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Epileptic Seizure Detection With a Reduced Montage: A Way Forward for Ambulatory EEG Devices

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ABSTRACT Electroencephalogram (EEG) is one of the fundamental tools for analyzing the behavior of brain and particularly helpful for treatment of epilepsy and detection of associated seizures. For long-term recording of EEG signals, current research is heading towards simple, unobtrusive and ambulatory devices with a small number of channels. The primary contribution of this paper is to assess the performance difference between the seizure detection results using features from all channels versus only the channels in/around the temporal region. For this purpose, we develop a supervised seizure detection algorithm that uses time domain features extracted sequentially for every 1-second epoch. By using this algorithm, we obtained sensitivity values of 0.95 and 0.92, specificity values of 0.99 and 0.99 and false positive per hour values as 0.16 and 0.21 for all 23 channels and 10 temporal region channels, respectively. These results show that restricting the EEG analysis to temporal region results only in a graceful and gradual degradation of classifier performance. We conclude that EEG ambulatory devices with a montage local to the temporal region could demonstrate satisfactory performance. This presents a promising way forward for the use of ambulatory devices with compact wearable design.

INDEX TERMS Electroencephalography, seizure, epilepsy, classification, learning, RUSBoost, SMOTEboost, temporal region, EEG.

I. INTRODUCTION

Epilepsy is one of the most common and chronic disorders of the brain. About 1% of the world population is reported to be suffering from this disease [1]. Epilepsy has been around since recorded history and has been treated according to the techniques and technology in vogue, e.g., trephining. With the passage of time and advancement in medical science and technology, different treatment methods have evolved. With regards to epilepsy, scientific research on automatic seizure detection started about 40 years ago [1]. The neurons generate electrical signals when they perceive stimuli from the environment or interact with each other for performing different activities [2]. The electrical signal generated by a single neuron is not strong enough to be detected. However, when a cluster of neurons act in concert, they generate an electrical signal which is strong enough to be detected and recorded. This recorded electrical signal, produced by the neurons, is called electroencephalogram (EEG) [3].

EEG signals are recorded with the help of multiple electrodes placed either on the scalp or inside the skull (intracranial). A standard montage referred to as 10-20 system is most commonly employed to record the electrical activity of the brain. EEG has opened a new era in studying and understanding the structure and functionality of brain and has assumed its position as an important technique in monitoring and treating different brain disorders such as epilepsy, short term memory loss, emotion recognition and sleep disorders [4]–[8], etc.

EEG is one of the most important tools for brain diagnostics, but it also has certain limitations. In traditional EEG, the electrodes that sense the brain activity are connected to a computer that records the measured signals in its memory. The number of electrodes, also referred to as channels,

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vary from 23 to 256 for different recording standards and applications. Sensing, recording and processing this multi-channel signal requires significant power, storage and computational resources, roughly proportional to the number of channels [9]. For a typical EEG recording session, the subject must visit the laboratory because the sensing and recording equipment is fixed and immobile [10]. Besides this, when the EEG of an individual is recorded using the traditional method, it is carried out under controlled conditions to suppress interference and anomalies from other sources and the background activities of the brain. However, this limits the observation and recording period and the brain disorder may not manifest during the recording window [11], [12]. The long-term recording of EEG in a controlled environment causes discomfort to the subject who must control its movement and must wear the gear/cap on its head with conductive gel for several hours. Not to mention, it hampers the routine activities of the subject [12].

To mitigate the limitations of traditional EEG enumerated above, recent research is directed towards mobile wireless EEG recording devices, which provide the advantage of recording in a natural environment for extended duration. This could allow the device to collect more data and possibly improve the odds of observation of seizure in a patient. For example, cEEGrid has 10 electrodes printed on a flexible sheet that could be easily pasted around the ear. Size of electrodes vary from 3-5 mm with distance between two electrodes designed to be 8-10 mm. These flexible electrodes are affixed around each ear. EEG signals are amplified with an amplifier, which is connected through WiFi or Bluetooth to a recording and/or processing device. The signals could be recorded in micro-memory cards. There are typically 20 channels recorded simultaneously, 10 from each side [12], [13].

There are several products in the market, which employ wireless transmission of EEG signals in real-time to a computing machine. Neurophone is one such very popular device, in which a mobile phone interface controlled by EEG signals is also achieved through mobile wireless EEG transmission [14]. In this product, an Emotiv EPOC headset, which has 16 electrodes is employed. This headset uses 14 channels for recording purposes and two electrodes are taken as reference. These electrodes are arranged roughly according to 10-20 scheme so that they cover maximum area on the scalp. Then the recorded signals are transferred to a mobile thorough wireless transceiver, and a cell phone is operated on basis of the signals received from the headset. This Emotiv EPOC headset also contains gyroscopic sensors that help in maintaining the orientation of subject's head. Recently, another 8-channel low power EEG headset is introduced, which also transmits the signals through a wireless module. This 8-channel sensor platform was integrated into a wearable device which enables easy and fast monitoring of the subject. Also, these electrodes don't need any conductive gel because they are designed in a way that they give performance comparable to traditional electrodes [15].

The EEG signals are amplified during recording, after which different signal processing techniques from both time and frequency domain analysis could be used for extracting the required features, such as wavelet transform [16], empirical mode decomposition [17], [18], and scattering transform [19]–[23], and dynamic mode decomposition [24], [25], etc. For analysis of these signals, different machine learning algorithms like support-vector machine (SVM), principal component analysis (PCA), linear-discriminant analysis (LDA), neural networks, decision-tree classifiers, and sometimes a combination of these techniques are employed [26]–[31].

In this paper, we aim to contribute in the domain of mobile EEG devices for detection of epileptic seizures. To the best of our knowledge, no ambulatory wireless device is available in the market for observation and long term monitoring of epileptic seizures using EEG signals. The challenge is to design a device that operates on battery, can support a wireless transceiver, and has an extended charge cycle, sufficient to considerably improve the yield of epileptic seizures to a level that allows reliable observation and monitoring of epileptic discharges in patients. The long-term recording of EEG signals is a frequent requirement for accurate detection of epileptic disorders. For example, the neurologists may require a patient to undergo induced seizures or to stay overnight in a medical facility for extended EEG recording sessions so that epileptic activity could be observed in their scalp EEG signals. Having an EEG device that patients could wear discretely and that does not impede their everyday activities might herald a breakthrough in the treatment of epilepsy. Such a device might be able to stimulate the development of algorithms and techniques that could reliably assess the short-term risk of an impending seizure for a patient, and consequently, inform the patient to take safety precautions.

Our approach is to analyze the performance of an epileptic seizure detection algorithm in the situation where we employ a simplified montage with considerably reduced number of EEG channels focused in the temporal region of the scalp. We study the effect upon the performance of a simple seizure detection algorithm when the number of channels is reduced from 23 channels in 10-20 configuration to 10 channels largely confined to the temporal region of the scalp. To assess the performance degradation caused by the use of a smaller number of channels, we apply the proposed method upon a well known dataset (know as CHB-MIT [32]). Although, there is some performance loss, the idea is that by reducing the number of channels employed for the detection of seizure activity, we can reduce the computational, storage and transmission complexity/cost of the device, enabling the design of ambulatory wireless EEG devices capable of long-term EEG recording. We also recognize some limitations of this study as the dataset used in this study is not recorded in an ambulatory scenario.

The rest of the paper is organized as follows: In Section II, we discuss the dataset and the proposed methodology for feature selection, supervised learning, and performance analysis

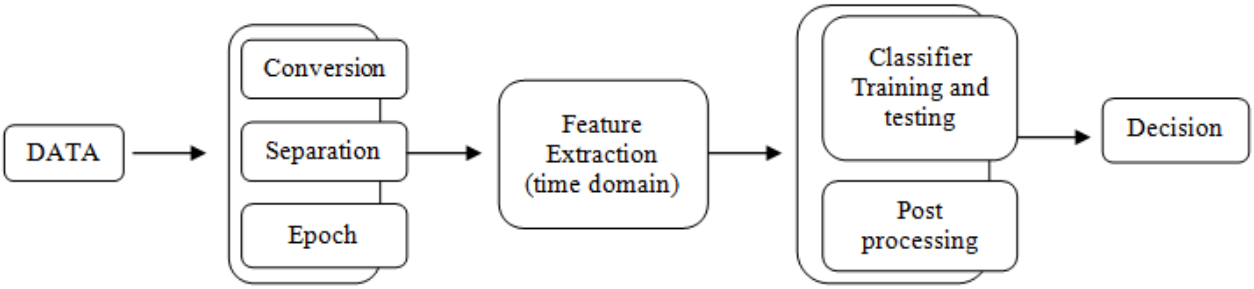

FIGURE 1. Block diagram of the proposed methodology for detection of seizures from EEG recorded data. The proposed methodology includes pre-processing, segmentation, feature extraction, classifier training and testing, followed by post-processing and detection of seizures.

in detail, followed by performance metrics and results in Section III. In Section IV, we discuss the limitations of the approach and future improvements. Conclusions are drawn in Section V.

II. METHODOLOGY

In this section, we present information about the publicly available dataset used in this work, and the steps involved in our algorithm such as feature extraction, classifier training, and post-processing, etc. A block diagram for the proposed methodology is given in Fig. 1.

A. DATASET

In this study, the EEG data used is from a publicly available dataset, referred to as CHB-MIT dataset [32]. This dataset has been very widely used, e.g., [33] and [34]. This EEG dataset is recorded from 24 patients at Children Hospital Boston (CHB). All the recordings are at 256Hz sampling rate with 16-bit resolution. The dataset consists of scalp EEG recording, and the number of channels in these records vary from 23 to 32. For all patients, we have 23 channels, except for the EEG recording of patient number 15, for whom 32 channels have been used. In recording of data, international 10-20 system of electrode placement was followed [5]. The total duration of the recorded data is 982 hours that are unevenly distributed over the patients. In total, we have 664 files out of which 129 files contain one or more epileptic seizures; the number of observed seizures also vary from patient to patient [33]. In our study, we have selected 60% data for training (supervised learning), which contains both seizure and non-seizure data and 40% data has been employed for testing and validation, which also contains both seizure and non-seizure representations. The choice of data for training and testing is based upon random sampling technique [35]–[37].

B. FEATURE EXTRACTION

This is one of the most important tasks before classification, because if the features are not chosen carefully, they will not capture enough information needed for the classifier to be able to distinguish between the signals representing different classes or labels. The performance of the classifier may

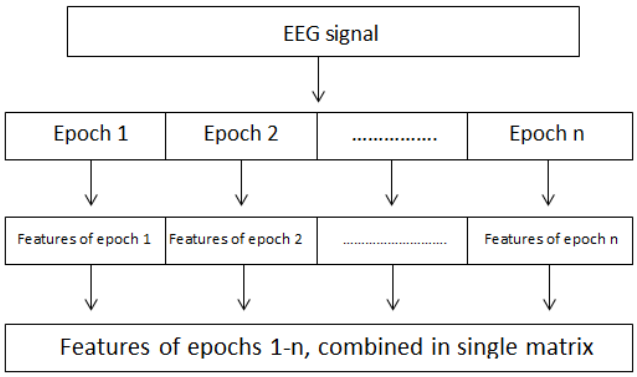

FIGURE 2. Segmentation of EEG signal into epochs for feature extraction followed by the concatenation of features to compose a feature vector.

be entirely unsatisfactory if either the features are too few to form the basis for discrimination (under-fitting), or they are too numerous to let the classifier learn their generalized characteristics on unseen data (over-fitting). Thus, it is very important to analyze the data first and then adopt the features suitable for the problem under study. This process is also referred to as feature engineering. As already discussed in the previous section, several features like coefficients of wavelet decomposition, frequency domain features, fuzzy entropy, etc. have been used in previous studies with varying amount of success. In our research, we employ time domain features as they are simple to measure and contain sufficient information for a reasonable performance of an automatic seizure detection system. As the EEG signal is not stationary, it is a common practice to segment the EEG signal into smaller epochs, and during these epochs, the signal is assumed to exhibit characteristics of a stationary signal. For the CHB-MIT dataset at hand, and for a sampling frequency of 256Hz, we divide the signal into segments (epochs) of one second duration – each one second epoch has 256 samples. After extracting the features for each epoch individually, the extracted features could be organized in the form of a matrix as shown in Fig. 2 [4].

Through this process of feature collection, as shown in Fig. 2, we compute the local statistical features of the data in each epoch, referred to as the time domain features. This is because we are computing these statistics directly from

the time-domain signals representing EEG channels without transforming the signals to the frequency domain. For this study, we are using a total of 8 time domain features, which are *Mean, Median, Mode, Standard Deviation, Kurtosis, Quartile, Range, and Skewness.*

C. CHANNEL SELECTION

There have been several recent advances in the area of EEG signal processing. Various techniques, algorithms and heuristics are used to process EEG waveform for monitoring and treatment of myriad of disorders related to brain. Among these methods, channel selection is an important technique for detection of different disorders and miscellaneous applications, such as seizure analysis, emotion classification, mental-task classification, sleep stage classification [37], etc. In this section, we focus on channel selection for seizure detection, which is usually based upon different criteria, such as filtering techniques, wrapper techniques, embedded techniques, hybrid techniques, human-based techniques [38], [39]. These traditional techniques do not focus on channels in a specific region, i.e., selected channels could be from different regions of the scalp. In contrast to these techniques for channel selection, in this paper, our focus will be on reducing the number of channels such that the residual channels are confined to a specific region of the scalp for seizure detection. The rationale for this choice is two-folds. Firstly, to assess the performance degradation of the seizure detection algorithm for a device with compact design using fewer electrodes concentrated in a region of the scalp. The secondary reason, for this choice of selecting a region for seizure detection, is inspired from the biological studies that associate seizure related activities mostly with the temporal region of the brain. This perspective, i.e., temporal lobe epilepsy (TLE) is discussed below in detail.

From anatomical and functional perspective, the human brain is divided into different regions, i.e., frontal region, temporal region, central region and posterior region. Brain studies suggest that specific regions of the brain are primarily responsible for their specific respective functions. For instance, the frontal part of the brain is concerned with intelligence and memory, and the posterior part of the brain is linked with visual functionalities, etc., [40]. Similarly, different areas of the brain, or when a bunch of neurons behave in an abnormal way, they give rise to different brain disorders. If the condition persists for a longer time, then that area becomes the focal point for certain disorders. For majority of epileptic patients, temporal region is the primary suspect as the source of the epileptic discharges. In adults, the majority of patients have temporal lobe epilepsy (TLE) [41]–[43].

Following the concept of TLE and the temporal region to be the main contributor in epilepsy, we successively remove those EEG waveforms from the dataset that have been recorded from channels away from temporal region. Hence from the given set of channels spread over the scalp, we select channels mostly local to the temporal region as shown in Fig. 3. In Fig. 3, we have marked the channels according

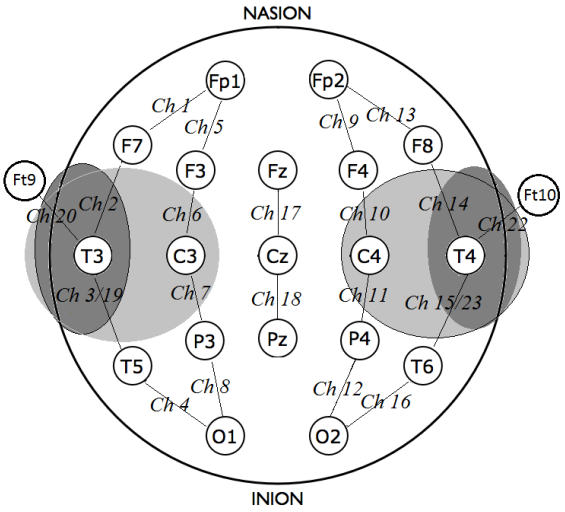

FIGURE 3. Different scenarios for temporal region and channel selection according to 10-20 system.

TABLE 1. Labeling of the differential channels in 10-20 system and the corresponding identifiers used in the CHB-MIT dataset.

Nodes name	Channel No.	Nodes name	Channel No.
Fp1-F7	1	Fp2-F8	13
F7-T3	2	F8-T4	14
T3-T5	3	T4-T6	15
T5-O1	4	T6-O2	16
Fp1-F3	5	Fz-Cz	17
F3-C3	6	Cz-Pz	18
C3-P3	7	T5-T3	19
P3-O1	8	T3-Ft9	20
Fp2-F4	9	Ft9-Ft10	21
F4-C4	10	T4-Ft10	22
C4-P4	11	T6-T5	23
P4-O2	12		

TABLE 2. Different scenarios considered in this study for selection of a subset of EEG channels.

Sr. No.	No. of channels	Left temporal channels	Right temporal channels
1	12	2,3,6,7,19,20	10,11,14,15,22,23
2	10	2,3,6,7,20	10,11,14,15,22
3	8	2,3,7,20	11,14,15,22
4	6	2,3,20	14,15,22

to the information provided by CHB-MIT dataset. We have the same configuration of channels for the first 10 patients, Patient 23 and Patient 24. Similarly, the patients numbered from 11 to 22 have the same configuration. The only patient with 32 channels is Patient 15, which has an irregular naming pattern for the electrodes and the corresponding channels. The sequence of channels with respect to nodes is given in Table 1.

For selection of temporal channels, we have considered 4 different scenarios, which progressively reduce the number of channels and restrict them to the temporal region of the brain. These scenarios are shown in Table 2.

For first scenario we select 12 channels, i.e., 6 channels from each side of the scalp, but we have an exception for Patient 15. For patient 15, we have 32 channels in the dataset but in case of reduced montage we have taken 2 extra channels from each side that is in total we have 16 channels for Patient 15. In case of scenario number 2, we have 10 channels, 5 from each side. Similarly, in third scenario, we have a total of 8 channels, four from each side. To reduce the number of channels from 5 to 4 on each side, we omit channel number 7 and 15, and retain channel number 6 and 14. In last scenario, we simplify the montage further, and now we have only 6 channels, 3 from each side of the brain in a symmetric configuration.

D. CLASSIFIER

The design of a classifier for seizure detection from EEG data is comparatively challenging, partly because the data is highly imbalanced, i.e., the number of epochs representing the seizure (epileptiform activity) class and the epochs representing the non-seizure (normal) class are very unevenly represented in both the training and testing parts of the dataset. The seizure class is very rare, while almost all the data is representative of the non-seizure class. The learning rate of the classifier for the seizure class becomes considerably slower, as most of the data it observes belongs to the non-seizure class. This situation is a typical example of a classification problem involving imbalanced or skewed data. As an example, let us assume that we have 50,000 epochs in the overall dataset. Out of the total 50,000, let's say 48,000, i.e., 96%, belong to the non-seizure class, i.e., normal activity, and the remaining 2000, i.e., 4%, to the seizure class. If we train a traditional classifier on this composition of data, there is overwhelming likelihood that our classifier may not deliver satisfactory performance due to inadequate training of the marginalized class [34].

To overcome this issue of class imbalance, there are two main approaches considered in literature: under-sampling and over-sampling. Random under-sampling (RUS) technique represents the former category, where the samples from majority class are removed and are balanced with the minority class. While for up sampling, we have synthetic minority over-sampling technique (SMOTE) in which extra samples are intelligently augmented to the minority class for balancing data representation [44]. In case of down-sampling, i.e., RUS technique, we have advantage of reduced computational cost because it speeds up the classifier training stage due to smaller number of samples as compared to SMOTE.

RUSBoost is a combination of random under-sampling and boosting techniques. In RUSBoost, we under-sample the majority class and use the boosting technique, in a similar way as AdaBoost uses it as a primary component. There is a slight difference in RUSBoost and AdaBoost. In RUSBoost, random under-sampling results in a new distribution, which is used to determine weights for the weak classifiers. In case of AdaBoost too, we have under-sampling, and datasets are created but these datasets are temporary, so classifiers use these temporary datasets thus improving the performance [34].

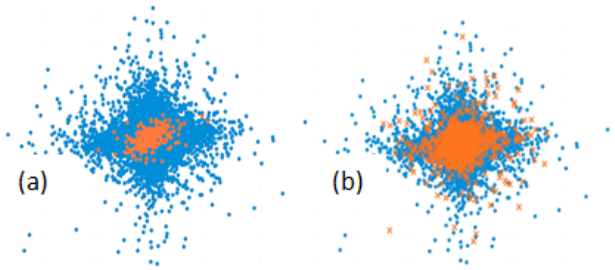

FIGURE 4. Scatter plots of data representing seizure (minority) class and non-seizure (majority) class in orange and blue colors, respectively. (a) Representation of classes before RUSBoost. The majority class samples shown in the blue color are over-represented. (b) The number of samples of minority and majority classes are balanced by RUSBoost by reducing the representation of majority class through undersampling.

In Fig. 4, we have two scatter plots. In Plot (a), we have original data representing the non-seizure class, which is about 99% of total data set, and seizure class is about 1% of total data. But in Plot (b), after the implementation of RUSBoost, this 99% is reduced to almost 50% and both classes are almost balanced.

E. POST PROCESSING

EEG signals cannot be recorded completely noise-free, although, these signals are mostly recorded under controlled conditions and in specially designed facilities to minimize noise effects and miscellaneous artifacts. Even in these controlled conditions, the recorded EEG signal is always coupled with noise, which may be thermal noise introduced from the measurement and amplification process, or noise due to proximity to other electrical appliances or artifacts arising due the movement of the subject or their eye movement, etc. Thus, it is not advisable to use these signals directly for training of classifier and still expect satisfactory results. In order to obtain good results, pre-processing and post-processing steps are almost always performed.

A typical pre-processing step is to perform low pass filtering before sampling the signal. This rejects the out-of-band noise and artifacts, and serves to ameliorate the effects of aliasing. We assume that the pre-processing step has been performed at the time of acquisition and sampling of the signal. However, we use two post-processing techniques at the output of the classifier to improve upon the performance of the raw labels detected by the classifier. These post-processing steps are very typical for the automatic seizure detection algorithms [45], [46]. The parameters of the post-processing filters are chosen based upon the statistical properties and physiological conventions pertaining to the manifestation of epileptiform activity in EEG waveforms.

1) The sequence of suggested labels obtained from the classifier is taken as an input to a run-length smoothing filter. This filter is designed to detect the seizure if its input consists of positive detections of seizure class

for N consecutive epochs, where N is typically chosen to have a value in the range of few epochs, i.e., 4 to 15 epochs [45]. The justification for this range of values is that a seizure is marked as observed by the neurologists only if it persists for at least this duration. Otherwise, short bursts of activity are dismissed as electrode-induced noise or an artifact, and not marked as seizures by the trained physicians. The choice of N as a parameter of this run-length-smoothing filter provides a trade-off between sensitivity and specificity (or equivalently between Type-I and Type-II errors), and provides an effective degree of freedom to choose an appropriate point on the receiver operating characteristic (ROC) curve.

2) The detected seizures in the output of the run-length-smoothing filter are represented by bursts of minimum length of N epochs (or seconds). However, if two such occurrences are very close to each other, they should really be consolidated as a single seizure activity. Such closely spaced positive detections are grouped together as a single seizure if they are separated by less than a minute, i.e., 60 epochs. This helps avoid over representation of positive detected events or seizures [46].

III. RESULTS

Before discussing the results, we define some basic terminology that will be used frequently in the analysis of results later in this section.

True positive (TP) is the counter that increments when the algorithm chooses a positive outcome and it coincides with the positive detection in the ground truth. We assume a TP event has occurred, if the positive labels epochs are detected for N consecutive epochs in a time window beginning from 1 minute prior to the start of the seizure and ending at 1 minute after the end of seizure. Note that this window, also referred to as seizure horizon, is defined with reference to the boundaries of positive event marked in the ground truth. The choice of this extended inclusion interval is in consonance with the accepted tradition in the EEG epileptic event detection literature [45], [46].

False positive (FP) is reported when the algorithm detects a positive value although we have zero label, i.e., non-seizure activtiy, marked in the ground truth. However, if we have FP detection within 3 minutes of a TP detection, it is not counted as a FP, as it may be observed owing to pre-ictal and/or post-ictal epileptic discharges on the horizon of a seizure. Note that this ambiguous interval, arising due to seizure horizon and its accompanying epileptic transients, is considered both before and after the TP event.

True negative (TN) is the true detection performed by our algorithm in non-seizure region.

False negative (FN) is an event where we have an epileptic seizure marked in the ground truth and our algorithm fails to detect that seizure as a positive detection.

From the aforementioned terminology, we derive further nomenclature that is used in the evaluation of results.

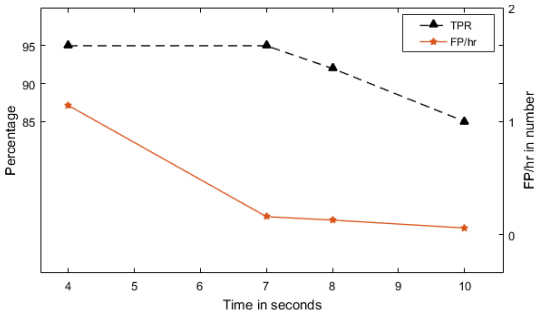

FIGURE 5. Comparison of TPR and FP/hr for different lengths of smoothing filter *N*, i.e., 4 sec, 7 sec, 8 sec and 10 sec.

- *True positive rate* also termed as sensitivity, is the probability of true detection of seizure. It can be estimated as

$$TPR = \frac{TP}{TP + FN} \tag{1}$$

- *True negative rate* also referred to as specificity, is the probability of true detection of non-seizure region. It is calculated as

$$TNR = \frac{TN}{TN + FP} \tag{2}$$

- *FP/hr:* It is the number of false detections reported by an algorithm per hour.
- *Accuracy:* It is the probability of true detection of both classes, i.e., seizure and non-seizure. It can be calculated as

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \times 100 \tag{3}$$

Note: It should be noted that in results when we use the term average for accuracy results, this refers to weighted average rather than mean/average, except in case of latency.

A. EVALUATION OF THE PERFORMANCE OF RUN-LENGTH-SMOOTHING FILTER FOR VARYING AMOUNTS OF FILTER MEMORY

As mentioned in the previous section, we have used run-length-smoothing filter in post-processing with N determining the amount of memory of the filter. We have used four values of $N = 4$ sec, $N = 7$ sec, $N = 8$ sec and $N = 10$ sec, and calculated TPR and FP/hr as shown in Fig. 5.

From Fig. 5, we can see that there is an inverse relation between TPR and FP/hr. At $N = 4$ sec, we have TPR $= 0.95$ and FP/hr $= 1.12$. Similarly, for $N = 10$ sec, the algorithm achieves FP/hr $= 0.06$, but the TRP drops by almost 10% to 0.85. We conclude that $N = 7$ sec provides a good trade-off as the parameter of the run-length-smoothing filter since it gives us very good TRP, i.e., 0.95, and FP/hr $= 0.16$, both of which are important to be within a reasonable range.

B. RESULTS FOR FULL MONTAGE (All 23 CHANNELS)

In this section, we discuss the performance of the proposed approach when features extracted from all the channels in

TABLE 3. Classifier Performance with features computed for full montage, i.e., all available channels.

Patient	TPR	TNR	FP/hr	Delay (sec)
1	1	1	0	4.5
2	1	1	0	12
3	1	1	0	3.9
4	0.66	0.99	0.01	19
5	1	0.99	0.17	16
6	1	0.99	0.10	3.25
7	1	0.99	0.03	7
8	1	0.99	0.11	11
9	1	0.99	0.03	5.5
10	1	1	0	7
11	1	1	0	13
13	0.5	1	0	5
14	1	0.99	0.23	7
15	1	0.99	0.046	9
16	0.75	0.91	5.22	1
17	1	1	0	9
18	1	1	0	3
19	1	1	0	7
20	1	1	0	4.6
21	1	0.99	0.07	4
22	1	1	0	3
23	1	0.99	0.14	4.33
24	1	0.98	1.11	4.6
Average	**0.95**	**0.99**	**0.16**	**6.83**

the EEG recording are utilized for both training and testing of the classifier. There is a total of 24 subjects in the CHB-MIT dataset and we apply our algorithm on all the records except Patient 12. The reason for excluding Patient 12 from analysis is because of the poor quality of the recorded signal. Among the remaining 23 subjects in the CHB-MIT dataset, the recordings corresponding to 22 of these subjects have a total of 23 channels each. However, there is one patient, i.e., Patient 15, for whom the channels are non-differential and the number of channels is 32. The results reported in Table 3 are for the patient specific classifiers, with run-length-smoothing filter of $N = 7$ sec, and have been obtained using same classifier structure for all the patients, i.e., RUSboost classifier followed by post-processing steps as explained in Section II-E.

From Table 3, we can see that using all the available channel data in the recordings, we obtain a TPR $= 0.95$, specificity $= 0.99$, and a very low FP/hr, i.e., 0.16, with an average delay of 6.88 sec. Accuracy calculated for these results is 0.9971.

These are the results for 23 patients because we have already excluded Patient 12 due to inconsistency in channels while recording data. We observe that the results could improve further if we exclude Patient 16 from analysis. The reason for this improvement is because of relatively atypical length of seizure observed in the records of Patient 16. Many of the seizures for Patient 16 are about 5-10 second in duration. A smaller value of N helps in improving sensitivity for Patient 16 at the cost of sharp rise in FP/hr for other subjects. By excluding the results of Patient 16 from the analysis, the TPR approaches to 0.98, TNR approaches to 0.998 and FP/hr declines to 0.075 with an average delay of 7.19 sec.

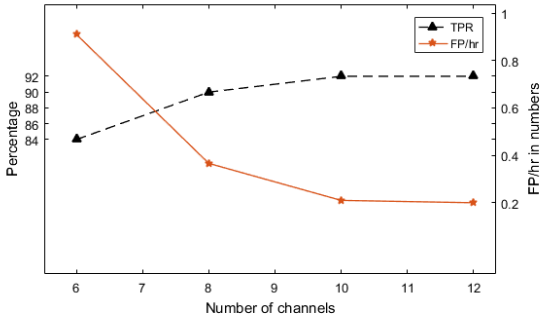

FIGURE 6. Comparison of TPR and FP/hr for different scenarios of temporal channels, i.e., 6, 8, 10 and 12 channels.

C. RESULTS FOR RESTRICTED MONTAGE

Proceeding one step ahead with the same settings of experiment as for 23 channels, i.e., $N = 7$ sec filter, RUSboost classifier, and patient specific method, we reduce the number of channels successively, and calculate the performance results, analyzing which channel/region is the most critical for seizure detection.

In order to perform this analysis, we repeated our experiment under 4 different scenarios, as mentioned in Section II-C in detail, i.e., 12 channels, 10 channels, 8 channels and 6 channels.

From Fig. 6, we can see that the dotted line, representing TPR, is increasing slightly with increasing number of channels in previous subsection, but as the number of channels are 10 or 12, it has negligible variation, i.e., TPR ≈ 0.92. However, as we further decreased number of channels to 8, TPR decreased to 0.90 and FP/hr increased to 0.366. Further decreasing the number of channels to 6, TPR decreased to 0.84 and FP/hr increased to 0.91. Thus, it can be said that TPR is directly proportional to number of channels. But for FP/hr, represented with a solid line, the number of false alarms decrease with increase in number of channels. However, for 10 channels and 12 channels, there is negligible difference in FP/hr, i.e., from 0.20 to 0.21.

Evaluating the results for all four scenarios in which we have different number of channels ranging from $4 - 12$, we can conclude that second scenario, i.e., 10 temporal channels, provides us a good trade-off with sensitivity of 0.9236, specificity value of 0.997, false positive rate per hour of 0.21, an accuracy of 99.62%, and average delay of 7.1 sec. Detailed results for each patient for 10 channels are shown in Table 4. If we exclude patient number 16, as we did in all channel results before, then our TPR will become 0.932, TNR increases to 0.997, FP/hr decreases to 0.13 with an average delay of 7.07 seconds.

D. ALL CHANNELS VS. TEMPORAL CHANNELS COMPARISON

From Tables 3 and 4, we can draw a comparison between the results obtained for both the temporal channels case and all channels case. In Fig. 6, we are comparing the FP/hr for all channels and the temporal channels for 23 patients.

TABLE 4. Results-per patient for temporal channels (10 channels).

Patient	TPR	TNR	FP/hr	Delay (sec)
1	1	1	0	4.5
2	1	1	0	12
3	1	1	0	3.9
4	0.5	0.99	0.16	21
5	1	0.99	0.23	17
6	1	0.99	0.18	2.25
7	1	0.99	0.03	9
8	1	0.98	1.14	10
9	1	0.99	0.09	5.5
10	1	1	0	6
11	0.5	1	0	13
13	0.75	1	0	5
14	0.75	1	0	7
15	1	0.99	0.09	9
16	.75	0.92	4.76	1
17	1	1	0	8
18	1	1	0	6
19	1	1	0	7
20	1	0.99	0.07	5.6
21	1	0.99	0.21	4
22	1	1	0	5
23	1	0.99	0.14	4.33
24	1	0.98	1.11	4.6
Average	**0.92**	**0.99**	**0.21**	**7.1**

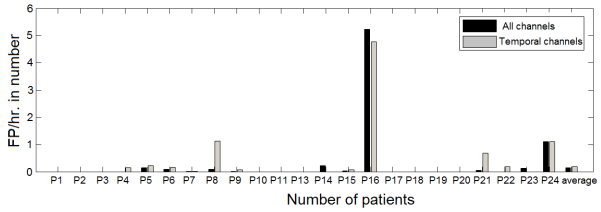

FIGURE 7. Comparison of FP/hr of all channels vs. temporal channels patient wise and in last we have average results of FP/hr.

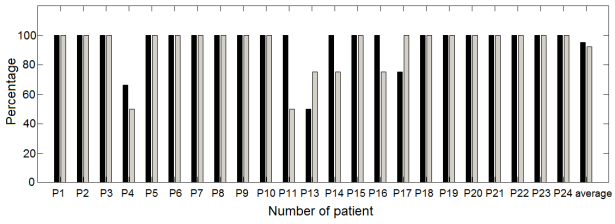

FIGURE 8. Comparison of TPR of all channels vs. temporal channels patient wise and in last average value of TPR is plotted.

In Fig. 7, we can see that for 12 patients we have same number of FP/hr for all channels and the temporal channels, for 6 patients we have slightly higher FP/hr rate as compared to all channels, but overall there is not that much difference between all channels and temporal channels.

In Fig. 8, we can see patient wise comparison of TPR for all channels and temporal channels. From Fig. 8, we can clearly see that we have almost same value of TPR for 17 patients out of 23, 4 patients gave better value of TPR with all channels as compared to temporal channels, while on other hand, we have two patients, i.e., patient number 13 and 17, which showed better TPR value with only temporal channels.

TABLE 5. Comparison of average values of TPR, TNR, FP/hr and delay for all channels and temporal channels for 23 patients and 22 patients, respectively.

Name	TPR	TNR	FP/hr	Delay (sec)
23 patients all channels	0.95	0.99	0.16	6.83
22 patients all channels	0.98	0.99	0.075	7.19
23 patients temporal channels	0.92	0.99	0.21	7.1
22 patients temporal channels	0.93	0.99	0.133	7.07

This might happen because in case of these two patients, the seizure might be focused in the temporal region and other channels may have unrelated background activity. Thus, we might get better detection only with temporal channels for these patients.

Table 5 summarizes the discussion by comparing the results of TPR, TNR, FP/hr and delay for all channels and the temporal channels, respectively. From the table we can see that TPR for all channels is 0.95, while in case of the temporal channels, it decreases to 0.92, which could be tolerated if the priority is to decrease the number of electrodes used for acquisition to enable a compact system design and longer battery life of the device.

In Table 5, TNR for both cases is almost the same, i.e., 0.99, and FP/hr for all channels is 0.16, while for the temporal channels, it leads by 0.05. In case of delay, the temporal channels lead by 0.13 seconds from all channels.

E. COMPARISON OF RESULTS BETWEEN 23 PATIENTS AND 22 PATIENTS

As discussed above, in CHB-MIT data set, we have a total 24 patients and we excluded Patient 12 for inconsistent file sequence and calculated results for 23 patients only. Out of these 23 patients, for Patient 16, our algorithm shows some odd results as compared to other patients due to reason that this patient has seizure length in between 5-10 sec. With a filter size of 7 sec, most of the seizure events remain undetected by our algorithm. However, if we exclude Patient 16, and calculate our results for remaining 22 patients, we observe some increase in TPR and decrease in TP/hr as shown in Table 5.

From Table 5, we can clearly see that as the performance results for all channels averaged over the 22 patients (instead of 23 patients) are considered, the TPR increases from 0.95 to 0.98, FP/hr decreases from 0.16 to 0.07, and in a similar way, accuracy increased from 99.7% to 99.87%. Also, for temporal channels for 22 patients, TPR increased from 0.92 to 0.93, FP/hr decreased from 0.21 to 0.13 and accuracy increased from 99.61% to 99.75%.

F. COMPARISON OF RESULTS WITH EXISTING TECHNIQUES:

Although, the standard 10/20 system is used for electrode placement in recording of EEG for most of the clinical studies and neurological lab recordings, several methods have been

TABLE 6. Performance comparison of seizure detection techniques.

Seizure Detection Methods	No. of Channels Employed	No. of Patients Evaluated	Sensitivity	Specificity	Accuracy
Das et al. [47]	7	5	–	–	99%
Chakrabarti et al. [48]	18	24	–	–	86.7%
Selvakumari et al. [49]	12	24	96.55%	95.63%	95.63%
Proposed Method	23	23	95%	99.8%	99.71%
Proposed Method	10	23	92.4%	99.7%	99.62%

proposed in the literature to reduce the number of electrodes in order to minimize computational cost and hardware complexity. To reduce the number of EEG electrodes, Tekgul *et al.* [50] proposed an algorithm for automatic seizure detection in neonates, and compared the results of full and reduced montage [50] obtained from a dataset having 151 recordings obtained from 139 infants. In this work, nine channels were considered in the reduced montage configuration. Among these nine channels, eight channels were chosen from the temporal and frontal regions, while a single additional channel was selected from the central region. With full montage, the algorithm could detect 187 seizures from 31 recordings obtained from 30 patients. On the other hand, with reduced montage, i.e., with 9 channels, 166 seizures were detected from 29 patients. Using the reduced montage, the sensitivity and specificity of 96.8% and 100%, respectively, were obtained with respect to full montage.

Chang *et al.* also proposed channel selection algorithm for epilepsy detection [51] and presented results using the CHB-MIT data set. Out of the 24 patients in CHB-MIT dataset, only 6 patients were selected, i.e., 1, 3, 6, 7, 10 and 22. The evaluation of their result is based on two main criteria. Firstly, the false positive rate of the patient must be less than 0.2 per hour. Secondly, at least one alarm generated in the pre-ictal period would be regarded as a successful detection. Success rate is considered to be equal to the number of true detections divided by total number of seizures used for testing. If a patient satisfies both the above conditions, it will be counted as a patient upon which the algorithm completed successfully. With 22 channels, the number of successful patients were 5 out of 6 patients. For reduced number of channels, 75 different montages involving 3, 4, 5 or 6 channels were successively adopted, and the success rate for the best combination of channels (maximum up to 6 channels) reached to 85%.

Some recent works [47]–[49] also considered the topic of channel selection and presented the performance results using CHB-MIT dataset. A summary of the performance comparison of these methods with the proposed method is given in Table 6. It should be noted that in the prior work on the topic of EEG channel selection, including [47]–[51], the method of reduction in the number of channels is proposed so that either the best detection accuracy is obtained or sensitivity is maximized for a fixed false positive rate subject to the constraint on a fixed number of maximum channels. In contrast to these earlier works, this paper considers the reduction of channels focused on a specific region of the scalp (temporal region) so that the feasibility of an ambulatory wireless EEG device with prolonged battery life could be evaluated for long-term recording and detection of epileptic seizures. We have presented results for both, the full montage, i.e., with all 23 available channels, and the reduced montage, i.e., with 10 (or less) channels in/around the temporal region of the scalp. By using our algorithm, we obtain sensitivity values of 0.95 and 0.92, specificity values of 0.99 and 0.99 and false positive per hour values as 0.16 and 0.21, for all channels and 10 temporal channels, respectively. If we consider the results for only 6 selected patients (as in [51]), i.e., 1, 3, 6, 7, 10 and 22, we obtain 100% sensitivity and 0.02 false positive alarms per hour for all channels. In case of reduced montage (10 temporal channels), we have 100% sensitivity and 0.035 false positive alarms per hour. On comparing these results with those reported in [51], in case of reduced montage of 10 channels, our algorithm detects all the seizures in these 6 patients correctly where each patient has FP/hr < 0.2. Also, our proposed method shows comparable (or better) performance relative to the performance of methods such as [47]–[49] when the number of channels and the selected patients are almost the same. Most importantly, there is no significant loss in performance caused by spatial restriction and reduction in number of electrodes. A slight reduction in performance might be tolerable if the priority is to design a lightweight, wearable and wireless EEG acquisition and recording device for automatic detection of epileptic seizures.

IV. LIMITATIONS

There are some limitations of this study, which are identified next and could be considered in a future research effort. The first limitation of this work is that the performance comparison drawn between the scenarios of full and reduced montage is only based upon the CHB-MIT dataset. CHB-MIT dataset is the most widely used EEG dataset for epileptic signal analysis, and it is considered a de-facto standard for epileptic seizure detection studies. The dataset is very large and includes sufficient number of patients to be considered a reasonable representative of the variety of seizures observed in pediatric patients. However, the seizures have not been individually labelled for their types or focal regions and one might argue whether it is sufficient to assess the proposed detection technique only upon this dataset and how accurately its performance might generalize over other patients who might experience different types of seizures. This uncertainty could be resolved by extending the study to other recorded datasets with diverse set of patients with respect to age, sex, and medical history, etc. Another obvious limitation of the study is that the CHB-MIT dataset, used in this study, is

not EEG seizure data recorded in an ambulatory situation. The detection of seizure might be much more challenging in wireless ambulatory situation due to the additional artifacts produced by the movement of limbs, and it merits detailed performance analysis to be able to draw any conclusions. One possible approach in the ambulatory scenario might be to employ a sophisticated artifact removal algorithm prior to detection of seizure.

V. CONCLUSION

In this paper, we have considered the reduction of EEG channels for seizure detection by comparing the performance results of sensitivity, specificity, and FP/hr obtained using all the channels in the EEG recording, i.e., 23 channels, versus the results obtained using only 10 channels in the temporal region. After analyzing the results, we see that there is some performance loss observed when applying reduction in number and restriction in space on EEG channel measurements, but this loss of relative performance could be justifiable if we compare it with computational cost, hardware complexity and energy consumption for larger number of channels spread over the scalp. The results establish a successful feasibility for the design of an efficient ambulatory EEG device that features fewer channels, less computation, reduced hardware cost, and low energy consumption as compared to a device utilizing all channels in a standard 10-20 system.

REFERENCES

[1] U. Braun, S. F. Muldoon, and D. S. Bassett, "On human brain networks in health and disease," in *eLS*. New York, NY, USA: American Cancer Society, 2015, pp. 1–9. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9780470015902.a0025783, doi: 10.1002/9780470015902.a0025783.

[2] M. R. Keezer, S. M. Sisodiya, and J. W. Sander, "Comorbidities of epilepsy: Current concepts and future perspectives," *Lancet Neurol.*, vol. 15, no. 1, pp. 106–115, Jan. 2016.

[3] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, "Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis," *Seizure*, vol. 26, pp. 56–64, Mar. 2015.

[4] M. Diykh, Y. Li, and P. Wen, "EEG sleep stages classification based on time domain features and structural graph similarity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 11, pp. 1159–1168, Nov. 2016.

[5] J. N. Acharya, A. J. Hani, J. Cheek, P. Thirumala, and T. N. Tsuchida, "American clinical neurophysiology society guideline 2: Guidelines for standard electrode position nomenclature," *Neurodiagnostic J.*, vol. 56, no. 4, pp. 245–252, Oct. 2016.

[6] T. Lajnef, S. Chaibi, P. Ruby, P.-E. Aguera, J.-B. Eichenlaub, M. Samet, A. Kachouri, and K. Jerbi, "Learning machines and sleeping brains: Automatic sleep stage classification using decision-tree multi-class support vector machines," *J. Neurosci. Methods*, vol. 250, pp. 94–105, Jul. 2015.

[7] M. M. Rahman, M. I. H. Bhuiyan, and A. R. Hassan, "Sleep stage classification using single-channel EOG," *Comput. Biol. Med.*, vol. 102, pp. 211–220, Nov. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0010482518302427

[8] A. R. Hassan and M. I. H. Bhuiyan, "Computer-aided sleep staging using complete ensemble empirical mode decomposition with adaptive noise and bootstrap aggregating," *Biomed. Signal Process. Control*, vol. 24, pp. 1–10, Feb. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1746809415001500

[9] A. E. Vijayan, D. Sen, and A. P. Sudheer, "EEG-based emotion recognition using statistical measures and auto-regressive modeling," in *Proc. IEEE Int. Conf. Comput. Intell. Commun. Technol.*, Feb. 2015, pp. 587–591.

[10] P. Aspinall, P. Mavros, R. Coyne, and J. Roe, "The urban brain: Analysing outdoor physical activity with mobile EEG," *Brit. J. Sports Med.*, vol. 49, no. 4, pp. 272–276, Feb. 2015.

[11] R. S. Naunheim, M. Treaster, J. English, T. Casner, and R. Chabot, "Use of brain electrical activity to quantify traumatic brain injury in the emergency department," *Brain Injury*, vol. 24, no. 11, pp. 1324–1329, Oct. 2010.

[12] S. Debener, R. Emkes, M. De Vos, and M. Bleichner, "Unobtrusive ambulatory EEG using a smartphone and flexible printed electrodes around the ear," *Sci. Rep.*, vol. 5, no. 1, Dec. 2015, Art. no. 16743.

[13] T. S. Grummett, R. E. Leibbrandt, T. W. Lewis, D. DeLosAngeles, D. M. W. Powers, J. O. Willoughby, K. J. Pope, and S. P. Fitzgibbon, "Measurement of neural signals from inexpensive, wireless and dry EEG systems," *Physiol. Meas.*, vol. 36, no. 7, pp. 1469–1484, Jul. 2015.

[14] A. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, and R. D. S. Raizada, "NeuroPhone: Brain-mobile phone interface using a wireless EEG headset," in *Proc. 2nd ACM SIGCOMM Workshop Netw., Syst., Appl. Mobile Handhelds (MobiHeld)*, 2010, pp. 3–8.

[15] L. Brown, J. van de Molengraft, R. F. Yazicioglu, T. Torfs, J. Penders, and C. Van Hoof, "A low-power, wireless, 8-channel EEG monitoring headset," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. (EMBC)*, Aug. 2010, pp. 4197–4200.

[16] A. R. Hassan, S. Siuly, and Y. Zhang, "Epileptic seizure detection in EEG signals using tunable-Q factor wavelet transform and bootstrap aggregating," *Comput. Methods Programs Biomed.*, vol. 137, pp. 247–259, Dec. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260716304370

[17] A. R. Hassan, A. Subasi, and Y. Zhang, "Epilepsy seizure detection using complete ensemble empirical mode decomposition with adaptive noise," *Knowl.-Based Syst.*, vol. 191, Mar. 2020, Art. no. 105333. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0950705119306045

[18] A. R. Hassan and M. A. Haque, "Epilepsy and seizure detection using statistical features in the complete ensemble empirical mode decomposition domain," in *Proc. IEEE Region Conf. (TENCON)*, Nov. 2015, pp. 1–6.

[19] M. Akin, "Comparison of wavelet transform and FFT methods in the analysis of EEG signals," *J. Med. Syst.*, vol. 26, no. 3, pp. 241–247, 2002.

[20] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," *J. Neurosci. Methods*, vol. 123, no. 1, pp. 69–87, Feb. 2003.

[21] J. C. Woestenburg, M. N. Verbaten, and J. L. Slangen, "The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain," *Biol. Psychol.*, vol. 16, nos. 1–2, pp. 127–147, Feb. 1983.

[22] B. Boashash, *Time-Frequency Signal Analysis and Processing: A Comprehensive Reference*. New York, NY, USA: Academic, 2015.

[23] M. Z. Ahmad, A. M. Kamboh, S. Saleem, and A. A. Khan, "Mallat's scattering transform based anomaly sensing for detection of seizures in scalp EEG," *IEEE Access*, vol. 5, pp. 16919–16929, 2017.

[24] M. S. J. Solaija, S. Saleem, K. Khurshid, S. A. Hassan, and A. M. Kamboh, "Dynamic mode decomposition based epileptic seizure detection from scalp EEG," *IEEE Access*, vol. 6, pp. 38683–38692, 2018.

[25] M. Bilal, M. Rizwan, S. Saleem, M. M. Khan, M. S. Alkatheir, and M. Alqarni, "Automatic seizure detection using multi-resolution dynamic mode decomposition," *IEEE Access*, vol. 7, pp. 61180–61194, 2019.

[26] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 4, no. 2, p. R1, 2007.

[27] I. Guler and E. D. Ubeyli, "Multiclass support vector machines for EEG-signals classification," *IEEE Trans. Inf. Technol. Biomed.*, vol. 11, no. 2, pp. 117–126, Mar. 2007.

[28] Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann, and J.-H. Chen, "EEG-based emotion recognition in music listening," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 7, pp. 1798–1806, Jul. 2010.

[29] S. Ghosh-Dastidar and H. Adeli, "Improved spiking neural networks for EEG classification and epilepsy and seizure detection," *Integr. Comput.-Aided Eng.*, vol. 14, no. 3, pp. 187–212, May 2007.

[30] A. Subasi and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8659–8666, Dec. 2010.

[31] A. R. Hassan and A. Subasi, "Automatic identification of epileptic seizures from EEG signals using linear programming boosting," *Comput. Methods Programs Biomed.*, vol. 136, pp. 65–77, Nov. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260716304928

[32] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, Jun. 2000.

[33] A. Shoeb, D. Carlson, E. Panken, and T. Denison, "A micropower support vector machine based seizure detection architecture for embedded medical devices," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 4202–4205.
[34] S. Amin and A. M. Kamboh, "A robust approach towards epileptic seizure detection," in *Proc. IEEE 26th Int. Workshop Mach. Learn. Signal Process. (MLSP)*, Sep. 2016, pp. 1–6.
[35] M. Csikszentmihalyi and R. Larson, "Validity and reliability of the experience-sampling method," in *Flow and the Foundations of Positive Psychology*. Dordrecht, The Netherlands: Springer, 2014, pp. 35–54.
[36] T. Chaperon and F. Goulette, "Extracting cylinders in full 3D data using a random sampling method and the Gaussian image," in *Proc. Vis. Modeling Vis. Conf. (VMV)*, 2001, pp. 1–9.
[37] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," *EURASIP J. Adv. Signal Process.*, vol. 2015, no. 1, p. 66, Dec. 2015.
[38] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, Jan. 2003.
[39] H. Liu and L. Yu, "Toward integrating feature selection algorithms for classification and clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 4, pp. 491–502, Apr. 2005.
[40] R. S. Feldman and M. Garrison, *Understanding Psychology*, vol. 10. New York, NY, USA: McGraw-Hill, 1993.
[41] U. Seegers, H. Potschka, and W. Löscher, "Transient increase of P-glycoprotein expression in endothelium and parenchyma of limbic brain regions in the kainate model of temporal lobe epilepsy," *Epilepsy Res.*, vol. 51, no. 3, pp. 257–268, Oct. 2002.
[42] V. L. Morgan, B. Abou-Khalil, and B. P. Rogers, "Evolution of functional connectivity of brain networks and their dynamic interaction in temporal lobe epilepsy," *Brain Connectivity*, vol. 5, no. 1, pp. 35–44, Feb. 2015.
[43] H. Laufs, K. Hamandi, A. Salek-Haddadi, A. K. Kleinschmidt, J. S. Duncan, and L. Lemieux, "Temporal lobe interictal epileptic discharges affect cerebral activity in 'default mode' brain regions," *Hum. Brain Mapping*, vol. 28, no. 10, pp. 1023–1032, 2007.
[44] N. V. Chawla, A. Lazarevic, L. O. Hall, and K. W. Bowyer, "SMOTEBoost: Improving prediction of the minority class in boosting," in *Proc. Eur. Conf. Princ. Data Mining Knowl. Discovery*, 2003, pp. 107–119.
[45] L. Orosco, A. G. Correa, P. Diez, and E. Laciar, "Patient non-specific algorithm for seizures detection in scalp EEG," *Comput. Biol. Med.*, vol. 71, pp. 128–134, Apr. 2016.
[46] A. Varsavsky, I. Mareels, and M. Cook, *Epileptic Seizures and the EEG: Measurement, Models, Detection and Prediction*. Boca Raton, FL, USA: CRC Press, 2016.
[47] A. B. Das, M. J. H. Pantho, and M. I. H. Bhuiyan, "Discrimination of scalp EEG signals in wavelet transform domain and channel selection for the patient-invariant seizure detection," in *Proc. Int. Conf. Electr. Electron. Eng. (ICEEE)*, Nov. 2015, pp. 77–80.
[48] S. Chakrabarti, A. Swetapadma, and P. K. Pattnaik, "A channel selection method for epileptic EEG signals," in *Emerging Technologies in Data Mining and Information Security*, A. Abraham, P. Dutta, J. K. Mandal, A. Bhattacharya, and S. Dutta, Eds. Singapore: Springer, 2019, pp. 565–573.
[49] R. S. Selvakumari, M. Mahalakshmi, and P. Prashalee, "Patient-specific seizure detection method using hybrid classifier with optimized electrodes," *J. Med. Syst.*, vol. 43, no. 5, p. 121, May 2019.
[50] H. Tekgul, B. F. D. Bourgeois, K. Gauvreau, and A. M. Bergin, "Electroencephalography in neonatal seizures: Comparison of a reduced and a full 10/20 montage," *Pediatric Neurol.*, vol. 32, no. 3, pp. 155–161, Mar. 2005.
[51] N.-F. Chang, T.-C. Chen, C.-Y. Chiang, and L.-G. Chen, "Channel selection for epilepsy seizure prediction method based on machine learning," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug./Sep. 2012, pp. 5162–5165.

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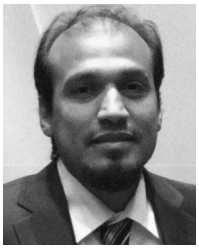

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