IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Vol.-7, Issue-8, Aug 2019 E-ISSN: 2347-2693

EEG Based Epilepsy Seizure Analysis and Classification Methods: An Overview

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DOI: https://doi.org/10.26438/ijcse/v7i8.328346 | Available online at: www.ijcseonline.org

Accepted: 27/Aug/2019, Published: 31/Aug/2019

Abstract: Epilepsy has always baffled humans, in particular, the approach one needs to take for curing or at least subside its severity. Epilepsy is a continual lingering neurological ataxia generated by intermittent, transient, superfluous, wanton and unfounded seizures. Epilepsy never indicates cause of a person's seizures or their severity. Electroencephalogram (EEG) is the tool of choice for analysis and diagnosis of epilepsy along with different automatic and visual inspection techniques. Several researchers have proposed diverse techniques for classification and analysis of epilepsy. Different pre-processing, feature extraction and classification approaches are presented. This paper attempts to catalogue various techniques and algorithms proposed so far for epileptic seizure analysis along with shortcomings thereof to facilitate further research in this complex area. This will help in online seizure detection and timely diagnosis.

Keywords*:* Epilepsy, Seizure, Electroencephalogram (EEG), Brain, Wavelet, Hilbert-Huang Transform

I. INTRODUCTION

Brain is the most critical organ in our central nervous system. It is the organ for thoughts, emotions, sensations and origin of all control actions for the body movements. Brain is highly complex with millions of neurons wherein chemical processes that generate electrical potential occur. Often, an uncontrolled or abnormal electrical activity occurs resulting in temporary malfunctioning of sensory structure termed *Seizure*. Seizure has three prominent stages: Aura, Ictus and Post–Ictal. Nature of seizure depends on the brain lobe affected [1].

Seizure, per se, is not a disease in itself but merely indicates some abnormal brain condition. However, if seizures occur repeatedly then it is a neurological disorder termed *Epilepsy*. Epilepsy can be categorized as partial or generalized. Partial epilepsy adversely impacts some parts of the brain leading to temporal paralysis. Generalized epilepsy involves electrical discharges that spread all over the brain resulting in loss of consciousness. Seizure classification with their occurrence chances is shown in figure 1.

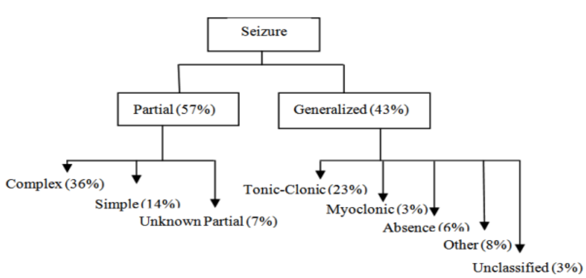

Fig. 1 Epileptic seizure classification [1]

As per the published WHO report ("World Health Organization-Fact sheet of Feb., 2017"), around 50 million people suffer from epilepsy worldwide. It is more prevalent in low and middle income countries [2], [3]. Epilepsy can affect all, from neonatal to old person. Brain activity can be recorded using Electroencephalogram (EEG). EEG recording is done by placing 10-20 electrodes on the subject. Seizure manifests as spike or a sharp wave change in recorded EEG data. Epileptic seizure analysis involves following stages: Pre-processing, Extraction of features, Classification and Post processing.

In the Pre-processing stage, EEG signals are normalized and filtered to overcome artifacts of noise, eye blink and other unnoticeable movements. Normalization based on novelty-median decaying memory technique [4] reduces dataset complexity. Artifacts are removed by selecting proper bandwidth of the filters. Different filters, e.g., Butterworth filter [5], Gabor filter [6], Kalman Filter [7], FIR filter [8], [9], IIR filter [10], Band Pass filter [9], [11], Notch filter [12], Adaptive filter [12] have been used by researchers for artifact removal. After the pre-processing process, EEG signal has to be analyzed by a medical professional visually, which is a time consuming and tedious job. As a result, considerable interest has been generated in automatic analysis of EEG patterns. Visual inspection based qualitative assessment using Numerical analysis is presented in [13] that considers separate EEG epoch for seizure and non-seizure event windows (application of linear EEG dataset analysis). As EEG signals are inherently non-linear and non-stationary, researchers have directed efforts in calculating the features for EEG processing.

Fourier transform [14] is a good technique for data analysis but has certain limitations. It doesn't show sudden changes adequately as it represents data as a sum of sine waves. Continuous oscillating behavior of sine waves is problematic for accurate analysis of signals. So, wavelet transform has been adopted for more precise results. Wavelet is a rapidly decaying wave like oscillation that has zero mean. Wavelet has distinct shapes and sizes; some well-known are: Morlet, Daubechies (db), Coiflets, Biorthogonal, Mexican Hat, Symlets etc. with different decomposition levels. Availability of wide range of wavelet is the key strength of wavelet analysis. Choosing an appropriate wavelet depends on its application.

Many other algorithms can be collaborated with wavelet transform, e.g., Chaos wavelet transform, Dual complex tree wavelet transform, Discrete wavelet transform with Mixture of Experts, etc. that makes feature extraction process more appropriate. However, problem of handling non-linearity persists in wavelet transform along with another disadvantage that it doesn't extract discrete features but only the continuous ones. This problem can be overcome by Hilbert-Huang Transform [15] which is adaptive and applicable to both continuous and discrete signals. In Hilbert-Huang, signal decomposition is done by Empirical Mode Decomposition (EMD) to obtain Intrinsic Mode Functions (IMFs). Apart from these, some other techniques that have been used by researchers are: Matching Pursuit [16], Random Forest (RF) [17], Auto Regression (AR) model [18], [19], Lyapunov exponent [20], [21], Hidden Markov Model (HMM) [22] and Recurrent Quantification Analysis (RQA) [23]. Different features such as: Morphological, Time, Frequency, Time-frequency and MFCC (Mel Frequency Cepstral Coefficients) can be extracted by these techniques.

For increasing classification speed and accuracy, feature set dimension should be reduced after feature extraction. Using input data matrix, dominating features can be extracted using: Principal component Analysis (PCA) [24], Independent component Analysis (ICA) [25], Correlation [26] and Convolution [27]. After the feature selection stage, reduced input matrix set is fed to a classifier for identifying different seizure stages based on target matrix set. For identification, most frequently used techniques are: Support Vector machine (SVM) [14], Artificial Neural Networks [28], [29] and some modified algorithms: Neural Network [30], [26] and Recurrent Neural Network (RNN) [20]. For more accurate classification, Support Vector Machine classifier has been tested with different kernel [31]. Few other prominent classification methods are: Unsupervised fuzzy clustering [32], Linear Discriminate Analysis (LDA) [33] and Probabilistic Neural Network (PNN) [34], [31].

Classification performance can be improved by Post-processing in which threshold variation and smoothing are used [35]. Performance analysis measures such as Accuracy (Acc.), Sensitivity (Sen.), Specificity (Spec.), FDR (False Detection Rate) and Latency are used to judge the success rate of employed technique. This could lead to development of an automatic brain computer interface device (wearable) for epileptic victims spread worldwide. With the development of this device, epileptic patient can freely move like normal ones and system can be integrated with GPS to acquire and transmit various patient parameters for timely diagnosis [36].

Further, this paper is organized as: Section 2 covering commonly used dataset for Epileptic seizure analysis and Section 3 comprising a detailed historical background of epileptic seizure analysis techniques with their performance measures and limitations. Thereafter, Section 4 contains the discussion part while Section 5 concludes and outlines the future challenges.

II. DATA SET

Most of the researchers have used publically available data set of Bonn University (CHB-MIT) [37] and RG. Andrzejak dataset [38] which is freely available online while paid dataset is available at Freiburg University [39]. Some other self-recorded datasets (at different universities and hospitals) are also available and used by researchers as mentioned in forthcoming tables.

III. REVIEW OF SEIZURE ANALYSIS

Different research approaches for EEG signal analysis are presented in the sub-sections below along with their performance. These can also be analyzed with different image processing techniques like energy computation methods, image segmentation based feature extraction and classification method or pattern matching techniques. But these image processing methods have not been surveyed in this paper. Specifically, Signal processing techniques have been showcased.

III.I Visual Inspection Based

M.J. van der Heyden et al. [13] presented an EEG signal qualitative assessment based on visual investigation where numerical analysis for medically intractable temporal lobe epilepsy has been presented. For visual inspection, different seizure and non-seizure windows are selected for pattern matching using numerical methods. Here, features used for non-linear characterization are: coarse-grain correlation dimension and coarse-grain entropy. Use of High pass filters make epochs stationary before a time scale of 2 sec. Features based on coarse-grain entropy segregate effectively and linear autocorrelation improves classification accuracy. This leads to a conclusion that non-linear analysis provides precise result for differentiating ictal and non-ictal EEG.

Two major limitations of this technique are high computational complexity and time consumed.
Visual inspection is inadequate for handling information contained in the signal. Hence, we will now discuss signal processing techniques.

III.II Time Domain Techniques

This domain includes methods which are based on Linear prediction and Component analysis. In Linear prediction, output of the system is analyzed based on input while in Component analysis, unsupervised mapping is used. Here, methods such as PCA, ICA and LDA are used for reducing the dimensionality of dataset. In PCA, orthogonal feature subset is used (Eigen vector) while ICA considers each measured signal as a linear combination of independent signals and decomposes multi-dimensional data linearly to statistical independent components. LDA finds a linear combination of features that can separate two or more classes [24], [25]. Techniques belonging to this domain give linear relationship for prediction purpose but for an in-depth analysis, spectrum analysis is a must. Time-Frequency domain analysis generates spectral information.

III.III Time-Frequency Techniques

III.III.I Fourier Transform Based

The Fourier transform refers to the decomposition of function of time or signal in to the frequencies that make it up. It also refers to: i) the frequency domain representation and ii) the mathematical operation that associates this representation to a function of time.

Leonardo Duque-Munoz et al. [14] proposed Short Time Fourier Transform (in which small and equal length signals are transformed for fast computation) with Support Vector Machine classifier for class (A,E) having classification accuracy 100%, class (A,D,E) accuracy as 100% and class (A,B,C,D,E) accuracy as 96.58%. With KNN classifier, accuracy for these classes is 99.50%, 98.12% and 95.78%, respectively.

While this approach gives good performance (for analysis, dataset is converted into linear and stationary) but in real time, EEG signals are non-linear and non-stationary. For online seizure detection, its implementation becomes difficult. Hence, wavelet transform came into picture for more precise results.

III.III.II Wavelet Transform Based

The Wavelet transform, despite being similar to Fourier transform; is much more to the windowed Fourier transform. It uses the functions that are localized in: i) Fourier space and ii) Real space. It is an infinite set of many transforms that depends on the merit function used for its computation. That's why this "wavelet transform" is used for different applications and in distinct situations. The two divisions are: i) *Discrete Wavelet Transform*, which uses orthogonal wavelets and is good for signal processing and compression and ii) *Continuous Wavelet Transform*, which uses non-orthogonal wavelets and the data is highly co-related.

Shahidi Zandi et al. [40] used WPT (Wavelet Packet Transform) algorithm for online seizure detection and computed combined seizure index (CSI) for every channel. The approach achieves 90.5% classification accuracy for epileptic seizure detection with small FPR (False Positive Rate) of 0.51 h^{-1} and median latency of 7 sec. 86% of the seizures are detected 15 sec after electrographic onset and 51% within 5-10 sec. The method detects different states fast but the accuracy is somehow reduced and is required to be improved. It is unable to lateralize and localize the seizure focus in extra temporal area.

Abdulhamit Subasi et al. [41] proposed AR (Auto Regression) model with MLE Pre-processing and wavelet neural network classifier for EEG signal analysis. Logistic Regression, Feed forward error back propagation artificial neural network and Wavelet Neural Network classifiers have been used with Pre-processing technique (AR model with MLE). Performance comparison shows Classification accuracy as 89.3%, 90.6% and 93%; Specificity 89.2%, 91.5% and 92.4%; Sensitivity 89.4%, 89.8% and 93.6% and Area under ROC curve as 0.887, 0.894 and 0.918. WNNs and FEBANNs require large data along with some other parameters for convergence. These parameters have to be provided manually as there is no system that will select these automatically to generate the highest accuracy.

M. Sharanreddy et al. [42], [43] asserted that a Hybrid technique could provide more fruitful results. They proposed a hybrid technique that combines multi-wavelet transform and ANN. Appropriate entropy algorithm has been used (called Improved Approximate entropy) to measure inconsistency and classifies epilepsy seizure with 90% accuracy [42] and also employed for normal, epilepsy and brain tumor classification with accuracies of 98%, 93% and 87%, respectively [43]. Results are verified on 500 EEG signals for seizure, tumor and infection identification and are able to highlight seizure and tumors.

Ling Guo et al. [44] used DWT for feature extraction and K-NN as the classifier. To improve the computational speed and classification accuracy, feature dimensionality should be reduced. For this, GA (Genetic Algorithm) technique is proposed. Main purpose is to target the feature selection that will improve discriminatory performance by reducing feature dimensionality. Overall accuracy of this technique is 93.5%. Genetic Programming based feature extraction is computationally expensive. Increase in original feature dataset size along with number of training data would bring a marginal increase on the computational cost which makes developed method inappropriate for real-time applications.

Anindya Bijoy Das et al. [45] proposed dual tree wavelet transform with SVM classifier and achieved 100% sensitivity and specificity and more than 96% accuracy along with high computational speed. Results are promising; however, they need to be verified with long term data.

SG Dastidar et al. [46] proposed a Wavelet chaos NN with mixed band feature space. L-M BPNN gives higher accuracy of 96.7% for healthy, ictal and inter-ictal conditions.
Sang-Hong Lee et al. [47] extracted Phase Space Representation and Euclidian Distance features with wavelet transform calculated on seizure dataset. Non-overlap area distribution feature selection technique has been used to select 4 features out of 24. Neural network with weighted fuzzy membership function gives accuracy 98.17%, specificity 100% and sensitivity 96.33%.

Yusuf U Khan et al. [48] used skewness and kurtosis features and normalized coefficient of variation (NCOV) wavelet features with simple linear classifier for automatic prediction of onset seizure. This technique gives 100% sensitivity, small quiescence of 3.2 sec. and a mean False Detection Rate (FDR) of 1.1 per hour. Results are promising and timely identified; however, FDR is high and is required to be reduced.

Isa Conradsen et al. [49] developed a non-invasive system for epilepsy detection that uses movement features (based on surface Electromyogram (EMG) and motion sensors) as an energy measure of sub-bands using discrete wavelet transform and wavelet packet transform. These features are classified using SVM and MISA system showing superiority over uni-model in the sense of sensitivity, low latency rate and FDR.

Yong Zhang et al. [50] demonstrated Wavelet Packet Decomposition with db2 at 5th decomposition levels providing Accuracy of 100% (ApEn + SVM), 99.4% (ApEn + ELM (Extreme Leaning Machine)), 96.3% (SampEn (Sample Entropy) + SVM) and 99.6% with (SampEn + ELM) techniques. Best part of this technique is the reduced training time with good accuracy. Moreover, it is good in order to check different brain states and latency.

Nasser Omer et al. [4] propounded swarm Negative Selection classification algorithm for feature selection and classified by DWT (Discrete Wavelet Transform). It gives accuracy with different Training- Testing values: (40% training - 60% testing) gives accuracy 99.15%; (60 training- 40% testing) gives 99.47% and (80 training - 20% testing) gives 99.22% accuracy. The method outperforms many other methods.

Musa Peker et al. [51] proposed somewhat complex classifiers for epilepsy detection. First, features are collected with Dual tree complex wavelet transform which is fed as input vector to a complex-value neural network. Results of applying the present approach with 10-fold cross validation for class (A,D,E), class (ABCD-E), class (ACD-E), class (AB-CD-E) are: Accuracy of 99.30%, 99.15%, 98.37%, 98.28%; Sensitivity 99.40%, 100%, 99.05%, 98.91% and Specificity 98.80%, 97.89%, 96.67%, 98.28%, respectively. This method can be used as an accurate classifier but results need to be verified on a larger dataset.
Few more methods and their details are mentioned in Table 1.

Table 1: Time-Frequency Domain (Wavelet Transform) Based Methods and some Modified Techniques

S. No., Ref. No.,Year, Publication	Technique/Method	Input variables /Parameters/Features	Results/ Limitation/ Future scope	Data set
1. [5] 2012 "Journal of Med. Imaging and Health Info., 238-243"	Wavelet (db4) + 50 Hz Butterworth Notch Filter Normalization **Classifier**: Linear	Wavelet entropy and mean absolute deviation	100% sensitivity **Limitation:** Average prediction time is very high.	Freiburg, Germany
2. [9] 2014 "Journal of Biomedical Informatics" Journal Elsevier	Wavelet (db2) + Band Pass Filter **Classifier**: CNBC (Collective Network Binary Classifier) with Multi- Dimension Partical Swarm Optimization (MD PSO)	Morphological , Time, Frequency, Time–frequency, Non-linear, MFCC (Mel Freq. CepstralCoeff.)	Average sensitivity rate> 89% Average specificity rate> 93% **Limitation**: Scope of Improvement in classification performance.	CHB-MIT
3. [24] 2010 "Expert System With Applications" Elsevier	DWT (db4) + PCA, ICA, LDA **Classifier**: SVM	Mean, Average Power, SD, Ratio of absolute mean values	**Acc. Spec. Sen.** **PCA** 98.75% 98.5% 99% **ICA** 99.5% 99% 100% **LDA** 100% 100% 100% **Limitation:** Training time for the classification using LDA feature extraction and SVM classifier is higher than PCA and ICA extraction.	Andrzejak et al. (2001) database
4. [28] 2005	**Feature Extraction:** Wavelet (db2)	(1) MAV (Mean Absolute values)	Accuracy with ANN classifier:	"Sleep Lab. Deptt. of

"Expert system with applications" , Elsevier	**Classifier:** ANN (Back propagation)	(2) Avg. wavelet coeff. Of power for all sub-band (3) SD of coeff. for all sub-band (4) Ration of absolute mean values	**Alert** **Drowsy** **Sleep** **Acc.** 95±3% 93±4% 92±5% **Sen.** 93.4% 88.1% 89.3% **Spec.** 90.9% 89.2% 91.7% **Limitation:** (1) Over-fitting problem occurs during NN training. The error on the training set is driven to a very small value but when new data is given to the network the error is large. There is no generalized solution for new data input, while the network has memorized many training examples. (2) The method indicates different brain states but does not lead to exact seizure detection.	Psychic Health and Diseases."
5. [31] 2011 "Neurocomputing" journal Elsevier	Wavelet + Probabilistic neural network (PNN) **Classifier:** SVM	Energy, SD, Entropy, Energy + SD	Comparative study for EEG signal classification with wavelet families as Haar, Daubechies (order 2-10), Coiflets (order 1-10) and Biorthogonal (order 1.1,2.4,3.5 and 4.4) are compared. Coiflet 1 shows highest accuracy and efficiency out of these families, hence is most suitable for EEG signal analysis. **Limitation**: Selection of an appropriate mother wavelet through parameterization leads to improvement of performance as compared to random selection of the mother wavelet.	Two dataset used. (1) Sir Ganga Ram Hospital, New Delhi. **(2)** Andrzejak et al.
6. [32] 1998 "IEEE *Trans.* on Biomed Engineering"	Wavelet Analysis + PCA + Unsupervised Fuzzy Clustering	Statistical moment calculation, correlation analysis, spectrum estimation, time-freq. decomposition. (Variance, Skewness, Kurtosis)	Method utilizes unsupervised fuzzy clustering with very few parameters derived from feature extraction by wavelet transform of two EEG channels. To increase forecasting strength of clustering process, no. of EEG channels should be added to increase no. of input parameters. Classify behavior stages for 16 instances, determine pre-seizure condition before 0.7 to 4 min. and classify stages such as slumber, relaxing, operating and alertness, wakefulness, seizure.	EEG from HBO-exposed rats, included first seizure and before first seizure event
7. [34] 2008 "Measurement" Journal Elsevier vol. 41	Wavelet Packet Decomposition (db4) + Filter based Fisher Criterion + Probabilistic Neural Network (PNN)	Part decomposition coefficient, Statistical information of wavelet coeff., sub band energy, Transformation modes of coeff.	Accuracy: 90.8% **Limitation**: Accuracy should be improved so that method can be implemented for online prediction.	BCI competition, 2003
8. [35] 2014 "IACSIT International Journal of Engineering and Technology"	Wavelet (db5) Decomposition		Wavelet decomposition allows optimal selection of its levels with minimum entropy values, high power spectral density, pertaining to epileptic waveform & Hurst Exponent. Proposed Fractal dimension based algorithm for epilepsy treatment and preventive measure before online seizure algorithm shows 87.5% accuracy.	Children hospital, Boston
9. [52] 2012 "SIViP(2014)8:1323-1334" Journal Springer	**Feature Extraction** : DWT with 5^{th} decomposition level **Classifier** : ANN	Approximate Entropy (ApEn)	**Class** **Accuracy (%)** A–E 100 B–E 92.5 C–E 100 D–E 95 BCD–E 94 ABCD–E 94 Out of 6 classes, only two classes' acc. is 100% and rest classes require classification accuracy improvement.	Bonn University, Germany
10. [53]	Wavelet Transform	Line length features	For different classes such as Z-S	Andrzejak et al.

2010 "Journal of Neuroscience Methods" Elsevier	**Classifier**: ANN		classification accuracy 99.6%, specificity 100% and sensitivity 99.4% is achieved while with ZNF − S class 97.75%, 95.61%, 98.55% and with ZONF − S class 97.77%, 94.6% and 98.61% accuracy, specificity and sensitivity is achieved respectively. **Limitation**: The database has been preprocessed by removing artifacts via visual inspection. It's a limitation of assessing method and thus extensive assessment is required under real clinical situations.	(2001)
11. [54] 2005 "Computer methods and programms in Biomedicine" Journal Elsevier	**Pre-processing** : Lifting Algorithm Wavelet Transform (db4) **Classifier** : MLPNN with L-M algorithm , back propagation and Logistic Regression (LR)		MLPNN with L—M algorithm, back propagation and logistic regression classifier for normal and epilepsy classification gives accuracy 93%, 92% and 89% respectively. While Sensitivity for these algorithms are 92.8%, 91.6% and 89.2% and acceptable classification success rate are .902, .889 and .853, shows that MLPNN with L-M algorithm is better compared to back propagation and logistic regression algorithm. This algorithm is used to reduce computational load as seen in classical wavelet transform. It can be used for supporting physician but accuracy requires improvement.	Bipolar EEG channels F7-C3, F8-C4, T5-O1 and T6-O2. 24 hr EEG recording for both epileptic and normal subjects
12. [55] 2008 "Expert system with Applications" journal Elsevier	**Feature Extraction**: DWT + Mixture of Experts system **Classifier**: ANN	Mean, Max of absolute values, Average Power, SD, Ratio of absolute mean, Distribution distortion of coefficient in each sub-bands	Accuracy with hidden layers 1, 2, 4, 6 is 93.17%, 92.50%, 91.75% and 90.88%. Specificity: 94%. Sen. (seizure free): 92.5%. Sen. (epileptic seizure zone): 93% Total classification accuracy: 93.17%. **Limitation**: Better accuracy as compared to alone NN but more accuracy for real time seizure classification is required.	Andrjezak et al. (2001).
13. [56] 2006 "Expert System with applications" Elsevier	DWT + MLPNN & Mixture of Experts (ME)	(1) Mean of the absolute values (2) Avg. power (3) Standard Deviation (4) Ratio of the absolute mean values	MLPNN & ME increased results from DWT are: **Sensitivity** 93.6% to 95% **Specificity** 92.6% to 94% **Accuracy** 93.2% to 94.5% **Limitation**: Hardware implementation for online seizure detection is required.	Andrzejak, et al. (2001)
14. [57] 2006 "Ann.of Biomed. Engg. "	Wavelet Artificial Neural Networks (WANNs)		Classification accuracy for events inter-ictal, pre-ictal, ictal and IB conditions are: 86.6%, 72.6%, 84.5% and 69.1% respectively. Pre-ictal condition can be predicted 36.4 sec. ahead from the occurrence of seizure. **Limitation**: Pre-ictal seizure identification accuracy is required to improve timely treatment.	Wistar rats (14–25 days old). Hippocampal slices obtained for male
15. [58] 2013 "Journal of Med. Imaging and Health Informatics" , Vol. 3	Wavelet Decomposition upto level IV **Classifier**: Linear	Inter quartile range (IQR) and statistical features	Accuracy 95.6% Sensitivity 100% Specificity 100% **Limitation**: Misclassification in set C and set D class.	Bonn University, Germany
16. [59] 2013 "IEEE Tran. on Biomedical Engg." Vol. 60, No.12,	Wavelet (db 4) then Lacunarity and Bayesian Linear Discriminate Analysis **Post-processing steps**: Smoothing with Moving Avg. Filter (MAF), Threshold Judgment, Multichannel Integration and Collar	Lacunarity and Fluctuation index	Sensitivity : 96.25% FDR : 0.13/h Mean delay : 13.8 sec **Limitation**: Average sensitivity is high but patient wise variation in sensitivity is high (69%- 100%).	University Hospital of Freiburg, Germany

	Technique			
17. [60] 2013 "Neural Computation and Application" Journal Springer	Discrete Wavelet Transform + Sixth order Butterworth Band-Pass Filter **Classifier**: K-NN, Multilayer Perceptron, Naive Bayesian, LDA, SVM		Genetic Algorithm feature selection is used to analyze EEG signals. Results show that ensemble system gives boost to classification accuracy. **Limitation**: Accuracy is increased with ensemble system but still error rate is more than 10% which is not suitable for BCI system.	BBCI
18. [61] 2013 "International journal of computer application vol. 63"	DWT **Feature Selection**: ICA,PCA **Classifier**: SVM with kernal: RBF, Linear, Gaussian and Polynomial	Power spectrum, entropy, mutual information	Based on features as: power spectrum, entropy, mutual information, etc. SVM classifier with different Kernels is used to evaluate performance for seizure classification. **Limitation**: Method should be implemented to design brain computer interface device that can check method validity/performance.	
19. [62] 2013 "International Journal of Neural System"	**Feature Extraction**: CWT **Classifier**: DT (Decision Tree), K-NN, PNN, SVM	HOS + Textures features extracted	**Accuracy** 96% **Sensitivity** 96.9% **Specificity** 97% SVM with RBF gives good accuracy.	Bonn Univ.
20. [63] 2016 (Expert system with application) journal elsevier	Signal Decomposition up to 6th level with Dual-Tree Wavelet Transform **Classifier**: General Regression Neural Network	Energy, SD, RMS, Mean, Shannon Entropy, Max. Peaks	Ictal and non-ictal events classified in a very short duration of 0.028 sec and having maximum hit rate and correct rejection rate shows method effectiveness that it can be used for accurate and fast diagnosis of seizures. **Future Scope:** (1) Classification of different seizure stages (2) Localizing seizure foci and its spatiotemporal connection with other brain regions.	Two data sets used are: Univ. of Bonn, Germany. 2. The second EEG recorded dataset using the Grass Telefactor EEG Twin3 machine.
21. [64] 2016 "IJIRCCE" journal vol.4 issue 7	DWT with symlet8 + Multi Resolution Analysis with Digital Low Pass Finite Impulse Response Filter with Hamming Window Order 40 and cut off frequency is 32 Hz **Classifier**: ANN	Mean, Entropy, SD	Comparison of seizure and non seizure with data set at different decomposition level with different extracted parameter as Mean, SD and Entropy at decomposition level D6, D7, D8 and A8. Using this neural network, 96% accuracy is obtained. **Limitation:** For many practical problems, similar input patterns may have different output requirements.	
22. [65] 2016 "Electronics Letter, vol. 52, No. 11"	2D DWT for Time-Frequency Image Feature Extraction DWT with Haar Transform **Classifier**: SVM		Sensitivity 98.7 % Specificity 100 % Accuracy 99.37% Positive predictive rate 100 % Negative predictive rate 98.76 % **Limitation**: It requires hardware implementation for real time seizure validation.	**Dataset 1**: Royal Brisbane and Women's Hospital, Brisbane, Australia. **Dataset 2:** Cork University Maternity Hospital, Ireland
23. [66] 2016 "IEEE journal of Biomed. and Health Info."	Wavelet (db3, db5, coif 3, sym 4) **Classifier**: SVM and KNN		A wearable device with accelerometer sensor is proposed as a new solution in the detection and diagnosis of PNES. Sensitivity 100%, leave-one-out-error 6.67% with few false alarms. **Limitations:** 1) Algorithm is developed for a wrist worn device so the accuracy of seizure detection varies with the device placement on the arm. 2) Since it examine seizures of extent more than 20 sec, any seizure of lesser extent will	Royal Melbourne Hospital in Melbourne, Australia

			go undetected. 3) System is still to be validated in home conditions. For now, the system is tested and developed in hospital settings where patients do not engage in lot of activities where different situations persist than real home cases.	

III.III.III Hilbert-Huang Transform Based

All earlier mentioned methods utilize wavelet transform by variable resolution to resolve the non-stationary problem of FFT; however, these methods consider fixed frames. This limitation can be resolved by Hilbert-Huang Transform. This will automatically take care of non-linear and non-stationary real time signals to decompose using EMD (Empirical Mode Decomposition) method and get the IMFs (Intrinsic Mode Functions). Unlike a theoretical tool, HHT is just like an algorithm and preserves the characteristics of varying frequency. Based on this methodology, researchers have tried to find the performance measures.

Ram Bilas Pachori et al. [67], [68] used EMD method to get IMF and Fourier Bessel expansion for mean frequency feature of IMF. This has been used to differentiate ictal and seizure-free event in EEG signals [67]. Seizure-free and ictal conditions segregate from EEG using second order difference plot. EMD method that has been employed with 95% confidence ellipse area shows that with a 4000-window size group F12, F13, F14, F23, F24, F34 give average classification accuracies of 95.75%, 95.75%, 88.5%, 96.25% and 82.5%, respectively. The results have been obtained with different electrodes position or different brain lobes activity performance but what is required is a comprehensive result applicable to all lobes [68].

Rajeev Sharma et al. [26] proposed Phase space representation (PSR) feature based EEG signal analysis in which EEG signal is decomposed first to get IMF using EMD. Afterwards, 2D and 3D PSR features are used as inputs to the classifier. Two performance measure values are: 95% confidence ellipse area for 2D and Inter Quartile Range (IQR) of Euclidian distance for 3D PSR shows 98.67% seizure classification accuracy with LS-SVM classifier.

Mohammad Zavid Parvez et al. [69] proposed feature extraction using high frequency component from Discrete Cosine Transform (DCT) and IMF. EMD has been used as an input to LS-SVM (Least Square–Support Vector Machine) to classify ictal and inter-ictal EEG signal and gives 96.10% sensitivity. Proposed method does improve sensitivity yet it is infeasible for online prediction.

S. M. Shafiul Alam et al. [70], [71] described EMD chaos approach to discriminate EEG signal into healthy and epileptic events with seizure-free and seizure time interval using features Largest Lyapunov exponent (LLE) and correlation dimension (CD). This approach yields fruitful results in classification of healthy and seizure activities [70]. HOS movements of EMD to classify seizure with ANN classifier provide 100% accuracy, 100% specificity and 100% sensitivity with faster speed. One important benefit with the above mentioned technique is that it is directly applicable to real time EEG signals. This method lacks hardware implementation and for some classes, performance is not too good so need to test for all the seizure classes [71].

Remaining methods and their details are mentioned in table 2.

Table 2: Time-Frequency Domain (Hilbert-Huang Transform) Based Methods and few ModifiedTechnique

S. No., Ref. No., Year, Publication	Technique/Method	Input variables /Parameters/Features	Results/ Limitation/ Future scope	Data set
1. [72] 2009 IEEE *Transactions on Information Tech. in Biomedicine*"	Time Frequency Analysis techniques with PSD **Classifier**: ANN		With set Z,S acc. 100%, with Z,F,S acc 100% with Z,F,N,S,O accuracy is 89% **Limitation:** The class Z and O is having high misclassification rates so results are not as per expectation. These classes don't have major impact on study because both belong to healthy individuals (with eye open and close).	Andrzejak et al.
2. [73] 2013 "Biomed EngLett" Springer	EMD	Instantaneous area of analytic IMF use at 95% of CTM area used	Sen: 90%; Spec: 89.31%; PPV: 89.81%; NPV: 93.71%; ERD: 24.25% **Limitation**: Low signal to noise ratio, hence require noise suppression before applying the technique.	
3. [74] 2014 "Expert system with application" Journal Elsevier	EMD + Phase Space Representation (PSR) to obtain IMF + LS-SVM class. evaluated using kernals: RBF, Mexican hat and Morlet		1) 95% confidence ellipse area for 2D phase space representation. 2) Inter Quartile Range (IQR) of Euclidian Distance for 3D Phase Space Representation of IMF of EEG. **Limitation:** Should be tried on large dataset of EEG signals which may consist of signals with longer duration (like in hours). The kernel and its parameters are selected	Andrzejak et al.

			based on the trial and error method. Developing a strategy for selection of optimum kernel and its parameters is required.	
4. [75] 2015 "Information science and application" Journal Springer	EMD + Kruskal−Wallis Statistical test **Classifier**: Neural Network	Average Renyi entropy and average negative entropy of IMFs	Accuracy : 98.83% Approach is suitable for surgery specialist to locate the epileptic zone.	
5. [76] 2016 (Knowledge based system) journal elsevier	Time Frequency Domain Methods as: CKD, EMBD, WVD, Spectrogram, Extended Spectrogram + Wrapper Method with Sequential Forward Feature Selection	Mean, SD, Skewness, Kurtosis, Coefficient of Variation	Proposed Time-Frequency based machine learning approach. Three feature sets: statistical, image and signal based are used. **Experiment results**: 1. Compact kernel distribution (CKD) shows better performance than TFD. 2. Feature fusion strategy shows 86% classification accuracy while TF approach with CKD shows 82% accuracy. 3. Accuracy is improved using SFFS wrapper feature selection method. 4. Multiclass strategy shows 86.61% accuracy with one v/s one multiclass which is 0.91% higher than binary classifier.	
6. [77] 2016 "IJCSNS"	EMD+PHA (Potential based Hierarchical Agglomerative Clustering Method)		Accuracy 98.84% Specificity 98.58% Sensitivity 100% **Limitation**: Requires testing on other existing datasets; need to check scope of enhancement with larger dataset.	CHB-MIT

III.IV Miscellaneous Techniques/Methods

Some other techniques such as Higher Order Spectrum Analysis (HOS), Recurrence Quantification Analysis (RQA), Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), etc. have also been proposed by researchers and further covered in this section.

N. B. Karayiannis et al. [78] proposed neonatal epileptic seizure identification for short segments of EEG signal using Quantum Neural Network (QNN) and Feed forward neural network (FFNN). Training set accuracy with FFNN for seizure and non-seizure classification is 80.75% and 85.05%; QNN gives accuracy of 81.46% and 84.47%; Testing set classification accuracy (with FFNN) for seizure and non-seizure is 79.39% and 83.84%; with QNN accuracies are 79.82% and 83.56%, respectively.

Alex Van Esbroeck et al. [79] used multi-task learning approach to address the issue of variation in inter-patient and intra-patient seizure morphology and to improve trade-off between latency, sensitivity and FPR. This approach distinguishes seizure and non-seizure events with 83% accuracy and reduces FPR to 70%. Limitation with this approach is that while it reduces FPR, it still does not clear if it is associated with demographic characteristics or patient or the number of seizures.

Soroor Behbahani et al. [80] proposed Heart Rate Variability by localization and lateralization of seizure events that lead to automatic change in functionality of epileptic patients. These effects can be classified using SVM classifier. For classification consistency, LOOCV (Leave one out cross validation) technique is used. Classification accuracy with this approach is 86.74% and 79.41% for right and left hand side focus seizure respectively. Efforts have been made to find relationship between HRV and brain activity so that online seizure detection device can be developed.

Maria Tito et al. [81] demonstrated EEG signal analysis in an offline mode for seizure prediction. In the proposed technique 2-dimensions: window-based minima of correlation sum and dimension have been used, which shows seizure prediction with K-fold cross validation having 91.84% accuracy, 92.31% sensitivity and 91.67% specificity.

In Weiting Chen et al. [17], EEG signal of a new born with normal, statistical and segmentation features all together are fed to Random Forest (RF) classifier and achieves 92.52% correct rate with high F-1 score of 95.26%. This approach outperforms other 7 classifiers such as SVM with linear and RBF kernels, LDA, ANN, ML, LR, DT. Approach shows sensitivity and specificity as 93.78% and 87.50% with 100% feature set values. Results are far better than previous approach of seizure prediction for neonatal.

L. Murali et al. [23] showed that for seizure identification, improved adaptive filter is considered the best tool for pre-processing as compared to notch and wavelet filter. An efficient tool for low power adaptive filter with recurrence quantification analysis (RQA) is proposed. Major benefit of RQA is that it gives better information about small duration non-linear and non-stationary EEG signals. Adaptive FIR filter with parallel interval sample of direct form is used in filter architecture to reduce power consumption issue. For this, ingenious compressor that utilizes verilog HDL and mapped to 65-nm technology node is used. RQA based recurrence plot shows system sensitivity 97.4% and specificity 93.5% and 10% reduction in power consumption.

Luigi Chisci et al. [7] proposed online seizure prediction with Autoregressive modeling. Least square parameter estimator and SVM (for binary classification) distinguish ictal, pre-ictal and inter-ictal states for online EEG data series. It has significant role in monitoring/control units. It can also monitor the changes when resistant-drug is given to epileptic patient. Method shows 100% sensitivity, and if regularization is done with Kalman filter based SVM classifier, it significantly reduces false alarm rate.

To reduce medical practitioner's efforts for analyzing long duration EEG recording, automatic epileptic seizure detection system is proposed [82]. This system utilizes multistage non-linear pre-processing filters with diagnostic LAMSTAR (Large Memory Storage and Retrieval Neural Network) Artificial Neural Network (ANN). The proposed technique shows accuracy of 97.2% with miss rate of 1.6% that indicates good performance in terms of automatic epileptic seizure detection.

Amal Feltane et al. [83] propounded the detection of seizure automatically in rats using Laplacian EEG and SVM Classifier with Adaptive Boosting and comparison between two dataset performances. Dataset EEG gives average Sensitivity 91.96%, Specificity 89.36% and Accuracy 90.66%; and with other dataset of Andrzejak et al. shows 100%, 98.44% and 99.22% Sensitivity, Selectivity and Accuracy. Results for two datasets give large variation in performance when tested with other datasets.

Emigdio Z-Flores et al. [84] proposed collaboration of Matching Pursuit algorithm with Holderian regularity based features and basic statistical features to create final input feature matrix. Forest Algorithm classifies epileptic and non-epileptic condition with perfect accuracy in most of the cases and 97.6% in difficult cases. Above mentioned method can be used for online seizure detection and diagnosis.

Umut Orhan et al. [85] presented a new approach to extract features using Probability Distribution based Equal Frequency Discretization (EFD). As per the number of data points in each interval, probability densities are calculated. For classes: epileptic seizure and non-epileptic seizure detection, two probability density functions are defined and polynomial curve fitting is used to calculate mean square error (MSE). For these functions, classification accuracy achieved is 96.72% and with MLPNN, the classification accuracy achieved is 99.23%. Proposed method shows that non-linear techniques can easily classify epileptic seizures.

In S. Divya et al. [86], EEG signal analysis with ELM (Extreme Learning Machine) classifier has been proposed with EMD based features such as Variance, Skewness and Kurtosis to discriminate different classes such as ictal and healthy; ictal and inter-ictal; seizure and non-seizure; healthy, seizure and ictal. Proposed method shows accuracy and sensitivity 100% for class ictal and inter-ictal; seizure and non-seizure; ictal and healthy; healthy, ictal and inter-ictal. This method's performance should be checked with larger EEG dataset.

K.A. Abuhasel et al. [87] proposed a collaboration of techniques: Particle Swarm Optimization and integrated Neural Network with fuzzy membership function to get optimized parameter of training. Proposed method improves accuracy by updating weights of NN utilizing Fuzzy membership function. Experimental results for classifying class (Z-S) with accuracy is 99.5% where optimal parameter α, β are 0.1; for class (ZNF-S) is 97.73% for parameter α, β are 0.1 or 0.2 and for class (ZNFO-S) is 97.64% where α = 0.1 and β is 0.1 or 0.2.

Ashwani Kumar Tiwari et al. [88] proposed EEG signal analysis based on scale invariant feature transform, localization of key points and Linear Binary pattern method for computation of key-point and histogram feature. Extracted features are classified using SVM classifier for seizure, non-seizure and normal events. With the proposed technique classification accuracy of normal-epilepsy (ZO-S) class is 100%, seizure free and epilepsy (NF-S) class is 99.45%, Normal-seizure free and epilepsy (ZO-NF-S) class is 98.80% and Non seizure and epilepsy (ZONF-S) class is 99.31%. Method shows better performance over other existing methods for different class's classification.

Milica Miloševic et al. [89] described differentiated motor seizure to normal nocturnal events in children using accelerometry signals. Features are selected based on filter mRMR and LS-SVM methods in sequence matters to reduce the feature set that diminishes complication and computation cost. LS-SVM method is used in both forward and backward search mode to select best feature set. Performance analysis measure for (tonic-clonic) seizure gives 100% sensitivity and high False Detection Rate as 10.5 h^{-1}. Limitation with this method is that features selected are optimal for ACM measure set-up for the selected population only.

M. Bedeeuzzaman et al. [90], [91] show that the properties of normal EEG are different from statistical properties. To distinguish ictal, inter-ictal and normal conditions, Inter Quartile Range (IQR), a median based measure of statistical diffusion as feature is used with linear classifier. Due to absence of any transform, direct features such as maximum, minimum and SD are fed to the classifier that reduces system complexity and provides 100% classification accuracy [90]. Pre-ictal and inter-ictal EEG recording to find evidence for changes from pre-ictal to seizure conditions has been proposed. Both are differentiated based on the characteristics for this MAD and IQR features of signal, and extracted and classified using Linear classifier showing 100% and zero FPR in case of a 12-patient recording [91].

Yueming Wang et al. [92] proposed seizure onset detection for a long term EEG signal with higher FDR and face problem of artifacts due to movements and blinks. For this, state space model based on Cauchy Observation Noise (SSMC) encodes continuous change in epileptic seizure signal and rejects drastic changes of artifacts. For 10 patients, EEG data of 367 hours recording shows 100% sensitivity with 0.08 h^{-1} FDR and 8.10 sec median time delay. Markov model or RNN (Recurrent Neural Network) model can further be used with state model to reduce artifacts of EMG/EOG.

Some methods beside those listed above and their details are mentioned in table 3.

Table 3: Miscellaneous Techniques for Seizure Analysis

S. No., Ref. No., Year, Publication	Technique/Method	Input variables /Parameters/Features	Results/ Limitation/ Future scope	Data set
1. [10] 2014 "Clinical Neurophysiology" Journal Elsevier	IIR Filter **Classifier**: SVM	(1) spectral power of frequency band (2) Relative spectral power	Sensitivity 75.8% & FDR 0.1 h^{-1} **Limitation**: While computational time is less but sensitivity and specificity needs to be improved	Univ. Hospitals of Coimbra, Portugal & Freiburg
2. [11] 2016 "IEEE Journal of Biomed. And Health Info."	PDC (Partial Directed Coherence) + Band Pass Filter **Classifier**: SVM		Proposed method gives 67.77% selectivity, 91.44% sensitivity, 99.34% specificity, 98.3% correct rate and 95.39% average detection rate that makes the approach suitable for seizure interval detection. **Limitation**: It is difficult to identify small duration seizure interval accurately by proposed technique. Additionally, the data length of ictal period is significantly less than those of inter-ictal period, as a result of this the average selectivity is naturally lower as compared to average specificity.	Jiaotong University
3. [12] 2015 "Circuits Sys. Signal Process"	RQA (Recurrent Quantification Analysis) + Notch Filter, Wavelet Filter (db8), Adaptive Filter	RQA parameter is based on the measure of diagonal and vertical lines. Diagonal line measures include determinism, average diagonal line length and entropy. Vertical line measures include laminarity and trapping time.	With adaptive filter sensitivity 97.4% and specificity 93.5% is achieved and leakage power is reduced to 10%. **Limitation**: To reduce leakage power& design complicacy, no. of transistors are increased that will increase resistance.	CHB-MIT dataset
4. [16] 1988 "Electroencephalography and clinical neurophysiology"	Matching pursuit Algorithm	Localization	Matching Pursuit algorithm is a valuable tool for continuous seizure analysis. But it is limited to a single channel sequential analysis. It has the advantage of decomposing and displaying signals that are changing rapidly and frequently.	
5. [20] 2005 "Expert System With Application" Journal Elsevier	Lyapunov Exponents based feature extraction **Classifier:** Recurrent Neural Network	(1) Mean of absolute value (2) Max. of absolute values (3)Avg. Power (4)Standard Deviation	Classification performance with RNN and MLPNN are presented for health, seizure free epileptic zone and epileptic seizure conditions which are classified with accuracy of 97.38%, 96.88% and 96.13% with RNN and 92.25%, 91.13% and 90.63% for MLPNN and shows better performance of RNN for these cases.	Andrzejak et al.
6. [22] 2011 "Biomedical Engineering online"	HMM (Hidden Markov model)		Detection of chronic seizures is achieved with: Mean sensitivity: 95.7% Mean specificity: 98.9% Optimality index: 0.995	
7. [25] 2007 "J Med System" journal Springer	Fast ICA + ANN		In Fast ICA method using Kurtosis feature, independent components are extracted one after the other. With this approach, Sensitivity and Specificity achieved as: 98% and 90.5% **Limitation**: Since the time series analysis of EEG signals is unsatisfactory, hence requires expert clinicians to evaluate which is still not used in clinical studies.	
8. [27] 2016 "Comput. Methods in	Convolution + CNN	Incorporate geometry and texture information	Accuracy: 78.33%. **Limitation:** Accuracy is very less	Dataset from EMU for advanced

Biomechanics and Biomed. Engg. : Imaging & Visualization"				epilepsy diagnostics
9. [29] 2007 "Information Sciences" journal Elsevier	Brain Computer Interface System include high order statistics based on bi-spectrum+ LDA, SVM, NN comparison	1) Four coeff. of AR 2) Four features related to PSD 3) Four features related to 3rd order statistics	Implementation of Brain computer interfacing device is required for seizure detection for actual performance evaluation.	BCI
10. [30] 2012 "Medical & Biological Engg. & Computing" Springer	Multi Resolution Analysis & Wavelet Variance **Classifier**: 1-NN and SVM		Classification of different tasks based on Bonn Univ. dataset gives 100% accuracy and 99% for Freiburg Univ. dataset. **Limitation:** MRA has a high dimensionality of extracted features. Normally, a feature selection procedure is required in order to avoid an over-fitting problem in the classification.	Two EEG databases from Bonn Univ. and University of Freiburg are used
11. [33] 2009 "Neural networks" Journal Elsevier	CSP filter + Linear Discriminate Analysis (LDA)	Features: Activity, Mobility and Complexity	1) Time domain parameters are compared with parameters which are commonly used in logarithmic band power estimates. 2) With change in frequency of the signals, transition between calibration and feedback is calculated for some subjects.	
12. [93] 2002 "Med. Biol. Eng. Comput."	MDPE (Multi-dimension Probability Evolution)	Auto-correlation, variance, Power Spectrum and non-linear parameter with MDPE	Linear and non-linear parameter (variance and MDPE) are suitable for seizure classification. Although MDPE produce few false positive alarms but no firm evidence that suggest MDPE or any other non-linear statistic considered, outperforms variance-based methods at identifying seizures.	"National Hospital for Neurology and Neurosurgery", London
13. [94] 2006 "annOper Res" Journal Springer	Optimization based mining techniques **Classifier**: SVM		Optimization based data mining techniques are used to classify brain's position. Brain condition (normal and abnormal) is judged by statistical cross validation and SVM classifier. In future, feature reduction and multi class classifiers can be used for localization of epileptogenic zone.	
14. [95] 2006 "Clinical Neurophysiology" Journal Elsevier	ReliefF method + Back Propagation Neural Network		Avg. seizure and non-seizure identification rates are 91% and 95%, an avg.FRR (false rejection rate) and detection rate is 95% and 93% with a false seizure detection rate of 1.17 h^{-1}.	North Hospital of Amiens
15. [96] 2008 "Signal Processing" Journal Elsevier	Linear Time Varying Autoregressive (TVAR) process for parametric representation for 2nd order system	Coefficients of the Fourier–Bessel (FB) series	To diagnose clinical neurophysiology conditions, parametric representation of EEG signal presented for quantitative study.	
16. [97] 2009 " Clinical Neurophysiology" Elsevier	Burg Maximum Entropy Auto Regression Model	Oscillation Frequency, Regularity and Amplitude	Auto regression model based parameters converted as seizure indicator are used for seizure indication that identifies temporal and spatial consistency for seizure detection which is a helpful tool for neurologist. **Future scope:** Seizure detection is delayed by 30 sec. because of algorithm nature (namely, ordered-statistic filter) and with future improvements that overcome the timeliness of detection; the method has been used for seizure warning in real-time applications.	
17. [98] 2009 "Annals of Biomed. Engg."	Probability Estimation Method	(1) Relative power (2) Bounded variation (3) Mean of avg. cross correlation (4) Relative Bounded variation (5) Relative Derivative (6) Relative Bounded variation (7) Relative mean of avg. cross correlation (8) Relative avg. amp. (9) Relative scale energy (10) coefficient of	Scalp EEG seizure detection by probability estimation based features for recording of 525 hrs, having 88 seizure cases in 21 subjects shows 0.79 Sensitivity, 0.62 h^{-1} FDR and 21.3 sec. median detection delay for 10 K-fold cross validation testing performance and detector based alternate feature combination gives 0.81 sensitivity, 0.60 h^{-1} FPR and 16.9 sec median detection delay. **Limitation**: For reliable performance, method requires large amount of human scalp data and feature list comparison with analyzed feature.	Vincent's Hospital Melbourne

		variation of amplitude		
18. [99] 2012 "J Med Syst" Journal Springer	HOS (High Order Spectra) + PCA + 8 classifier used as ANN, MLP, RBF Network, RF, Rotation Forest, Logistic Regression, Model Trees, Simple Logistic Regression and Bagging	10 cross fold validation classification with 15 features extracted reduced to 8 with PCA	15 High order statistical features extracted using PCA shows nonlinearity and high dimensionality of epileptic signals. Eight classifiers are used for performance analysis in terms of true positive rate (TP) and area under curve (AUC) of receiver operating characteristics (ROC). Logistic Regression model achieves highest 97.5% TP for pre-ictal condition and average 96.8% TP with PCA variance percentage selected at 100% shows 99.5% AUC. **Limitation:** PCA converts the data to a new projection space which do not rank the original features in order of their effectiveness for achieving discrimination between the classes.	
19. [100] 2014 "Journal of Experimental & Theoretical Artificial Intelligent" Taylor &Fransis	HRV + Multilayer Perceptron NN with five training algorithm used		**Generalized** **Partial** **Accuracy** 88.33% 84.72% **Sensitivity** 88.66% 83.33% **Specificity** 90% 86.11% The proposed methodology can only be an additional evaluation technique and will not replace any physician. Although classifiers show good performance, there is considerable degradation of performance in various types of epileptic seizures. This is probably due to the patients having different types of epilepsy and the networks may not have ample generalization capability. This indicates that seizure detection, prediction and classification with neural networks need a customized network that is specific for each patient.	Freiburg Germany univ. hospital and the Coimbra, Portugal Univ. Hospital
20. [101] 2014 "Neurocomputing " Journal Elsevier	Different Transform Techniques : DCT, DCT-DWT, SVD **Classifier:** LS-SVM		Measure of seizure as: Average Sensitivity 91.36% (average result of all kernels and lobes) **Limitation:** Computational time is high	*University Hospital of Freiburg, Germany*
21. [102] 2015 "Theory and application of applied electromagnetics, Lect. notes " Springer	Rank Test (Wilcoxon Test and Ansari Bradley Test) for feature selection + Gaussian Mixture Model (GMM)	**Temporal domain feature**: Entropy, Mean, Harmonic Mean, Range, IQR, MAD, Moment, Skewness, Kurtosis, Percentile, Gradient. **Time spectral feature:** Wavelet Transform **Spectral domain feature**: Wavelet Energy, Pseudo Spectrum estimate, Fast approximate Entropy	Accuracy : 86.93% Sensitivity: 86.26% Specificity: 87.58% **Limitation**: Needs improvement in performance.	CHB–MIT dataset
22. [103] 2015 "IEEE *Trans on Biomed. Engg*."	Rational Discrete sTFT + Naive Bayes, Logistic Regression, Support Vector Machine (SVM), *K*-NN and MLP architectures	Absolute mean, Absolute median, Absolute SD, Absolute max. value of coefficient, Absolute min. value of coeff.	Proposed adaptive and localized time frequency representation by rational functions. Features are extracted using rational discrete short time fourier transform and classified by multilayer perceptron classifier. Result for class (E-A) shows 99.8%, class (E-B) 99.3%, class (E-C) 98.5%, class (E-D) 94.9% and class (E - A,B,C,D) shows 98.1% classification accuracy. **Limitation:** Not applied on large dataset and higher frequency range >50 Hz.	Univ. of Bonn
23. [104] 2015 "Inter. journal of computing ", vol. 14 no. 1	Maximal Short-Term Lyapunov Exponent + ICA		Specificity : 99.7% Sensitivity : 90.6% Accuracy : 99.6% for two classes (non-epileptic and epileptic)	Andrzejak et al. and Bonn Univ. dataset
24. [105] 2015 "Theory and application of applied electromagnetics, Lect.	Rank Test (Wilcoxon Test and Ansari Bradley Test) for feature selection + Gaussian Mixture	**Temporal domain feature**: Entropy, Mean, Harmonic Mean, Range, IQR, MAD, Moment, Skewness, Kurtosis,	Accuracy: 86.93% Sensitivity: 86.26% Specificity: 87.58%	CHB–MIT dataset

notes " Springer	Model (GMM)	Percentile, Gradient. **Time spectral feature**: Wavelet Transform **Spectral domain feature**: Wavelet Energy, Pseudo Spectrum estimate, Fast approximate Entropy		
25. [106] 2016 BMC Med. info. and decision making.	Context Learning Method		Context model to extract hidden inherent feature and temporal information in EEG with steps segmentation, dictionary learning and sequence translation. Error rate 22.93% **Limitation:** 1) Curse of dimensionality 2) Method is fast if training model exists in EEG dictionary 3) Still error rates are not at the least level.	CHB-MIT
26. [107] 2016 "Brain Informatics" Journal Springer	Optimum Allocation Sampling Technique (OAT) + Logistic Model Trees (LMT), Multinomial Logistic Regression (MLR), with a Ridge Estimator and SVM classifier’s	Mean, Median, Mode, Standard Deviation, First Quartile, third quartile , inter-quartile range , Skewness, Kurtosis, min., and max.	OAT with SVM shows very poor accuracy as 36% and with MLR show 82.67% accuracy.	Andrzejak et al.
27. [108] 2016 "Metrology and Measurement system"	Adaptive Directional Time-Frequency Distribution	Instantaneous frequency and amplitude features as: Mean, Variance and Kurtosis are obtained	Signal having rhythmic and spikes those are difficult to analyze by t-f technique. It requires two energy distributions: one along time axis for rhythmic activity and the other along frequency axis that covers spike energy distribution. To improve resolution adaptive optimization of t-f kernel is required at each point but it will increase computation. **Accuracy** 97.5% **Sensitivity** 99.0% **Specificity** 96.0%	
28. [109] 2016 "IEEE Trans. of Biomed. And Health Info."			Method used for identifying artifacts. Mainly two types of artifacts are considered: 1) Physiological artifacts that are event related; are classified based on clustering algorithm. 2) Non biological artifacts that are identified using electrode scalp impedance information. Artifacts identification and removal with 83.92% accuracy. Accuracy is increased if feature reduction and classification approach is included with preprocessing.	
29. [110] 2016 "IEEE Trans. on Biomedical circuits and systems "	Non-linear Support Vector Machine		SoC is verified with rapid eye blink tests that indicate 95.1% sensitivity and false alarm/hour is 0.27. It consumes energy of 1.83microJ/classification. **Limitation**: Sensitivity is less as compared to other existing methods.	Boston-MIT children hospital EEG data set

Next, we review some other works that proposed hardware implements for wearable device and their performance statistics.

Peng Li et al. [111] proposed Sample and Distribution entropy methods for more precise and timely identification of inter-ictal, ictal and normal conditions for short span EEG signals (5 seconds). Sample entropy method is more sensitive to normal and epilepsy (inter-ictal and ictal) EEG events while Distribution entropy method along with normal and epileptic events successfully identify the inter-ictal and ictal condition of epilepsy. Success rate measured by covered area under the curve for normal and inter-ictal epilepsy is 0.97; normal and ictal is 0.96; while with distribution entropy ictal and inter-ictal is 0.85. The success rate shows that this approach can be implemented for real time seizure detection for portable amplifiers.

M. Anil Kumar et al. [36] demonstrated a wearable device for epileptic patient which is simple, cheap, light weight and portable. With this device, patient’s body parameter such as blood pressure, temperature, heartbeat rate etc. can be monitored and if any drastic change is observed, it sends an alarm for immediate intervention. This system can be augmented by adding GPS system to have an eye on patient parameters along with location for timely action in case of any emergency.

Chen Zhang et al. [112] propounded a hardware design based on area and energy efficient closed loop machine learning system, for seizure detection and termination. For long term patient monitoring with limited training set, support vector machine classifier provides relevancy between features such as power, area, latency and specificity. To obtain high sensitivity and specificity, Dual-detector architecture which involves two area-efficient linear support vector machine classifiers along with a weight-and-average algorithm provides sensitivity of 95.1% and specificity as 96.2% and a small latency of 1 sec. For a seizure length of 4.07 sec, it provides seizure onset and termination detection delay of 2.98 sec and 3.82 sec., respectively. While MLPNN shows excellent classification accuracy, there is difficulty in building effective NN topology due to non-reproducibility and complex hardware implementation that makes it impractical. As a solution, SVM may be most suitable for binary classification of epileptic seizure onset detection.

IV. DISCUSSION

Epilepsy seizure detection has been an active area of research for decades. Statistical data has been widely used to arrive at prominent features for classifying a seizure condition. First attempts at classification were visual inspection based which could not handle complexity and non-linearity of the data and the results were pretty coarse. To reduce data complexity to manageable levels, researchers turned to dimensionality reduction techniques such as PCA, ICA and LDA etc. These provided better results than visual inspection; however these could not provide a deeper look into the seizure conditions.

Time-Frequency domain techniques such as Fourier Transform along with neural networks or support vector machines based classifiers provided much better results as they generated spectral information. Researchers then tried another method such as wavelet-based for better accuracy and it paid off. Researchers combined several techniques such as auto regression, neural networks and wavelets to generate viable online classification and analysis with higher accuracies of almost 100%. However training time and computational complexity posed two serious issues left to be tackled.

To deal with non-linear and non-stationary real time signals, researchers turned to Hilbert-Huang transformation which used EMD to get IMFs. The HHT when used in conjunction with ANNs and SVMs provided faster convergence and very high accuracy.

Lastly, we looked at some scattered attempts e.g. Quantum Neural Networks, Largest Lyapunov Exponent, Recurrent Neural Networks, Particle Swarm Optimization etc. which tried to improve on the speed and accuracy for seizure analysis and classification.

We noticed that there have always been issues with all the algorithms and techniques such as speed of convergence, computational complexity or viability to real world scenario and/or handling non-linearity and non-stationary nature of EEG. As and when new and better algorithms surfaced, researchers have tried to apply them for better analysis and classification of epilepsy seizure. The crux of the matter is that a method that has good performance measure is a pre-requisite for online prediction of seizure and identification of seizure in a small time for timely diagnosis. All these techniques will help health care professionals in building an automated and fast detection mechanism for seizures with only EEG as input. Considerable time saved in evaluating an EEG signal could lead to starting a treatment earlier, benefitting the patient.

V. CONCLUSION

Different epileptic seizure detection techniques proposed so far, e.g. visual analysis, automatic epileptic seizure detection techniques, brain computer interfacing devices for online EEG signal analysis and its on-chip hardware implementation have been discussed and results are shown in above tables. Authors have proposed cheap, rugged and simple wearable device that incorporates GPS system for epileptic seizure detection but these techniques are limited in terms of detecting seizure occurrence with superior performance only a few minutes before its occurrence.

Epilepsy can’t be cured but seizures can be controlled with meditation, diet or surgery in some individuals. There is dearth of devices that can detect seizure hours ago or at least minutes ago so that timely and proper diagnosis can be done to avert mishap. Although anti-epileptic drugs are available which are really cheap (at the cost of US $ 5 per year, as per WHO report) [3], still there exist treatment gap because 80% of the epileptic cases are noticed in middle and low income countries and three fourth of the poor strata people do not get timely treatment when needed. More focused research is required to invent affordable, simple and portable device that will timely indicate the situation and medicine availability to protect more human lives. In future, we would like to propose a device based on stable reinforcement learning (RL) [21] to detect seizures.

Compliance with ethical standards
Conflict of Interest: The authors declare that they have no conflict of interest.

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