**Epileptic Seizure Detection**

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Abstract-

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**Introduction-**

Epilepsy is a chronic disorder, the hallmark of which is recurrent, unprovoked [seizures](https://www.epilepsy.com/node/2000007). A person is diagnosed with epilepsy if they have two unprovoked seizures (or one unprovoked seizure with the likelihood of more) that were not caused by some known and reversible medical condition like alcohol withdrawal or extremely low blood sugar.

The seizures in epilepsy may be related to a [brain injury](https://www.epilepsy.com/information/professionals/co-existing-disorders/head-trauma-post-traumatic-epilepsy) or a family tendency, but often the cause is completely unknown. The word "epilepsy" does not indicate anything about the cause of the person's seizures or their severity.

Many people with epilepsy have more than one [type of seizure](https://www.epilepsy.com/node/2002206) and may have other symptoms of neurological problems as well. Sometimes [EEG (electroencephalogram) testing](https://www.epilepsy.com/node/2001241), [clinical history](https://www.epilepsy.com/node/2001211), family history, and outlook are similar among a group of people with epilepsy. In these situations, their condition can be defined as a specific [epilepsy syndrome](https://www.epilepsy.com/node/2000114).

Seizures and epilepsy are not the same. An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. Epilepsy is a disease characterized by an enduring predisposition to generate epileptic seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition. Translation: a seizure is an event and epilepsy is the disease involving recurrent unprovoked seizures.

The above definitions were created in a document generated by a task force of the [**International League Against Epilepsy (ILAE)**](http://www.ilae.org/) in 2005. The definitions were conceptual, (theoretical) and not sufficiently detailed to indicate in individual cases whether a person did or did not have epilepsy. Therefore, the ILAE commissioned a second task force to develop a practical (operational) definition of epilepsy, designed for use by doctors and patients. The results of several years of deliberations on this issue have now been published (Fisher RS et al. A practical clinical definition of epilepsy, Epilepsia 2014; 55:475-482) and adopted as a position of the ILAE.

A commonly used definition of epilepsy heretofore has been two unprovoked seizures more than 24 hours apart. This definition has many positive features, but also a few limitations. This definition does not allow the possibility of "outgrowing" epilepsy. Inclusion of the word "provoked" seems to imply that people who have photosensitive seizures provoked by flashing lights or patterns do not have epilepsy; whereas, most people think that they do. Some individuals who have had only one unprovoked seizure have other risk factors that make it very likely that they will have another seizure. Many clinicians consider and treat such individuals as though they have epilepsy after one seizure. Finally, some people can

have what is called an epilepsy syndrome and these individuals should meet the definition for having epilepsy even after just one seizure. You should not have an epilepsy syndrome but not epilepsy. The new definition of epilepsy addresses each of these points.

Detection of seizures is a challenging task from EEG signal acquired from epileptic patients. By just visualising the EEG signals prediction or detection of seizures requires an expert, which may suggest about already occurred seizures or by seeing of pattern of EEG signal, he may able to predict it. There may be chance of wrong prediction due to various causes like human error, disturbance in EEG signal etc. With the use of various feature extraction and classification methods, it is possible to detect epileptic seizures with good accuracy [2]. The acquired EEG signal may classify in following ways: the very first one is scalp EEG and another one is EEG data collected through invasive approach. For data collection through scalp, there are some standards of placing the electrodes. The very common and famous international standard is 10-20 electrode placement system. Data collected through scalp is very common and most general way to move forward our research. The collected EEG signals, from healthy patient and epileptic patients may be differentiated using certain set of parameters. In epileptic signal, it may be observed as four parts of stage like pre-ictal, ictal, inter-ictal and post ictal. Part of EEG signal before the very first seizure is termed as pre-ictal, whereas after the last seizure observed in signal known as post-ictal. Ictal period represents duration of seizures, whereas inter-ictal shows part of signal between two successive seizures [3]. During epilepsy, patient may loss his senses; even he may face various injuries, which may cause of his death. Hence it is required to detect epilepsy on time so that patient may get cured.

* 1. RELATED WORK

Research work related to epilepsy detection on the basis of EEG recoding has already been started 3 to 4 decades before. Presently, it has already gone to higher level with very much precision and accuracy. Now a day’s computer based analysis is widely used and majorly having various kinds of problem likes event detection in between two successive seizures and seizure analysis etc. There are various algorithms have already been given, which help us to do the same.

For seizure detection, STFT has been used followed by rule based classifier presented in . Different time frequency methods has been used for detection of epilepsy using XGBoost.

has been shown in . Time-frequency methods have been used for the detection of abnormalities in new born EEG [Related to detection of epileptical seizures other methods have also been proposed presented in number of research papers such as time domain analysis , frequency domain analysis , etc.

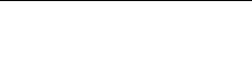
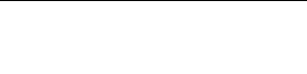
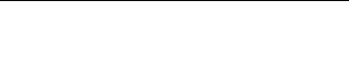
In various research papers, there are numbers of features have been extracted to classify the epileptical seizures, some of them are mean, variance, standard deviation, skewness, kurtosis, spectral density, spectral flux, entropy etc .With the use of different features, various machine learning methods have been used by researchers for classification of epileptical seizures. Support vector machine random forest, decision tree , k-NN (nearest neighbour) classifier fuzzy logic system , naïve bayes classifier etc. are some of them which are able to give high level of detection accuracy. Some of researchers also used combination of numbers of classifiers, which may help for improving accuracy of seizure detectio

1. **Methodology-**

To detect epileptical seizures, this paper has followed various steps presented in Fig.1 along with the use of already existing dataset to carry out research work presented in .The database is publicly available and provided by university of Bonn, Germany. As it is mentioned that this available data is already pre-processed, hence without using any noise removal technique dataset has been used as it is. Further, STFT has been done of EEG data.

***A. Time-Frequency Analysis of EEG Data***

There are numbers of time-frequency methods available to perform analysis. For real time processing STFT is more preferable to wavelet transform methods. In this paper, STFT has been used to perform time-frequency analysis of EEG data. This method is useful for localization of frequency / time in time / frequency respectively. STFT transform one dimensional (time domain) EEG data to two dimension (time-frequency). In this work hamming window of size odd (N/4), where, N is the number of data points, has been used.



Extraction of Gamma

Band Frequency

Random Forest (RF) Classifier

Extraction of Statistical Features

STFT

(Short-Time Fourier Transform)

EEG Data

Detection of Epileptic Seizures

* 1. Dataset Description

### Data collection

The initial requirement is to collect the dataset of brain signals. For this, different monitoring tools are used. Typically, the mostly used devices is EEG , because their channels or electrodes are implanted by glue on the surface of the scalp as per 10–20 International system at different lobes. Each of them has a wire connection to the EEG device, providing timely information about the variations in voltage, along with temporal and spatial information. As highlighted in Fig. [2](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7248143/figure/Fig2/), the EEG channels are placed on the subject’s scalp, and the electrical signals are read by the EEG monitoring tool and it displays these raw signals over the screen. Further, these raw signals have been carefully monitored by the analyst and classified into ‘seizure’ and ‘non-seizure’ states.

### Data transformation

After data collection, the next crucial step is to transform the signal data into a 1-D Table format. The reason for this is to make it easier for analysis and provide necessary knowledge like seizure detection. This datum is raw because it has not been processed yet. Therefore, it will not be suitable to give relevant information. To do the processing, different feature selection modalities have been applied. This step also presents the dataset as supervised, which means that it provides the class attribute with possible class-values.

* 1. **Principal Component Analysis**

**Principal Component Analysis** (**PCA**) is a statistical procedure that uses an orthogonal transformation which converts a set of correlated variables to a set of uncorrelated variables. **PCA** is a most widely used tool in exploratory data analysis and in **machine learning** for predictive models

**3.3Classification Techniques-**

**3.4.1. XGBoost**

[XGBoost](https://xgboost.ai/)is a decision-tree-based ensemble Machine Learning algorithm that uses a [gradient boosting](https://en.wikipedia.org/wiki/Gradient_boosting) framework. In prediction problems involving unstructured data (images, text, etc.) artificial neural networks tend to outperform all other algorithms or frameworks. However, when it comes to small-to-medium structured/tabular data, decision tree based algorithms are considered best-in-class right now. Please see the chart below for the evolution of tree-based algorithms over the years. Use ofXGBoost and Gradient Boosting Machines (GBMs) are both ensemble tree methods that apply the principle of boosting weak learners using the gradient descent architecture. However, XGBoost improves upon the base GBM framework through systems optimization and algorithmic enhancements.

Table3: results obtained by applying XGBoost on Bonn EEG dataset after applying PCA

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | Confusion Matrix | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | [22, 4]  [1, 13] | [17, 4]  [2, 17] | [19, 3]  [0, 18] | [18, 2]  [0, 20] | [19, 0]  [0, 20] | [16, 1]  [1, 22] | [20, 0]  [ 3, 17] |
| S-O | [20, 0]  [0, 20] | [20, 4]  [0, 16] | [22, 2]  [1, 15] | [11, 2]  [1, 26] | [20, 2]  [1, 17] | [16 , 1]  [0, 23] | [19 , 0]  [0 , 21] |
| S-N | [22, 1]  [1, 16] | [18, 1]  [5 , 16] | [17, 1]  [3, 19] | [21, 1]  [0, 18] | [23, 2]  [0 , 15] | [20, 2]  [1, 17] | [18, 2]  [0, 20] |
| S-F | [18, 3]  [4, 15] | [15, 3]  [6, 16] | [16, 3]  [2, 19] | [20, 4]  [0, 16] | [20, 4]  [2, 14] | [20, 1]  [4, 15] | [13, 3]  [4, 20] |
| S-ZO | [35, 7]  [1, 17] | [35, 7]  [0, 18] | [48, 1]  [4, 7] | [44, 3]  [1, 12] | [38, 2]  [0, 20] | [40, 1]  [0, 19] | [39, 1]  [2, 18] |
| S-NF | [43, 5]  [4, 8] | [39, 3]  [3 , 15] | [40, 3]  [5, 12] | [45, 2]  [2, 11] | [41, 4]  [ 2, 13] | [42, 1]  [3, 14] | [42, 1]  [3, 14] |
| S-ZONF | [79, 4]  [1, 16] | [76, 6]  [1, 17] | [82, 4]  [0, 14] | [82, 5]  [0, 13] | [79, 3]  [1, 17] | [83, 2]  [2, 13] | [72, 6]  [1, 21] |
| ZO-NFS | [19, 12]  [21, 48] | [21, 22]  [20, 37] | [26, 11]  [10, 53] | [31, 6]  [11, 52] | [22, 8]  [21, 49] | [31, 4]  [9, 56] | [30, 8]  [12, 50] |
| ZO-NF | [31, 17]  [5, 27] | [39, 11]  [1, 29] | [27, 7]  [8, 38] | [31, 7]  [5, 37] | [39, 4]  [10, 27] | [30, 9]  [8, 33] | [33, 10]  [3, 34] |
| S-O-F | []  [] | []  [] | []  [] | []  [] | []  [] | []  [] | []  [] |

Table4: results obtained by applying XGBoost on Bonn EEG dataset after applying PCA

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | **Accuracy Score** | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | 0.87 | 0.97 | 0.92 | 1.00 | 0.95 | 0.95 | 0.92 |
| S-O | 0.80 | 0.97 | 0.97 | 0.82 | 0.85 | 1.00 | 0.92 |
| S-N | 0.92 | 0.90 | 0.92 | 0.95 | 0.97 | 1.00 | 0.95 |
| S-F | 0.87 | 0.9 | 0.80 | 0.92 | 0.80 | 1.00 | 0.92 |
| S-ZO | 0.90 | 0.86 | 0.93 | 0.88 | 0.91 | 0.88 | 0.93 |
| S-NF | 0.86 | 0.90 | 0.86 | 0.95 | 0.91 | 0.93 | 0.93 |
| S-ZONF | 0.94 | 0.92 | 0.94 | 0.92 | 0.95 | 0.97 | 0.94 |
| ZO-NFS | 0.66 | 0.61 | 0.72 | 0.76 | 0.62 | 0.76 | 0.71 |
| ZO-NF | 0.66 | 0.78 | 0.80 | 0.78 | 0.73 | 0.72 | 0.73 |
| S-O-F |  |  |  |  |  |  |  |

**3.4.2. Random forest-**

## Random Forest

Since decision trees are likely to over fit, the random forest was created to reduce that. Many decision trees make up a random forest model. A random forest consists of bootstrapping the dataset and using a random subset of features for each decision tree to reduce the correlation of each tree, hence reducing the probability of over fitting. We can measure how good a random forest is by using the “out-of-bag” data that weren’t used for any trees to test the model. Random forest is also almost always preferred over a decision tree since the model has a lower variance; hence, the model can generalize better.

Table 2: Table: results obtained by applying Random forest on Bonn EEG dataset after applying

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | Confusion Matrix | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | [21, 2]  [4, 13] | [17, 2]  [5, 16] | [19, 0]  [2, 19] | [16, 2]  [3, 19] | [19, 1]  [0, 20] | [15, 2]  [1, 22] | [21, 2]  [0, 17] |
| S-O | [20, 0]  [2, 18] | [20, 0]  [7, 13] | [23, 0]  [2, 15] | [12, 0]  [4, 24] | [20, 1]  [4, 15] | [16, 0]  [2, 22] | [19, 0]  [2, 19] |
| S-N | [22, 1]  [2, 15] | [19, 4]  [1, 16] | [19, 1]  [1, 19] | [21, 0]  [2, 17] | [23, 0]  [2, 15] | [20, 1]  [1, 18] | [18, 0]  [3, 19] |
| S-F | [19, 3]  [3, 15] | [17, 4]  [3, 16] | [15, 3]  [3 , 19] | [20, 0]  [3, 17] | [20, 2]  [4, 14] | [21, 3]  [0, 16] | [15, 2]  [3, 20] |
| S-ZO | [36, 0]  [7 , 17] | [35, 0]  [8, 17] | [50, 2]  [2, 6] | [42, 3]  [4, 11] | [38, 0]  [5, 17] | [40, 0]  [ 7, 13] | [40, 1]  [3, 16] |
| S-NF | [44, 3]  [5, 8] | [39, 3]  [3, 15] | [41, 4]  [4, 11] | [47, 0]  [3, 10] | [42, 1]  [4, 13] | [43, 2]  [2, 13] | [43, 2]  [2, 13] |
| S-ZONF | [80, 0]  [6, 14] | [77, 0]  [8, 15] | [82, 0]  [6, 12] | [81, 1]  [7, 11] | [80, 0]  [5, 15] | [84, 1]  [2 , 13] | [73, 0]  [6, 21] |
| ZO-NFS | [13, 27]  [7, 53] | [17, 24]  [15, 44] | [17, 19 ]  [9, 55] | [23, 19]  [5, 53] | [13, 30]  [8, 49] | [17, 23]  [1, 59] | [21, 21]  [8, 50] |
| ZO-NF | [32, 4]  [23, 21] | [39, 1]  [16, 24] | [32, 3]  [13, 32] | [34, 2]  [15, 29] | [38, 11]  [10, 21] | [30, 8]  [14, 28] | [35, 1]  [20, 24] |
| S-O-F | [5,0,15], [4,12,3], [2,2,17] | [7,1,13] [4,15,5]  [0,0,15] | [1,1,21] [1,21,1]  [0,1,13] | [14,0,2] [3,18,3]  [11,0,9] | [6,1,10] [3,20,2]  [4,0,14] | [4,0,19]  [1,17,2]  [1,1,15] | [6,0,12] [2,17,5] [2,2,14] |

Table 5:Table: results obtained by applying Random Forest on Bonn EEG dataset after applying PCA

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | **Accuracy Score** | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | 0.85 | 0.97 | 0.92 | 1.00 | 0.97 | 0.95 | 0.92 |
| S-O | 0.80 | 0.97 | 0.97 | 0.82 | 0.85 | 1.00 | 1.00 |
| S-N | 0.92 | 0.90 | 0.92 | 0.95 | 0.97 | 1.00 | 0.95 |
| S-F | 0.87 | 0.9 | 0.80 | 0.92 | 0.80 | 1.00 | 0.92 |
| S-ZO | 0.91 | 0.86 | 0.93 | 0.88 | 0.91 | 0.88 | 0.93 |
| S-NF | 0.86 | 0.90 | 0.86 | 0.95 | 0.91 | 0.93 | 0.93 |
| S-ZONF | 0.94 | 0.92 | 0.94 | 0.92 | 0.95 | 0.97 | 0.94 |
| ZO-NFS | 0.66 | 0.61 | 0.72 | 0.76 | 0.62 | 0.76 | 0.71 |
| ZO-NF | 0.66 | 0.78 | 0.80 | 0.78 | 0.73 | 0.72 | 0.73 |
| S-O-F | 0.56 | 0.61 | 0.58 | 0.68 | 0.66 | 0.60 | 0.61 |

**3.4.3. Decision tree-**

## Decision Trees

A decision tree is a model where it runs a sample down multiple “questions” to determine its class. The classifying algorithm works by repetitively separating data into sub-regions of the same class and the tree ends when the algorithm has divided all samples into categories that are pure, or by meeting some criteria of the classifier attributes.

Decision trees are weak learners, and by that, I mean they are not particularly accurate, and they often only do a bit better than randomly guessing. They also almost always overfit the training data.

Table 1: results obtained by applying Decision tree on Bonn EEG dataset after applying PCA

1. Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | Confusion Matrix | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | [20, 3]  [5, 12] | [16, 3]  [4, 17] | [16, 3]  [2, 16] | [18, 0]  [0, 22] | [19, 1]  [0, 20] | [15, 2]  [2, 21] | [18, 5]  [2, 15] |
| S-O | [20, 0]  [2, 18] | [20, 0]  [5, 15] | [21, 2]  [3, 14] | [10, 2]  [1, 27] | [19, 2]  [0, 19] | [15 , 1]  [0, 24] | [19, 0]  [0, 21 ] |
| S-N | [23, 0]  [5, 12] | [18, 5]  [2, 15] | [16, 4]  [1 , 19] | [20, 1]  [2, 17] | [22, 1]  [1, 16] | [20, 1]  [4, 15] | [17, 1]  [1, 21] |
| S-F | [20, 2]  [2, 16] | [17, 4]  [3, 16] | [15, 3]  [4, 18] | [19, 1]  [4, 16] | [20, 2]  [6, 12] | [19, 5]  [3, 13] | [15, 2]  [0, 23] |
| S-ZO | [36, 0]  [9, 15] | [36, 0]  [7, 18] | [48, 4]  [1, 7] | [42, , 3]  [2, 13] | [38, 0]  [1, 21] | [38, 2]  [4, 16] | [40, 1]  [ 3, 16] |
| S-NF | [40, 7]  [3, 10] | [36, 6]  [2, 16] | [41, 4 ]  [5, 10] | [45, 2]  [1, 12] | [40, 3]  [2, 15] | [43, 2]  [3, 12] | [43, 2]  [3, 12] |
| S-ZONF | [79, 1]  [4, 16] | [76, 1]  [4, 19] | [79, 3]  [3, 15] | [81, 1]  [6, 12] | [80, 0]  [2, 18] | [83, 2]  [7, 8] | [71, 2]  [7, 20] |
| ZO-NFS | [0, 40]  [0, 60] | [21, 20]  [29, 30] | [20, 16]  [15, 49] | [29, 13]  [16, 42] | [20, 23]  [11, 46] | [22, 18]  [8, 52] | [30, 12]  [16, 42] |
| ZO-NF | [28, 8]  [18, 26] | [33, 7]  [10, 30] | [24, 11]  [10, 35] | [30, 6]  [11, 33] | [22, 27]  [8, 23] | [30, 8]  [9, 33] | [24, 12]  [11, 33] |
| S-O-F | [7,0,13] [7,11,1]  [6,3,12] | [9,0,12] [7,13,4]  [5,1,9] | [16,1,6] [2,18,4]  [3,2,9] | [8,1,7] [2,18,4]  [9,2,9] | [12,1,4]  [3,16,6] [11,0,7] | [11,3,9 [1,14,5],4 0,13] | [11,1,6]  [3,17,4]  [7,3,8] |

Table 6: Table: results obtained by applying Decision Tree on Bonn EEG dataset after applying PCA

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | **Accuracy Score** | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | 0.85 | 0.77 | 0.8 | 0.95 | 0.93 | 1.00 | 0.95 |
| S-O | 0.72 | 0.85 | 0.85 | 0.92 | 0.87 | 0.97 | 0.95 |
| S-N | 0.85 | 0.87 | 0.87 | 0.95 | 0.95 | 0.9 | 0.90 |
| S-F | 0.85 | 0.8 | 0.75 | 0.82 | 0.87 | 0.95 | 0.87 |
| S-ZO | 0.91 | 0.88 | 0.91 | 0.91 | 0.98 | 0.90 | 0.93 |
| S-NF | 0.81 | 0.86 | 0.85 | 0.95 | 0.91 | 0.91 | 0.91 |
| S-ZONF | 0.95 | 0.95 | 0.94 | 0.93 | 0.98 | 0.91 | 0.91 |
| ZO-NFS | 0.60 | 0.51 | 0.69 | 0.71 | 0.66 | 0.74 | 0.72 |
| ZO-NF | 0.67 | 0.78 | 0.73 | 0.78 | 0.56 | 0.78 | 0.71 |
| S-O-F | 0.50 | 0.51 | 0.71 | 0.60 | 0.58 | 0.63 | 0.60 |

Table 5:Table: results obtained by applying Random Forest on Bonn EEG dataset after applying PCA

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Data Cluster | **Accuracy Score** | | | | | | |
|  |
|  | N=3 | N=4 | N=5 | N=6 | N=7 | N=8 | N=9 |
| S-Z | 0.85 | 0.97 | 0.92 | 1.00 | 0.97 | 0.95 | 0.92 |
| S-O | 0.80 | 0.97 | 0.97 | 0.82 | 0.85 | 1.00 | 1.00 |
| S-N | 0.92 | 0.90 | 0.92 | 0.95 | 0.97 | 1.00 | 0.95 |
| S-F | 0.87 | 0.9 | 0.80 | 0.92 | 0.80 | 1.00 | 0.92 |
| S-ZO | 0.91 | 0.86 | 0.93 | 0.88 | 0.91 | 0.88 | 0.93 |
| S-NF | 0.86 | 0.90 | 0.86 | 0.95 | 0.91 | 0.93 | 0.93 |
| S-ZONF | 0.94 | 0.92 | 0.94 | 0.92 | 0.95 | 0.97 | 0.94 |
| ZO-NFS | 0.66 | 0.61 | 0.72 | 0.76 | 0.62 | 0.76 | 0.71 |
| ZO-NF | 0.66 | 0.78 | 0.80 | 0.78 | 0.73 | 0.72 | 0.73 |
| S-O-F | 0.56 | 0.61 | 0.58 | 0.68 | 0.66 | 0.60 | 0.61 |

# Literature review-

# Epileptic Seizure Classification ML Algorithms

## Binary Classification Machine Learning Algorithms in Python

(May 28,2019) Jerry Yu

# A review of epileptic seizure detection using machine learning classifiers.

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Epilepsy is a serious chronic neurological disorder, can be detected by analyzing the brain signals produced by brain neurons. Neurons are connected to each other in a complex way to communicate with human organs and generate signals. The monitoring of these brain signals is commonly done using Electroencephalogram (EEG) and Electrocorticography (ECoG) media.

Epilepsy, Applications of machine learning on epilepsy, Statistical features, Seizure detection, Seizure localization, Black-box and non-black-box classifiers, EEG signals

# Classification of epileptic seizure dataset using different machine learning algorithms

# ([Volume 21](https://www.sciencedirect.com/science/journal/23529148/21/supp/C), 2020)[Khaled MohamadAlmustafa](https://www.sciencedirect.com/science/article/pii/S2352914820305943" \l "!)

Seizure associated with abnormal brain activities caused by epileptic disorder is widely typical and has many symptoms, such as loss of awareness and unusual behavior as well as confusion. In this paper, a classification of the Epileptic Seizure dataset was done using different classifiers. It was shown that the Random Forest classifier outperformed K- Nearest Neighbor (K-NN), Naïve Bayes, Logistic Regression, Decision Tree (D.T.), Random Tree, J48, Stochastic Gradient Descent (S.G.D.) classifiers with 97.08% Accuracy, ROC = 0.996, and RMSE = 0.1527. Sensitivity analysis for some of these classifiers was performed to study the performance of the classifier to classify the Epileptic Seizure dataset with respect to some changes in their parameters.

Epileptic seizure,K-nearest neighbour,Classification,Decision tree,Random forest,Feature extraction,Sensitivity analysis.

# Automatic Epileptic Seizure Detection Using Scalp EEG and Advanced Artificial Intelligence Techniques(2015) David Hignett, Abir Hussain, Dhiya Al-Jumeily.

The epilepsies are a heterogeneous group of neurological disorders and syndromes characterised by recurrent, involuntary, paroxysmal seizure activity, which is often associated with a clinic electrical correlate on the electroencephalogram. The diagnosis of epilepsy is usually made by a neurologist but can be difficult to be made in the early stages. Supporting paraclinical evidence obtained from magnetic resonance imaging and electroencephalography may enable clinicians to make a diagnosis of epilepsy and investigate treatment earlier. However, electroencephalogram capture and interpretation are time consuming and can be expensive due to the need for trained specialists to perform the interpretation. Automated detection of correlates of seizure activity may be a solution. In this paper, we present a supervised machine learning approach that classifies seizure and nonseizure records using an open dataset containing 342 records. Our results show an improvement on existing studies by as much as 10% in most cases with a sensitivity of 93%, specificity of 94%, and area under the curve of 98% with a 6% global error using a *k*-class nearest neighbour classifier. We propose that such an approach could have clinical applications in the investigation of patients with suspected seizure disorders.

# A review of epileptic seizure detection using machine learning classifiers

(Mohammad Khubeb Siddiqui1† , Ruben Morales‑Menendez1\*, Xiaodi Huang2† and Nasir Hussain,2020)

Epilepsy is a serious chronic neurological disorder, can be detected by analyzing the brain signals produced by brain neurons. Neurons are connected to each other in a complex way to communicate with human organs and generate signals. The monitoring of these brain signals is commonly done using Electroencephalogram (EEG) and Electrocor‑ ticography (ECoG) media. These signals are complex, noisy, non-linear, non-stationary and produce a high volume of data. Hence, the detection of seizures and discovery of the brain-related knowledge is a challenging **task**. Machine learning classifers are able to classify EEG data and detect seizures along with revealing relevant sensible patterns without compromising performance. As such, various researchers have developed number of approaches to seizure detection using machine learning classifers and statistical features. The main challenges are selecting appropriate classifers and features. The aim of this paper is to present an overview of the wide varieties of these techniques over the last few years based on the taxonomy of statistical features and machine learning classifers—‘black-box’ and ‘non-black-box’. The presented state-of-the-art methods and ideas will give a detailed understanding about seizure detection and classifcation, and research directions in the future. Epilepsy, Applications of machine learning on epilepsy.

# Automatic seizure detection based on imaged-EEG signals through fully convolutional networks

* [Catalina Gómez](https://www.nature.com/articles/s41598-020-78784-3#auth-Catalina-G_mez), ,[Pablo Arbeláez](https://www.nature.com/articles/s41598-020-78784-3#auth-Pablo-Arbel_ez), [Miguel Navarrete](https://www.nature.com/articles/s41598-020-78784-3#auth-Miguel-Navarrete), [Catalina Alvarado-Rojas](https://www.nature.com/articles/s41598-020-78784-3#auth-Catalina-Alvarado_Rojas), [Michel Le Van Quyen](https://www.nature.com/articles/s41598-020-78784-3#auth-Michel-Quyen) & [Mario Valderrama](https://www.nature.com/articles/s41598-020-78784-3#auth-Mario-Valderrama) ( 11 December 2020)
* Seizure detection is a routine process in epilepsy units requiring manual intervention of well-trained specialists. This process could be extensive, inefficient and time-consuming, especially for long term recordings. We proposed an automatic method to detect epileptic seizures using an imaged-EEG representation of brain signals. To accomplish this, we analyzed EEG signals from two different datasets: the CHB-MIT Scalp EEG database and the EPILEPSIAE project that includes scalp and intracranial recordings. We used fully convolutional neural networks to automatically detect seizures. For our best model, we reached average accuracy and specificity values of 99.3% and 99.6%, respectively, for the CHB-MIT dataset, and corresponding values of 98.0% and 98.3% for the EPILEPSIAE patients. For these patients, the inclusion of intracranial electrodes together with scalp ones increased the average accuracy and specificity values to 99.6% and 58.3%, respectively. Regarding the other metrics, our best model reached average precision of 62.7%, recall of 58.3%, F-measure of 59.0% and AP of 54.5% on the CHB-MIT recordings, and comparatively lowers performances for the EPILEPSIAE dataset.

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