# Two-Channel Epileptic Seizure Detection with Blended Multi-Time Segments Electroencephalography (EEG) Spectrogram

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**Abstract— Automated seizure detection using clinical electroencephalogram (EEG) data have been a challenging problem for the last decades. Current solutions for tracking seizures include using epilepsy seizure diaries or mobile apps to be maintained by patients or caregivers as well as non-EEG wearable solutions (e.g. smartwatch). This is due to the fact that interpretation of EEG signals can be complicated by physiological artifacts or other variations in EEG (e.g. cortical slowing). Commercially available tools for seizure detection suffer from unacceptably high false-alarm rates and they are often not based on EEG. They often require to have more than 20 EEG electrodes recordings to be able to detect and label seizures. In this paper, we demonstrate a technique capable of detection seizures with two electrodes and a low false-alarm (FA) rate in 24 hours. Using a low number of electrodes is important because often patients require to undergo a complex, lengthy and sometimes painful process of wearing an EEG cap with a high number of electrodes for nearly five days in epilepsy monitoring units. This work considers a blended time-segment EEG signal processing for epileptic seizure detection using Convolutional, Long Short-Term Memory (Conv-LSTM). Extensive experiments have been conducted on Temple University Hospital (TUH) EEG corpus. We introduce a novel and open-code solution that involves an electrode ranking pre-processing as well as fusion of multi time-segments EEG spectrogram in short-time Fourier transform (STFT) analysis. Our implementation achieved 0.17 FA/24 hrs with 2.04% sensitivity and using only two channels. Source code of our analysis is available on the NeuroSyd github channel.**

## I. Introduction

Epilepsy is a common neurological disorder characterized by recurrent seizures. Its prevalence is around 1% people suffer from the disorder [1]. Even with the help of anti-epileptic drugs, the condition is intractable in about 30% of people living with epilepsy [2]. The symptoms include injuries, behavioural, developmental and cognitive disorders, and even death [3]. Sudden and unexpected death in people with epilepsy, SUDEP, is the leading cause of death if epilepsy is uncontrolled. Usually at-risk individuals are otherwise healthy and autopsy provides no other explanation for the cause of death other than SUDEP. This means patients and their caregivers quality of life are significantly impacted [4, 5]. Long-term ambulatory physiology monitoring for brain signals using wearable electroencephalogram (EEG) signals could open the way for continuous monitoring but it is not turned into a reality yet. One of the issues at the heart of the challenge in realizing long-term wearable monitoring is the lack of comfort and reliability of many EEG electrodes. If we can reduce the number of electrodes and yet maintain or even improve accuracy of seizure detection we may be able to develop technique for longer terms monitoring of EEG signals. Another challenge is to detect epileptic seizures accurately [6, 7]. Numerous researchers have attempted successful seizure detection using wearable EEG in number of seizure detection devices. For the diagnosis of epilepsy, occurrence of two unprovoked seizures are usually required, but one unprovoked seizure is sufficient for diagnosis if the risk of further unprovoked seizures is high. Therefore, the ability to correctly identify seizures and also assess the chance for further seizures play an important role in reducing epilepsy misdiagnosis and seizure management and therapy decisions. Further, manually interpreting EEG is a time-consuming task, given it requires input by highly trained experts with years of training and experience. However, due to the unacceptably high false-alarm rates, transforming automated EEG analysis technology into a commercial product for clinician usage has been largely limited [8]. Further compounding the issue is the complex, lengthy and sometimes painful process the patients must endure to reach a diagnosis. This includes the need to wear a full 10-20 electrode cap for a number of days. Though the well-recognised $10-20$ electrodes configuration provides clinicians enough information for seizure diagnosis, there are limitations in clinical practice due to the large data housing and computational power required to store and process this information

Recently, thanks to the big data collection and rapid improvement in low-cost powerful computational infrastructure, the deep learning algorithm could be applied to different areas to improve performance. Using AI techniques to do seizure prediction and detection has also attracted growing attention [9, 10]. With the help of AI to assist in automatic seizure detection, patients' quality of life can dramatically increase.

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In this paper, we describe an innovative method to optimize channel selection and minimize false alarm for seizure detection using convolutional long short-term meomory network (Conv-LSTM) [11]. To this end, we propose a detail solution for seizure detection using blended multi time-segments electroencephalography to minimize false alarm in seizure detection, including feature selection, channel selection, segmentation selection, model selection and post processing. Our proposed methods include (1) extract raw EEG spectrogram [12] features as deep learning input; (2) using F3-F7, P3-O1 as two channels of information instead of the full set of 22 electrodes; (3) combine Conv-LSTM and dense layer for our detection; (4) using average methods for predicting seizure time in different time feature segmentation and overlap the detection results; (5) discard short seizure prediction and concatenate nearby long seizure prediction. The numerical experiments are compared using TUH EEG seizure corpus dataset [13] to investigate che effectiveness of the proposed methods in minimizing false alarm for seizure detection task. The scoring algorithm used to deal with the overlap between the hypothesis versus ground truth (i.e. reference) is Time-Aligned Event Scoring (TAES) [14]. Further points were awarded based on the Neureka 2020 Epilepsy Challenge. As far as we know, this is the first method using blended multi time-segments for seizure detection with only two channels.

The rest of the paper is organised as follows. The next section reviews the related literature (see Section II). Section III discusses properties of the dataset that is used in this research. Section IV describes the method for optimizing channel selection. Section V introduces the proposed method of *blended multi-time segments for seizure detection* (BMTSSD). Section VI describes the numerical experiments and evaluation of the model. Finally, Section VII concludes the paper and discusses future directions for the work.

## II. Related works and prior arts

A variety of seizure detection approaches have previously been applied to the TUH EEG dataset [13]. A hidden Markov model (HMM) [15] was used to achieve 30.32% sensitivity with 244 FA/24 hrs measured by Any-Overlap (OVLP) score [14]; CNN and LSTM combined methods are used to achieve 30.83% sensitivity with 6 FA/24 hrs [16]; Channel-based LSTM method reached 39.46% with 11 FA/24 hrs [8]. Researcher also tried to optimize channel selection, however results decreased dramatically which reached 31.15% with 308 FA/24 hrs when using 2 channels [17].

The output of the related work mentioned above are measured by the Any-Overlap (OVLP) score, which assesses the overlap in time between a reference and hypothesis event. However, time-aligned event scoring (TAES) is more strict than the OVLP score metric which only considers the percentage of overlap between the two events. In other words, the results of the above work would become much worse when measured in TAES score. For example, the best performance from CNN and LSTM combined methods got 12.48% with 7.58 FA/24 hrs using all channels, the sensitivity is only one of third compared with measured by OVLP score with more false alarm.

Table 1. Summary of TUH EEG datasets

| Dataset Type | Train Dataset | Dev Dataset | Eval Dataset |
|---|---|---|---|
| File numbers | 4597 | 1013 | 1023 |
| Sessions | 1185 | 238 | 152 |
| Patients | 592 | 50 | 50 |
| Files with seizures | 867 | 280 | 235 |
| Sessions with seizures | 343 | 104 | 78 |
| Patients with seizures | 202 | 40 | 42 |
| Number of seizures | 2370 | 673 | 511 |
| Overall duration (s) | 2,708,284,00 | 613,232.00 | 543135.00 |
| Background duration (s) | 2,540,144,77 | 554,786.89 | 505250.37 |
| Seizures files duration (s) | 635,490.00 | 230,031.00 | 187129.00 |
| Seizure duration (s) | 168,139.23 | 58,445.11 | 37884.63 |

## III. Dataset

Table 1 summarizes the datasets being used in this work: the Temple University Hospital (TUH) seizure corpus dataset v1.5.1, [18] there are a total of 1185 sessions with 592 in the training dataset and 238 sessions with 50 patients in development dataset. TUH dataset consist of 202 and 40 patients with seizures in training and development dataset respectively. Besides, the ratio of seizure duration and background duration in training set and development set are approximately 15.1:1 and 9.5:1 respectively. The majority of the EEG data was sampled at 250Hz (87%) with the remaining data being sampled at 256 Hz (8.3%), 400 Hz (3.8%), and 512 Hz (1%). [19]. Two general unipolar montages are used in TUEG, (1) Average Reference (AR) and (2) Linked Ears Reference (LE), which are used to help further classify three types of files tcp_ar (AR Method only), tcp_le (LE Method only), and tcp_ar_a (both AR and LE Method). [19]. The first two files contain 21 channels whereas the third file only includes 20 channels. In order to make reliable prediction, we further split the training dataset into three sets, 60% for training, 20% for validation and 20% for testing (dev2), which means that we test our model twice (dev & dev2) before test on final hidden evaluation dataset.

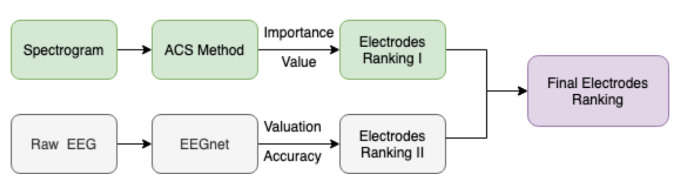


Figure 1. Channel selection procedure

## IV. Channel Selection

We made the channel selection with two ranking techniques that is based on 1) our team's previous research output published in Ref. [20] and 2) feeding only one electrode information into a simple and fast CNN structure (EEGNet, as seen in Ref. [21]). We then selected channels by ranking valuation accuracy. We made our final channel selection decision based on two channel ranking results and did further experiment on high ranking channels.The purpose of the two methods for channels selection is to make the selection more reliable. The procedure are shown in Fig. 1.

### *IV-A. Supervised Learning in Automatic Channel Selection*

The automatic channel selection (ACS) approach was designed to be run offline, presenting a cost/time effective approach with regards to human resource time, and future online analysis. Firstly, the labelled data is transformed by applying fast Fourier transform (FFT) to the raw EEG data, to obtain frequency information from all channels. Next, the FFT values are sliced, transforming the data into 1 Hz bins in the range of 1–47 Hz. The $\log_{10}$ transform is then applied to the values. The resulting transformed data is a $N\times47$ matrix, where 47 is the number of 1 Hz bins in the range of 1–47 Hz. Each individual channel is now a feature to be fed to the classifiers. At this stage, the between-channel correlation is disregarded. This is to avoid confusion arising from the importance of the correlation between channels, rather than the importance of the actual channels themselves. Consequently, the importance level of each feature or channel is determined by one or multiple classifiers. The various chosen classifiers included Gradient Boosting, AdaBoost and Random Forest. In cases where multiple classifiers were used the final importance level of each channel was the sum of importance values obtained from all classifiers.

### *IV-B. Fast Single Electrode training for channel ranking*

Another method we used for electrodes ranking is training the classifier to only feed one electrode one time and rank channels based on the valuation accuracy. In order to make this method less time-costly, we only trained one epoch for comparison as there are a total of 21 electrodes to test. In the meantime, the deep learning model structure we chose is "EEGNet" [21], a simple and fast CNN structure which has been widely used in the BCI domain. Unlike previously mentioned methods which use frequency information in training, this approach trains the raw EEG directly.

## V. Blended Multi-Time Segments for Seizure Detection

This section presents our proposed method "Blended Multi Time-Segments" that can be used to largely decrease the false alarm for the seizure prediction and detection.

### *V-A. Pre-processing*

Although raw EEG data information can be directly fed into neural network, lack of frequency information will make the network harder to extract important features. Wavelet [22] and Fourier transforms [23] are two widely used methods that could translate time-series EEG into a three dimension matrix that composed of both frequency and time information. In this work, we used the short-time Fourier transform (STFT) to translate raw EEG signals into a spectrogram with three different window lengths of 3s,5s,7s. In addition, due to differences in the recording sample rate, we re-sampled the data all into 250 Hz. Therefore, a 3s EEG signal with 2 channels will be formatted to a data shape with (2,750), we use window length 250 (1s) and 50% overlapping when doing the STFT, so the data shape will become (5,2,126). Then the DC component (at 0 Hz) was removed in the spectrogram and we add one more axis before feeding to the neural network, so the final data shape become (5,2,125,1). The Eq. 1 shows the Fourier transform that calculates the information for the frequency domain, where m represents the window length and n for the nth sample. The magnitude is calculated by the square of the absolute value after the STFT [24].

$$X(m,\omega) = \sum_{n=0}^{end} x[n]\omega[n-m]e^{-j\omega n} \tag{1}$$

$$M(m,\omega) = |X(m,\omega)|^2 \tag{2}$$

One of the big challenges in many classification tasks is the data imbalance issue: that is the number of some classes is much more than the rest. [25] Seizure detection also encounters this issue; in the TUH dataset shown in the Table 1, the ratio of background-to-seizure duration is 15.1:1 in training dataset and 9.5:1 in development dataset. If we train it without any further processing, it will be harder for the network to learn to predict the small number class (seizure in this case). To overcome this, first we generate more seizure segments by using the overlapping techniques when doing the STFT. In particular, we slide a 1s and 3s window along the time axis when we select out the certain time segments for the seizure and background information respectively, which could decrease the imbalance ratio three times smaller. Furthermore, during the training we put k times weight on predicting seizure loss based on the ratio of background-to-seizure number $k$ using Keras class weight function. For the valuation dataset, we up-sampled the seizure segments by randomly repeating to make it have the same number as the background segments.

### V-B. Conv-LSTM

CNN and LSTM have been two widely used methods for computer vision and natural language processing [11, 26]. In this work, we use three Conv-LSTM blocks [11] combined with three fully connected layers. The code is implemented with Keras Conv-LSTM module, and the first Conv-LSTM layer has 16 $2 \times 3$ kernels using $1 \times 2$ stride. The next two Conv-LSTM blocks both use $1 \times 2$ stride and $1 \times 3$ kernel sizes, whereas the Conv-LSTM block 2 uses 32 filters and Conv-LSTM block 3 uses 64 filters. Following the three Conv-LSTM blocks are three fully connected layers with sigmoid activation and output sizes of 896,256 and 2, respectively.

### V-C. Post Processing

In order to predict the seizure in every 1s, the post processing is needed as we only have predictor that could predict seizure every M seconds (*M*= 3s,5s,7s). Average methods are applied to help get every 1s reliable prediction: 1) although predictor makes prediction every M seconds, it moves only 1s after finishing once prediction; 2) The specific second possibility of having seizure is equal to the average of the results that predictor predicts. After applying average method for these three predictors, we classify the results based on the possibility threshold, which could help us select the high confidence prediction to decrease the false alarm. The system only selects the overlap area that 3s,5s,7s predictor predicts. The reason for this is it allows the model to make predictions combining both short and long period information, which will be more reliable. We also discard the seizure prediction which is shorter than 5s and concatenate the prediction if two seizure prediction periods are less than 10s. We found that the shortest seizure sustainable time in the training dataset is 5s and the shortest space time for two seizures is 10s.

### V-D. Evaluation Metrics

To evaluate the output of the model, the challenge organisers applied the TAES method. This metric was designed to consider the balance between correct detection of number of events, as well as their duration. The critical parameters used in this challenge to calculate sensitivity and specificity measures such as true positives (TP), true negative (TN) and false positive (FP), are described in detail by Shah and colleagues [14].

$$TP = \frac{H_{stop} - H_{start}}{Ref_{dur}}, \quad R_{start} \leq H \leq R_{stop}$$

$$TN = \frac{1 - (TH_{stop} - TH_{start}))}{Ref_{dur}}, \quad R_{start} \leq H \leq R_{stop}$$

$$FP = \begin{cases} \frac{H_{stop} - H_{start}}{Ref_{dur}} & 0 \leq H_{stop} - R_{stop} \leq 1, R_{start} \leq H_{start} \\ \frac{R_{start} - H_{start}}{Ref_{dur}} & 0 \leq H_{start} - R_{start} \leq 1, H_{stop} \leq R_{stop} \\ 1 & otherwise \end{cases}$$

$$TN = 1 - TP$$

Where the R and H represent the hypothesis and reference events respectively, and $Ref_{dur}$ represent the reference events duration. equal weight is assigned to each event, with a partial score based on the amount of overlap also given to each event. After then, the sensitivity and false alarm are calculated based on the value of the TP, TN, FP. The FN score is the fraction of the time the reference term was missed divided by the total duration of the reference term.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

Moreover, the objective of this work is not only to increase sensitivity and decrease false alarm, but also to try to reduce the number of electrodes as much as possible. We use the score formula proposed by the *Neureka 2020 Epilepsy Challenge*, which show in below:

$$\text{Points} = \%SENS - \alpha * FA/24\ hrs - \beta * \frac{\text{(channel numbers)}}{19}$$

where the $\alpha = 2.5, \beta = 7.5$, and SENS, FA represents for the sensitivity and false alarms, respectively.

## VI. Results and Discussions

### VI-A. Channel Selection

First we applied the *automatic channel selection* and *fast single electrode training for channel ranking* methods to get the results of the electrodes ranking. Our two methods of ranking result are shown in Fig. 2. We combined the two electrode ranking method results into one figure, and the importance value comes from the ranking method which reflects how often it is used during training in the Random Forest classifier; the train and valuation accuracy come from method two which reflects the first epoch results when we put a signal electrode into a fast structure training. The important value and valuation accuracy are the two factors that we focus on to rank the final electrodes. Regarding the channel selection, the five electrodes F3, F7, P3, O1 and O2 ranked highest in both two ranking methods, and the electrodes we chose were paired in the format F3-F7 and P3-O1 as these are two pairs of nearby electrodes, to give the two channels format that was fed into the model. Interestingly, literature shows that left temporal lobe epilepsy is the common type of epilepsy, with focal seizures in the left temporal lobe seizures being the most common seizure type.

### VI-B. *Final Result*

The threshold is an important factors that will influence the sensitivity, false alarm and score. The Fig. 3 shows the 3s,5s,7s, and $3s\&5s\&7s$ sensitivity versus the FA/24 hrs line curves when choosing the threshold range from 0.92 to 0.99. From the figure we can see that, there is a trade off inside the sensitivity and false alarm, as the lower confidence threshold value, the higher sensitivity as well as higher false alarm and vise versa. For the 3s, 5s, 7s segment, the 3s result is perform better in low sensitivity situation whereas 5s and 7s have better performance in higher sensitivity situation. However, in clinical settings, if the system will be used to help patients, then the False alarm should be as low as possible. For a reliable system, the false alarm should less than 1 FA/24 hrs. Thus the overlap $3s\&5s\&7s$ with high confidence (0.98 or 0.99) will be a better choice, as it performs best in minimizing the false alarm, and with the consideration that this task is trained and tested on totally different patients, and the TAES is the most strict metrics among the all seizure event detection tasks, the low sensitivity is understandable. Table 2 give the top five teams scores in the test dataset, our team ranked the second place which reach only 0.17 FA/24 hrs using two electrodes.

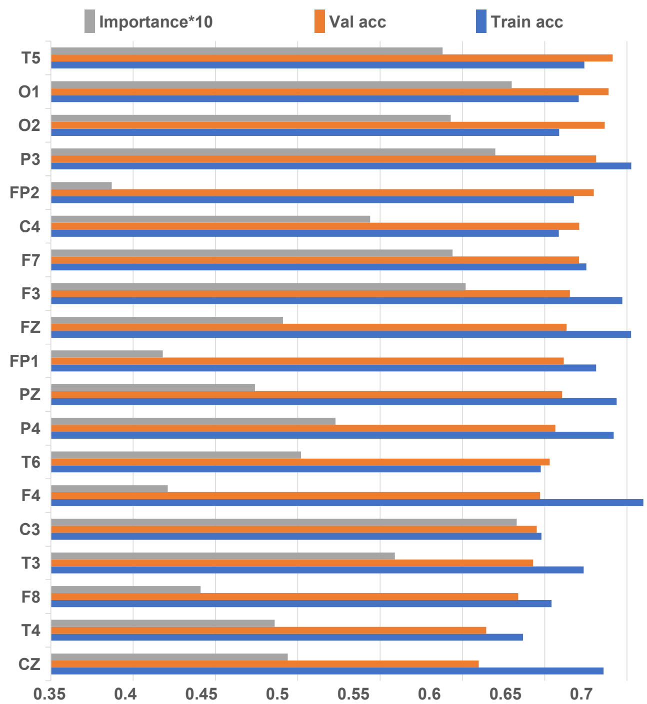


Figure 2. Electrode ranking results; The importance value and valuation accuracy are two factors when we choose electrodes to form sensing channels.

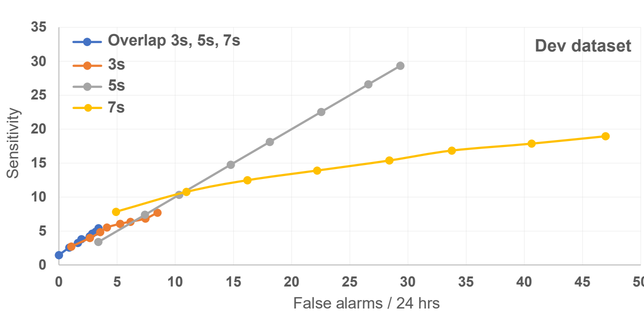


Figure 3. Threshold Range From 0.92-0.99

Table 2. Neureka challenge results: The top 5 teams performance score on the test dataset

| Rank | Teams | Sensitivity | FAs/24Hr | Channels | Score |
|---|---|---|---|---|---|
| 1 | Biomed Irregulars | 12.37 | 1.44 | 16 | 2.46 |
| 2 | **NeuroSyd** | **2.04** | **0.17** | **2** | **0.82** |
| 3 | USTC-EEG | 8.93 | 0.71 | 17 | 0.45 |
| 4 | RocketShoes | 5.98 | 3.36 | 3 | -3.6 |
| 5 | Lan Wei | 20.00 | 15.59 | 4 | -20.56 |

## VII. Conclusion

Epileptic seizure prediction and detection capability has been studied and improved over the last four decades. A board-certified EEG specialist is required by law to diagnose the epilepsy, however, it takes several years of training and practice by the clinician, to obtain the capability in detecting seizures. If a machine is able to achieve accuracy at the level of or above an epileptologist or EEG technician, such system could be used as an advisory system to the clinician in EEG analysis for epilepsy patients. It is also noted that if such system includes lesser number of electrodes it becomes more mobile and more comfortable for patients to wear. It is therefore important to demonstrate an accurate seizure detection system that relies on a small number of electrodes. Such system could also pave the way for future development of ambulatory seizure warning or logging systems and long-term EEG monitoring devices, which is particularly important for patients with refractory epilepsy management. Proposed method has achieved 1.46% sensitivity with 0 FA/24 hrs in development dataset and 2.04% sensitivity with 0.17 FA/24 hrs in evaluation dataset using only two channels, which has the potential to be further improved to use in the clinical practice.

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