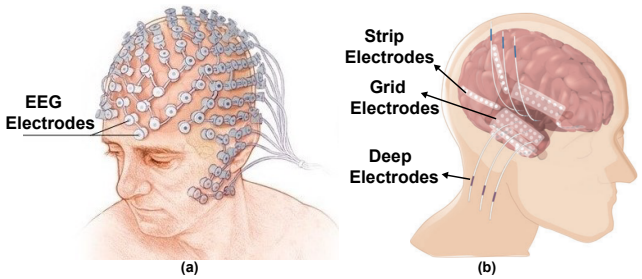

Fig. 2. Placement of electrodes in (a) sEEG (Source: *Mayo Foundation*), and (b) iEEG (Source: *Epilepsia ILAE*).

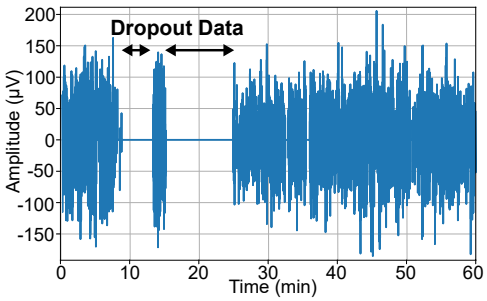

Fig. 3. An example of dropout data from an epileptic patient.

iEEG signals are recorded using invasive electrodes placed directly on the brain. As illustrated in Figure 2b, these electrodes can either be *subdural* or *depth*. The first is placed on the brain as grids or strips and cover a larger surface area, whereas the latter is inserted deep into the brain, thereby providing higher accuracy [8], [9]. iEEG provides 20 to 100 times higher signal quality than sEEG, is more immune to motion artifacts, and provides seizure localization [10], [11]. The main disadvantage of using invasive electrodes is the risk of complications after the surgery [9].

EEG data can also be classified as *long-term* or *short-term* based on the duration of the recordings. Short-term EEG recordings are similar to routine EEG scans, whereas long-term EEG recordings span for extended periods, from months to years. Long-term EEG is usually performed to correlate clinical behavior with an EEG phenomenon. EEG recordings may contain unusable data, called *dropout*, as shown in Figure 3. They are caused by a machine-related error and should be removed for better processing. Dropout could be a constant value, a constant pattern, or low amplitude values and may span from a few seconds to a couple of hours. Small intervals of dropout data can be ignored.

III. Discussion and Comparative Analysis of Various Datasets

A. Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Data

Melbourne-University provides an EEG dataset that contains long-term iEEG, recorded from 3 patients with the lowest seizure prediction performance from the NeuroVista trial [12]. Invasive strip (4×4) electrodes are placed on the focal hemisphere of the patients to record a total duration of 1,155 hours of data with 16 channels and a sampling rate of 400 Hz. The data was used in a seizure prediction competition held on Kaggle and then was provided as part of a crowd-sourcing ecosystem for epilepsy prediction. The dataset contains one hour of preictal recording before each seizure, which is broken into six 10-minute files. There are also 5-minute gaps between preictal recording and seizure occurrence, called seizure horizon onset, which allows enough time to predict and warn the patient for an oncoming seizure. Moreover, to prevent overlapping with postictal and preictal stages, interictal segments are recorded with a gap of 4 hours before and after each seizure. The duration of interictal segments is 1-hour, which is split into six 10-minute files [12]. The data is divided into training and testing, which are placed in two different folders.

One of the main challenges in using this dataset for epilepsy prediction is that the recording of data took more than one year. The testing data was recorded 6 months after the training data in which the patient was under medication, thereby causing significant differences between the distribution of the test and train sets and complicating the prediction task This causes a common problem named *covariate shift*, *concept drift*, or *data mismatch* [12]. The Melbourne dataset is in .mat format and can be easily read using MATLAB or the SciPy library of Python. Table I shows the details of the dataset, including recording duration, number of seizures, number of channels, and sampling rate.

TABLE I
Details of the Melbourne Dataset

Dataset Features	***Patient 1***	***Patient 2***	***Patient 3***
Gender	Female	Female	Female
Age (years)	22	51	50
Recording Period (days)	559	393	374
Total Recording (hours)	173	507	475
# of Seizures	390	204	545
# of train files (interictal)	570	1836	1908
# of train files (preictal)	256	222	255
# of test files (interictal)	16	18	18
# of test files (preictal)	46	279	188
# of Channels	16	16	16
Sampling Rate (Hz)	400	400	400

B. American Epilepsy Society Dataset

The American Epilepsy Society dataset contains iEEG data of 7 subjects (2 humans and 5 dogs) with a total duration of 1,333.7 hours. The number of channels varies from 15 to 24 among the subjects, while the sampling rate is 5000 Hz and 400 Hz for humans and dogs, respectively. The recordings are structured similar to the Melbourne dataset with 1 hour of recordings divided into six 10-minute files and a seizure horizon onset of five minutes. Interictal files from the dogs have a week gap with seizures, while interictal files from humans have a gap of 4 hours [13].

Several hours of EEG data for the first human subject contains dropout data across all channels, caused by 60 Hz noise, which is coupled through recording machines. Notch filters could be used to remove this noise. The details of the dataset are shown in Table II.

C. CHB-MIT sEEG Dataset

The CHB-MIT dataset contains sEEG data recorded at a sampling rate of 256 Hz from 23 epileptic patients at the Children's Hospital of Boston [14]. The dataset is divided into cases, each representing one patient, except for case 1 and case 21, where the data are recorded from the same patient with a gap of 1.5 years. Although the number of

TABLE II
DETAILS OF THE AMERICAN EPILEPSY DATASET

Case	# of Channels	Sampling Rate (Hz)	# of Train Files	# of Test Files	Duration (hours)
Patient 1	15	5000	68	195	43.8
Patient 2	24	5000	60	150	35
Dog 1	16	400	504	502	167.7
Dog 2	16	400	542	1000	257
Dog 3	16	400	1512	907	403.2
Dog 4	16	400	901	990	315.2
Dog 5	15	400	480	191	111.8

TABLE III
DETAILS OF THE CHB-MIT DATASET

Case	Gender	Age (years)	# of Seizures	Duration of Recordings (hh:mm:ss)
chb01	Female	11	7	40:33:08
chb02	Male	11	3	35:15:59
chb03	Female	14	7	38:00:06
chb04	Male	22	4	156:03:54
chb05	Female	7	5	39:00:10
chb06	Female	1.5	10	66:44:06
chb07	Female	14.5	3	67:03:08
chb08	Male	3.5	5	20:00:23
chb09	Female	10	4	67:52:18
chb10	Male	3	7	50:01:24
chb11	Female	12	3	34:47:37
chb12	Female	2	40	20:41:40
chb13	Female	3	12	33:00:00
chb14	Female	9	8	26:00:00
chb15	Male	16	20	40:00:36
chb16	Female	7	10	19:00:00
chb17	Female	12	3	21:00:24
chb18	Female	18	6	35:38:05
chb19	Female	19	3	29:55:46
chb20	Female	6	8	27:36:06
chb21	Female	13	4	32:49:49
chb22	Female	9	3	31:00:11
chb23	Female	6	7	26:33:30
chb24	Not provided	Not provided	16	21:17:47

channels varies from 23 to 26, the following 18 channels are common among all patients: 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. Unlike Melbourne and American Epilepsy Society datasets, the CHB-MIT dataset does not contain preictal or interictal labels but can be extracted using seizure timings provided in meta-data files of every patient. This can be applied for all cases except case 24, where the start and the end time of the file are not specified. The dataset has 198 seizures, and the files are in .edf format [15]. The details of this dataset are shown in Table III.

D. Bonn Dataset

The Bonn EEG dataset contains sEEG and iEEG from 5 subjects with a sampling rate of 173.61 Hz. The data is collected from patients experiencing a seizure-free interval (folders N and F), from patients having a seizure (folder S), and from healthy patients at rest (folders Z and O). There are 100 samples in each folder where every sample has a record duration of 23.6 seconds. Unlike other available datasets, the Bonn dataset contains healthy labels. However, due to the short total duration of 3.3 hours and the use of a single channel to record the data, the Bonn dataset is not preferred for epilepsy prediction algorithm development [24].

TABLE IV
DETAILS OF THE EUROPEAN EPILEPSY DATASET

Patient	Gender	Age	Samp. Rate (Hz)	# of Channels	# of Seizures	Duration (hours)
FR_264	F	48	256	67, 91	8	140.5
FR_253	F	37	512	31, 58	7	262.1
FR_1146	M	22	1024	116	26	113.6
FR_1096	F	32	1024	100	9	163
FR_1084	F	48	1024	93, 117	94	250.6
FR_970	M	15	256	119, 122	19	205.1
FR_958	F	14	1024	97, 121	16	232.2
FR_922	M	39	1024	85, 109	30	114.6
FR_916	M	23	1024	85, 109	52	430.8
FR_862	F	16	256	61, 85	9	233.6
FR_620	M	42	1024	39, 63	7	255.1
FR_590	M	18	1024	99, 122	13	252.2
FR_583	F	22	256, 1024	41, 65	23	203.5
FR_565	M	13	256	93, 117	14	229.1
FR_548	M	17	1024	85, 109	31	143.6
FR_384	F	50	256, 1024	95, 119	15	139
FR_375	M	35	256	57, 81	26	184
FR_273	F	3	256	47, 68	7	203.4
FR_1150	F	32	1024	125	9	158.7
FR_442	M	21	1024	71, 95	22	186
FR_139	F	53	256, 512	45, 60	6	172.6
FR_115	M	34	256	86	26	229.4
FR_1125	F	11	1024	63, 87	14	158.5
FR_1077	F	29	1024	122	9	185.8
FR_1073	F	47	1024	72, 96	20	228.8
FR_818	F	27	1024	47, 71	9	252.7
FR_635	F	63	1024	82	21	119.2
FR_CM_32	M	10	2500	102	9	207.1
PA_inv_13245	F	43	1024	57	31	357.6
PA_inv_13089	F	29	1024	64	8	475.9

E. The European Epilepsy Dataset (Private)

The European Epilepsy dataset is the largest available EEG dataset, including data for 30 invasive patients over multiple days of recording and a total duration of 6,488 hours [25]. Although there are two packages, scalp and intracranial EEG, this paper only refers to the intracranial EEG package of the European Epilepsy dataset. The number of channels and sampling rate vary widely among the patients ranging from 31 to 124 and 256 Hz to 2500 Hz, respectively, which is much higher than other available datasets. The dataset includes a few scalp electrodes for Electrooculography (EOG) and Electrocardiogram (ECG), which record the electrical activity of the eyes and heart, respectively. The files of this dataset are not labeled as preictal or interictal, however, they can be extracted using the timing information of the 590 seizures present in the dataset. Further, the dataset provides information about seizure types and origin of the seizure, which can help develop patient-specific machine learning algorithms to predict the seizure location in the brain. Finally, the dataset includes details about subclinical seizures, which show abnormal electrical activity in the brain with no physical symptoms. The details of the dataset are shown in Table IV.

F. Summary and Overall Comparison

Table V summarizes and compares all the datasets, where the European Epilepsy dataset provides the largest number of subjects, number of channels, and duration.

TABLE V
SUMMARY OF THE AVAILABLE EEG DATASETS

dataset	*Type*	*Preictal Label*	*# of Subjects*	*# of Channels*	*Sampling Rate (Hz)*	*Duration (hours)*
Melbourne	iEEG	Yes	3	16	400	1,155
American Epilepsy Society	iEEG	Yes	7	15-24	400-5000	1,333.7
CHB-MIT	sEEG	No	23	23-26	256	979
University of Bonn	sEEG + iEEG	No	5	1	173.61	3.3
European Epilepsy dataset	iEEG	No	30	31-125	256-2500	6,488

TABLE VI
REPORTED RESULTS ON EPILEPSY PREDICTION ALGORITHMS

Ref.	dataset	*Pre-processing*	*Feature Extraction*	*Classification*	*Post-processing*	*Sensitivity %*	*FPR* h^{-1}	*Accuracy %*
[16]	Melbourne	Down-sampling	STFT	CNN	-	87.85	-	-
[17]	American Epilepsy Society	-	STFT	CNN	K-of-N method	75	.21	-
[18]	CHB-MIT	-	Time/Frequency Domain, Wavelet Transform, Cross Correlation, Graph Theory	2-layer LSTM	-	99.28-99.84	.02-.11	-
[19]	CHB-MIT	-	Deep Convolutional Autoencoder	BiLSTM	-	99.72	.004	99.66
[20]	CHB-MIT	-	STFT + CNN	LSTM	K-of-N method	98.21	.13	-
[21]	CHB-MIT	Filtering	Combination of Common Spatial Statistics	CNN	Kalman Filtering	92.2	.12	90
[22]	Bonn	-	-	Stacked BiLSTM	-	89.21	.06	91
[23]	CHB-MIT	-	STFT	CRGNN	-	89	-	75.6

IV. DATASET USAGE IN EPILEPSY PREDICTION SYSTEMS: DISCUSSION, CHALLENGES, AND INSIGHTS

Two main metrics for epilepsy prediction are generally used to evaluate the prediction accuracy of machine learning models, namely, *sensitivity* and *false positive rate* (FPR). Sensitivity is defined as the probability of seizures to be correctly predicted, while FPR is the rate of detecting seizures incorrectly per hour. *Accuracy* can be derived from sensitivity and FPR [26], [27]. Other metrics include *complexity* and *power consumption*, which are of great importance, especially in hardware accelerators.

An epilepsy prediction system requires various steps, including *pre-processing*, *feature extraction*, *classification*, and *post-processing*. Pre-processing aims to prepare and clean the data using filtering, artifact removal methods, and augmentation. Feature extraction can be used to extract the most important features in the *time domain* such as mean, variance, kurtosis, and skewness, in the *frequency domain* such as spectral power in different frequency bands and *Short-Time Fourier Transform (STFT)*, and in the time-frequency domain such as *Wavelet Transform* [28]. Various classifiers are used to classify EEG data, including *Convolutional Neural Networks* (CNN) [16], [17], [21], *Long Short-term Memory* (LSTM) [18], [20], *Bidirectional LSTM* (BiLSTM) [19], [22], and *Convolutional Gated Recurrent Neural Network* (CGRNN) [23]. Post-processing methods may be used to enhance classification accuracy, using the *K-of-N* method [17], which also reduces the FPR. Schemes that use handcrafted features instead of automatic feature extractions (by CNN as an example) can have lower training times, complexity, and power consumption.

Table VI compares various reported prediction schemes. The performance depends not only on the machine learning algorithm and the used methods for pre-processing and post-processing but also on the used dataset. The worst results, reported in [16] and [17], are for the Melbourne and American Epilepsy Society datasets, respectively. Both of these datasets have data drift, where EEG data is collected at different times (6 months apart in Melbourne), and thus are hard to train compared to other datasets. A possible solution is to extract non-time domain features from the data, such as frequency domain features [16].

Due to the limitation in recording the data from patients, a low number of samples is another challenge in datasets, which might lead the model to biased machine learning performance. To increase the number of samples, different datasets can be combined while ensuring that the electrode locations match. For example, in [29], the Bonn dataset is used to train the system, and the CHB-MIT dataset is used to validate and test the system.

V. CONCLUSION

This paper analyzed and compared various EEG datasets used for epileptic seizure prediction. The European Epilepsy dataset contains the longest recording duration with the highest number of patients compared to other datasets, thereby can be an excellent candidate to develop accurate machine learning models to predict epilepsy. Various machine learning models for epilepsy prediction were analyzed and compared, and the impact of the dataset was discussed. This work can be of great importance for researchers in EEG prediction systems.

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