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SPECIAL SECTION ON NEW TRENDS IN BRAIN SIGNAL PROCESSING AND ANALYSIS

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Focal and Non-Focal Epilepsy Localization: A Review

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ABSTRACT The focal and non-focal epilepsy is seen to be a chronic neurological brain disorder, which has affected ≈ 60 million people in the world. Hence, an early detection of the focal epileptic seizures can be carried out using the EEG signals, which act as a helpful tool for early diagnosis of epilepsy. Several EEG-based approaches have been proposed and developed to understand the underlying characteristics of the epileptic seizures. Despite the fact that the early results were positive, the proposed techniques cannot generate reproducible results and lack a statistical validation, which has led to doubts regarding the presence of the pre-ictal state. Various methodical and algorithmic studies have indicated that the transition to an ictal state is not a random process, and the build-up can lead to epileptic seizures. This study reviews many recently-proposed algorithms for detecting the focal epileptic seizures. Generally, the techniques developed for detecting the epileptic seizures were based on tensors, entropy, empirical mode decomposition, wavelet transform and dynamic analysis. The existing algorithms were compared and the need for implementing a practical and reliable new algorithm is highlighted. The research regarding the epileptic seizure detection research is more focused on the development of precise and non-invasive techniques for rapid and reliable diagnosis. Finally, the researchers noted that all the methods that were developed for epileptic seizure detection lacks standardization, which hinders the homogeneous comparison of the detector performance.

INDEX TERMS Focal epilepsy, non-focal epilepsy, time and frequency domain features, nonlinear features, machine learning algorithms, EEG signal analysis.

I. INTRODUCTION

Epilepsy is described as the momentary occurrence of symptoms as well as signs due to irregular synchronous or excessive neuronal activities in the human brain [1]. Furthermore, epilepsy is also defined as the long-term predisposition of the human brain to produce epileptic seizures, which can lead to psychological, cognitive, neurobiological or social consequences [1]. The patients are said to suffer from epilepsy if they encounter any one of these following conditions: (i) A minimum of 2 unprovoked (or reflex) seizures which occur at least 24 h apart; (ii) An unprovoked (or reflex) seizure, with a similar seizure recurrence risk (≥60%) after the reflexed seizures in the next 10 years; and (iii) The interpretation of the epilepsy disorder [2].

Several involuntary body movements, involving the entire body or some body parts can be caused by epilepsy. These episodes are usually accompanied by a loss of bladder or bowel control functions. The epileptic seizures happen due to extreme or abnormal electrical charge disturbances within the different parts of the brain. The seizures also vary from a momentary attention lapse to prolonged spasms [3]. Partial or focal epileptic seizures primarily affect one hemisphere of the brain. The human brain comprises of 2 hemispheres, with 4 lobes in every hemisphere, i.e., frontal, partial, temporal and the occipital lobes. Focal epilepsy can affect either the complete hemisphere or some lobes in the hemisphere. The non-focal signals can be detected from the brain hemispheres which have not been affected by the epileptic seizures [3]–[6].

Epilepsy has led to a massive burden on the global medical system, while the gap between the disease occurrence and treatment remains unpredictably large. In their report, the World Health Organisation (WHO) stated that epilepsy is a very common neurological syndrome, affecting $\geq$50 million people, globally. Around 80% of the epileptic patients are seen to live in the low or the middle-income countries [7]. Despite the development and availability of many novel antiepileptic medications, around 33% of the affected people still suffer from regular seizures. Furthermore, even after the control of the epileptic seizures, the unpredictable and stochastic nature of these seizures can prove to be life-threatening [8].

The medical treatment is significantly improved if the clinical epileptic seizures are easily detected. This information is used for maintaining accurate seizure-related dairies, which further help in providing treatment during the higher seizure susceptibility. This ability to precisely and rapidly detect the epileptic seizures can help in providing treatments for the progressing seizures. Also, the detection of the seizures before their occurrence could be very advantageous [9].

The EEG signals or the electrophysiological nerve activities in the brain have to be acquired for diagnosing and localising the epileptic seizures clinically. These EEG signals can provide a lot of useful information regarding the position and the markers of the disease. These signals also provide data regarding the neurological conditions, activities, and the mental inadequacy [10]. Rhythmic sinusoidal activities are determined from the EEG signals. For analysing the EEG signals, 5 frequency bands are normally used, i.e., Delta (up to 4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–26 Hz), and Gamma (26–100 Hz) [11]. The EEG signals in the epileptic patients display 2 abnormal activities, 1) Ictal – which occurs during the epileptic seizures; and 2) Interictal or seizure-free activity occurring between the 2 epileptic seizure episodes. The ictal EEG signals are seen to be continuous or uninterrupted waveforms having sharp and spiky wave complexes. The interictal EEG signals are seen to be temporary waveforms which exhibit spikes, spiky or sharp waves [12]. In a few of the epilepsy patients, the doctors have to acquire the EEG signals from the deep brain structures or from the surface of the brain. The intracranial signals are recorded for determining the regions of the brain where the epileptic seizures are initiated. These signals also help in understanding if the patients can be benefited from the neurosurgical re-sectioning of the brain components. Many neurologists stated that these signals disclose the intriguing dynamics occurring in the brain during the acute epileptic seizures and seizure-free intervals. Hence, these intracranial recordings can be effectively applied for the nonlinear signal analysis. Usually, the doctors rely on the identification of the interictal (seizure-free) EEG signals for predicting the onset of the disease, since the ictal signals are very rare. Hence, a longer duration of the EEG signals is required for visual monitoring and analysis, for localising the normal, ictal and the interictal episodes in the patients [13].

The univariate nonlinear analysis can estimate the features like the predictability, entropy or the dimensionality of the individual dynamics data derived from the input signals. Furthermore, these signals are used for measuring and analysing the bivariate nonlinear measures for detecting the interactions between the different dynamics. The features that are selected and extracted from the EEG signal can be evaluated based on their time-domain [14]–[17] or frequency-domain characteristic features [18], [19], joint time-frequency distribution [20]–[23], chaotic [24]–[26], or their Empirical Mode Decomposition (EMD) characteristics [27], [28]. In many studies, the feature combination is carried out for increasing the accuracy and the general performance of the whole system [29].

The EEG wave morphology noted between the focal or non-focal epileptic seizures is similar, which makes it difficult to visually distinguish between them [30]. Hence, machine learning algorithms are used for automating the detection and localisation techniques, as they provide accurate and precise EEG signal interpretation. Also, researchers developed hybrid techniques for improving the detection accuracy. These techniques combined the feature extraction processes and the machine learning algorithms. In one study, the researchers combined the fuzzy logic and Genetic Algorithm (GA) for classifying the focal and non-focal epileptic seizures [31]. Furthermore, researchers also developed a hybrid computational GA-based technique for detecting the features and the electrode sites, which helped in predicting the optimum seizures [32]. Besides, many machine learning algorithms were also combined [33]–[38].

In this study, the authors present an analysis on the non-focal and the focal epilepsy detection processes. They analysed the contributions made by the advanced monitoring and closed-loop epilepsy detection methods, which are used in hospitals and patient care centres. This paper is prepared in following way. Section 2 provides the focal and non-focal detection methods. Section 3 describes the classification algorithms. Section 4 illustrates the machine learning regularisation. The main observations are discussed in section 5. While, the paper conclusion is presented in section 6.

A. EPILEPTIC SEIZURES CLASSIFICATION

The classification of the various epileptic disorders has been very controversial and debatable for many years. In 1981, the International League Against Epilepsy (ILAE), the main commission that classifies and defines the various epilepsy-related terminologies, proposed the International Classification of the epileptic seizures [39]. The seizures classification are shown in Figure 1 [40]. Later, in 2010, the ILAE proposed a few changes in the nomenclature and the approach which is involved in the flexible multidimensional framework. However, the details of this new class are still evolving based on the results provided by the various studies [41].

One suggestion involved the replacement of the term ''partial'' by ''focal'' for the seizures which originated in

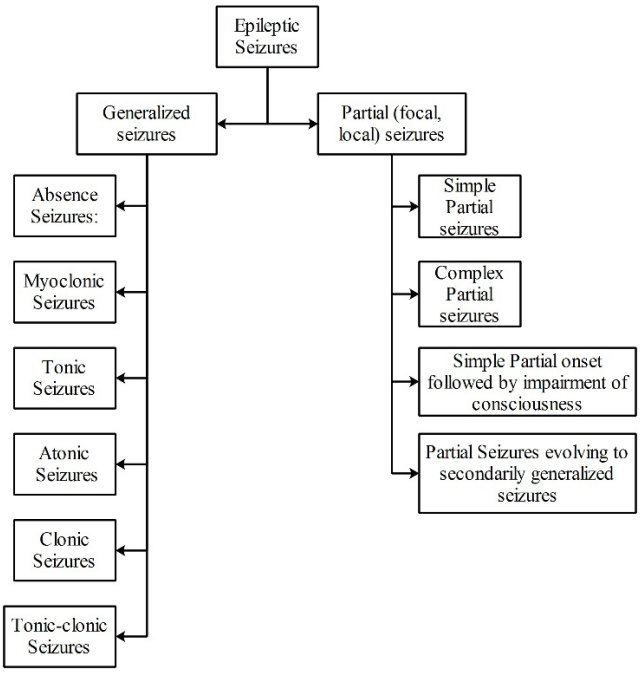

FIGURE 1. The seizure classification.

the neuronal networks from one of the cerebral hemispheres. Thereafter, the focal seizures are not classified as simple or complex, based on the presumed changes in the consciousness levels. Thus, the symptoms and signs of the focal seizures must be properly diagnosed, even if the individual displays bilateral motor manifestations. The generalised seizures originate within the bilaterally-distributed cortical or the cortical-subcortical networks, which rapidly become involved without any focal point, and can also engage the structures of the cortical and the subcortical, but not the whole cortex. Though the different syndromes include the generalised or the focal epilepsy seizure types, the researchers must determine whether the epilepsy results due to focal pathology, since they include many surgical options. Epilepsy is also categorised as metabolic or structural and could occur due to infectious or immune causes. Owing to the different complex definitions and systems involved in epilepsy, an appropriate classification scheme must be developed which provides advanced knowledge about the field, but can be easily understood by the common people or laymen [42], [43].

B. EEG SIGNAL CHARACTERISTICS

EEG signals help in determining the epilepsy seizure types and syndromes in the patients, which further helps in predicting the prognosis of the disease and use of proper antiepileptic medication. The EEG results assist in the multi-axial epilepsy diagnosis, with regards to whether the epilepsy seizures are idiopathic or symptomatic, focal or generalised, or a component of the particular epilepsy syndrome [44]. The focal and the generalised seizures show overlapping clinical and electrographic manifestations, while the uni-hemispheric epilepsies can blur these boundaries further. On the other hand, the conceptual classification of the focal and the generalised seizures is very clinically useful and valid. This classification, along with the descriptions provided by the patients, further helps the clinician to diagnose the type of seizure. If the history is not clear (i.e., un-witnessed ''blackouts'' or a brief loss of awareness), the EEG signals can help in distinguishing between the complex partial seizures with focal IED and no seizures with a generalised IED [45]. The focal and the non-focal EEG signals (derived from the Bern-Barcelona EEG database [46]) have been described in Figure 2.

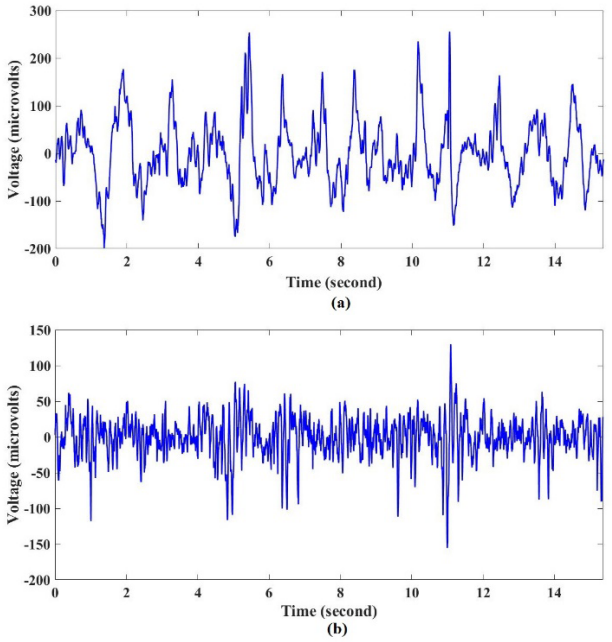

FIGURE 2. The EEG signal for (a) Focal Epilepsy (b) non-Focal Epilepsy.

II. METHODES

A. FOCAL EPILEPSY DETECTION

The focal epilepsy detection systems can detect and differentiate between the existing focal and non-focal seizures and can provide the doctors with the detailed seizure-related data, which helps in epilepsy management. Furthermore, the detection systems provide a rapid treatment process for the early-onset seizures, thereby decreasing the spread of the seizures and arresting their clinical complications. The seizure detection scheme should be able to detect the absence or presence of the existing seizures. A majority of the seizure detection algorithms include 2 major stages: 1) Stage 1 includes appropriate quantifiable features, like the biomarkers or the EEG features, which are assessed from the patient data; 2) Stage 2 applies a threshold or a model-based measure to all the features for determining the presence or the absence of the seizures. This is known as the classification and could involve the use of a threshold value or models which have been derived using the machine learning algorithms [47].

Many studies have applied the bivariate measures for seizure prediction, like the nonlinear interdependence [48], phase synchronisation and the cross-correlation [49]. In one study, when the researchers compared the bivariate and the univariate system performances, with regards to the seizure prediction [50], the bivariate techniques showed a better performance than the univariate measures. Generally, the univariate and the bivariate systems provide different but complementary and very relevant information [51]. Hence, for characterising the preictal stages and achieving a better clinical performance across the different patients, many univariate and bivariate features must be combined for developing proper seizure localisation implements and tools [52].

When all these features are included in a technique, it leads to a compromise between the accuracy and the speed criteria (i.e., more accurate data lowers the speed of the system, and vice-versa). Many feature-based computation processes use the line length method [53], frequency [54] or linear time-frequency analysis (i.e., Wavelet Transformation) [55], Principle Component Analysis (PCA) [56], and a higher-order spectral analysis [57]–[59]. The various classification techniques use the Support Vector Machines (SVM) [60]–[62], Artificial Neural Network (ANN) [63], [64], Fuzzy logic model [65], Markov modelling [66], and the deep learning algorithms [67], [68]. Analysis modelling using the supervised machine learning algorithms can be carried out during the training and the testing stages and includes 3 sub-steps: pre-processing, feature computation, and feature extraction or feature reduction. Every process is a specialised research field and has not been described here [69]. Figure 3 presents the block diagram algorithm for the general focal estimation, which is supported by the supervised machine learning algorithms.

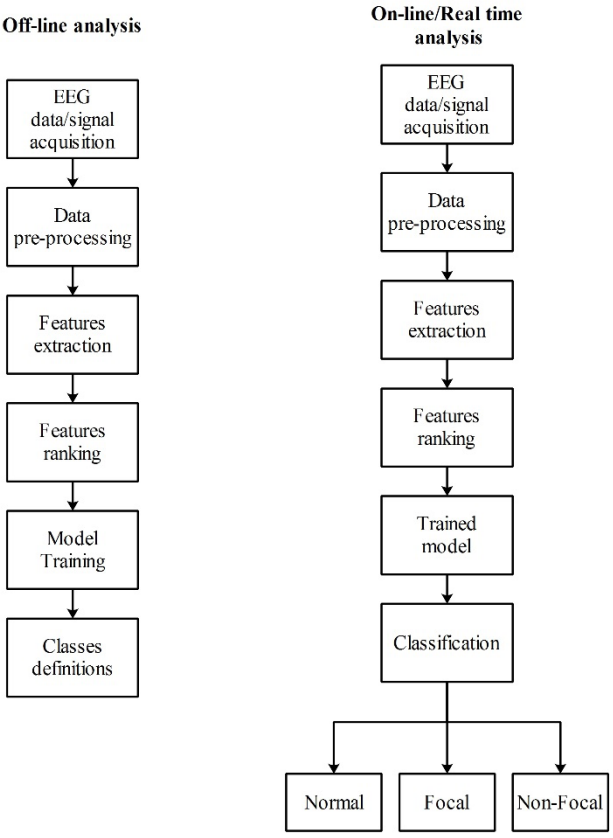

FIGURE 3. The general focal estimation algorithm block diagram.

B. EEG DATABASE AND ACQUISITION PROCESS

The focal and the non-focal epileptic seizure detection studies consider both the scalp and the iEEG recordings. The scalp EEG signals are acquired with the help of surface electrodes that are attached at an equal distance on the scalp; while the iEEG signals are derived by the intracranial electrodes that are placed in the regions having suspected epileptogenicity, which are identified using the structural, clinical or functional data, collected before implantation [70].

The earlier studies used the local databases which were developed using the data from the patients who were evaluated before their epileptic surgeries. However, these studies were restricted to the analysis of the short time period before the seizures, small sample size and few ictal actions. This restricted the probability of evaluating the specificity of algorithm in the interictal epoch. In their study, Eftekhar *et al.* [71] applied the coefficients of nonparametric correlation for Kendall's tau and noted a statistically significant correlation in the sensitivity of the different systems, based on the number of the seizures and the mean capturing time period between the seizures. They stated that long-term recording data, with numerous seizures, was necessary, for enabling the reliable estimation of the algorithm specificity and sensitivity, ideally during future testing [72]. In the past few years, many web-based databases were developed in the University of Freiburg, University of Bonn, and the Boston Children's Hospital. The European Database on Epilepsy [73] is seen to be the biggest existing seizure prediction database, which consists of information for 2500 seizures and 45,000 h of EEG recordings. All this data was acquired from $\geq$250 patients, out of which, 50 underwent iEEG, with $\leq$122 channels that were sampled at a frequency of 250–2500 Hz. Besides the above-mentioned databases comprising of the EEG signals, which were acquired in the epilepsy-monitoring units, many recent studies [74], [75] adopted the data collected by the Neuro Vista ambulatory monitoring system. This system provided continuous iEEG data for many months, however, from very few patients [76]. Cook *et al.* [50] assessed the safety and performance of the seizure advisory system in the 15 Neuro Vista-implanted patients. These long iEEG signal recordings, derived from the naturally-occurring seizures, would prove to be very beneficial for the epilepsy seizure prediction in future.

C. EEG SIGNAL PRE-PROCESSING

The detection and the elimination of the EEG signal artefacts can be a complex and difficult task. However, it is important for the development of good systems for EEG analysis.

A majority of the important physiological artefacts include the ElectroOculoGraphy (EOG) artefacts, muscular activities, respiration, and the body or head movements [77]. Many studies have described techniques for detecting and eliminating the EEG artefacts. However, these described techniques require an individual manual adjustment, or are based on the inflexible and restricting decision criteria, and have proved to be very unsatisfactory [78], [79]. The techniques used for correcting the eye movement artefacts were based on the autoregressive process of subtracting the EOG signals from the EEG [80]. In their study, Maddirala and Shaik [80] proposed a novel algorithm for eliminating the muscle artefacts by applying the Singular Spectrum Analysis (SSA) and the Adaptive Noise Canceler (ANC) for removing the EOG artefacts from the EEG signals. De Vos *et al.* [81] proposed a novel algorithm for removing the respiration-related artefacts by decomposing the EEG signals using the ICA. Furthermore, O'Regan *et al.* [82] proposed a novel algorithm using the support vector machines for eliminating the head movement-related EEG signal artefacts, which were categorised and eliminated as a different class.

D. EEG ANALYSIS APPROACHES

The EGG variations before the seizures can be theoretically sensed for determining the oncoming seizures [83]. The earlier EEG-based techniques used for identifying the focal patterns used to rely on the linear processes for determining the EEG features using a sliding window [84]–[86]. Such models used the nonlinear signal processing techniques for studying the spontaneous formation of the temporal, spatial, and spatiotemporal patterns. In the past few years, automated techniques for EEG analysis have emerged based on the normal brain dynamics. These novel techniques involve the transient and limited synchronisation of the disorganised neuronal activity and display a synchronised and persistent state which can incorporate numerous brain regions during the epileptic seizures [87], [88]. Though the EEG signals provide a large amount of data which can be deduced using automated techniques, the patients find it tedious to constantly wear the EEG electrodes for a long time period. It is also difficult to read the prolonged surface electrode signals owing to increasing impedance. Some patients can develop a few skin abrasions because of their prolonged exposure to the surface electrodes [89]–[91]. Studies describing the various focal epilepsy detection techniques are presented in Table 1.

E. FEATURES SELECTION AND EXTRACTION

Generally, the features are categorised based on their domains: time, frequency, joint time-frequency and nonlinear [85]. These features can be extracted from the derived signals using a single electrode. On the other hand, some features are seen to combine many electrodes, and these have been used in this review. Based on the notations, described earlier [92], [93], $\lambda(t) \in K^T$ refers to the vector which contains the time series from one electrode, T indicates the sample number in λ while $\lambda(t)$ refers to the time derivative. A $\lambda(t)$ feature is represented as x, and the Matrix $X = [x_1, \ldots, x_F]$ comprises all features from all samples, xirefers to the vector with a single feature, and F denotes the number of features.

1) TIME DOMAIN FEATURES

As the EEG signals are seen to be multi-component and non-stationary, the time domain features are not predominantly used in the EEG analysis. However, many techniques have been used for determining the EEG characteristic features which describe the EEG signals, enabling their classification. One such technique used for computing a non-stationary time series like the EEG signals involves considering them as many stationary segments.

a: STATISTICAL FEATURE ANALYSIS

Diykh *et al.* [94] proposed a few statistical analysis techniques for extracting the necessary features from the 1 second EEG epoch, which are described below:

$$\text{Maximum} \quad X_{Max} = Max[x_n] \tag{1}$$

$$\text{Minimum} \quad X_{Min} = \text{Min}[x_n] \tag{2}$$

$$\text{Range} \quad X_{Rang} = X_{Max} - X_{Min} \tag{3}$$

$$\text{Mean} \quad X_{mean} = \frac{1}{n}\sum_{1}^{n} x_i \tag{4}$$

$$\text{Median} \quad X_{me} = \left(\frac{N+1}{2}\right)^{th} \tag{5}$$

$$\text{First Quartile} \quad X_{Q1} = \frac{1}{4\,(N+1)} \tag{6}$$

$$\text{Variation} \quad X_{Var} = \sum_{n=1}^{N}(x_n - X_{mean})\frac{2}{N-1} \tag{7}$$

Standard Deviation

$$X_{SD} = \sqrt{\sum_{1}^{n}(x_n - X_{mean})}\frac{2}{n-1} \tag{8}$$

$$\text{Kurtosis} \quad X_{Ku} = \sum_{n=1}^{N}(x_n - X_{mean})\frac{4}{(N-1)X_{SD}^4} \tag{9}$$

$$\text{Skewness} \quad X_{Ske} = \sum_{n=1}^{N}(x_n - X_{mean})\frac{3}{(N-1)S_{SD}^3} \tag{10}$$

$$\text{Second Quartile } X_{Q2} = \frac{4}{4(N+1)} \tag{11}$$

The EEG data can show a symmetric or a skewed distribution. The symmetric distribution of the time series is measured by the mean and standard deviation, while the skewed distribution uses the median, range and quartile for measuring the centre and spread of the EEG dataset. However, the feature mode, which provides the frequency values, is applied for measuring the location of the time series. The remaining statistical features, like the variation, skewness, minimum, and kurtosis, are also used for determining the vital time series-related data [95], [96].

TABLE 1. Summary of the focal and non-focal epilepsy detection studies.

Author/year	Database	Classifier Type	Extracted Feature	Epoch/ Processing Time	Patients	Findings
Xia et al. (2015) [165]	University Hospital of Freiburg	Bayesian Linear Discriminant Analysis (BLDA)	S-transform with Singular Value Decomposition (SVD) features	820 183.07 (h)	20	The validation of Segment-based and event-based level. Se= 96.40%, Sp= 99.01%, with a FPR= 0.16/h.
Songa and Zhang (2016) [166]	Collected (Invasive EEG recordings)	Extreme Learning Machine (ELM)	Sample entropy	10 30 (m) for each patient.	21	Se=86.75%, Sp=83.80%. Proposed classification framework faster than SVM in training.
Sargolzaei et al. (2015) [153]	Collected	K-means clustering	General Linear Model (GLM) based Sequential Feature Selection (SFS).	Variables (9 to 90 s)	16	Classifier Acc=96.87% The developed approach adopting Functional Connectivity Networks (FCNs) of the EEG scalp recording system in conjunction through graph concept of feature analysis.
Yuan et al. (2012) [167]	University Hospital of Freiburg	Using ELM to train Single hidden Layer Feed forward Network (SLFN)	The fractal intercept derived from fractal geometry	4-s 179.57 (h)	21	The segment-based Se= 91.72%, Sp= 94.89%. For the event-based assessment, Se= 93.85% with a FPR= 0.35/h.
Xie and Krishnan (2013) [168]	University of Bonn University Hospital of Freiburg	k-Nearest Neighbour	Signal representation by using of Wavelet-functional linear model	-	10 21	Classification Acc=100.00 % (database from University of Bonn), and Ac=99.00% (database from University of Freiburg). Capture discriminative random components of EEG.
Rangaprakash (2014) [169]	Collected	K-means clustering	Correlation between Probabilities of Recurrence (CPR)	- 10 (m) for each patient.	16	The nonlinear recurrence plot based phase synchronisation amount for the connectivity study in the brain.
Pathaka et al. (2018) [170]	University Hospital of Freiburg	Area Under the ROC Curve (AUC) for classical Line Length (LL) and Modified Line Length (MLL)	Various features	Variable (2 – 5) for each patient 1 (h) for each patient	21	The finding delay and FPR for LL and MLL are 0.951, 11.903 s, 0.201/h and 0.954, 11.698 s, 0.198/h individually.
Zandi et al. (2010) [171]	Collected data	Threshold	Combined seizure index	63 seizures 75.8 (h)	14	Se=90.50%, false detection rate: 0.51/ h, median detection delay: 7 s
Bhattacharyya et al. (2018) [172]	Bern Barcelona	Least-Squares Support Vector Machine (LS-SVM)	Rhythm separation using empirical wavelet transform	3750 signal pairs. 160 epoch 80 (h)	5	Acc=90.00%, Se=88.00% and Sp=92.00%, for 50 pairs. Ac=82.35%, Se=81.60% and Sp=83.46%, for 750 pairs.
Soleimani et al. (2012) [173]	University Hospital of Freiburg	Neuro-fuzzy	Time and wavelet domain features	10 (s) for each patient	21	Acc= 99.52%, FPR: 0.1417/h
Sriraam and Raghu (2017) [174]	Bern Barcelona	SVM classifier with 10-fold cross validation	26 various features	3750 signal pairs. 20 (s) for each signal pair	5	Acc=92.15%, Se= 94.56%, and Sp=89.74%
Khan et al. (2017) [175]	Data collected from MSSM A subset of the public CHB-MIT	A hybrid of decision tree and k-Nearest Neighbour	Convolutional Neural Networks	Variable (1-28) 135 (m) for each patient Variable (9-42) 30 (m) for each patient	28 22	Se=87.80% and a low FPR= 0.142/h A robust features set can be learned directly from scalp EEG.
Karthick et al. (2018) [162]	Collected from Montreal Neurological Institute and Hospital (MNIH)	SVM	19 various time and frequency features	-	32	The developed scheme could warn the health care crew when a patient is hospitalised for intracerebral EEG
Martinez-del-Rincon et al. (2017) [176]	University of Bonn University Hospital of Freiburg Universitario Carlos Haya (HRUCH) Malaga, Spain	Non-linear SVM	Wavelet decomposition. Bag-of-Words (BOW) feature representation	100 signal 23.6 (s) for each epoch Variable (2-5) for each patient 3693.2 (s) - 112.52 (h)	5 21 5	The mean F1-measure displays a 10% enhancement over the second-best ranked
Niknazar et al. (2013) [177]	University of Bonn	Eastern Cooperative Oncology Group (ECOG)	Time delay, embedding dimension	100 signal 23.6 (s) for each epoch	5	Acc=98.67%
Garcés Correa et al. (2015) [178]	University Hospital of Freiburg	Threshold Wavelet decomposition	Relative power spectrum	89 89 (h)	21	Se=85.39% Long-term iEEG seizures detection
Liu et al. (2012) [179]	Collected data	SVM	The variation coefficients such as relative energy, relative amplitude, coefficient of fluctuation index	509 (h)	21	Se=94.46%, Sp=95.26%, false detection rate: 0.58/h
Deivasigamani et al. (2016) [180]	Bern Barcelona	Adaptive Neuro Fuzzy Inference System (ANFIS)	The using of Dual Tree Complex Wavelet Transform (DT-CWT)	3750 signal pairs. 20 (s) for each signal pair.	5	Acc=99.00%, Se=98.00%, Sp=100.00% The Positive predictive value (PPV) 100%, the Negative Predictive value (NPV) 98.03% Matthews correlation coefficient=98.04%
Chatterjee et al. (2017) [181]	Bern Barcelona	SVM k-Nearest-Neighbour	Multifractal Detrended Fluctuation Analysis (MFDFA)	3750 signal pairs 20 (s) for each signal pair.	5	For SVM Acc=92.18% For k-Nearest-Neighbour Acc=91.68%
Singh and Pachori (2017) [182]	Bern Barcelona	LS-SVM	Discrete Fourier transform (DFT) based filter bank	3750 signal pairs. 20 (s) for each signal pair.	5	Focal Acc= 89.7% Non-Focal Acc=89.52% Provide low computational complexity
Das and Bhuiyan (2016) [164]	Bern Barcelona	KNN city-block distance	EMD-DWT, log-energy entropy	3750 signal pairs/ 2 (s) epoch 80 (h)	5	Acc=89.40% Identifying the epileptogenic zones at fast computational process.
Panda et al. (2010) [183]	Collected	SVM	Wavelet energy, entropy, standard deviation	500 epochs of (100 signals per epoch)	5	Acc=91.20%
Sharma et al. (2017) [184]	Bern Barcelona	LS-SVM with different kernel function	Different entropy based features	3750 signal pairs. 20 (s) for each signal pair.	5	Acc=95.00% The developed scheme can be used to recognise added neural diseases such as: epilepsy, autism, dementia, and alcoholism.
Sharma et al. (2016) [55]	Bern Barcelona	LS-SVM	19 different features from Wavelet based entropy	3750 signal pairs. Variable epoch	5	Acc=94.25%, se=91.95%, Sp=96.56% specificity.
Aarabi and He (2012) [185]	University Hospital of Freiburg	-	Dimension, correlation entropy, noise level, Lempel-Ziv complexity, largest Lyapunov exponent	49 seizures 316 h	11	Se=79.9%, 90.2% with average FPR= 0.17/h and 0.11/h respectively
Sharma et al. (2015) [186]	Bern Barcelona	LS-SVM	EMD with Intrinsic Mode Functions (IMFs)	3750 signal pairs. Different epoch size	5	Acc=87.00%
Bhattacharyya et al. (2017) [187]	Bern Barcelona	LS-SVM	Tuneable-Q Wavelet Transform (TQWT)	3750 signal pairs. 50 epoch 20 (s) for each.	5	Acc=84.67%. Can be used for complexity measure of other multivariate biomedical signals.

TABLE 1. *(Continued.)* **Summary of the focal and non-focal epilepsy detection studies.**

Bedeeuzzaman et al. (2014) [188]	University Hospital of Freiburg	Binary linear classifier	MAD, IQR	1 (m) for each record	21	Se=100%, FPR: 0 (for 12 patients), average prediction time: 51 to 96 m
Arunkumar et al. (2017) [34]	Bern Barcelona	Five classifiers: NBC, RBF, BFDT, KNN, SVM and NNge	Entropy measures	3750 signal pairs. 50 epoch 20 (s) for each	5	Ac= 98.00%, Se=100%, Sp=96.00% Features computation time is 0.054 seconds that support the real time processing
Zhou et al. (2013) [189]	University Hospital of Freiburg	Bayesian Linear Discriminant Analysis (BLDA) classifier	Fluctuation index and lacunarity on wavelet scales	4 s without overlapping	21	Se=96.25%, FPR=0.13/h, mean delay time: 13.8 s
Azami et al. (2017) [190]	Bern Barcelona	Multi scale fuzzy entropy	Refined Composite Multi scale Fuzzy Entropy based on the standard deviation (RCMFEσ) and mean (RCMFEμ)	750 signal	21	The proposed approaches enhance the problem solutions of undefined MSE and RCMSE values for short signals.
Gehlot et al. (2015) [191]	Bern Barcelona	Threshold	EMD	3750 signal pairs. 20 (s) for each	5	The typical mean of Euclidean distances (AMED) and average standard deviation of Euclidean distances (ASED) are calculated from 3-D phase space plan.
Park et al. (2011) [161]	University Hospital of Freiburg	SVM classification using double cross validation	Using of spectral power in nine bands in a 20 s long window of iEEG	interictal (at least 1 h) preictal (30 m preceding a seizure onset)	18	Se=97.50%, with total 80 seizure events and a low FPR= 0.27/h and total FPR= 13.0% over a total of 433.2 interictal hours. High sensitivity as well as specificity are achieved by spectral power linear features from nonlinear classification.
Bajaj et al. (2017) [192]	Bern Barcelona	LS-SVM	Rhythm-based correlation features	750 signals 20 (s) for each	5	Acc=99.20%. Can be appropriate conducive for surgeons to stop focal seizure at early stage
Williamson et al. (2012) [193]	University Hospital of Freiburg	SVM	Eigen spectral features	15 (s)	21	Se=85.5%, false prediction rate: 0.033/h
Rai et al. (2015) [194]	Bern Barcelona	K-means and fuzzy C-means	Ratio of AM Bandwidth (BAM) and FM bandwidth (BFM)	750 signals 20 (s) for each	5	Acc=99.02%
Zhu et al. (2013) [195]	Bern Barcelona	SVM	DPE methodology	50 signals 750 signals	5	Acc=84.00%
Chatterjee et al. (2017) [181]	Bern Barcelona	SVM k-Nearest Neighbour	MFDFA-based feature sets	100 signals 20 (s) for each	5	Acc=92.18% Acc=91.68% Proposed method can analyse a huge EEG recordings datasets that containing of more signals
Wu et al. (2017) [196]	Collected database	RBF-SVM	PCA features selection	-	15	Acc=80.76% and 75.00%

Acc: Accuracy, Se: Sensitivity, Sp: Specificity, h: Hour, m: Minute, s: Second

b: HJORTH TIME DOMAIN DESCRIPTORS

Hjorth [97] characterised the EEG signals based on the interdependence between the EEG values. The researchers proposed a novel technique, based on the concept of deriving the quantifying parameters and using their efficiency for determining their auto-correlation functions. Hjorth introduced the different parameters as the descriptors of graphical characteristic features of the EEG signals, with regards to the slope, amplitude, and the slope spread. These descriptor names, like, ''mobility'', ''activity'' and ''complexity'' are retained; however, the descriptor ''complexity'' is redefined as the ''complexity of first order''. This provides an absolute value of the spread of the slope as the standard deviation per unit time.

c: EEG CROSS-CORRELATION

Correlation is defined as the mathematical technique, which is similar to the convolution process. In correlation, the sequence between the energy of signals can measure the similarity which is known as a cross-correlation technique [98]. If the signal correlates with itself, the resultant sequence is known as the autocorrelation sequence. Consider 2 signal sequences, $x(n)$ and $y(n)$, with a finite energy. Thus, the cross-correlation between these signals is seen as:

$$\hat{R}_{xy}(m) = \begin{cases} \sum_{n=0}^{N-m-1} x_{n+m} y_n & m \geq 0 \\ \hat{R}_{xy}(-m) & m < 0 \end{cases} \quad (12)$$

Wherein; $m = \ldots -2, -1, 0, 1, 2, \ldots$ and is defined as the time shift parameter index or the lag; xy subscript indicates the sequences that are being correlated. The order of the subscript with x preceding y indicates the direction in which one of the sequences gets shifted, with regards to the other. If both the $x(n)$ and $y(n)$ signals consist of a determinate sample number, L, the resultant cross-correlation sequence is seen to consist of $2M - 1$ samples.

d: PRINCIPLE COMPONENT ANALYSIS (PCA)

PCA refers to a statistical technique which is used for transforming the input space into a novel lower dimensional space, while the coordinate system can be swapped using the linear transformation. In the PCA, the axes (or the components) that belong to the novel coordinate system are seen to be the linear combination of the primary axes. Furthermore, the major axis (or the principal component) represents the direction of the maximal variation, noted in the dataset. However, the minor axis, which is orthogonal to the major axis, is seen to characterise the direction of the second biggest deviation in datasets, and so on. Thereafter, in the new re-oriented space, a majority of the data variation is concentrated within the initial few components. As a result, the components which consist of valid information regarding the data variability are reserved, while the other components are disregarded. This reduces the dimensionality without affecting the data accuracy in any way [99]–[101].

The basic PCA technique is theoretically simple. Firstly, the values of the d-dimensional mean vector, i.e., μ and the m × m covariance matrix, R, are estimated for the complete dataset. Thereafter, the Eigenvectors and the Eigenvalues

are figured and arranged according to the decreasing Eigenvalues, i.e., Eigenvectors, g_1 having an Eigenvalue of δ_1, while g_2 has an Eigenvalue of δ_2, etc. Then, the k Eigenvectors are selected, by observing the complete Eigenvector spectrum. Usually, one dimension, which implies the inherent dimensionality of the subspace, controls the ''signal''. Noise is another dimension. Finally, a k × k matrix A, with columns consisting of k Eigenvectors is formed and pre-processed as described earlier [102]:

$$x' = A^T(x - \mu) \tag{13}$$

e: INDEPENDENT COMPONENT ANALYSIS (ICA)

ICA refers to a feature extraction technique that can manipulate the random and multivariate signals into signals with jointly-independent components. This method is used for extracting these independent components from all assorted signals. Furthermore, in this technique, the independence refers to the fact that the data carried by a single component is not inferred from other components. This indicates that the independent quantities with joint probability are acquired as a product of the probability of each component. Assume the presence of c source signals of independent scalar, such that x_i (t), $i = 1, 2, \ldots,$ c wherein, t refers to the time key: $1 \leq$ t $\leq$ T. For the notational convenience, the researchers grouped the c values into vector x(t) and further assumed that this vector has a 0 mean. Based on the independence hypothesis, and the hypothesis of no noise, the researchers described the multivariate density function as [103]–[105]:

$$P(x(t)) = \prod_{i=1}^{c} Px_i(t) \tag{14}$$

Assume that the d-dimensional data vector can be spotted at every instant:

$$y(t) = Ax(t) \tag{15}$$

Wherein; A refers to the $m \times n$ scalar matrix, while $n \geq m$. The ICA recovers the source signals from all detected signals. This equation is used for obtaining the real matrix, W, as follows:

$$z(t) = Wy(t) = WAx(t) \tag{16}$$

In the previous equation, z refers to the value of the source, $x(t)$. The researchers aimed to compute $W = A^{-1}$, however, the value of A or its inverse is not known.

f: LINEAR DISCRIMINANT ANALYSIS (LDA)

The LDA method is used for generating new variables which group the primary predictors. This can be obtained by maximising the differences among the predefined groups, related to the novel variable. Furthermore, the predictor scores are combined for designing the single novel composite variable, i.e., discriminant score. LDA also refers to an excessive data dimension reduction process which can compress the multi-dimensional predictors to form a 1-D line [106]. Finally, the researchers expected that every class displays a normal distribution of the discriminant scores, with the highest probable differences in the mean scores of the classes. Furthermore, the overlapping degree amongst the discriminant score distribution is used for measuring the success of LDA. The discriminant scores are determined using the discriminant function, with the following form [107]:

$$D = w_1Z_1 + w_2Z_2 + w_3Z_3 + \cdots + w_nZ_n \tag{17}$$

As shown in Eq. (17), the discriminant score refers to the weighted linear predictor combination. All weights are calculated for maximising the difference between the mean discriminant class scores. Generally, the predictors with dissimilar class mean values show a larger weight; whereas the predictors with similar class means show small weights.

2) FREQUENCY DOMAIN ANALYSIS

The spectral or frequency domain analysis refers to the description of the details regarding the multiple frequency components involved in signal construction. A Fourier Transform (FT) process is used for computing all signal components. Many researchers developed novel FT-based processes for extracting the EEG features that are used in the parametric and non-parametric techniques for determining the 1D signal in the frequency domain. Many non-linear mechanisms are used for generating the EEG signals. A lot of research has been devoted to developing these non-linear methods [108]. The Power Spectral Density (PSD) technique used to analyse the focal and non-focal EEG signals is described in Figure 4.

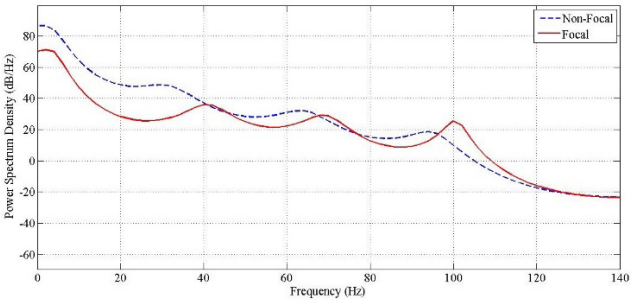

FIGURE 4. The Power Spectral Density for the focal and non-focal EEG signals.

a: NON-PARAMETRIC ANALYSIS TECHNIQUES

Polat and Güne? [109] proposed a novel technique for epileptic identification, wherein they initially computed the autocorrelation between the time sequenced dataset. In Step 2, the power spectrum was estimated by applying FT processes to the autocorrelation sequences. The Welch technique was used for estimating the average value over a period of time, for determining the PSD values. If the available data derived from the signals comprises of sample x(n) wherein n = 1, 2, . . . , N, the periodogram spectra can be estimated as follows:

$$\hat{P}_{PER}(f) = \frac{1}{N}\left|\sum_{n=1}^{N} x(n)e^{-i\omega fn}\right|^2 \tag{18}$$

Here, $\hat{P}_{PER}(f)$ refers to the periodogram power estimation. Based on the Welch frequency estimation technique, the signals can be separated into the overlapping fragments, and each data fragment is windowed, all periodograms are estimated and averaged. $x_l(n), l = 1, \ldots, S$ refers to the data segments, with M as the length of every segment. A 50% overlap is generally selected. Finally, the Welch spectrum is estimated as follows:

$$\hat{P}_w(f) = \frac{1}{S}\sum_{l=1}^{S}\hat{P}_l(f)$$
$$\hat{P}_l(f) = \frac{1}{M}\frac{1}{P}\left|\sum_{n=1}^{M} v(n)\, x_l(n)\, e^{-i\omega fn}\right|^2 \quad (19)$$

Here $\hat{P}_l(f)$ refers to the periodogram estimation of the l_{th} segment, $v(n)$ denotes a data-window, P = average of $v(n)$, i.e., $P = 1/M\sum_{n=1}^{M}|v(n)|^2$; $\hat{P}_w(f)$ refers to the Welch PSD value, M denotes the length of every signal fragment (segment); while S denotes the segment number.

b: PARAMETRIC ANALYSIS TECHNIQUE

The main disadvantage of using the non-parametric technique is the spectral leakage because of the windows. This limitation can be overcome by the model-based power spectrum or the parametric methods. Also, compared to the non-parametric technique, the parametric allows better frequency resolution. In the parametric process, the signal was considered as a random stationary process. Then, the signal was modelled as the filter output, with the noise as its input. Thereafter, the corresponding filter parameters were determined. The Auto-Regressive (AR) model is a parametric process which interprets the signal as the linear combination of its earlier activities in addition to the uncorrelated noise [85], [110], [111], as follows:

$$e_i = \sum_{j=0}^{p} A_j x_{i-j} \quad (20)$$

where A_j refers to the model coefficient matrix, p = model order, x_i = input EEG signal, while e_i = multivariate 0 mean uncorrelated vector. Furthermore, the A_j matrix was obtained after solving the linear equation, $m \times p$:

$$\sum_{j=0}^{p} A_j R(\text{j-k}) = -R(-k), \quad k = 1, \ldots, m \quad (21)$$

Wherein; m = no. of channels, p = calculated order of AR model, $R(k)$ refers to the covariance matrix biased values. The researchers carried out the AR spectral analysis for the EEG signal dataset employing the technique proposed by Franaszczuk *et al.* [112] and Fernandes *et al.* [113].

3) TIME-FREQUENCY ANALYSIS

The primary objective of using the Time-Frequency Distribution (TFD) analysis is to derive a function which characterises the energy densities of the signals in the time and the frequency domains. Intermediate Frequency (IF) and the Spectral Delay (SD) are common terms used in the TFD analysis. IF represents a local maximal frequency at a specific time which corresponds to the sine wave frequency for the best-analysed signal. On the other hand, SD refers to the estimation of the frequency-time arrival for the combined time-frequency example. The TFD analysis is used for indicating the time and the frequency laws for every signal component within the time-frequency domains. This simplifies the IF and SD calculation. This process also provides information regarding the amplitude and the duration of every signal component, along with its instantaneous bandwidth which refers to the IF surrounding the spread spectra [114].

a: DISCRETE WAVELET TRANSFORM (DWT)

The Wavelet Transform (WT) analysis is an important and crucial in automated process of seizure detection and has been used in many studies. Based on the Wavelet Analysis [23], the signal is characterised by the set of linear combination of functions, which are acquired after expanding and translation the individual function. This single function is identified as the mother wavelet and can be used for interpreting the primary signal into a few sub-signals which are half its spectra and size. In the case of the Discrete Wavelet Transform (DWT), all scaling and translating factors are expressed as the power of 2. DWT uses some Quadrature Mirror Filters (QMF), which are known as the high-pass and the low-pass filters. In the DWT level 1, the input signal is passed over the conjugate low and the high pass filters, simultaneously [115]. The output achieved is in the form of coefficients, called the wavelet coefficients. The result obtained from the low-pass filter, called approximation, gets sub-decomposed, while the output from the high-pass filter, called detail, is not sub-decomposed.

This process is repeated recursively to generate a single-sided, pyramid-like structure. It is very important to select the appropriate no. of decomposition levels and mother wavelet. The decomposition level number is selected according to their dominant frequencies. The mother wavelet function is selected from the Daubechies wavelets after a visual examination. In their study, Tzimourta *et al.* [116] proposed a novel automated seizure detection technique based on the WT analysis for decomposing the 2 epoch segments into 5 wavelet decomposition levels. Thereafter, the necessary features are submitted to the SVM classifier for the classification. Figure 5 describes the wavelet decomposition process [114].

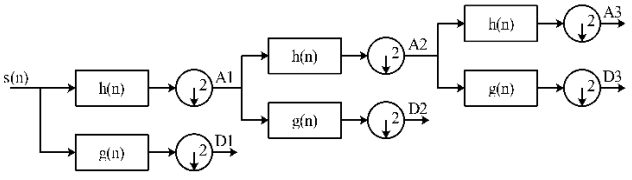

FIGURE 5. Wavelet decomposition process.

b: SPECTROGRAM

A spectrogram distribution denotes a single processing technique which can be used for analysing the multicomponent

non-stationary signals. This technique extracts several frames from an analysed signal, having a moving window, over a period of time. Every extracted frame is stationary and the FT is applied. A spectrogram distribution can be defined as follows [117]:

$$P(t,\omega) = \left| \frac{1}{\sqrt{2\pi}} \int e^{-j\omega\tau} s(\tau)\, h(\tau - t)\, d\tau \right|^2 \qquad (22)$$

In their study, Stamoulis *et al.* [118] applied the spectrogram distribution for detecting the onset of new focal EEG seizures. This process applies high-frequency neural network modulations, for analysing the EEG signals from the frontal and temporal lobes. The limitation of this method is that it uses finite-sized windows. A narrow window can provide a low frequency but a better time resolution. On the other hand, wide windows generate poor time resolution but a better frequency resolution. However, the wider windows violate the stationary conditions [119].

c: THE EMPIRICAL MODE DECOMPOSITION (EMD)

An EMD process is a type of adaptive technique that analyses the non-stationary and non-linear signals [120]. This process comprises of a data-driven and local separation of signals in slow or fast oscillations. The EMD process aims to decompose the signals into the Intrinsic Mode Functions (IMFs). In the past few years, novel processes were recommended for the classification and analysis of the focal epileptic EEG seizure signals based on the EMD. The average frequency of the IMF was used as a factor for identifying the differences between the ictal and the seizure-free EEG signals [121]. The normal and the epileptic seizure EEG signals were compared using the Hilbert weighted frequencies for the different IMFs [122].

The EMD process is an adaptive, simple and a nonlinear process which provides variability in a specific time series [123]. This process generates a few IMFs that are frequency and amplitude-modulated (AM and FM) waves. The scalp EEG seizures along with their 13 IMFs have been described in Figure 6. It can be seen that the specific IMF4, 5 and 6 oscillations appeared during the time of the seizure.

Hence, these functions are applied for the seizure detection. The specific frequencies appear in varying modes as the EMD process depends on the frequency of the EEG signal. This distinguishes the EMD process from the DWT technique.

4) NON-LINEAR TECHNIQUES

The frequency domain processes determine the rhythmic oscillations within the signals but are restricted by their inability to detect the nonlinear coupling or the phase locking amongst the harmonics within that spectra [124]. All biological systems are effectively described based on the nonlinear processes, which is also applicable for the EEG signal analysis.

The variations in the EEG signals are not easily noted by visual inspection alone since they are very chaotic and variable in nature. Hence, an automated system must be developed that can categorise the various sleep stages using the signal processing methods based on a statistical analysis of nonlinear and linear characteristics of the EEG signals. The time and the frequency analysis cannot provide very accurate results since these processes cannot detect the minute data from the EEG signals owing to their nonlinear and non-stationary status [125]. The nonlinear dynamics are used for sleep EEG signals for differentiating the various sleep stages. Chouvarda *et al.* [126] analysed the different sleep stages using fractal dimensions, approximation and sample entropies. These methods showed a variation in the features at differing sleep stages.

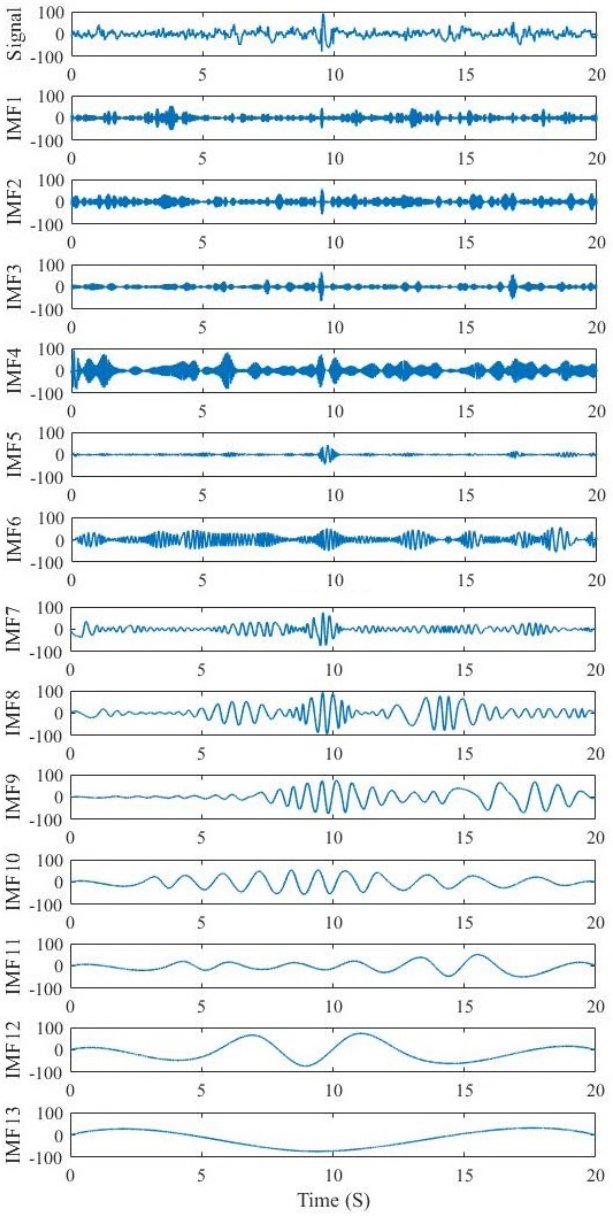

FIGURE 6. EEG IMFs Decompositions.

a: SPECTRAL ANALYSIS EIGENVECTOR TECHNIQUES

The Pisarenko method is used for computing PSD. It consists of sharp peaks that localised at expected frequencies [127]. Besides, Polynomial $K(f)$ holds 0s on a unit circle and is used for estimating PSD:

$$K(f) = \sum_{k=0}^{m} a_k e^{-j2\pi fk} \tag{23}$$

wherein $K(f)$ is the necessary polynomial, a_k = coefficients of the polynomial, and m = order of the Eigen filter $K(f)$. This polynomial is expressed as an autocorrelation matrix, R, for the input signal. Assume that white noise is used in the signals:

$$R = E\left\{x(n)^* \cdot x(n)^T\right\} = SPS^{\#} + \sigma v^2 I \tag{24}$$

where $x(n)$ denotes the detected signal; S denotes the path of the signal in the dimension matrix $(m+1) \times B$; while, B refers to the signal subspace dimensions; R denotes an autocorrelation matrix for the elements $(m+1) \times (m+1)$; p refers to the signal power, of the dimension matrix, $(B) \times (B)$; σv^2 denotes the power of the noise; $*$ refers to the complex conjugate; I is an identity matrix; # denotes the complex conjugate transposed; T refers to the transposed matrix. S is a signal route matrix, which is represented as: $S = [Sw_1 Sw_2, \ldots, Sw_L]$, $i = 1, 2, \ldots, B$. For all the practical applications, the autocorrelation matrix, $\hat{R}$, must be constructed using the autocorrelation lags:

$$\hat{R}(k) = \frac{1}{N} \sum_{n=0}^{N-1-k} x(n+k) \cdot x(n), \quad k = 0, 1, \ldots, m \tag{25}$$

Wherein; k denotes the autocorrelation lag index; and the no. of the signal samples are denoted by N. Thereafter, the autocorrelation matrix gets transformed to:

$$\hat{R}(k) = \begin{bmatrix} \hat{R}(0) & \hat{R}(1) & \hat{R}(2) & & \hat{R}(m) \\ \hat{R}(1) & \hat{R}(0) & \hat{R}(1) & \cdots & \hat{R}(m-1) \\ \hat{R}(2) & \hat{R}(1) & \hat{R}(0) & & \hat{R}(m-2) \\ & \vdots & & \ddots & \vdots \\ \hat{R}(m) & \hat{R}(m-1) & \cdots & & \hat{R}(0) \end{bmatrix} \tag{26}$$

b: ENTROPY

Entropy is defined as the measurement of the rate of data generation which is used for separating the beneficial signals from the background noise. Generally, a higher entropy value is seen to correspond to the increased unpredictability and irregularity, whereas a lower value indicates a higher regularity. Furthermore, entropy indicates a nonlinear index which reflects the chaos in the system [128], [129]. Entropy is applied for analysing the epileptic EEG signals and detecting the occurrence of an epileptic attack or for inspecting the seizures. Entropy is classified into spectral or embedding entropy. The spectral entropy is defined as the entropy which is calculated from the amplitude component of a power spectra in the signal; while the embedding entropies are directly estimated using a time series [130].

The mean spectral entropy is based on the power spectrum of a signal and is used for estimating the time series regularity. Also, the amplitude component of a power spectrum is used for computing the probabilities for estimating the entropy value. The spectral entropy [131] can be assessed with the help of the normalised Shannon entropy that can quantify the spectral complexity in a time series. FT is applied for deriving the PSD of the datasets time series representation. PSD denotes the power scattering of the signal based on the signal components (frequencies) [132]. For obtaining the power level of every frequency, the FT for the signal can be calculated, while the power of the frequency factor can be denoted by the P_f. The normalisation of power is derived by calculating total power ($\sum P_f$) and then, dividing the power value, consistent to the frequency of $\sum P_f$ as:

$$p_f = \frac{P_f}{\sum P_f} \tag{27}$$

Entropy can be computed by power multiplication in every frequency and logarithm of the inverse of that power value. Thereafter, the spectral entropy is calculated as follows [133]:

$$En_{sh} = \sum p_f \log \frac{1}{p_f} \tag{28}$$

The embedding entropy values are seen to provide a lot of information regarding the manner in which the EEG signals fluctuate with respect to time. This is carried out by comparing the time series using a delayed version of the same [134]. A popular embedding entropy technique includes the Kolmogorov-Sinai (KS) technique, which estimates the signal uncertainty with regards to time [135] using the embedded signals. KS entropy also refers to a metric entropy value that is 0 for the non-chaotic signals and is >0 for the chaotic signals. The entropy value is determined by locating the points which are nearer to one another on the trajectory in space but are not correlated with time. The divergence rate of the point pairs generates the KS value.

Other entropy approaches used for the process of feature extraction from EEG signals are Approximate Entropy [136], Sample Entropy [137], Renyi's Entropy [88], Permutation Entropy [138], Tsallis Entropy [139], Kolmogorov entropy [140], Fuzzy Entropy [141] and the Normalised Bispectrum Entropy [124].

5) GENETIC ALGORITHM

It is significant to select suitable features for improving the accuracy and efficiency of the classifiers. Different feature selection techniques, like the wrapper-selection and filter-selection, were developed. In one study, the researchers applied the GA and Fisher discriminant analysis (FDA), for the variable range of the EEG signals, and compared their performance. GA is a type of optimisation technique which is based on the Darwinian evolution theory and genetics [142]. The conventional gradient-based optimisation processes are

seen to search for an optimal point in the multidimensional optimisation surface by iteratively refining the solution. However, GA enables the parallel collection of the candidate solutions. Using this technique, GA shows a high probability of searching for a global optimum point instead of the conventional techniques that get stuck at the local optima near the primary prediction. The initial individual population in the GA technique represents a probable solution for the optimisation problem. Thereafter, the evolution procedure is based on the selection, crossover and mutation. As per the Darwinian principle of 'the survival of the fittest', this GA process can derive the optimal solutions after carrying out iterative computations. Crossover and mutations maintain the population diversity. GA handles the huge search space effectively and avoids the local prime solutions after combining the exploration as well as the exploitation processes [143]–[145].

III. CLASSIFICATION ALGORITHMS

After carrying out the steps for detection, and presuming that all extracted features can distinguish between the seizure and non-seizure EEG states, the data is used for classifying the features into their respective categories. Hence, a decision-making step and data classification in the feature space is necessary. This is a global technique which includes a feature selection stage and another step wherein the features can be combined for optimising the system performance.

The data classification aims to define the boundaries between the classes and label them according to their features. The data classification classifier can be simple like altering the feature thresholds or complicated like using the machine learning algorithms. In the multidimensional feature space, the margin is converted into a separate hyper plane. This process aims to determine the hyper planes which have a maximal distance from the classes [17].

Many classification and clustering techniques were developed, like the association rules, LDA, ANNs, Hidden Markov Modelling (HMM), fuzzy logic, k-means clustering, and SVMs, for epileptic seizure detection. Many studies have described the mathematical basis of all these techniques. This study presents a brief overview of these techniques. The association rules can be used for inspecting the feature set and establishing a simple relationship between all features. Thresholds help in making decisions. The Monitor algorithm was proposed by Truccolo *et al.* [146]. This algorithm used the thresholding of the waveforms into a feature space for detecting the focal epilepsy seizures of the single-neuron dynamics. Furthermore, Zijlmans *et al.* [147] investigated the ictal and the interictal high-frequency oscillations and proposed a threshold-based method for determining the interictal spikes. In their study, Niederhauser *et al.* [148] used a time-frequency feature threshold. Mitra *et al.* [149] determined a set of rules (varies from the threshold) for the artefact rejection, along with those for estimating the general seizure quality.

For the complex relationship between the features, automated techniques, like the LDA [150], fuzzy logic [151], and k-means clustering [152], [153] have been used for detecting the epilepsy seizures. The popular classifiers are ANN and SVM-based.

ANNs can be defined as a mathematical example based on the low-level functions of the biological neurons. In the ANN technique, the knowledge regarding the problem can be distributed in every functional neuron and the connecting weighted links between the neurons. This neural network must be appropriately trained for generating the necessary mapping. During the training stage, the feature vectors act as the input while the network can adjust the variable parameters, biases and the weights, for establishing the relationship concerning the input and output values. Based on the network's ability to learn from the established patterns, the ANNs help in classifying the epileptic seizure detection [154] or spikes [155]. Similar to the ANNs, the SVM-based processes are also applied for epilepsy detection by determining the hyperplanes for the multidimensional data. The SVM process aims to determine the hyperplane within a feature space which optimally separates 2-more classes. Furthermore, the SVM technique can generate a specific solution for minimising the expected misclassification-related risks. The training algorithms apply the solutions derived from a popular quadratic programming-related optimisation problem, which is computationally effective and generates global solutions [75].

IV. MACHINE LEARNING REGULARISATION

After classifying the data, a regularisation function has to be added for decreasing the false alarms. For this purpose, techniques like Kalman filtering [156] and firing power method [157], which consider the temporal signal dynamics are used. They aim to improve the classifier specificity after restricting the false alarm generation. The firing power method measures the no. of predictions which are categorised as preictal during SOP. If this value is higher than the normalised threshold, it generates an alarm. Many studies used the firing power process and reported satisfactory results [158]. Teixeira *et al.* [159] used a fixed threshold of 0.5; where some others [160] compared various thresholds (0.10, 0.15, . . . , 0.85) and noted that the lower threshold values led to low FPRs. No one reported optimal threshold values. In one study, the researchers used the AR modelling coefficients as SVM input values and compared the performance of their technique with the non-regularised classifier using iEEG signals derived from 9 patients in the University of Freiburg database. They noted a significantly improved performance; however, they did not conduct any statistical testing. Kalman filtering is also used in many reports [156]. Park *et al.* [161] used the 2^{nd}-order discrete-time Kalman filter for smoothening the undesired SVM output fluctuations. Teixeiria *et al.* [160] compared these regularisation methods and noted that the firing power technique used a conservative approach while raising alarms. The researchers

stated that it was a better technique as it could maintain a longer memory of the classification dynamics and created time constraints for raising alarms. They also noted that the Kalman filtering raised many alarms, which was impractical [160].

V. DISCUSSION

A lot of effort and time has been directed towards improving the prediction of the seizures; however, the conversion of the existing methods into the development of clinical devices has not been possible. Majority of the algorithmic and analytical studies have indicated that the physiological transition to a seizure state is not a random process and a specific build-up is responsible for seizure development. The heterogeneity between all studies indicates that the ictogenesis mechanisms are very complicated and hence, appropriate precaution must be taken for dealing with this seizure state. In this study, the researchers have summarised, analysed and discussed all the progress which has been made in the focal epileptic seizure prediction field. Out of all the various techniques, the nonlinear and bivariate linear methods have been very promising for seizure prediction. Though a few of the nonlinear univariate methods can be predictive, they have been unable to show a better performance than the linear methods, which has limited their application in the focal seizure prediction studies. The bivariate methods can be very helpful in determining the brain dynamics. The phase synchronisation techniques show a better predictive capacity than the nonlinear bivariate methods.

As mentioned here, many researchers applied the WT or the entropy-based techniques. WT, in combination with other methods, like chaos, can decompose the EEG signal into different fixed scales, associated with the signal's sampling rate, for differentiating between the normal and the epileptic EEG signals, as described in Table 1. The entropy-based processes are used for quantifying the level of the disorder (or order) in the EEG signals, during the focal epileptic seizure. Furthermore, the EMD process has been used as an alternative to the traditional time-frequency methods. It is seen to be an adaptive decomposition process which depends on the frequency of the EEG signal (rather than the fixed cut-off frequency used in the WT). In the past few years, epilepsy detection is based on many tensor models and other modelling techniques which analyse the multimodal data and gather a lot of data regarding the complex behaviour. This technique helps in analysing multiple domains simultaneously, like the 3-way array epilepsy feature tensor that has the time samples $\times$ frequency $\times$ electrode modes.

A combination of the univariate and the bivariate features is a good alternative. Many studies aimed to investigate the cross time and the frequency features, coupled in the feature extraction block [162]–[164]. They reported satisfactory results in comparison to the conventional spectral power features. These features were based on the univariate phase-amplitude coupling along with the bivariate amplitude-amplitude coupling. It would be helpful to investigate other coupling types for improving the feature extraction during the detection and prediction of the focal epileptic seizures. Furthermore, combining many features for tracking the preictal stage can also enhance the feature space dimensions, which has increased the need to develop better feature selection algorithms. Though many researchers have validated the performance of their classifiers using statistical evaluation-based methods, the feature selection methods have not been statistically tested. Hence, it is vital to evaluate the statistical operations of the proposed feature selection method with other methods. Many seizure prediction studies have mentioned the need to develop better subject-specific and individually-tailored algorithms, while some described the main discriminative features for all issues. Furthermore, the out-of-sample testing must be regarded during feature selection. Also, samples must not be used for evaluating the performance of the feature selection techniques.

Many classifiers have been studied for seizure prediction. However, a comparison between them is difficult because of heir heterogeneous input features, pre-processing, and diverse patient data. Many researchers showed that combining the linear and the nonlinear classification methods can be helpful. The ANN classifiers are commonly used for determining the patterns which are revealed during feature extraction. These classifiers provide vital data about the EEG seizures and help in differentiating the normal and the seizure rhythms. SVM is a technique similar to ANN, but is easier and faster to implement than the ANN, with comparable results. Hence, SVMs are replacing the ANNs for seizure detection.

The epilepsy detection is based on 2 steps. Step 1 involves the development of precise and non-invasive detection techniques. The major issue noted in this step involves the identification of the artefacts that can interfere with the signal. The other step is involved in drug delivery and neuro stimulation, wherein the signal recording or therapy could be very invasive, but the developed techniques aim to detect the onset and precisely quantify the seizure strength.

Another issue noted during seizure detection involves the standardisation of all techniques. Firstly, all different metrics used for evaluating the detector performance must be combined for homogenous comparison. Secondly, a few guidelines are necessary for recording the EEG signals (scalp or intracranial) and their duration (the amount of data derived after few seconds is different from that obtained after an hour), while implementing the algorithms.

VI. CONCLUSIONS

This critical review highlights the need to improve and optimise the framework of the focal and non-focal epileptic seizure detection techniques. Every prediction method must be subjected to further investigation for improving the final outcome of the proposed techniques. Furthermore, a comprehensive point of view must be achieved while developing the seizure prediction block diagram, which combines the data

acquisition and performance evaluation steps. This would ensure a better and more realistic system performance.

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