# A Novel Blending Hilbert -Kolmogorov Approach for Epileptic Seizures detection

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***Abstract*—This paper introduces a new seizure detection method based on EEG signals using Hilbert Transform (HT) and Kolmogorov Complexity (KC). The new method is named Blending Hilbert–Kolmogorov (Blending HT-KC) approach. In the Blending HT-KC method, the EEG signal is converted firstly into a complex helical sequence and then into a binary sequence. From the analytic signal, the instantaneous amplitude-based features are obtained and, from the logical signal, the KC features are extracted. The extracted attributes will then fed into the Support Vector Machine Classifier (SVM). The proposed approach is examined for four classification problems to distinguish between Ictal (during seizure) and normal states as well as between ictal and interictal (between seizures) states of epilepsy. The experimental results demonstrate the excellent performance and suitability of the proposed methodology for the detection of seizure activity.**

***Index Terms*—EEG, Epilepsy, seizure detection, regularity**

## I. Introduction

Epilepsy is a brain disease connected with sudden and recurrent seizures. Epileptic seizures represent an abnormal state of brain activity, characterized by synchronous discharge of large groups of neurons [1]. A seizure can result in many symptoms, for example, convulsions, loss of awareness, memory distortion and/or other signs of epilepsy, which often place the patient in dangerous situations that are likely to involve harm, including drowning (if the seizure occurs while bathing or swimming), burns and head injury. Despite the existence of dietary, drug and surgical treatment options, approximately one in three epileptics suffers from seizures that cannot be controlled by any available remedy. The incidence of seizure can vary from at least once per year to recurrent fits that occur several times per day. The patient and his/her family are thus likely to be constantly worried about the possibility of seizures occurring due to their unpredictable nature. The most important tool used by doctors to diagnose epilepsy is electroencephalogram (EEG), which records the brain's electrical activity and thereby reveals the state of the nervous system. The printed EEGs of patients are usually examined by expert neurologists by means of visual inspection in order to identify atypical patterns, such as spikes and sharp waves, which manifest during ictal phases (seizures) [2]. However, this process of visual analysis is both tedious and very time-consuming, especially when taking into account the need to treat many patients in a short period of time. Hence, there exists an urgent need for an automated means of detecting epileptic seizures, which should serve to greatly reduce the time spent reading long EEG traces.

Over the past two decades, the elaboration of automatic seizure detection techniques has become a key area of interest for researchers working in the medical, engineering and physics fields. In this regard, several EEG analysis algorithms have been proposed, including the time domain (Hjorth parameters [3], linear prediction (LP) error energy [4]), the frequency domain (fast Fourier transform (FFT)) [5] and the time-frequency domain (short-time Fourier transform (STFT) [6], wavelet transform (WT) [7], Wigner-Ville distribution (WVD) [8]). In addition, nonlinear quantifiers of complexity, such as the largest Lyapunov exponent [9], entropies [10], correlation dimension [11] and detrended fluctuation analysis (DFA) [12], have also been widely used in relation to seizure detection, mainly due to their ability to incorporate the non-stationary nature of the EEG signal. The review presented in [13] summarises those prior works concerning automated seizure detection that have applied the aforementioned nonlinear parameters. Basically, the approaches described in the literature for the detection of seizures involve the extraction of seizure-related features from EEG signals and the classification of such features by means of a machine learning algorithm, for example, the extreme learning machine (ELM) [14], Bayesian linear discriminant analysis (BLDA) [15], k-nearest neighbour (KNN) [16], support vector machine (SVM) [17], decision tree (DT) [18], quadratic discriminant analysis (QDA) [19] and different types of artificial neural networks [20]. The most commonly used classifier is the SVM due to its ability to deal with big data as well as its kernel function, which supports both linear and nonlinear data [21]. The most important task involved in the development of any scheme for detecting seizures is the selection of suitable attributes. However, due to the abundance and diversity of the attributes that can be detected/measured from an EGG signal, this is not a straightforward issue. We earlier proposed a method for distinguishing epileptics in the ictal state from healthy individuals using DFA scaling exponent, which provides information regarding

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regularity and long-range correlations in EEG time series [12], and we reported a 98% accuracy level. Polat and Gunes [22] used FFT with a DT classifier to classify the EEG signals of healthy and epileptic subjects, and they reported an accuracy level of 98.72%. The temporal statistics associated with the EEG signal's amplitude per channel have also been successfully used [23]. In [24], the authors utilised wavelet features and a low-complex SVM classifier. They reported an average classification accuracy of 95.3%. In 2015, Guler and Ubeyli [25] presented a new system for the classification of epileptiform EEG signals through the use of composite features given as inputs to an SVM classifier. The classification accuracy obtained was approximately 90%. In [26], the features describing the morphology of the EEG (relative spike amplitude and spike rhythmicity) were used, which had promising results in relation to automatic epileptic seizure identification. In the same context, Chaurasiya et al. used FFT together with an SVM, and they achieved a classification accuracy rate of 97.00% [27]. Recently, Pratiher et al.[28] have proposed a new seizure detection scheme based on a combination of the entropy measure and multifractal analysis. The extracted features are fed into four different classifiers, namely the DT, BLDA, SVM and KNN. The authors found the SVM to be the best classifier, reporting an accuracy of 99.01%, sensitivity of 98.02% and specificity of 100%. A review of the prior literature shows that when seeking to improve the recognition accuracy of an epileptic seizure detection system, researchers have typically used a mixture of two or more features obtained from different domains and more than one classifier. For instance, 55 features derived from the time domain, frequency domain and information theory were used in the work by Temko et al. [29].

In this research, our main contribution is the extraction of two features from the complex helical sequences and binary sequences of EEG signals. First, the Hilbert transform is applied to the EEG signal to get the amplitude envelope; then, Kolmogorov Complexity is estimated from the same EEG signal after its binarization. Finally, the obtained features are used as input to the support vector machine (SVM) classifier for automatic epileptic seizure detection.

This paper is organized as follows: in Section 2, the EEG database used in this work is briefly introduced, and then the selected features and the proposed automated seizure detection scheme are described. Section 3 exhibits the experimental results, discussion, and comparison between the proposed technique and existing methods. Finally, Section 4 presents concluding remarks and highlights of future research directions.

## II. MATERIAL AND METHODS

### A. EEG Data Description

The EEG time series used to validate the efficiency of the proposed method in epileptic seizure detection were taken from the University of Bonn, Germany. The EEG data consist of five sets, denoted as Z, O, N, F, and S. Each set contains 100 single-channel segments of 23.6s, which were selected from multichannel EEG recordings with a 173.61Hz sampling rate after visual inspection for artefacts. Sets Z and O are the extracranial EEGs of five healthy volunteers according to the international 10–20 system. The subjects were awake and relaxed, with their eyes open for set Z and closed for set O. The segments for sets N, F, and S were acquired from five epileptic patients via electrodes implanted into the lateral and basal regions. The type of epilepsy identified was temporal lobe epilepsy, with the epileptogenic focus at the hippocampal formation. Sets N and F were recorded during interictal periods from the epileptogenic area and from the hippocampal formation of the opposite hemisphere, respectively. Set S only contained seizure activity selected from all recording sites exhibiting ictal activity. Readers can refer to [30] for additional information about this dataset.

### B. Kolmogorov Complexity (KC)

The KC measure of an object denotes the model complexity of an object and describes its randomness [31]. As proposed by Lempel, the basic principle of the KC algorithm is that the complexity of a string (a sequence of zeros and ones) is correlated by a computer program, which is required to generate the string of interest [32]. Hence, the complexity of the sequence is estimated by the number of bits of the shortest computer program that produces this string. The KC can be calculated as:

$$KC(x) = min(l(p)/U(p) = x) \tag{1}$$

where $p$ is the computer program, and $l(p)$ is the length of $x$ output string of the $U$, where $U$ is referred to the universal Turing machine e.g computer.

From a theoretical point of view, the expected value of the KC matches the value of Shannon entropy [33]. Usually, a regular string generates high KC values. For detailed literature on the KC refer to [34]. Before calculating the KC of an EEG signal, we must convert this signal to a binary sequence. The conversion is performed with a thresholding technique in which every sample is compared to a threshold. If the sample is less than the threshold, zero is assigned to this sample. Conversely, if the sample is greater than the threshold, the sample takes a value of one. The median, average, variance, standard deviation (SD) are possible threshold values that can be used for a signal. According to previous studies [35], [36], the SD is used as the threshold in this research work.

### C. Hilbert Transform (HT)

HT is a linear operator that has been extensively used in the analysis of nonstationary signals [37]. The HT is a time-domain to time-domain transformation that shifts the phase of a signal -90 and + 90 degrees. It returns the complex helical sequence $z(t)$, sometimes called the analytic signal, from the real signal $x(t)$, such that $z(t) = x(t) + Jx_H(t)$, where $x_H(t)$ is the HT of $x(t)$. The HT of the signal $x(t)$ is defined as the convolution of $x(t)$ with $(\frac{1}{\pi t})$ , as given by the following equation:

$$x_H(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} (x(\tau)) \frac{1}{1-(\tau)} d\tau \quad (2)$$

where the integral is to be interpreted as a Cauchy principal value. This convolution can be thought of as a filtering operation with a quadrature filter that shifts all of the sinusoidal components by a phase shift of $\frac{-\pi}{2}$. $x_H(t)$ has the same amplitude and frequency content as the original real signal $x(t)$ and includes phase information that depends on the phase of the original signal. The analytic signal $z(t)$ can be expressed in polar coordinates as:

$$z(t) = a(t) \exp(j\theta t) \quad (3)$$

where $a(t)$ and $\theta(t)$ are the instantaneous amplitude and phase of $z(t)$, calculated as follows:

$$a(t) = \sqrt{(x^2(t) + x_H^2(t))} \quad (4)$$

$$\theta = \arctan(\frac{x_H(t)}{x(t)}) \quad (5)$$

The instantaneous amplitude (amplitude envelope) is the amplitude of the complex Hilbert transform. The instantaneous frequency is the time rate of change of the instantaneous phase angle. For a pure sinusoid, the instantaneous amplitude and frequency are constant. The instantaneous phase is a saw tooth, reflecting the way in which the local phase angle varies linearly over a single cycle.

### D. Support vector machine SVM

Support vector machine is a highly nonlinear classifier proposed by Vapnik [38]. SVM maps training data samples into a higher dimensional space and looks for discovering a separating hyperplane with the maximal margin (distance from the separating boundary to the closest training sample). However, the identification results with SVM tend to be very sensitive to the selection of kernel (quadratic, polynomial and radial basis function (RBF) kernels). The SVM without kernel transformation is termed as linear kernel SVM.

### E. Performance Measurement

The performance of the SVM classifier is evaluated by the following measures:

$Accuracy = \frac{TP+TN}{N} \times 100\%$

$Sensitivity = \frac{TP}{TP+FN} \times 100\%$

$Specificity = \frac{TN}{TN+FN} \times 100\%$

where,

- TP (True Positive): Number of EEG signals that is known as epileptic signal and recognized correctly by the detection technique as ictal state.
- TN (True Negative): EEG signals clinically marked as normal and recognized correctly by the detection technique as ictal state.
- FP (False Positive): EEG signals clinically marked as normal but classified as epileptic by the suggested system.
- FN (False Negative): Number of EEG signals that is known as epileptic signal but are classified as normal state by the proposed technique.
- N is the number of trials.

## III. Workflow of the Proposed Blending HT-KC Approach

The proposed method named a blending HT-KC approach provides a parallel structure to detect effeciently the seizures. Figure 1 shows a block diagram of the proposed methodology implemented in this work, it consists on:

- One side of the flowchart, the Hilbert transform is applied to the input EEG signal data in order to get the analytic signal. Only the absolutes values of the resulting signal are considered. Then, a new set of time series indicating the amplitude of the EEG signal at each time-point (the instantaneous amplitude) is obtained.The mean of the instantaneous amplitudes (MIA) is considered as the first extracted feature from EEG signals.
- The second part, the input EEG signal is converted to binary sequences, where, the number of bits of the shortest computer program that can create this binary sequence is estimated using kolmogorov complexity (KC) which is the second extracted feature.

Finally, the extracted features are trained with SVM classifier for seizure detection.

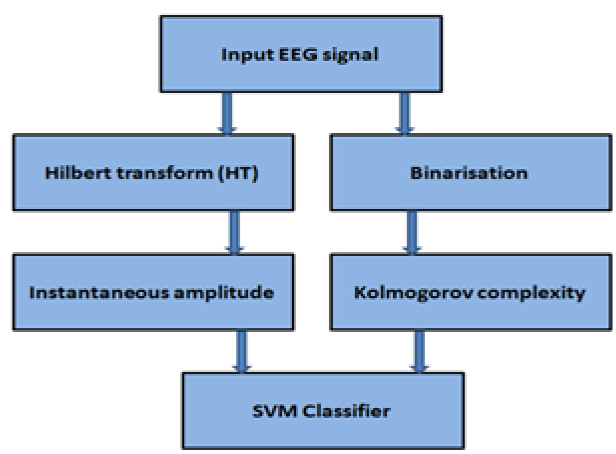


Fig. 1. The block diagram of the blending HT-KC approach.

## IV. RESULTS AND ANALYSIS

In order to test the performance of the proposed seizure detection system, we performed four experiments to separate:

- EEG dataset S from EEG dataset Z
- EEG dataset S from EEG dataset N
- EEG dataset S from EEG dataset F

- EEG dataset S from EEG datasets N and F

The evaluation of the diagnostic performance measures of the SVM classifier was done using a K-fold cross validation [39]. In which the data set was divided into $(K = 10)$ groups. During each trial, 90% of the data was selected randomly and used for training the classifier. The remaining 10% was used to test the classifier. Fig2, Fig3, Fig4 and Fig5 show the hyperplanes with polynomial Kernel for SVM-based classification for experiments 1–4, respectively. The results of SVM classifier executions for the four experiments are shown in Table I.

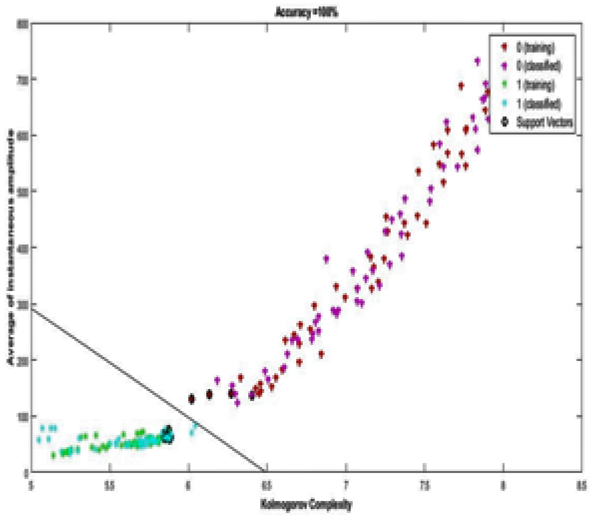


Fig. 2. SVM Hyperplane for the two class $(SetZ/SetS)$ Epilepsy detection technique.

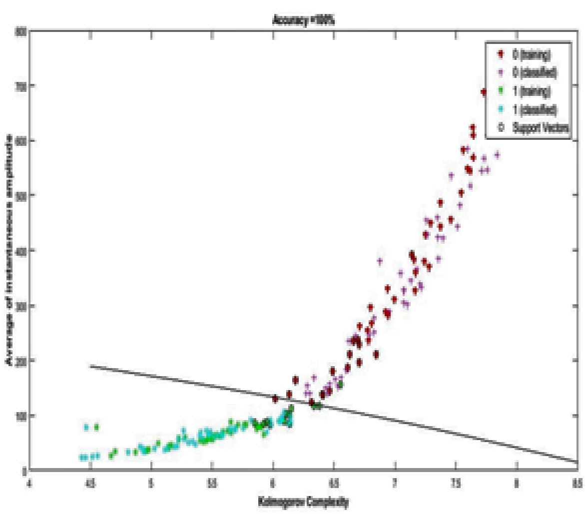


Fig. 3. SVM Hyperplane for the two class $(SetN/SetS)$ Epilepsy detection technique.

From fig 2, 3, 4 and 5, we can observe that the presented technique has a strange discriminatory power in all experiments under consideration.

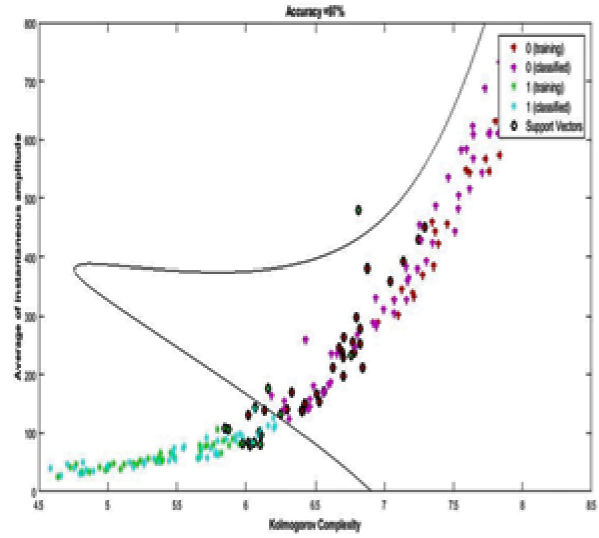


Fig. 4. SVM Hyperplane for the two class $(SetF/SetS)$ Epilepsy detection technique.

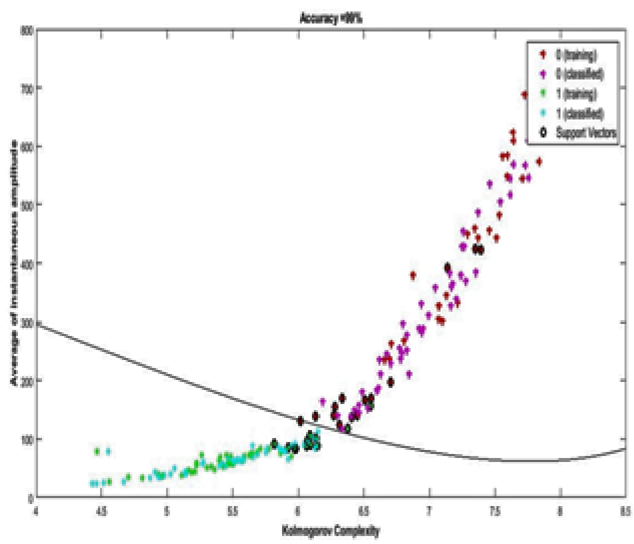


Fig. 5. SVM Hyperplane for the two class $(SetsNandF/SetS)$ Epilepsy detection technique.

TABLE I
SVM CLASSIFIER PERFORMANCE ANALYSIS OF THE PROPOSED SEIZURE DECTION SYSTEM

| **Experiment** | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Error Rate** | 0 | 0 | 0.03 | 0.01 |
| **Correct Rate** | 1 | 1 | 0.97 | 0.99 |
| **Sensitivity** | 1 | 1 | 0.98 | 1 |
| **Specificity** | 1 | 1 | 0.96 | 0.98 |
| **Specificity** | 100% | 100% | 97 % | 99% |

The statistical results presented in Table I for experiment 1 reveals that a classification accuracy, specificity and sensitivity of 100%, 100% and 100% were obtained, respectively. This demonstrates the excellent efficiency of the feature union of MIA and KC in distinguishing subjects enduring seizures from normal subjects. For experiments 2, 3 and 4, which deal with seizure onset detection in epileptic patients, the recognition accuracies were 100%, 97% and 99%, respectively. This shows the feasibility of our methodology for continuously monitoring patient status or for detecting seizures using only interictal EEG data. In this context, different research works have proposed diverse techniques for epileptic seizure detection using the Bonn University dataset. Table 2 shows a comparison of recognition accuracy between the proposed blending HT-KC approach and different methods that have used the same database. In table II, we present a listing of the authors, classification task and classification accuracy.

TABLE II
COMPARISON WITH SEVERAL PREVIOUS STUDIES OF EPILEPTIC SEIZURE DETECTION

| Authors | Year | Experiment | Accuracy (%) |
|---|---|---|---|
| **Ahammad et al. [40]** | 2014 | Z Vs. S | 98.50 |
| **Kaya et al. [41]** | 2014 | Z Vs. S | 99.50 |
| **Kumar et al. [42]** | 2014 | Z Vs. S | 100 |
| **Fu et al. [43]** | 2015 | Z Vs. S | 99.85 |
| **Yalcın et al. [44]** | 2015 | Z Vs. S | 99.67% |
| **Kamath [45]** | 2015 | Z Vs. S | 100% |
| **Das et al. [46]** | 2016 | Z Vs. S | 100% |
| **Bhattacharyya et al. [47]** | 2017 | Z Vs. S | 100% |
| **Sharma et al. [48]** | 2017 | Z Vs. S | 100% |
| **Bhati et al. [49]** | 2017 | Z Vs. S | 99.30% |
| **Blending HT-KC approach** | - | Z Vs. S | **100%** |
| **Boubchir et al. [50]** | 2014 | N Vs. S | 97.50% |
| **Boubchir et al. [51]** | 2014 | N Vs. S | 99.33% |
| **Jae-Hwan Kang [52]** | 2015 | N Vs. S | 99.62% |
| **Zhenxi et al. [53]** | 2016 | N Vs. S | 96% |
| **Dazi Li et al. [54]** | 2016 | N Vs. S | 99.82% |
| **Jaiswal et al. [55]** | 2017 | N Vs. S | 99.10% |
| **Zhang et al. [56]** | 2018 | N Vs. S | 99.85% |
| **Blending HT-KC approach** | - | N Vs. S | **100%** |
| **Li et al. [57]** | 2014 | F Vs. S | 96.62 % |
| **wang et al. [58]** | 2014 | F Vs. S | 94.50 % |
| **wang et al. [59]** | 2015 | F Vs. S | 96.50% |
| **Samiee et al. [60]** | 2015 | F Vs. S | 94.90% |
| **Murugavel et al. [61]** | 2016 | F Vs. S | 95.85% |
| **Zhang et al. [62]** | 2016 | F Vs. S | 93.00% |
| **Riaz et al. [63]** | 2016 | F Vs. S | 93.00% |
| **Blending HT-KC approach** | - | F Vs. S | **97%** |
| **Pachori and Patidar [64]** | 2014 | N,F Vs. S | 97.75% |
| **Sharma and Pachori [65]** | 2015 | N,F Vs. S | 98.67% |
| **Kumar et al. [66]** | 2015 | N,F Vs. S | 98.33% |
| **Tiwari et al. [67]** | 2017 | N,F Vs. S | 95.45% |
| **A.Mutlu [68]** | 2018 | N,F Vs. S | 97.33% |
| **Blending HT-KC approach** | - | N,F Vs. S | **99.00%** |

As shown in Table II, for experiments 1 and 2, the results of the Blending HT-KC method are ideal (ACC=100%). For the experiment 3, the results obtained (97%) by the presented method, though they do not match those found in Sharma et al.'s [40] work (98.10%), are better than most others. A possible explanation for the failure of this experiment to get an ACC of 100% could be due to the fact that some characteristics of interictal activity recorded from the epileptogenic zone (Set F) might also be present in ictal activity (Set S), which makes it difficult to find a neat separation between them. For the fourth experiment, the Blending HT-KC method has achieved an average accuracy of 99%. To summarize, the results of the proposed blending HT-KC approach compare favourably with the existing literature. Therefore, an automated system based on the proposed approach can offer feedback to experts for fast and precise identification of seizures' EEG signals.

From a medical point of view, there are various types of epilepsy/seizures (tonic-clonic seizures, myoclonic seizures, and seizures absence). It should be noticed that the blending HT-KC epileptic seizure detection method was tested only on patients diagnosed with temporal lobe epilepsy, other seizures types may escape detection, especially taking into account the nature, duration and singularities of each seizure type. This is a limitation of the proposed method.

## V. CONCLUSION

A detection system can produce one or more attributes that are representative measures of various aspects of the information that a given signal contains. Consequently, certain features result in increased specificity, while others result in increased sensitivity. Due to the potentially complementary nature of the different features, a mixture of methods is crucial for obtaining the maximum amount of information.

In the present research work, a combination of the amplitude of Hilbert transform (EEG signal envelope) and the kolmogorov complexity measure was used to analyse EEG recordings to identify epileptic seizure activity. Our blending HT-KC approach does not assume the existence of any particular mechanism. Instead, it aims to compare the degree of regularity of different time series. We have demonstrated that the degree of regularity seen in ictal seizure activity is high when compared to that seen in the healthy and interictal states. The presented approach therefore shows promise, not only in terms of offering greater insight into the evolution of the regularity of brain activity, but also in supporting neurologists in the context of epileptic seizure detection.

## REFERENCES


[1] A. L. Reid, "Knowledge of Epilepsy in Students Attending the University of Mississippi Oxford Campus," Diss. University of Mississippi, 2017.

[2] P. D. Williamson, J. A. French, V. M. Thadani, J. H. Kim, R. A. Novelly, S. S. Spencer, D. D. Spencer and R. H. Mattson, "Characteristics of medial temporal lobe epilepsy: II. Interictal and ictal scalp electroencephalography, neuropsychological testing, neuroimaging, surgical results, and pathology," Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society, vol. 34.6, 1993, pp. 781-787.

[3] B. Hjorth, "EEG analysis based on time domain properties," Electroencephalography and clinical neurophysiology, vol. 29.3, 1970, pp. 306-310.

[4] A. Semih, Z. Telatar, O. Erogul, "Epileptic EEG detection using the linear prediction error energy," Expert Systems with Applications, vol. 37.8, 2010, pp. 5661-5665.

[5] P. Kemal, S. Güneş, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform," Applied Mathematics and Computation, vol. 187.2, 2007, pp. 1017-1026.

[6] M. K. Kemal, I. Güler, A. Dizibüyük, M. Akin, "Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real time application," Computers in biology and medicine, vol. 35.7, 2005, pp. 603-616.

[7] S. Abdulhamit,"EEG signal classification using wavelet feature extraction and a mixture of expert model," Expert Systems with Applications, vol. 32.4, 2007, pp. 1084-109.

[8] G. Ling, D. Rivero, J. DoradoJuan, R. Rabuñal, A. Pazos, "Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks," Journal of neuroscience methods, vol. 191.1, 2010, pp. 101-109.

[9] E. D. Übeyli, "Lyapunov exponents/probabilistic neural networks for analysis of EEG signals," Expert Systems with Applications, vol. 37.2, 2010, pp. 985-992.

[10] U. R. Acharya, H. Fujitad, V. K. Sudarshana, S. Bhate, J. E. W. Koh, "Application of entropies for automated diagnosis of epilepsy using EEG signals: A review," Knowledge-Based Systems, vol. 88, 2015, pp. 85-96.

[11] k. Lehnertz, C. E. Elger,"Can epileptic seizures be predicted? Evidence from nonlinear time series analysis of brain electrical activity," Physical review letters, vol. 80.22, 1998, pp. 5019.

[12] A. Adda, H. Benoudnine,"Detrended fluctuation analysis of EEG recordings for epileptic seizure detection," International Conference on Bioengineering for Smart Technologies (BioSMART), 2016.

[13] U. R. Rajendra, S. V. Sreec, G. Swapnad, R. J. Martisa, J. S. Suri, "Automated EEG analysis of epilepsy: a review," Knowledge-Based Systems, vol. 45, 2013, pp. 147-165.

[14] S. Yuedong, J. Crowcroft, J. Zhang,"Automatic epileptic seizure detection in EEGs based on optimized sample entropy and extreme learning machine," Journal of neuroscience methods vol. 210.2, 2012, pp. 132-146.

[15] Y. Shasha, W. Zhou, Q. Yuan, Y. Zhang, Q. Meng,"Automatic seizure detection using diffusion distance and BLDA in intracranial EEG," Epilepsy and Behavior, vol. 31, 2014, pp. 339-345.

[16] O. Sutton,"Introduction to k nearest neighbour classification and condensed nearest neighbour data reduction," University lectures, University of Leicester, 2012, pp. 1-10.

[17] B. E. Boser, I. M. Guyon, V. N. Vapnik,"A training algorithm for optimal margin classifiers," Proceedings of the fifth annual workshop on Computational learning theory, Pittsburgh, Pennsylvania, USA.1992.

[18] U. R. Rajendra, S. V. Sreec, G. Swapnad, R. J. Martisa, J. S. Suri, "Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals," International journal of neural systems, vol. 22.02, 2012.

[19] J. H .Kang, Y. G.Chung, and S. P. Kim,"An efficient detection of epileptic seizure by differentiation and spectral analysis of electroencephalograms," Computers in biology and medicine, vol. 66, 2015, pp. 352-356.

[20] S. K. Pravin, N. Sriraama, P. G. Benakopb, C. Jinagac,"Entropies based detection of epileptic seizures with artificial neural network classifiers," Expert Systems with Applications, vol. 37.4, 2010, pp. 3284-3291.

[21] A. Gardner, A. M. Krieger, G. Vachtsevano, B. Litt,"One-class novelty detection for seizure analysis from intracranial EEG," Journal of Machine Learning Research, vol. 7, 2006, pp. 1025-1044.

[22] K. Polat, S. Güneş,"Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform," Applied Mathematics and Computation, vol. 187.2, 2007, pp. 1017-1026.

[23] M. Valderrama, S. Nikolopoulos, C. Adam, V. Navarro, M. Le Van Quyen, "Patient-specific seizure prediction using a multi-feature and multi-modal EEG-ECG classificatio," XII Mediterranean Conference on Medical and Biological Engineering and Computing, 2010, pp. 77-80.

[24] Y. Liu, W. Zhou, Q. Yuan, S. Chen,"Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG," IEEE transactions on neural systems and rehabilitation engineering, vol. 20.6, 2012, pp. 749-755.

[25] I. Guler, E. D. Ubeyli,"Multiclass support vector machines for EEG-signals classification," IEEE Transactions on Information Technology in Biomedicine, vol. 11.2, 2007, pp. 117-126.

[26] V. P. Nigam, D. Graupe,"A neural-network-based detection of epilepsy, " Neurological research, vol. 26.1, 2004, pp. 55-60.

[27] S. Raghu, N. Sriraam, G. Pradeep Kumar, "Classification of epileptic seizures using wavelet packet log energy and norm entropies with recurrent Elman neural network classifier," Cognitive neurodynamics, vol. 11.1, 2017, pp. 51-66.

[28] S. Pratiher, S. Patra, P. Bhattacharya, "On the marriage of Kolmogorov complexity and multi-fractal parameters for epileptic seizure classification," 2nd International Conference on Contemporary Computing and Informatics (IC3I), 2016.

[29] A. Temko, E. Thomas, W. Marnane, G. Lightbody, G. Boylan,"EEG-based neonatal seizure detection with support vector machines," Clinical Neurophysiology, vol. 122.3, 2011, pp. 464-473.

[30] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, C. E. Elger,"Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," Physical Review E, Vol. 64.6(061907), 2001,pp. 1-8.

[31] A. N. Kolmogorov,"Three approaches to the quantitative definition of information" Problems of information transmission, vol. 1.1, 1965, pp. 1-7.

[32] A. Lempel, J. Ziv,"On the complexity of finite sequences," IEEE Transactions on information theory, vol. 22.1, 1976, pp. 75-81.

[33] J. G. Proakis, D. G. Manolakis,"Digital Signal Proccesing: Principle, Algorithm and Applications," Eds. Prentice-Hall International, INC, 1996, pp. 1-960.

[34] D. W. Loveland,"A variant of the Kolmogorov concept of complexity," Information and contro, vol. 15.6, 1969, pp. 510-526.

[35] S. Faul, G. Boylan, S. Connolly, W. Marnane, G. Lightbody, "Chaos theory analysis of the newborn EEG-is it worth the wait?," IEEE International Workshop on Intelligent Signal Processing, 2005.

[36] S. A. Akar, S. Kara, F.Latifoğlu, V.Bilgiç, "Analysis of the complexity measures in the EEG of schizophrenia patients," International journal of neural systems, vol. 26.02, 2016.

[37] M. Klingspor, Hilbert transform: Mathematical theory and applications to signal processing. Matematiska institutionen, Link¨opings universitet, 2015, pp. 1-76.

[38] V. Vapnik, The Nature of Statistical Learning Theory. Springer science and business media, 2013.

[39] B. Bishop, "CM: Pattern recognition and machine learning," J. Electron. Imaging, vol. 16, 2006, pp. 140-155.

[40] N. Ahammad, F. Thasneem, P. Joseph,"Detection of epileptic seizure event and onset using EEG," BioMed research international, 2014, pp. 1-7.

[41] Y. Kaya, M. Uyar, R. Tekin, S. Yildirim, "1D-local binary pattern based feature extraction for classification of epileptic EEG signals," Applied Mathematics and Computation, vol. 243, 2014, pp. 209-219.

[42] Y. Kumar, M. L. Dewal, R. S. Anand, "Epileptic seizures detection in EEG using DWT-based ApEn and artificial neural network," Signal, Image and Video Processing, vol. 8.7, 2014, pp. 1323-1334.

[43] K. Fu, J. Qu, Y. Chai, T. Zou, "Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals," Biomedical Signal Processing and Control, vol. 18, 2015, pp. 179-185.

[44] N. Yalcin, G. Tezel, C. Karakuzu, "Epilepsy diagnosis using artificial neural network learned by PSO," Turkish Journal of Electrical Engineering and Computer Sciences, vol. 23.2, 2015, pp. 421-432.

[45] C. Kamath, "Analysis of EEG dynamics in epileptic patients and healthy subjects using Hilbert transform scatter plots," Open Access Library Journal, vol. 2.1, 2015, pp. 1-14.

[46] A. B. Das, M. I. H. Bhuiyan, S. M Shafiul Alam, "Classification of EEG signals using normal inverse Gaussian parameters in the dual-tree complex wavelet transform domain for seizure detection," Signal, Image and Video Processing, vol. 10.2, 2016, pp. 259-266.

[47] A. Bhattacharyya, R. B. Pachori, A. Upadhyay, U. R. Acharya, "Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals," Applied Sciences, vol. 7.385 , 2017, pp. 1-18.

[48] M. Sharma, R. B. Pachori, U. R. Acharya, "A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension," Pattern Recognition Letters, vol. 94, 2017, pp. 172-179.

[49] D. Bhati, M. Sharma, R. B. Pachori, V. M. Gadre, "Time–frequency localized three-band biorthogonal wavelet filter bank using semidefinite relaxation and nonlinear least squares with epileptic seizure EEG signal classification," Digital Signal Processing, vol. 62, 2017, pp. 259-273.

[50] L. Boubchir, S. Al-Maadeed, A. Bouridane, "Haralick feature extraction from time-frequency images for epileptic seizure detection and classification of EEG data," 26th International Conference on Microelectronics (ICM), 2014.

[51] L. Boubchir, S. Al-Maadeed, A. Bouridane, A. A. Cherif, "Classification of EEG signals for detection of epileptic seizure activities based on LBP descriptor of time-frequency images," IEEE International Conference on Image Processing (ICIP), 2015.

[52] J. H. Kang, Y. G. Chung, S. P. Kim, "An efficient detection of epileptic seizure by differentiation and spectral analysis of electroencephalograms," Computers in biology and medicine, vol. 66, 2015, pp. 352-356.

[53] Z. Song, J. Wang, L. Cai, B. Deng, Y. Qin, " Epileptic seizure detection of electroencephalogram based on weighted-permutation entropy," 12th World Congress on Intelligent Control and Automation (WCICA), 2016.

[54] D. Li, Q. Xie, Q. Jin, K. Hirasawa, "A sequential method using multiplicative extreme learning machine for epileptic seizure detection," Neurocomputing, vol. 214, 2016, pp. 692-707.

[55] A. K. Jaiswal, H. Banka, " Local pattern transformation based feature extraction techniques for classification of epileptic EEG signals," Biomedical Signal Processing and Control, vol. 34, 2017, pp. 81-92.

[56] T. Zhang, W. Chen, M. Li, "Fuzzy distribution entropy and its application in automated seizure detection technique," Biomedical Signal Processing and Control, vol. 39, 2018, pp. 360-377.

[57] S. Li, W. Zhou, Q. Yuan, S. Geng, D. Cai, "Feature extraction and recognition of ictal EEG using EMD and SVM," Computers in biology and medicine, vol. 43.7, 2013, pp. 807-816.

[58] F. Wang, Q. Meng, Y. Chen, Y. Zhao,"Feature extraction method for epileptic seizure detection based on cluster coefficient distribution of complex network," WSEAS Transactions on Computers, vol. 13, 2014, pp. 351-60.

[59] H. Liu, Q. Meng, Q. Zhang, Z. Zhang, D. Wang, " A Novel Feature Extraction Method for Epileptic Seizure Detection Based on the Degree Centrality of Complex Network and SVM," International Conference on Intelligent Computing, ICIS 2016, pp. 170-180.

[60] K. Samiee, P. Kovacs, M. Gabbouj, "Epileptic seizure classification of EEG time-series using rational discrete short-time Fourier transform," IEEE transactions on Biomedical Engineering, vol. 62.2, 2014, pp. 541-552.

[61] A. S. Muthanantha Murugavel, S.Ramakrishnan, "Hierarchical multi-class SVM with ELM kernel for epileptic EEG signal classification," Medical and biological engineering and computing, Vol. 54, 2016, pp. 149-161.

[62] Z. Tao, C. Wan-Zhong, L. Ming-Yang, "Automatic seizure detection of electroencephalogram signals based on frequency slice wavelet transform and support vector machine," Acta Physica Sinica, vol. 65.3 (038703), 2016, pp. 1-7.

[63] F. Riaz, A. Hassan, S. Rehman, I. K. Niazi, K. Dremstrup, "EMD-based temporal and spectral features for the classification of EEG signals using supervised learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 24.1, 2015, pp. 28-35.

[64] R. B. Pachori, S. Patidar, "Epileptic seizure classification in EEG signals usi ng second-order difference plot of intrinsic mode functions," Computer methods and programs in biomedicine, vol. 113.2, 2014, pp. 494-502.

[65] R. Sharma, R. B. Pachori, "Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions," Expert Systems with Applications, vol. 42.3, 2015, pp. 1106-1117.

[66] T. S. Kumar, V. Kanhangad, R. B.Pachori, " Classification of seizure and seizure-free EEG signals using local binary patterns," Biomedical Signal Processing and Control, vol. 15, 2015, pp. 33-40.

[67] A. K. Tiwari, R. B. Pachori, V. Kanhangad, B. K. Panigrahi, "Automated diagnosis of epilepsy using key-point-based local binary pattern of EEG signals," IEEE journal of biomedical and health informatics, vol. 21.4, 2016, pp. 888-896.

[68] A. Y. Mutlu, "Detection of epileptic dysfunctions in EEG signals using Hilbert vibration decomposition," Biomedical Signal Processing and Control, vol. 40, 2018, pp. 33-40.