Journal of Medical Systems (2019) 43: 121
https://doi.org/10.1007/s10916-019-1234-4

PATIENT FACING SYSTEMS

# Patient-Specific Seizure Detection Method using Hybrid Classifier with Optimized Electrodes

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Received: 21 December 2018 / Accepted: 6 March 2019 / Published online: 26 March 2019


## Abstract

In this paper the EEG signal is analyzed by reconstructing the time series EEG signal in High dimensional Phase Space. The computational complexity in higher dimension is reduced by Principal Component Analysis for the High dimensional Phase Space output. Poincare sectioning is done for the first and second Principal Components (PCs). The intersection points of PCs and the Poincare section are collected and used for features calculation. Two layer of classification is done using SVM as first layer and Naive Bayes as second layer. The proposed methodology is evaluated using the CHB-MIT database for 23 subjects. The results are obtained using different channel combinations of EEG signal and highest of 95.63% accuracy, 95.7% sensitivity and 96.55% specificity is obtained for 12 electrode combinations which include electrodes from parietal and occipital lobes. This infers that most of the subjects have dysfunction in hearing (controlled by parietal) and vision (controlled by occipital) during the time of seizure. This GUI has channel selection option and seizure detection for every channel (23) for every 1 s.

**Keywords** High dimensional phase space · Principal component analysis · Poincare section · SVM · Naive Bayes · Optimized electrodes

## Introduction

At present, Humans are undergoing various kind of stress in their fast daily life and half of them are suffering from different neurological disorders [1]. Among the various neurological disorders of brain, epilepsy is the most common one affecting approximately 50 million population worldwide [2]. The unexpected and sudden electrical disturbances of the brain results in an acute disease called Epileptic seizures. Epilepsy is one of the most common diseases of the central nervous system. Epilepsy is unpredictable and can be detected by analyzing the brain signals (EEG). The people affected by this disease have the symptoms of abnormal sensations, twitching of arms, changes in vision, loss awareness, hear, smell or see things differently. But they usually do not have any physical symptoms in between seizures [3]. Cerebrum or cortex is the largest part of the brain responsible for controlling major functions of the body including thought and action. Cerebral cortex is the only area where origin of epilepsy arises. Cerebral cortex is divided into four lobes. They are frontal lobe, parietal lobe, occipital lobe, and temporal lobe. Each lobe is responsible for particular function.

- Frontal Lobe- controls reasoning, planning, parts of speech, movement, emotions, and problem solving
- Parietal Lobe- controls movement, orientation, recognition, perception of stimuli
- Occipital Lobe- controls visual processing
- Temporal Lobe- controls perception and recognition of auditory stimuli, memory, and speech

People may experience abnormal activities in sensation, movement, awareness, and behaviour during seizure as a

This article is part of the Topical Collection on *Patient Facing Systems*

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result they cannot perform normal task. These symptoms are seen only during the time of seizure.

Normally analysis of EEG signal is done in time series [4] or in frequency domain [5] or time- frequency [6, 7] or using non-linear methods [8, 9]. The non-linear analysis of signals will give accurate results. Here the signal in time-series form is converted to high dimensional phase space as in [10]. The attractors from higher dimensional phase space are used to analyse the signal. Takens in his work [11] proposed that the attractors reconstructed in high dimensional Phase Space from time series, have same properties as that in time series signal.

## Proposed methodology

### Work flow

The entire work flow chart is shown in Fig. 1. The EEG signals, for all the 23 Channels that were measured previously for a subject, is trained and stored. The currently measured EEG signals are tested using the trained feature vectors of the selected channels. The EEG signal is a non-linear and inter patient variability is seen in it. Hence the training is done separately for every patient. The methodology up to feature vector extraction is briefly described in Section "Methodology for feature vector extraction". The training phase is explained in Section "Testing phase for a subject" and testing is explained in Section "Optimization of electrodes". The optimization of channels is described in Section "Classification work". The classification frame work is explained in Section 2.6.

### Methodology for feature vector extraction

The process includes the conversion of input EEG signal of single channel to the feature vectors used for classification. The methodology of feature extraction is same for both testing and training. The input 1 s EEG signal of a single channel is initially represented in high dimension as given in *Section "Time-series to high dimension"*. The high dimensional signal is then reduced to lower dimension by using PCA (explained in *Section "PCA and poincare section"*). For the first and second Principal Components the Poincare sectioning (discussed in *Section "Feature for classification"*) is done. The intersection points are taken as explained below in Section "Training phase for a subject" and the features are calculated.

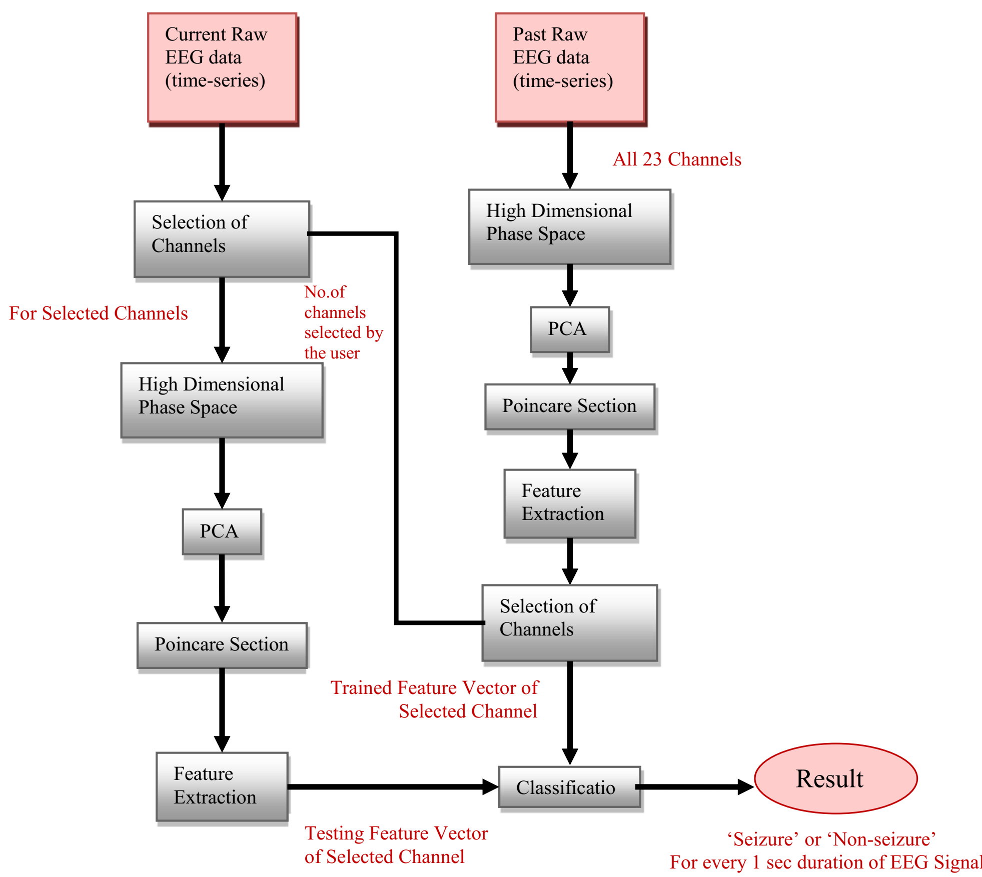


**Fig. 1** The entire work flow

### Time-series to high dimension

The High dimensional Phase Space Representation enables the sensing of dynamics of the non-linear EEG signal. The EEG signal recorded in Time-series is converted into High dimensional Phase Space Representation using Time delay embedding method as in [8]. The equation for Time delay embedding is given by

$$X[n] \rightarrow Y[n] = (X[n], X[n+\tau], \ldots, X[n+(m-1)\,\tau]) \tag{1}$$

where $\tau$ is the time lag and $m$ is the embedding dimension.

The value used for embedding dimension and time lag is 5 and 6 respectively as used in [13].

### PCA and poincare section

The Poincare section is the best way for analysing the trajectories of the attractors in higher dimensions. The complexity in higher dimensions is reduced by PCA method. The dimensionality reduction is done before Poincare because of the following reasons.1.Poincare section [12] of m dimensional space will have m dimensional surface. 2. If the dimension is reduced to 2D, now the Poincare section will be a line which cuts the plot to give the intersection points. For these reasons the linear uncorrelated Principal components (PCs) are obtained. From the obtained PCs, the first and the second PCs are used for constructing the 2D plot for Poincare sectioning. The intersection points of Poincare section is obtained by Poincare map method. The new 1D sequence is constructed by taking the first co-ordinate values of the obtained intersection points.

### Feature for classification

For the new 1D sequence as used in [13] the following seven features are calculated

1. Quantile: The 0.13 quantile value.
2. Interquantile range: The interquartile range is the difference between the first 0.25 and the third 0.75 quantile values.
3. Range:

$$Range = max(X) - min(X) \tag{2}$$

4. Shannon Entropy:

$$H_s(X) = -\sum P(X) log_2(P(X)) \tag{3}$$

5. Root Mean Square:

$$RMS_{Amp}(X) = \sqrt{1/N \sum_{k=1}^{N} X^2} \tag{4}$$

6. Coefficient of Variance:

$$COV(X) = \frac{\sqrt{\sum \frac{(X-\bar{X})^2}{N}}}{\bar{X}} \tag{5}$$

7. Energy:

$$En(X) = \sum_{k=1}^{N} |X(k)|^2 \tag{6}$$

where, X is the sequence of the intersection points and $\overline{X}$ is its mean value. N is the number of intersection points and P(X) is the probability distribution function. These features are given as input to the classifier.

### Training phase for a subject

Because of the non-linear characteristics and inter patient variability seen in the EEG signal, the training is done separately for the corresponding patient whose current EEG signal to be tested for the presence of seizure. Once the trained feature vectors are extracted it can be stored and used over the same subject for seizure detection in future. Here the EEG signal for all the 23 Channels in 10–20 electrode system of a particular subject is given as input. The input signal is represented in High Dimensional Phase Space and for the obtained output the PCA is performed in order to reduce the complexity. From the results the first and second Principal components are used for calculating intersection points by Poincare sectioning as explained in *Section* "*PCA and Poincare section*". By taking the first PC values of the intersection points the features are calculated as mentioned in *Section* "*Feature for classification*". By following the same procedures the feature vectors for all the 23 channels are calculated for several EEG signal containing both seizure and non-seizure segments. Thus the trained feature vectors for a particular patient are formed.

## Testing phase for a subject

Testing phase is designed in such a way that the channel to be tested is selected by the user. For the selected channels the same methodology of feature extraction is followed. In the classification, the obtained testing feature vectors are classified depending on the trained feature vectors of the selected channels.

### Optimization of electrodes

All the researchers have used 23 electrodes for analysis and their results of epileptic seizure are tabulated. Note that from the Table 1, the paper [14–16] have not specified the channels they used for the analysis. That is whether they have used all the 23 channels or single channel. In [13], M. Zabihi used 23 channels in his proposed work and it makes the detection more complex and consumes more time for the analysis. The usage of 23 channels is optimized depending on its location and function of brain at that particular location. Each electrode gives the data about different functions. By accounting the symptoms of epilepsy it is clear that the vision and hearing is affected during the time of epilepsy. Hence the electrodes responsible for vision and hearing are selected among the 23 channels will give better results.

### Classification work

To overcome the inter-patient variability seen in EEG signals, the classifier is trained for particular patient separately and then tested as shown in Fig. 2. Once the classifier is trained it can be used for further detection in future for the same patient. The First layer Classifier gives the output for the selected channels as 1/'yes' for seizure or 0/'no' for non-seizure signals. The output of first layer SVM classifies is given as input to the second layer Naive Bayes Classifier. The whole 23 channels SVM outputs is used to construct a sequence pattern which has a vector (23 × 1) which is used to train the NB classifier. Here the training rate of 50% is used and the result obtained is given in Table 1 and the performance is compared with the result available in the literature. By using hybrid classifier if there is an error in any one channel of the first layer classifier is rectified by the soft decision of the second layer classifier.

## Experimental results

The overall results are given in Fig. 3 from the time series to the Poincare section. The database used is discussed in *Section "Database"*. The evaluation parameters used are given in section "Performance measures". The performance of the proposed system with 23 different patient's EEG signals in the database is discussed in *Section "Results and discussion"*. The performance of the proposed work with different combination of electrodes is tabulated and discussed in *Section "Results for different channel combination"*.

### Performance measures

Three standard evaluation parameters used to measure the performance are,

$$Sensitivityy(SEN) = \frac{TP}{(TP+FN)} \tag{7}$$

$$Specificity\,(SPE) = \frac{TN}{(TN+FP)} \tag{8}$$

$$Accuracy(ACC) = \frac{TP+TN}{(TP+TN+FP+FN)} \tag{9}$$

where.

| | |
|---|---|
| *TP* (True Positive) | is the number of segments correctly detected as seizure, |
| *FN* (False Negative) | is the number of segments incorrectly detected as non-seizure, |
| *TN* (True Negative) | is the number of segments correctly detected as non-seizure, and |
| *FP* (False Positive) | is the number of segments incorrectly detected as seizure. |

**Table 1** Performance comparison for the detection of epilepsy

| *Paper* | *Training rate* | *Patient* | *Channel* | *Evaluation Parameters* | | |
|---|---|---|---|---|---|---|
| | | | | *ACC* (in %) | *SPE* (in %) | *SEN* (in %) |
| Proposed (All electrode) | 50% | *24* | 23 | 96.28 | 94.5 | 97.5 |
| | 50% | 23(excluding 15th subject) | 23 | 96.77 | 95.011 | 97.92 |
| [13] Zabihi and Kiranyaz | 50% | *24* | 23 | 94.69 | 94.8 | 89.1 |
| | 25% | 24 | 23 | 93.11 | 93.21 | 88.27 |
| [14] N. Rafiuddin | 80% | 23 | Not specified | – | 80.16 | – |
| [15] Y. Uzzaman Khan | 80% | 5 | Not specified | 91.8 | 83.6 | 100 |
| [16] B. Hunyadi | 80% | 22 | Not specified | – | 83 | – |

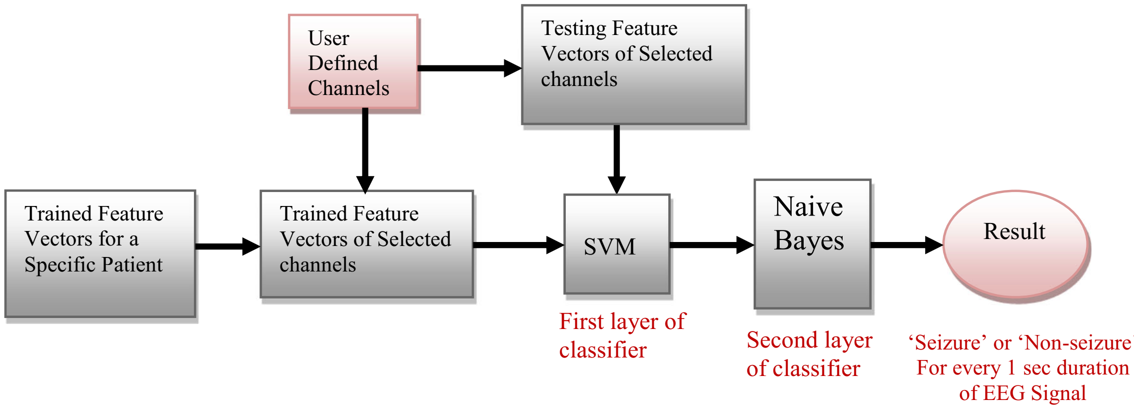


**Fig. 2** Block Diagram of Patient Specific Seizure Detection

## Database

The Database used for evaluating the performance is that CHB-MIT benchmark Database [17, 18]. It contains the EEG recordings of 23 subjects of various age groups. The sampling frequency of each recording was 256 Hz with 16 bit resolution. The International 10–20 electrode system was followed to record the EEG signal. The 23 common channels are FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8. The processing is carried out for each channel as given in Fig. 1. and final decision is taken as Seizure or Non-Seizure depending on all the selected channels output.

## Results and discussion

The proposed method is verified by using EEG recordings of 23 subjects of various age groups, from CHB-MIT benchmark Database [17]. This is a patient specific method. Therefore the EEG signal from all the 23 channels for a particular patient is recorded and stored in a database. For all the 23 channels, every one second EEG signal is segmented and the corresponding high dimensional phase space representation is done with time lag '5' and embedding dimension '6'. This gives the dynamics of the nonlinear EEG signal for a particular patient. Then the complexity in higher dimension is reduced by PCA. The first and second principle components are given as input to point care section. The features as discussed in section

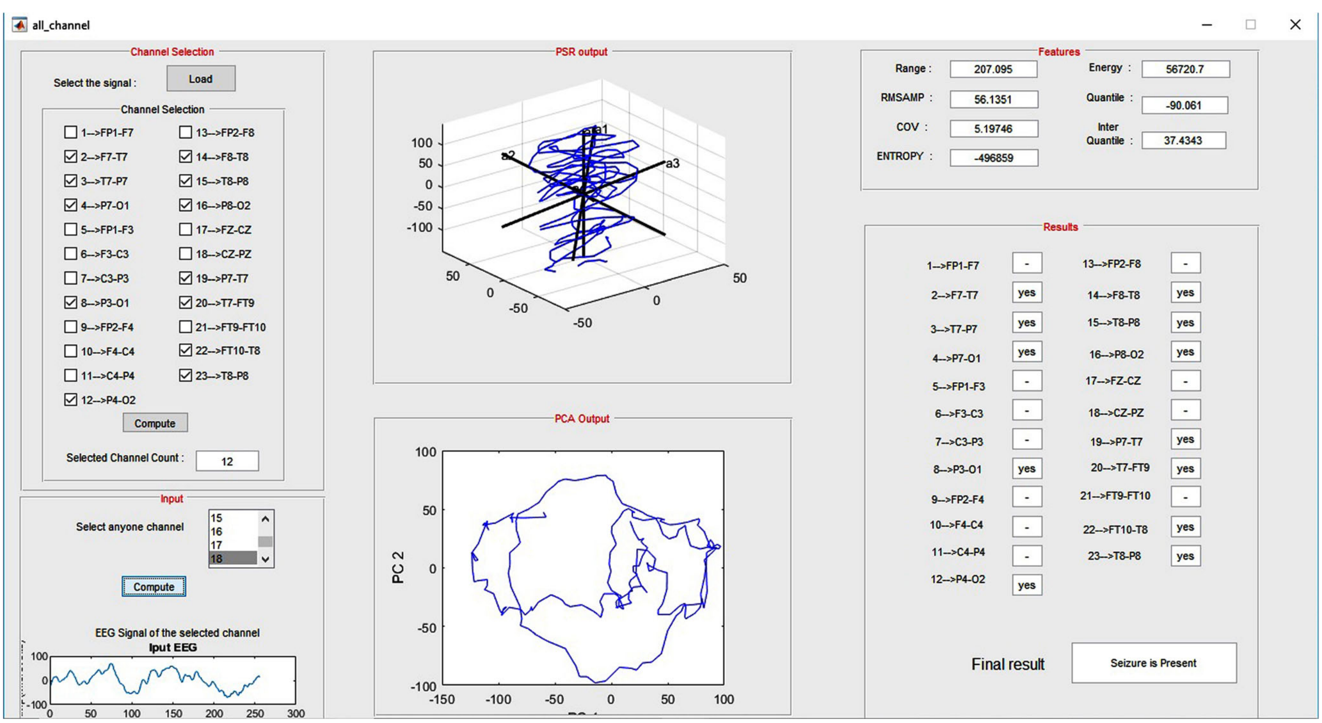


**Fig. 3** Framework for Patient Specific Seizure Detection - GUI

"Feature for classification" are derived and is used for training the first layer SVM classifier to give the output as seizure (1/'yes') or non-seizure (0/'no') of all the 23 channels individually. Here the training rate of the classifier is 50%. From the pattern received from the SVM classifier the second layer Naive Bayes classifier is trained to give the result as either seizure or non-seizure. Then the same process is repeated for everyone second of EEG signal.

The Layout design of GUI created for the seizure detection is shown in Fig. 3. The proposed GUI has seven panels such as 1. Channel selection panel, 2.input display panel, 3.PSR output display panel, 4.PCA output display panel, 5.Features display panel, 6.Result of all 23 channels display panel and 7. final result display panel. The initial step is to load the EEG signal of a patient. The signal loaded contains the EEG signal of 23 channels for 1 s duration. After the signal is loaded, the next step is to select the number of channels to be included in the analysis process. The user/doctor can select any number of channels from the listed 23 channels. The selection of check box '✓' denotes that the corresponding channel is selected for analysis. On selecting the compute button in the channel selection panel gives the count of channel selected. In order to view the EEG signal of selected channel the input panel is used, for example in this GUI (Fig. 3) as given in the channel selection panel, the channels 2,3,4,8,12,14,15,16,19,20,22 and 23 are selected for analysis. Therefore it shows the selected channel count as 12, ie., 12 numbers of channels out of 23 channels are selected for analysis. From the input channel the user/doctor can view the selected EEG signal of 1 s duration.

After analysis the selected channels PSR and PCA output will be displayed. To view the other channel's output the selection should be changed to the particular channel in the input panel and then click compute button. The output of PSR and PCA is for 1 s EEG signal. In the features display panel the values of the features computed for the selected channel are displayed. In the results display panel the seizure is present are not is displayed for all the selected channels. 'yes' means the patient is having seizure in the particular channel in that 1 s duration and 'no' means the patient doesn't have seizure in that particular channel for this 1 s duration. Final result is displayed as either seizure is present are not depending on the selected channels output in the final result display panel. For every 1 s this GUI gives information to the doctors/users from which regions/channels seizure originates/present. Based on that diagnosis purification of any patient will be easier. Therefore this GUI will assist the doctors in a better way.

Therefore using this, the user/doctor can easily diagnose whether the subject /patient is having seizure or not, in addition to that the user/doctor can able to identify the regions causes for the seizure. The user can compare this result with the subject's abnormal activity during that period to get the accurate diagnosis.

### Results for different channel combination

The performance measures for different combinations of channels are evaluated using proposed method as given in Fig. 2 and results are tabulated in Table 2. Selecting only the electrodes at temporal and occipital lobes (12 channels) gives 95.63% accuracy a highest sensitivity of 95.7% and specificity of 96.55%. As mentioned earlier in Section "Introduction", temporal lobe is responsible for speech and hearing; occipital is for vision control. From the results obtained, it is inferred that most of the subjects has abnormalities in vision, hearing and speech during the time of seizure. Hence analysis of 12 electrodes at temporal and occipital lobes is giving high rate of performance measures.

## Conclusion

The patient specific seizure detection method with channel selection is proposed. The performance of the proposed methodology is verified over the CHB-MIT database. The new feature sets for a specific patient classification framework gives an increased value of accuracy. From the results obtained it is inferred that most of the subjects in this database are mostly having problem in vision, hearing and speech at the time of seizure. Hence in the detection process 12 electrodes

**Table 2** Results for Different combinations of Channels using proposed methodology

| Lobes | Channels | No. Of Channels | Evaluation Parameters | | |
|---|---|---|---|---|---|
| | | | ACC (in %) | SEN (in %) | SPE (in %) |
| Temporal and Occipital | F7-T7, T7-P7, P7-O1, P3-O1, P4-O2, F8-T8, T8-P8, P8-O2, P7-T7, T7-FT9, FT10-T8, and T8-P8 | 12 | 95.63 | 95.7 | 96.55 |
| Frontal | FP1-F7, F7-T7, FP1-F3, F3-C3, FP2-F4, F4-C4, FP2-F8, F8-T8, FZ-CZ, T7-FT9, FT9-FT10, and FT10-T8 | 12 | 62.403 | 63.84 | 61.86 |
| Frontal and Parietal | FP1-F7, F7-T7, T7-P7, FP1-F3, F3-C3, C3-P3, FP2-F4, F4-C4, C4-P4, FP2-F8, F8-T8, T8-P8, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8 | 19 | 63.22 | 64.15 | 62.71 |
| Occipital | P7-O1, P3-O1, P4-O2 and P8-O2 | 4 | 91.18 | 90.26 | 91.92 |

placed at parietal lobe (responsible for hearing and speech) and occipital lobe (responsible for vision) plays a major role and gives the highest of 95.63% accuracy, 95.7% sensitivity and 96.55% specificity. This GUI has channel selection option and seizure detection option for every channel for every 1 s. Good choice for a doctor for easy diagnosis. Even this can be used as a user/echo friendly method for seizure detection and the region causes for the seizure.

**Availability of data materials** The Database used for evaluating the performance is that CHB-MIT benchmark Database. It contains the EEG recordings of 23 subjects of various age groups. The sampling frequency of each recording was 256 Hz with 16 bit resolution. The International 10–20 electrode system was followed to record the EEG signal. The 23 common channels are FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8

## Compliance with ethical standards

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors.

**Conflict of interest** No conflict of interest.

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