

# **Literature Survey Report**

## **Epileptic Seizure Detection using Machine Learning Algorithms**



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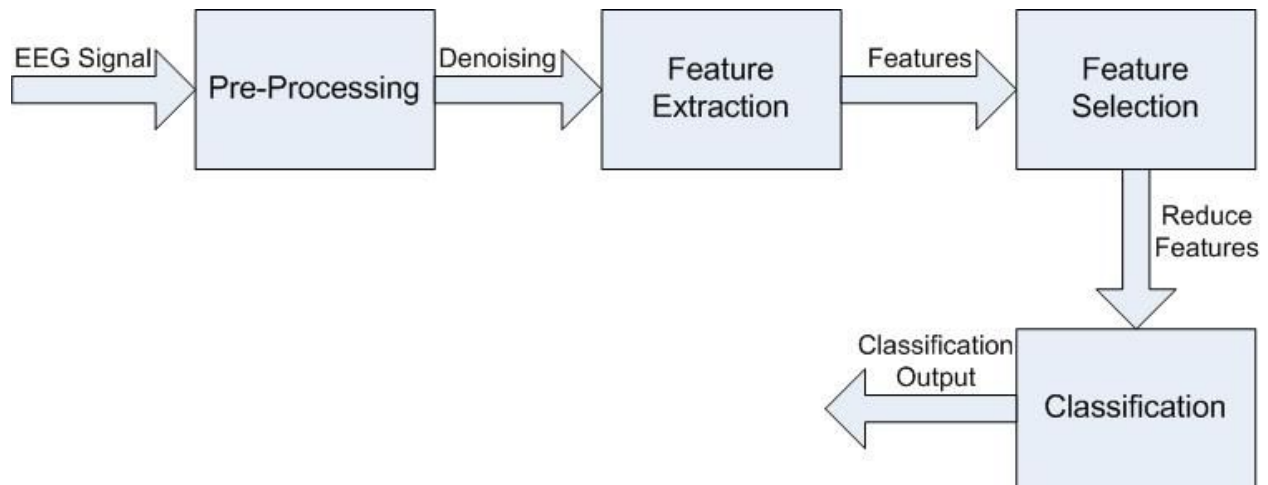
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## **Introduction:**

Epileptic seizures are manifestations of epilepsy, which are due to the sudden development of synchronous neuronal firing in the cerebral cortex and are recorded using the EEG, which is a measure of brain electrical activity. Clinical neurologists in daily practice commonly examine short recordings (usually 20-min recordings) of interictal periods.

The most common forms of the interictal periods are the individual or isolated spikes, the sharp wave, and the spike-and wave complex. These are perceived in the majority of patients with epilepsy. Visual seizure detection has not been proven very efficient. Efficient automated seizure detection schemes facilitate the diagnosis of epilepsy and enhance the management of long-term EEG recordings.

## **Methodology:**



## **Feature Extraction:**

Approaches are based on earlier observations that the epileptic seizures give rise to changes in certain frequency bands, such as  $\delta$  (0.4–4 Hz),  $\theta$  (4–8 Hz),  $\alpha$  (8–12 Hz), and  $\beta$  (12–30 Hz) bands.

## **Time-frequency based feature extraction:**

This approach is based on the t-f analysis of each EEG segment in order to obtain the power spectrum density (PSD) and extract features from it, which correspond to the fractional energy of windows defined on the t-f plane.

$$\rho(t, f) = \iiint e^{i2\pi v(u-t)} g(v, \tau) x^* \left( u - \frac{1}{2}\tau \right) \times x \left( u + \frac{1}{2}\tau \right) e^{-i2\pi f\tau} dv du d\tau$$

Unlike the STFT t-f representation, the Cohen's class of t-f representations is quadratic where  $t$  is the time,  $f$  is the frequency,  $x(t)$  is the signal,  $x^*(t)$  is its complex conjugate, and  $g(u, \tau)$  is an arbitrary function called kernel, which is different for each TFD.

Daubechies Wavelet Transform:

This captures both frequency and location information (location in time) unlike STFT.

### **Lyapunov exponent:**

The Lyapunov exponent or Lyapunov characteristic exponent of a dynamical system is a quantity that characterizes the rate of separation of infinitesimally close trajectories. Quantitatively, two trajectories in phase space with initial separation  $\delta \mathbf{Z}_0$  diverge (provided that the divergence can be treated within the linearized approximation) at a rate given by

$$|\delta \mathbf{Z}(t)| \approx e^{\lambda t} |\delta \mathbf{Z}_0| \quad \text{where } \lambda \text{ is the Lyapunov exponent.}$$

Correlation dimension:

For any set of  $N$  points in an  $m$ -dimensional space

$$\vec{x}(i) = [x_1(i), x_2(i), \dots, x_m(i)], \quad i = 1, 2, \dots, N$$

then the correlation integral  $C(\epsilon)$  is calculated by:

$$C(\epsilon) = \lim_{N \rightarrow \infty} \frac{g}{N^2}$$

where  $g$  is the total number of pairs of points which have a distance between them that is less than distance  $\epsilon$ .

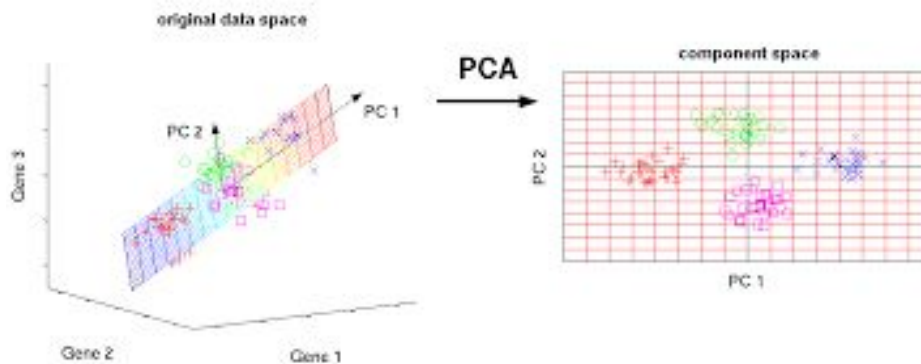
### **Possible features:**

- 1) Evolution of accumulated energy
- 2) Average EEG amplitude
- 3) variation coefficient,
- 4) dominant frequency
- 5) average power spectrum
- 6) Relative spike amplitude
- 7) Spike rhythmicity

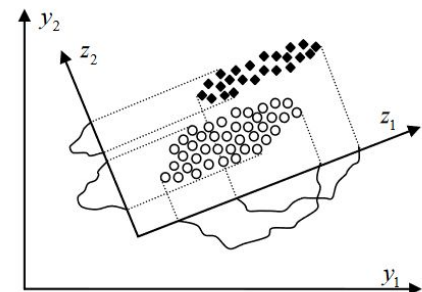
### **Feature space reduction:**

After an appropriate signal analysis, the feature vector is derived. Its dimension should be reduced since it is often too large and the design of classifiers for a large dimension suffers from various difficulties. Those are mostly numerical problems that involve operation with high-order

matrices. The reduction matrix should be determined such that there is no significant loss of information. The most often applied approach is the Karhunen-Loeve Expansion method, which, depending on the area of application, is also referred to as Principal Component Analysis (PCA). The main idea behind these methods is to determine the direction in which the scattering of the random vector is the greatest, through analysis of a covariance matrix.



However, such an approach is not always convenient for some applications. scatter matrices-based dimension reduction is reliable over PCA. Consider the adjoining figure where PCA would consider  $z_1$  as it has maximum variance and would sacrifice  $z_2$  which is more important for our application.



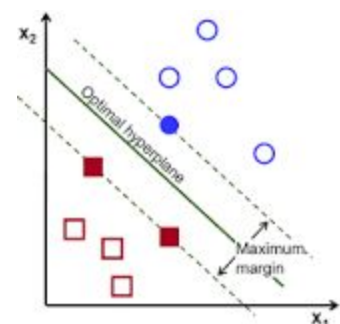
## **Classification :**

### Support vector machines (SVM):

A Support Vector Machine is a discriminative classifier formally defined by a separating hyperplane.

An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

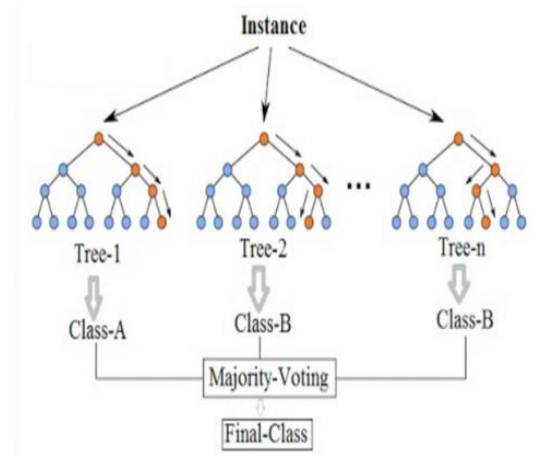
In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.



## Random Forest :

Random forest is an ensemble learning method for the classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode (most voted class) of the classes for classification process and mean of the outputs if it is a regression problem. This overcomes the overfitting nature of the decision trees on the training set.

Dataset is randomly split into overlapping subsets of different sizes. Each of the subsets have their own decision tree associated with them. For each of the test set the decision tree classify into classes and the mode class is considered the final one.



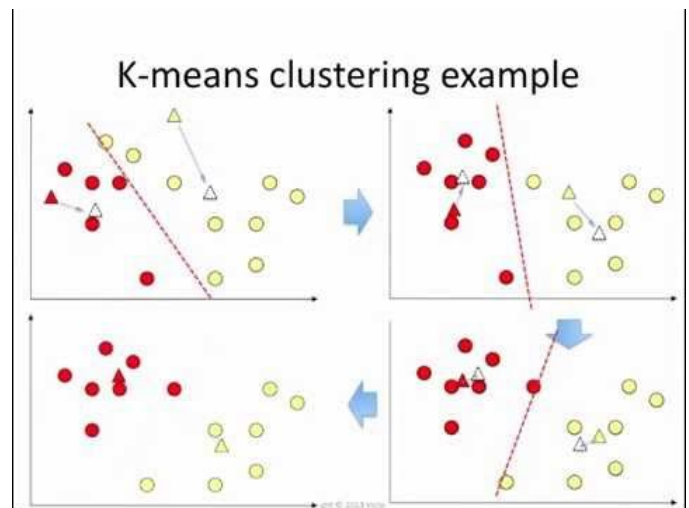
## k-means clustering:

Lloyd's algorithm popularly known as k means , is an iterative, data-partitioning algorithm that assigns  $n$  observations to exactly one of  $k$  clusters defined by centroids, where  $k$  is chosen before the algorithm starts.

The results of the  $K$ -means clustering algorithm are:

- 1) The centroids of the  $K$  clusters, which can be used to label new data
- 2) Labels for the training data (each data point is assigned to a single cluster)

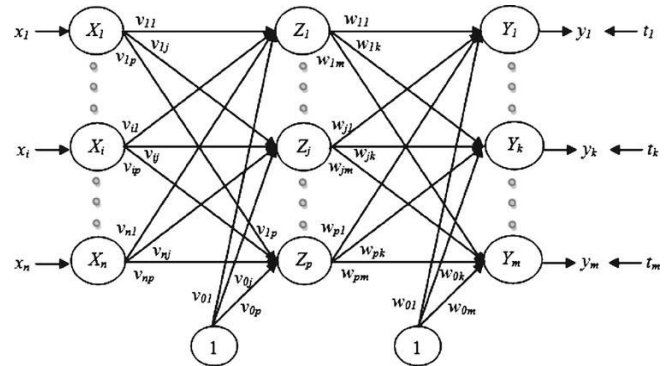
Rather than defining groups before looking at the data, clustering allows you to find and analyze the groups that have formed organically



## Multilayer perceptron (MLP)

MLP is a feedforward artificial neural network model that takes a vector of features from the given dataset as input and map them onto appropriate classes or outputs.

An MLP consists of at least three layers of nodes. It has an input layer, an output layer and one or more hidden layers. The input layer consists of the same number of nodes as the size of the input feature vector. The output layer has the same number of nodes as the number of classes that the input data should be classified into. MLP utilizes a technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron.



## Platform :

1. Python
2. MATLAB

## Dataset:

Bonn University EEG Database:

Andrzejak RG, Lehnertz K, Rieke C, Mormann F, David P, Elger CE (2001) Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state, [Phys. Rev. E](#), 64, 061907.

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