Real-time preictal detection through the application of machine learning to Electroencephalogram signals.

William Riddell

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Acronyms

AI Artificial Intelligence. 3

CNN Convolutional Neural Network. 2, 8, 9

EEG Electroencephalogram. 3

EEGs Electroencephalograms. 3, 4

ML Machine Learning. 3, 6

STFT Short-Time Fourier Transform. 8

1 Introduction

Over the last 20 years, Artificial Intelligence (AI) has seen a large evolution through the use of Machine Learning (ML); the statistical analysis of data which leads to the unveiling of characteristics and connections. (Awad & Khanna 2015). There has been a large uptake of applying ML techniques to biomedical data, increasing the speed and accuracy of prediction, detection, diagnosis, and prognosis.

Electroencephalograms (EEGs) measure the electrical signals in the brain. EEGs have a great use in giving an insight into the inner workings of the brain, for example allowing us to pick up abnormalities preceding and during their occurrence. "A seizure is a burst of uncontrolled electrical activity between brain cells (also called neurons or nerve cells) that causes temporary abnormalities in muscle tone or movements (stiffness, twitching or limpness), behaviours, sensations or states of awareness." (Medicine n.d.) Due to this, monitoring the brain's electrical activity through the use of an EEG, and applying analysis through an ML model may allow us to detect the preictal period. "An automated accurate prediction of seizures will significantly improve the quality of life of patients and reduce the burden on caregivers" (Acharya, Hagiwara & Adeli 2018)

1.1 Background

“Because of their unpredictable nature, uncontrolled seizures represent a major personal handicap and source of worry for patients. In addition, persistent seizures constitute a considerable burden on healthcare resources.” (?) Due to this both medication and surgery are available to applicable patients, although with 30% patients being refractory to drug therapy, and an equally bleak surgery success rate; 75% in lesional cases, and 50% in nonlesional cases for temporal lobe cases along with 60% in lesional cases and merely 35% in nonlesional for frontal lobse cases (?), a large population of patients would greatly benefit from the prediction of their uncontrollable seizures, along with an relief of burden for the healthcare system when working with seizure patients.

2 Proposed Method

2.1 Datasets

(Wong, Simmons, Rivera-Villicana, Barnett, Sivathamboo, Perucca, Ge, Kwan, Kuhlmann, Vasa et al. 2023) reviews 10 datasets available to download. It evaluates the way the EEGs were physically setup on the subject, the subjects themselves and the data’s properties. Wong et al. also states their opinion on what tasks suit what dataset, with the main two tasks being either detection or prediction.

Dataset
University of Bonn
CHB-MIT Scalp EEG
Melbourne-NeuroVista seizure trial (Neurovista Ictal)
Kaggle UPenn and Mayo Clinic’s Seizure Detection Challenge
Neurology and Sleep Centre Hauz Khas
Kaggle American Epilepsy Society Seizure Prediction Challenge
Kaggle Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge
TUH EEG Seizure Corpus (TUSZ)
Siena Scalp EEG
Helsinki University Hospital EEG

Table 1: The Datasets analysed

Within these datasets Wong et al. was also able to find the way the EEG nodes were positioned on the subject's cranium, along with whether the EEG nodes were either placed intracranial or extracranial. Wong et al. also the number of channels that are contained in the raw EEG data for each dataset.

Dataset	**Number of channels**	**Placement method**	**Type of signal**
University of Bonn	1	International 10–20 system, Intracranial	Scalp/Intracranial EEG
CHB-MIT Scalp EEG	18	International 10–20 system/Nomenclature	Scalp EEG
Melbourne-NeuroVista seizure trial (NeuroVista Ictal)	16	Intracranial	Intracranial EEG
Kaggle UPenn and Mayo Clinic's Seizure Detection Challenge	16–76	Intracranial	Intracranial EEG
Kaggle American Epilepsy Society Seizure Prediction Challenge	16	Intracranial	Intracranial EEG
Neurology and Sleep Centre Hauz Khas	1	International 10–20 System	Scalp EEG
Kaggle Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Data	16	Intracranial	Intracranial EEG
TUH EEG Seizure Corpus (TUSZ)	23–31	International 10–20 system / Nomenclature	Scalp EEG
Helsinki University Hospital EEG	19	International 10–20 system	Scalp EEG
Siena Scalp EEG	20/29	International 10–20 system/Nomenclature	Scalp EEG

Table 2: Channel Characteristics

Wong et al. also noted along with this data that the "University of Bonn dataset contains a mixture of both scalp and intracranial EEG data where scalp EEG from healthy subjects was taken, while intracranial EEG was taken from subjects with a history of seizures." (Wong et al. 2023). This may present a skew on the ML model during training.

Dataset	**Noncontinuous data**	**Short-term continuous data**	**Continuous data**
University of Bonn	Yes	No	No
CHB-MIT Scalp EEG	No	Yes	Yes
Melbourne-NeuroVista seizure trial (Neurovista Ictal)	N/A	N/A	N/A
Kaggle UPenn and Mayo Clinic's Seizure Detection Challenge	Yes	No	No
Kaggle American Epilepsy Society Seizure Prediction Challenge	Yes	No	No
Neurology and Sleep Centre Hauz Khas	Yes	No	No
Kaggle Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Data	Yes	No	No
TUH EEG Seizure Corpus (TUSZ)	No	Yes	No
Helsinki University Hospital EEG	No	Yes	No
Siena Scalp EEG	No	Yes	No

Table 3: Temporal properties

Wong et al. ordered the datasets into groups, either continuous or non continuous data. For the continuous data they separated out datasets which record for less that 24 hours in a single go, these were classified as "Short-term continuous" data.

Dataset	Number of subjects	Subject type
University of Bonn	10	Human
CHB-MIT Scalp EEG	23	Human
Melbourne-NeuroVista seizure trial (NeuroVista Ictal)	12	Human
Kaggle UPenn and Mayo Clinic's Seizure Detection Challenge	12	Human & Canine
Kaggle American Epilepsy Society Seizure Prediction Challenge	7	Human & Canine
Neurology and Sleep Centre Hauz Khas	10	Human
Kaggle Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Data	3	Human
TUH EEG Seizure Corpus (TUSZ)	642	Human
Helsinki University Hospital EEG	79	Human
Siena Scalp EEG	14	Human

Table 4: Subject properties

Wong et al. also was able to identify the number of subjects within each dataset. Within the two "Kaggle" datasets there are Canine subjects, making them unsuitable for this project.

Within the review, they also produced tables displaying the segment information for each dataset, breaking down the recording length and frequency, along with the number of events and segments. This information should not weight into which dataset suits the idea of preictal prediction so shall be left out in this background review. Wong et al. also discussed the idea of the class imbalance problem, where the number and length of each ictal period is unbalanced. Two datasets, "University of Bonn" and the "Neurology and Sleep Centre Hauz Khas" have addressed this issue and have balanced their data between ictal, preictal, interictal and nonictal periods.

Taking the research into account Wong et al. suggested which dataset suits either prediction or detection. “Since the aim of seizure prediction is to forecast impending seizures, EEG recordings that include preictal and interictal data should be used for the study, while the aim of seizure detection is to detect ongoing seizure events, hence, EEG recordings that contain ictal and interictal data should be used.” (Wong et al. 2023).

Dataset	**Application**
University of Bonn	Seizure detection
CHB-MIT Scalp EEG	Seizure detection/Prediction
Melbourne-NeuroVista seizure trial (NeuroVista Ictal)	Seizure detection/Prediction
Kaggle UPenn and Mayo Clinic's Seizure Detection Challenge	Seizure detection
Kaggle American Epilepsy Society Seizure Prediction Challenge	Seizure prediction
Neurology and Sleep Centre Hauz Khas	Seizure detection/Prediction
Kaggle Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Data	Seizure prediction
TUH EEG Seizure Corpus (TUSZ)	Seizure detection/Prediction
Helsinki University Hospital EEG	Seizure detection/Prediction
Siena Scalp EEG	Seizure detection/Predictio

Table 5: Suggested applications

From this evaluation the CHB-MIT Scalp EEG dataset has been chosen for the CNN model training.

2.2 Preprocessing

Short-Time Fourier Transform (STFT)

As the proposed CNN will be two-dimensional, it will be required that the input is a two-dimensional matrix. Due to this the EEG data will be transformed using STFT, representing the EEG signals into two-dimensional matrix of axis time and signal frequency.

Powerline Signal

The CHB-MIT dataset contains powerline noise contamination at 60Hz, to avoid any unwanted issues during the training of the CNN this noise has been removed. This was achieved by removing the frequency ranges of 57-63Hz and 117-123Hz (Truong, Nguyen, Kuhlmann, Bonyadi, Yang, Ippolito & Kavehei 2018). Furthering this, the 0Hz frequency was also removed due to the DC component of the powerline noise.

add image

Dataset Imbalance

A data imbalance occurs when there are more occurrences of a specific class. This is unavoidable when collecting raw seizure EEG data. (Wong et al. 2023) discussed two datasets,“University of Bonn” and the “Neurology and Sleep Centre Hauz Khas” which have addressed this issue already, although the CHB-MIT Scalp EEG dataset has not, and therefore requires a method to deal with this issue. The data imbalance between the interictal and preictal timespans are at best 9.5:1, and at worst 15.9:1 on a per subject basis within the CHB-MIT datasets, to address this (Truong et al. 2018) devised a method of generating extra preictal periods by using an sliding window method. This is where a window of x seconds is moved at a step speed of s, where $s < x$ such that data is generated. **add image**

2.3 Convolutional Neural Network (CNN)

2.4 Postprocessing

2.5 System Evaluation

3 Results

4 Discussion

5 Conclusion

References

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