

Analysis of Electroencephalogram Signals in Epileptic Seizure Recognition

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ABSTRACT:

SVM approach in machine learning is utilised in the exploration of Electroencephalography signals aimed at seizure disorder recognition. The nonlinear subtleties in the unique Electroencephalography are computed in the form of the Hurst (H) and classified using SVM. The method of Electroencephalography examination contains of two phases, explicitly the pre-processing and Feature extraction analysis. The synthetic thus created decision making system is familiar with classification of the signals which are available in brain, as whether it is a primary seizure or secondary seizure. EEG may be a brain signal processing technique that allows understanding the complex inner mechanisms of the brain and abnormal brain waves. The analysis of brain waves plays an important role within the diagnosis of varied brain disorders. The classification capability of the Hurst measures is verified by Support vector machine classification. By employing a target EEG signal, and pre-processing and also by performing Feature extraction desirable outcomes is obtained.

Key terms: SVM, Hurst exponent, EEG, Machine learning, Brain Waves

INTRODUCTION:

Brain is one of the complex difficult system of the human body. Currently several know-hows are available to record and read the EEG waves. Electroencephalogram (EEG) is unique amongst the procedures used to map the brain neurological signals [1,2]. The intelligence in signal processing methods permits the thoughtful of the multifaceted internal instruments of the brain and irregular brain waves has been presented to be related to specific brain complaints [3, 4, 5].

An EEG could even be a test that perceives electrical activity in your brain using small, flat metal discs (electrodes) attached to the scalp. The brain cells communicate via electrical impulse and are active all the time, even when we are asleep. Every function in our body is triggered by messaging systems from our brain [6, 7, 8].

Newly, the matter of involuntary seizures detecting have been attempted by several researchers. As an instance, using time domain method for pointed episodic and recurring releases in Electroencephalography signal throughout seizure movement is under study. Moreover, inside the incidence domain, a well-liked Fourier-based technique of spectral analysis methods is for analysing Electroencephalography signals can be used but they involve complex signal analysis procedures [9, 10, 11].

Feature removal procedure theatres a very imperative part of the organization presentation. In this method, nonlinear measure sort of correlation measurement, Fractal dimensions, and Hurst exponent method, enumerate the grade of difficulty of time series, Topographies has been chosen hence in these cases detention of transformation among epileptic patients will be more than the usual Electroencephalogram signal analysis process. Fuzzy set system can perform a significant role in the automation of decision making for various health related applications [12, 13, 14].

Epilepsy can also be a nervous syndrome so that categorizing it through quick means is necessary then waiting for recurring convulsions. Seizure can source irregular electrical activity within the brain and must modify awareness, perception, sensation, and performance of the human body movements [15, 16, 17]. Patient's information shifted signs during seizure upheld things to be the degree of the overstated cerebrum tissue. The target of this research is to research and classify the EEG signal using Hurst exponent. Brain signal had been extracted and augmented which are categorized to differentiate the normal brain conditions against epileptic conditions [18, 19].

In normal conditions seizures is of two types, that are primary and secondary. The primary seizure can be found easily but the secondary seizure cannot be found easily, hence it motivates us to take up this research to find out the secondary seizure which is normally difficult to find. In this research work we have attempted to identify the secondary seizure using the Hurst exponent [20, 21, 22].

BLOCK DIAGRAM:

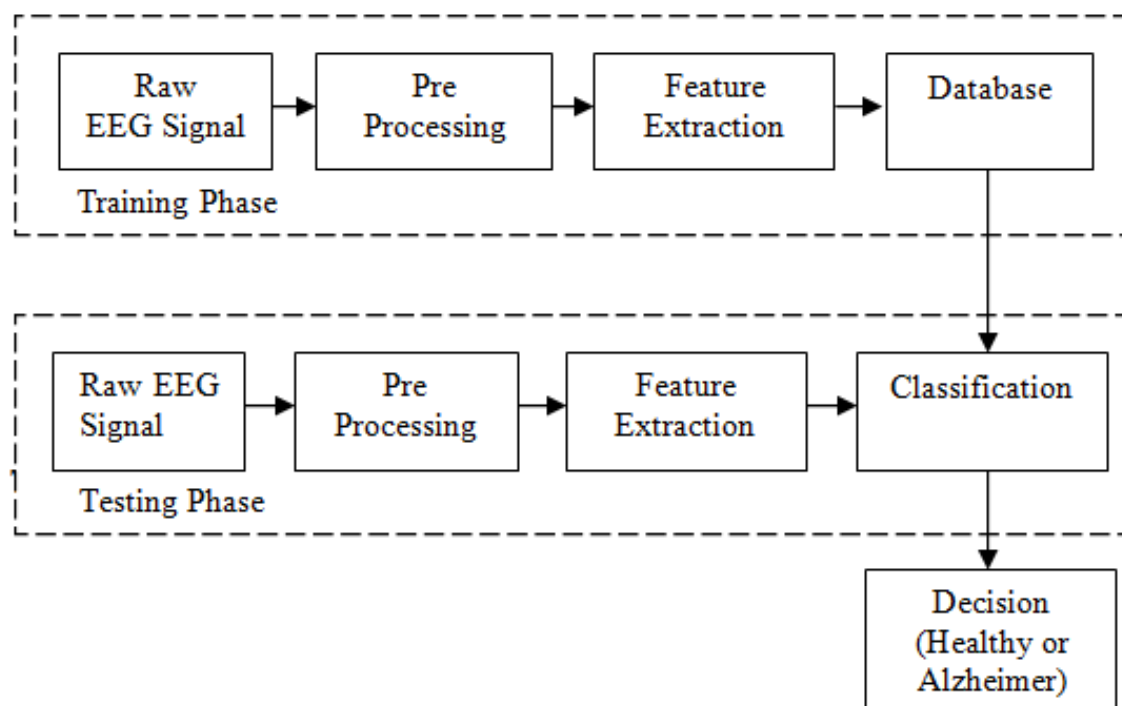


Figure 1. Block diagram of process of methodology

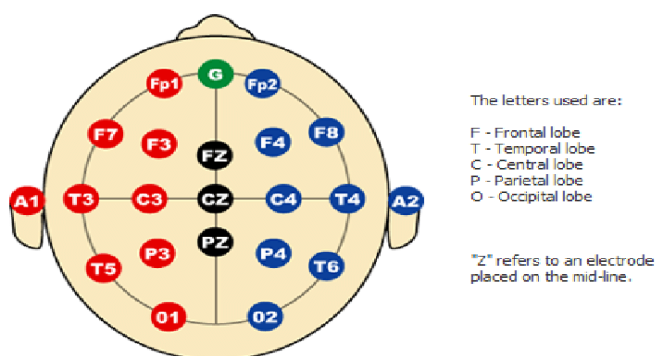
ELECTRODE PLACEMENT SCHEME:

Figure 2. Electrode placement in scalp

SETUP USED:

Data is generated through the aid of Super Sac Electroencephalography; signals are obtained by using SMS EEG 34 great spec system. The super spec ensures high resolution, reliable data [23, 24, 25]. The Electroencephalography module part includes connector box, linking cable and PC. Electroencephalogram signal data set used in this research investigation is obtained from Bonn University, Germany, [26] which is available in public domain. The whole data set consist of seven sets of data, each covering 100 single-of Electroencephalogram parts. Each segmentation has N=5097 sample facts over 24.6 seconds [27, 28, 29, 30].

BLOCK DIAGRAM COMPONENTS:

In this block diagram there are two phases two classify the raw signal EEG signal. The two phases are training phase and testing phase. Both the phases contain same components of the EEG signal, Pre-Processing, Feature extraction and the last component which varies with the two phases i.e., database is presented in training phase and classification is presented in the testing phase. From these two phases the main output is decided such that whether the person is healthy person or with Alzheimer (epilepsy) problem.

DATA BASE:

In Epilepsy study, the signal is taken from the human brain. Different subjects were considered for this signal mapping. The signal is classified using amplitude on Y-axis and time on X-axis. We have taken different types of signals from different humans that is classified from 1 to 4. Each signal is varied with respect to different humans with respect to the different parameters. For each signal there will be different noises and different waves. To get the Pre-Processing first we have to acquire the raw EEG signal and then this raw EEG signals will be sent to the next block for Pre-Processing or noise estimation and noise removal procedures. A sample database input collection is given in Figures 3 &4.

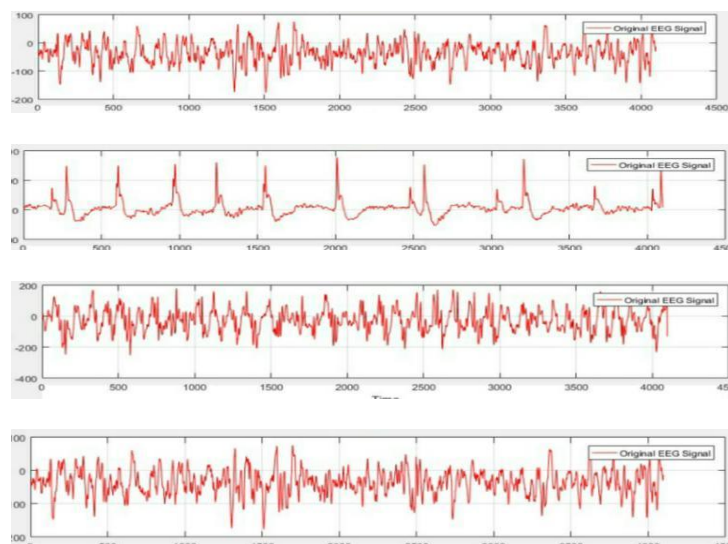


Figure 3 EEG Data Base.

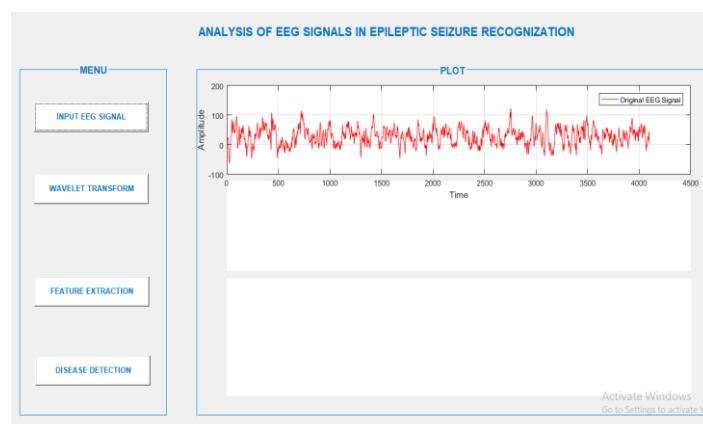


Figure:4 Input of EEG signal

PREPROCESSING:

Pre-Processing is the main part in the classification of EEG signals from a raw signal. If this stage contains errors or noises then the decision being made from these erroneous signals will also be a wrong one. To avoid this extra care has to be taken and the data has to be cleared. In Pre-Processing different types of methodologies were being studied but we have selected Wavelet Transform for removing the unwanted noise and the signals from the main raw EEG signal based on the extensive literature survey which we had done for this research work. Wavelet Transforms are Multiresolution transforms hence it will be useful when compared with other procedures. After sending the raw EEG signal into the Pre-processing unit and removing the unwanted signals the signals were. Figure 5 gives the outputs of the pre-processing stage. After removing the unwanted signals from the raw EEG, the signals are given to the feature extraction procedure, which is explained in the next section.

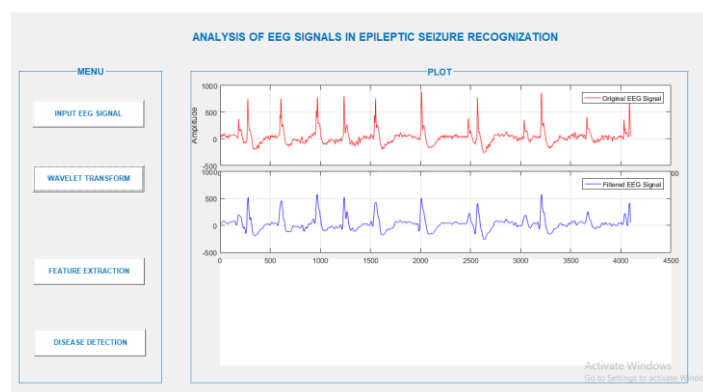


Figure:5 Pre-processing output of Epilepsy

FEATURE EXTRACTION METHOD:

Feature extraction method is the process of extracting useful information's from the signal. Based on this information's or the data, the decision-making process is carried out. Lot of procedures for extracting the information's have been carried out throughout the research community globally. In this research work we had considered the Support Vector Machine (SVM) algorithm and the Hurst exponent to get the right decision. SVM is used to reduce the dimensionality or hugeness of data. Non-linear and chaotic conditions are given utmost attention so that we have a proper output and this is compared with the normal signal information's. Based on the deviations the abnormality, in this case the Presence and absence of Alzheimer, which is done by SVM algorithm using the Hurst exponent. Figure 6 represents the feature extraction process for a given input signal.

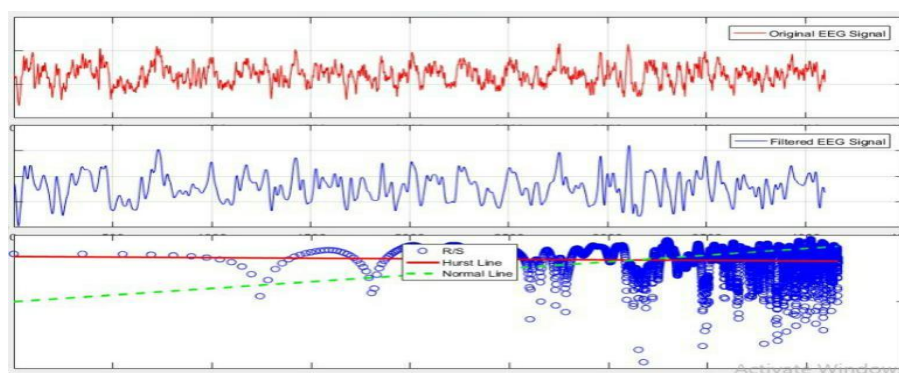


Figure:6 Feature Extraction output

CLASSIFICATION:

In this epilepsy recognition we can classify the normal and abnormal signals with the help of the proposed algorithm. The normal signal will be different from the abnormal signal. In the normal signal the spikes will not be more when compared to the abnormal signal. In abnormal signals the spikes will be more and this will be classified as the diseased signal. We can classify the signals into normal and abnormal based on the frequency spikes. If the frequency between the spikes and Hurst line is more than it is considered as a normal signal. If the frequency is less than it is considered as the abnormal signal.

Figure 7 shows a sample classification for a patient with Alzheimer, while Figure 8 shows the analysis for a subject without any abnormality.

WITH DISEASE:

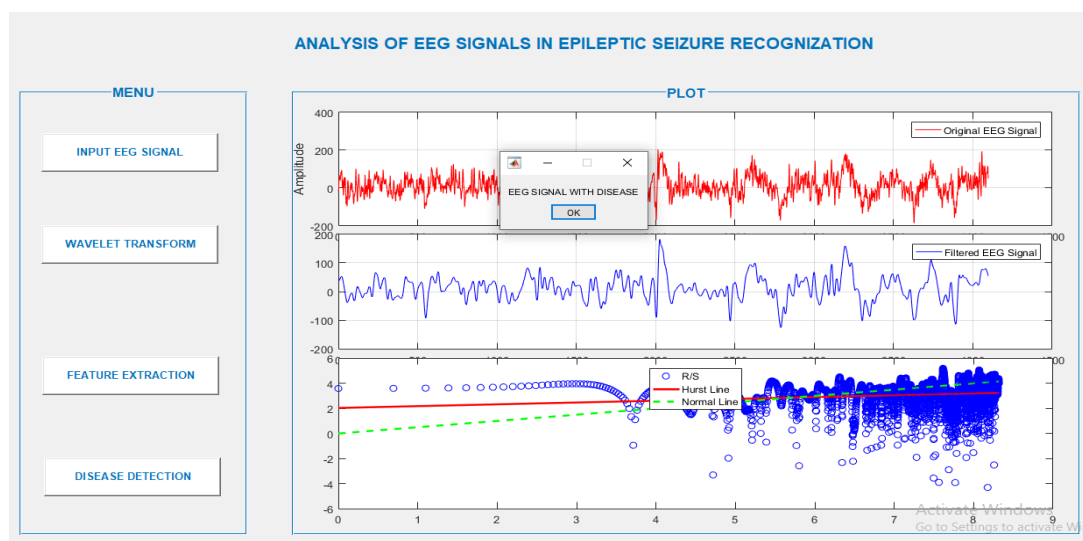


Figure:7 Analysis of EEG signals in Epileptic Seizure Recognition with disease

WITHOUT DISEASE:

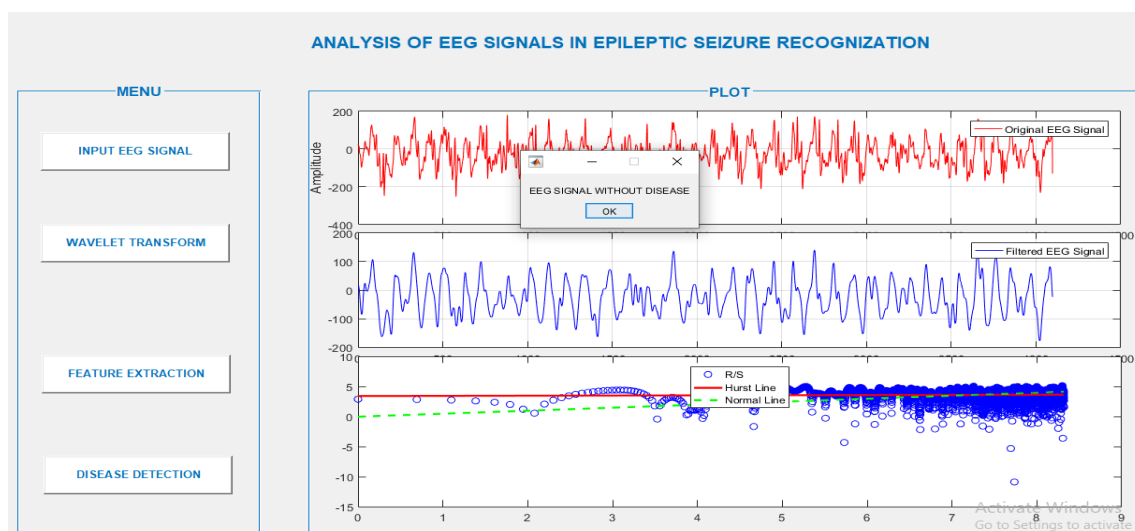


Figure:8 Analysis of EEG signals in Epileptic Seizure Recognition without disease

CONCLUSION:

In this research work we had represented the epileptic conditions of patients with seizure disease. We investigated disordered dynamics for the original patients by doing EEG and by nonlinear examination for understanding the confusion in neurology for epilepsy. We calculated the Hurst exponent and the Normal line by using the SVM classifier. We will be able to illustrate that the non-linear examination be able to also deliver the promising implement for identifying the qualified deviations of the

difficulty of the brain dynamics. The performance of testing model diagnostic system is found acceptable and this system can be integrated with various other studies in the upcoming research directions in the field of Epileptic Seizure Recognition.

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