European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 7, Issue 4, 2020

An Evaluation of a Computational Method to Extract Spike Based Features from EEG Signals to Analyse the Epileptic Seizures

R Sudarvizhi[1], A Jasmine Gilda[2], R Dhanalakshmi[3]

[1]*Master of Engineering(ME), Department of Computer Science and Engineering, RMK Engineering College, Chennai, India. sudarravichanran05@gmail.com*

[2]*Assistant Professor, Department of Computer Science and Engineering, RMK Engineering College, Chennai, India. ajg.cse@rmkec.ac.in*

[3]*Associate Professor, Department of Computer Science and Engineering, RMK Engineering College, Chennai, India. rdl.cse@rmkec.ac.in*

Abstract - Epilepsy causes sudden and unforeseen seizures in patients. Electroencephalogram (EEG) is a non invasive procedure used in brain control and epilepsy diagonsis. The non-stationary nature of EEG signals poses difficulty in extracting features of diagnostic importance by simple analysis method. For epileptic seizure detection from EEG signals,a simple classification methods is suggested in this paper. Publicly available dataset is chosen for testing the method..The Fourier transformation is used to convert EEG input signals from the time domain to the frequency domain for deeper analysis. Butter-worth band-pass filter is applied to get improved signal-to-noise ratio and decomposition is performs Discrete Wavelet Transform (DWT) for better spatial resolution. Based on the interval and extracted spike based features the normal and epileptic signals are classified using one of the machine learning algorithms known as Support Vector Machine (SVM).

1. Introduction

Neurological epilepsyDisorder portrayed by a ridiculous unusual movement from brain,where neurons delivers extra charges on electricity which leads to unsettling influence on typical body working. Epilepsy is notable by the abrupt uncommon seizures which happen arbitrarily and are brought about by concentrated, unraveled, and cognizant neuronal worksout in the cerebrum [7]. An epileptic seizure, can be characterized as a brief occasion of side effects because of synchronization of unusually exorbitant exercises of neurons in the brain and happens when there is an outbreak of electrical motivations in the cerebrum positively escaping their typical cutoff points. Almost four percent of total seizures are encountered by the world population at any phase of their lives,1% set up epilepsy.Until now,essentially epilepsy treated with prescriptions and medical procedure; no cure exists, and therapies with anticonvulsants are not totally viable for all of kinds of epilepsy. Epileptic patients are present in greater number in developing countries such as india,but there is no legitimate diagnostic technique.The EEG offers an incredible instruments for investigating brain activity associated with synchronous variations inadjacent neurons' membrane potential. Electroencephalogram (EEG) is a reliable and non-invasive procedure widely used to observe epilepsy behaviour in the brain and to diagnose it.The german expert discovered the EEG, Hans Berger, in 1929. Nowadays ,21 electrodes are used in the clinical use of EEG toidentify 5 simple waves. Electroencephalogram (EEG) is a signal recording of the brains electrical activity by various sensors(electrodes) set along the scalp. This estimates voltage changes occuring within the neurons of the brain due to ionic current streams[2]. From the surface of the scalp, they can be recorded as two-dimensional fields of time-shifting voltage. Neurologist studies EEG readings to track and organise disease patterns,such as pre-ictal spikes and seizures . For each kind of recording, the neurologist endeavors to decide the essence and place of EEG patterns and whether they are are associated with normal or abnormal neural activity. Patients with epilepsy are put under investigation for long haul which leads to an exceptionally huge EEG signal, the visual assessment is tedious and arduous; it takes several hours to look at a patients one-day information recording and additionally includes specialist administration. Customarily, the EEG recordings were analysed visually by aprofessional neurophysiologist to detect epileptic seizures or other present abnormalities. Accordingly, the analysis of patient recordings place a considerable weight on neurologists and minimise their efficacy. These impediments also prompted efforts to design and improve automated mechanisms to assist neurologists in characterising epileptic and non-epileptic EEG brain signals. For a very long time, Researchers on signal processing have provoked the brain to discover algorithms relating to revealing the Epilepsy dynamics utilizing signals of epileptogenic EEG. A lot of research work has recently been undertaken to differentiate epileptic and non-epileptic symptoms as an issue of classification. In prediction of seizures issue, one has four identified states,one of which specifically interictal, preictal , ictal and postictal .The entire cycle in automated epileptic stripping examination fundamentally comprises of data acquisition, signal pre-processing, feature extraction and classification. The most well-known procedure including a forecast of seizures strategies has to initially extract few windowed EEG signal features over some time and then to categorise subsequent set of characteristic in to two are two classes in particular: epileptic and non epileptic. Furthermore, in learning the brain patterns associated with normal, ictal and pre-ictal cases, the existence of noise and artefacts in the data problems. The significant muscle functions,blinking of eyes during signal processing and power line electrical noise are the sources of the objects[3]. The existing automated seizure detection technique utilize customary signal processing and machine learning strategies. A few techniques for seizure recognition depended on recognizing strong rythmic movements of the patient, anyway seizures don't generally introduce strong movements. These days, new strategies are utilized in order to identify epilepsy, such as correlation function, time domain analysis, frequency domain analysis, time-frequency domain analysis, analysis of artificial neural network bases, fuzzy logic based analysis, non-linear models, independent component analysis, Bayesian methods, support vector machines help and methods based on variance. The EEG signal is non-stationary in nature,so any clear features can hardly be extracted.. It is helpful for examining non stationary signals expressing frequency as shift rate in phase.Linear operators such as Fourier transform is effectively utilized as an approach to change EEG signals to the frequency domian from the time domain to remove any data disposal . The signals are generally pre-processed using butter-worth band-pass filter and discrete wavelet transform to get better spatial resolution and improved signal to noise ratio. For the most part, so as to identify epilepsy issues, neurologists need to analyse they try to determine the pathology that the patient endures based on this test, waveforms,spectrum and peaks.In addition, numerous distinctive function waveforms with different parameters features used in EEG signals, such as spike wave, slow wave, sharp wave, sine wave,spindle and K-complex. A function is a specific measurement extracted from apattern segment [4]. Wavelet Transform(WT) gives data with regards to the signal in both time and frequency domain which is most suitable for non-stationary signal sinceit precisely capture and locates associated spikes, entropy based and correlation - dimension characteristic of EEG background epileptic signal. Spikes can likewise be detected utilizing machine learning methods. There are different strategies for EEG spike detection such as artificial neural networks, morphological analysis, data mining, parametric methods, independent component analysis (ICA), clustering techniques and classification techniques. This work proposes an effortless epilepsy classification method for detection epilepsyEEG signal during epilepsy with good accuracy. Detection of epilepsy is time-consuming and involves carefull observations to assess the form of epilepsy and locate the cerebral cortex region responsible.This paper is organised in the manner as follows: description about the database and dataset used in evaluating the effectiveness of system proposed is initiated followed via pre-processing steps of raw EEG signals and their need such as using Butterworth filter to minimize the error in signal. Then discrete wavelet transformation is used to separate it in to sub bands. Based on the interval and extracted features the normal and epileptic signals are classified.

2. Related Work

Harikumar Rajaguru et al . suggested Fuzzy Outputs Optimization for Epilepsy Classification Use Linear Discriminant Analysis from EEG Signals[8]. The primary objective of this study is to investigate Linear Discriminant Analysis (LDA) feasibility in Fuzzy Performance Optimised classification of risk level of epilepsy by EEG signals. Classification of epilepsy risk levels on the basis of extracted parameters such as peaks, sharp and spiky waves, events, energy, length, variance and the fuzzy pre-classifier is used to covariate with the EEG signals. The LDA is then implemented on the Pre-classified data to seek precisely the optimised levels of risk that specifically characterise epilepsy patient risk level. Hemant Choubey et al. Used to identify and diagnose epilepsy with a reduced collection of extracted features[9]. Their conceptual Electroencephalogram (EEG) signal is a non-invasive approach to analyse the brain's electrical activity, and the chronological condition or signs of abnormality obtained from EEG data is epilepsy. A large number of features are needed to detect this abnormality for the classification of normal, inter-ictal and ictal signals from the EEG Signal. Coefficient of measurement of predicted operation and Hurst exponent with Higuchi Fractal Dimension is the limited collection of features that are necessary for EEG epileptic seizure detection. Signals using a k-NN classifier such as Accuracy , Precision and Jaccard with output parameters Coefficient. Coefficient. The author used computational intelligence to predict seizures Using the EEG data available.

Sally Al-Omar and Walid Kamali have developed a method for classifying EEG signals for epilepsy detection [10]. A number of parameters were derived from EEG signals using MATLAB. These parameters were then utilized in the classification of the signals by means of Feedforward Neural Network to make the correct diagnosis of the problem. Four Tests were performed to compare the efficiency of several parameters and to pick the output of several parameters as most efficien one. A test grouping the skewness, kurtosis and kurtosis when comparing their outcomes the most detailed results were provided by relative energy per frequency band, Which leads to the determination that the frequency is a very critical aspect which differs greatly between normal EEG signals and EEG epileptic signals Based on wavelet and statistical pattern recognition Zeljko Djurovic et al[12]. classified EEG signals to detect epileptic seizures. The suggested technique was applied to EEG data sets belonging to three classes of subjects: a) stable subjects, b) seizure-free epileptic subjects, and c) seizure-free epileptic subjects. The first step of this method is for a collection of wavelet-transformed EEG data features, such as energy, Entropy, and standard deviation of both the wavelet and EEG coefficients in separate waves. The dimensions of the function space used with scatter matrices was decreased. The outcomes indicated that the proposed algorithm possesses the ability to identify EEG signals and thus boost an epilepsy diagnosis.

For the calculation of the starting time of epilepsy seizures, the proposed multivariate time series analysis is of primary importance. To estimate the shift in the synchronisation between the two time series, a nonlinear synchronisation analysis method called Global Field Synchronization (GFS) was used. GFS was implemented in this analysis for the identification of epileptic seizures. Two sets of EEG data were used; the first set was taken from an unstable part of the brain before the seizure occurred (free seizure interval) and the second set from the opposite stable brain hemisphere. The results showed a substantial difference between selected data sets regarding the GFS value, Where the unhealthy portion had a lower GFS value than the safe portion. The Witnessed Reduction of synchronisation suggests a high degree of incoming enthusiasm for unhealthy part. The GFS exhibits such decreases in most EEG bands, which can in particular reflect the globality of the approach used in the observation of the degree of functional connectivity between different regions of brain.

3. Data Description

Across widely available databases such as Epilepsiae database, Temple University Hospital (TUH) database, Bonn University database and ieeg.org portal, a publicly available open access database called CHB-MIT database is chosen for the extraction of input EEG dataset for the proposed epileptic detection method. The CHB-MIT dataset consists of a total of 24 pediatric patient's multivariate scalp EEG recordings which was acquired at Boston Children's Hospital. The entire dataset duration is approximately 982 hours and contains 198 total identified seizures. For the recording of EEG data, the international 10-20 method of EEG electrode positions was used and to identify the epileptogenic region and evaluate their capacity for surgical intervention, subjects were observerd for upto several days after the removal of anti-convulsant medication.It is possible to download the datasets from the PhysioNetwebsite: http://physionet.org/physiobank/database/chbmit/ [5]. Based on the presence of seizures the records are classed into seizure and non-seizure records.The time series for the EEG datasets are recorded in .edf file formats containing a list of 664 .edf files. Every case records (named such as chb01, chb02, etc.) contains between 9 and 42 continuous .edf files . There were discontinuities between consecutively numbered .edf.files due to hardware limitations, most possibly with a gap of less than 10 seconds,during which the signals were not registered.The majority of .edf files contain precisely one hour of EEGdigitised signals,with the EEG digitised signals being the same. The shortest seizure takes 6 seconds and the longest time seizure is 752 seconds.19 electrodes are used to record signals via 23 channels (FP1-F7, F7-T7,T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FZ-CZ, CZ-PZ, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, P7-T7, T7FT9, FT9-FT10, FT10-T8, and T8-P8) via 19 electrodes that are arranged on the scalp surface, but there are a few signals which contain either 24 or 26 channel. EEG 256 Hz sampling frequency with 16-biresolution An important step in creating a seizure detection system is to select an appropriate EEG data set. Hence for validation of the detection method a selected number of normal and epileptic epochs were processed.The EEG data in the .edf files was translated to Matlab files (.mat) through Edf read toolbox. The resultant signals were plotted in both time domain as well as frequency domain. Figure 1 represents one of the epoch of raw EEG data is loaded into the MATLAB filtering process programme.In order to train the classifiers the entire patient records were included,Classification is then extended to all subject using features from channels in all parts of the brain that capture the EEG.

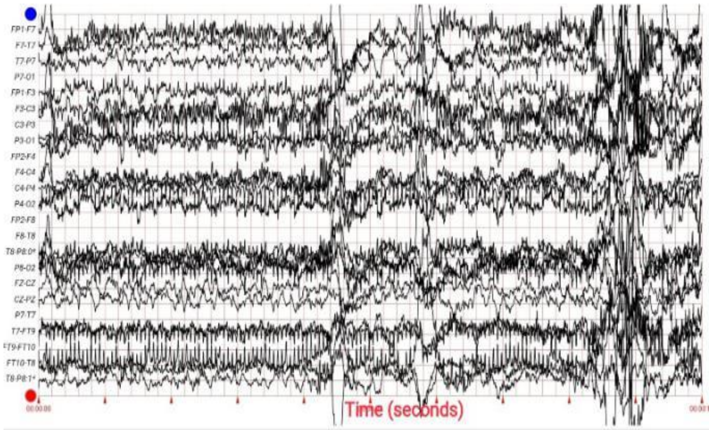

Figure 1. An epoch of raw EEG signal

3. EEG Signal Pre - Processing

In this proposed technique, the EEG signal goes through the accompanying cycle (figure 2) to discover the phases of epilepsy for use by a medical services proficient.

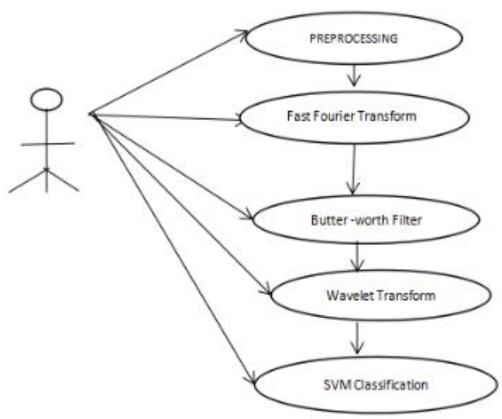

Figure 2. The phases of epilepsy detection

Before examination or arrangement happens, EEG signals in their crude structure need preprocessing. While recording the cerebrum action from scalp EEG surface cathodes, the EEG signals are spoken to in time space. By and large, time area technique does the examination of the sign dependent on schedule and size parts of sign. It is worthwhile to change the sign starting with one area then onto the next space so it gives knowledge and calls attention to the significant properties of the signs which can't be seen by visual examination of the first EEG signal in time area. A sign can be changed over between the time and recurrence areas with a couple of numerical administrators. Consequently for more profound investigation of the EEG dataset Fourier transform(FT) is utilized, a straight administrator utilized for dissecting nonstationary EEG flags by communicating recurrence as a pace of progress in stage, so the recurrence can shift with time space. recurrence area examination shows how the sign's vitality is circulated over a scope of frequencies alongside conveying data about the sign's greatness and stage at every recurrence. Recurrence space highlights (FDFs) are reported oncrude EEG signals being modified by discrete-Fourier Transformer. Fast Fourier Transformer (FFT) is a notable calculation to display discrete Fourier Transformer (DFT) [6]. So as to dissect the EEG flags, a few boundaries identified with recurrence can be removed, for example, Middle Recurrence, Percentile, Pinnacle of Recurrence, Relative Vitality by Recurrence Band and Ghostly Entropy. The Fourier change, decays time area work into weighted aggregates of sine and cosine capacities. FFT calculation depends on algorithm distance and Conquer . The shift of size N is partitioned to change the size of N1 and N2 . The example size utilized in this technique is N = 2k. The EEG signal is considered as x[n], n = 0,… ,N-1, which is acquired from a nonstop sign x(t) by testing at equivalent time stretches Δt. The discrete Fourier Change is given by the accompanying recipe:

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-i2\Pi kn/N} K = 0,...,N-1 \tag{1}$$

where [k] contains the data for the sign.

The sign x[n] can be recreated with the reverse discrete Fourier Change:

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[K] e^{i2\Pi kn/N} n = 0,...,N-1 \tag{2}$$

In MATLAB, it implements the FFT and IFFT algorithms. In MATLAB, the **fft** and **ifft** functions are used to calculate a signals Discrete Fourier transform (DFT) and the inverse of this transform, respectively. Function fft(data, N) has two significant input where, Data is a signal vector of and N is a transform scale.The ifft(Data, N) function works the same, but returns values from a time domain. The output of the FFT is complex.The magnitude and phase of any complex number can be determined by using MATLAB functions like **abs** and **angle**. Magnitude indicates the power of the frequency component compared to other components,while phase indicates the time alignment of the frequency components.Using these, the magnitude and phase components of the signal's frequency spectrum are represented .Biomedical signals like EEG are usually subject to noise and artifacts. It is necessary to appropriately eliminate these undesired signals without altering original brain waves. The primary goal of this proposed method validating the effectiveness of seizure classification& healthy subject based on their frequency range such as Delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (over 30 Hz), which are of clinical interest. Since the neuronal information in the EEG signals are below 100 Hz,Using lowpass filters, frequency components above this range will simply be disable. The signal is initially broken into non -overlapping epochs.In the artifact removal and number of distortions the option of epoch length plays an important role. In this method the EEG epoch was described by segmenting a raw EEG signal with a 10-second width in each direction. By shifting the window the next consecutive epoch was segmented from the raw EEG signal for 1 second. The Butterworth band-pass filter is used as a signal pre-processing filter since it gives a linear frequency response as possible to band pass. In CHB-MIT dataset several EEG recordings are contaminated by a power line noise at 60 Hz. Thus the FFT output is provided to Butterworth filter having a cutoff frequency between 0.5 Hz to 55 Hz inorder to reduce noise in the output signal along with removal of power line interference.

5. Discrete Wavelet Transform

The signals processed by Fourier transform contains frequency content of the signal over the analysis window with no information on time domain localization. For time domain localization the time window should be

short, however a large time window analysis is necessary for frequency domain localization. There arises a dilemma to know what frequency exists at what time interval, making Fourier transform to be related with Heisenberg's uncertainty principle. In order to overcome this uncertainty a method used to represent time-frequency domain of a signal in a more flexible way is known as wavelet transformation. The wavelet transformation is a continuation of Fourier transform designed to resolve issues of non-Stationary signals like EEG, sworking on a multi-scale basis rather than working on single scale (i.e time or frequency). It compresses time varying EEG signal and represents them in a form of simple building blocks known as wavelets. A wavelet is a mathematically oscillating function which start at zero in the form of a amplitude wave, increases and then decreases back to zero. The Wavelet transformations are categorised as: Continuous Wavelet transformation and Discrete Wavelet transformation in two groups.
The elementary functions of wavelet is generated byMother wavelet function translation and dilation represented as,Where a,b and R are scaling translate.Where, an is scaling boundary, b is interpretation boundary, t is time boundary and $\psi(t)$ is wavelet. an indicates the oscillatory recurrence and b signifies the moving position. The nonstop wavelet change (CWT) of a sign, is the fundamental of the sign duplicated by scaled and moved renditions of a wavelet work ψ and is characterized
by,

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t) \, {}^{1}\!/\!{}_{\sqrt{|a|}} \, \psi\left(t - {}^{b}\!/\!{}_{a}\right) dt \tag{3}$$

In constant wavelet change, a given sign of limited vitality is extended on a nonstop group of recurrence groups. A significant shortcoming of CWT is that scaling boundary a and interpretation boundary b change ceaselessly. So as to beat this Discrete Wavelet change (DWT) is used to deliver discrete yields.
The DWT doesn't change the data in the sign along these lines giving adequate data both to examination and combination of the first EEG signal. It is characterized as

$$DWT(j,k) = {}^{1}\!/\!{}_{\sqrt{|2^{j}|}} \int_{-\infty}^{\infty} x(t)\left(t - 2^{j} k /_{2^{j}}\right) dt \tag{4}$$

where an and b are supplanted by 2j and k2j, separately. Afew low pass (h[n]) and high pass channel (g[n]) execute wavelet update, known as quadrature reflect channels (QMFs) pair which isolates the information signalhigh-and low-recurrence segments .In general, the partitioning point is somewhere between 0 Hz and a large portion of the information examining rate. Contingent upon the prevailing recurrence segments of the sign which associates with the recurrence essential for arrangement, the quantity of decay levels are picked. The EEG signs of this dataset don't have any helpful data over 100 Hz, henceforth the EEG ages were deteriorated in to different recurrence groups utilizing Daubechies of request 4 (Db4) wavelet work with up to fourth level decay. for high pass channel of first stage,the yield of low pass channel is known as estimate (A1) and detail coefficient (D1).

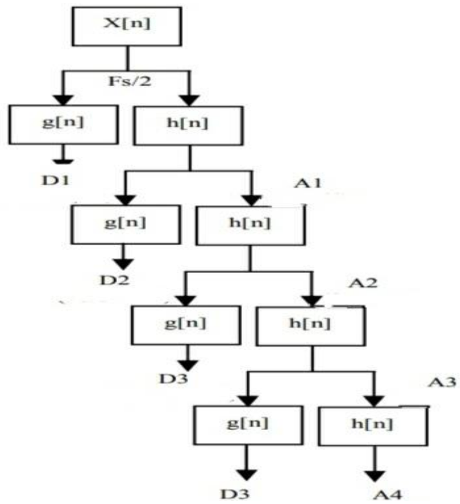

Figure 3. Wavelet Decomposition of Signal

A1, D1, A2, D2, A3, D3, A4 and D4 coefficients speak to the recurrence substance of the first sign and fs is the examining recurrence of the first sign x[n]. Spike based boundaries are removed from the fitting sub-groups of Discrete Wavelet change (DWT), which is additionally utilized for arrangement.

6. SVM Classification

The wavelet transform decomposes the EEG signal into different frequencies into which the exact location of epileptic region is detected by extracting spike based features. The occurrence of sharp waves, spikes, spike-wave complexes increases the signal amplitude which is seen as a morphological indicator for ictal rythmic activity of most types of epileptic seizures. Spikes can be clearly distinguished from background activity in a particular channel corresponding to an increase in energy of EEG signal. In order to characterise the spikes in time or frequency domain the shape of the spike is utilised by parametric models to break down the EEG signals into half waves acrossthe major peaks .To find the number of spike position,the amplitude threshold and length determined from each half wave added. The extracted features are subsequently introduced into Support Vector Machine (SVM) classifier that uses manifold learning, dimensionality reduction, and non-linear supervised classification. Initially SVM transforms data into an high dimensional space by plotting the training samples feature vectors of all samples and finds a hyper-plane seperating with full margin. The classifier had been trained with data for train-train and for classification into normal and epileptic spikes, unknown features are compared with commonly known features in the dataset in a form of train-test data. To conduct non-linear classification, a Gaussian radial basis function known as the kernel is used. The code for MATLAB "svmtrain" was applied to train the SVM classifier and "svmclassify" was used for classification.

7. Result and Discussion

The datasets obtained from CHB-MIT database are visualised in MATLAB environment. After pre-proceessing the discrete Fourier transform gave a output of EEG signal in its frequency component for better analysis and the cutoff frequency of butter-worth filter efficiently removed interference such as noise and artifacts.Using Discrete Wavelet transform with Db4 Wavelet function by quantitative analysis, coded using MATLAB and the Wavelet Toolbox,the EEG epochs were decomposed into approximate coefficient sub-bands.The bandwidth frequency coefficients are mentioned in table below.

Table 1: Bandwidth Frequency Coefficient

S. No	Approximation / Detail Coefficient	Bandwidth (Hz)
1	A1	0 – 17.5
2	D1	17.5 – 3.5
3	D2	8.75 – 17.5
4	D3	4.38 – 8.75
5	D4	2.18 – 4.38
6	A4	0 – 2.18

Due to the use of a suitable decomposition level clinical interest sub-bands such as omega, delta, theta, alpha, beta and gamma are separated then spike based parameters are derived from any signal coefficient. The parameters are trained and tested using SVM for classifying epileptic and non-epileptic seizures. Hence, 94.3 percent accuracy, 98.1 percent specificity and 91.5 percent sensitivity were provided by this process.

8. Conclusion

The proposed method proves to be efficient in classifying the EEG signals into epileptic and non-epileptic seizure. The algorithms used are very appropriate and simple, so that it can be easily implemented on EEG signal. The process flow is designed in such a way that the resolution of the signal is increased sequentially after every stages. The classification algorithm is trained and tested with desired waveform segments for higher specificity and sensitivity. Several spikes are detected by setting a minimum threshold limit for the estimated local maxima and minima of the signal. The obtained results can be used for clinical diagnosis and best suited for detecting abnormalities in brain

Reference

1. N.McGrogan, and L.S.Prof. Tarrassenko, Identification of Epileptic Seizures in Electroencephalogram Neural Network.1999.
2. Niedemeyer E. and da Silva F. L.: Electroencephalography: Basic Principles, Clinical Applications and Related Fields, 2004.
3. M.R.N.Kousarrizi, et. al, “Feature extraction and classification of EEG signals using wavelet transform, SVM and artificial neural networks for brain computer interfaces,” in Proceedings of the IJCBS , pp. 352–355,2009.
4. Dean Cvetkovic, Elif Derya Übeyli, and Irena Cosic. 2008. Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures: A pilot study. Digit. Signal Process. 18, 5 (September, 2008), 861–874. DOI:https://doi.org/10.1016/j.dsp.2007.05.009

5. A. H. Shoeb. “Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment”. Ph.D. Thesis, Harvard-MIT Program of Health Sciences and Technology, Massachusetts Institute of Technology, Cambridge, MA, September 2009.
6. Edward W. Kamen and Bonnie S. Heck: Fundamentals of Signals and Systems using the web and Matlab, 2000 by Prentice-Hall, Inc., the 3rd ed.
7. Fisher RS, Boas WvE, Blume W, Elger C, Genton P, Lee P, Engel J. Epileptic Seizuresand Epilepsy: Definitions suggested by the International League Against Epilepsy (ILAE) and the International Bureau for Epilepsy (IBE). Epilepsy, 2005; 46: 470-2.
8. H. Rajaguru and S. K. Prabhakar, "Optimization of fuzzy outputs for classification of epilepsy from EEG signals using linear discriminant analysis," 2017 International conference of Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, 2017, pp. 598-602.
9. Choubey, Hemant & Pandey, Alpana. (2018). Classification and Detection of Epilepsy using Reduced Set of Extracted Features. 560-564. 10.1109/SPIN.2018.8474100.
10. Al Omar, Sally & Kamali, Walid & Khalil, Mohamad & Daher, Alaa. (2013). Classification of EEG signals to detect epilepsy problems. 2013 2nd International Conference on Advances in Biomedical Engineering, ICABME 2013. 5-8. 10.1109/ICABME.2013.6648833.
11. Gajic, Dragoljub & Djurovic, Zeljko & Di Gennaro, Stefano & Gustafsson, Fredrik. (2014). Classification of EEG signals for detection of epileptic seizures based on wavelets and statistical pattern recognition. Biomedical Engineering: Applications, Basis and Communications. 26. 10.4015/S1016237214500215