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Detection and Classification Methods for EEG Epileptic Seizures

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ABSTRACT

Epilepsy is the maximum common brain disease which has been spreading largely around the arena. It takes place because of excessive or synchronous strange activities in human brain. To degree the electric seizure pastime of mind many technology and techniques had been developed. Nearly 80% of people with epilepsy stay in low- and center-earnings countries. It is estimated that as much as 70% of people residing with epilepsy should stay seizure-free if well diagnosed and handled. The chance of premature demise in humans with epilepsy becomes three times more than for the overall population. Three quarters of people with epilepsy living in low-profits nations do now not get the remedy they want. In many parts of the arena, human beings with epilepsy be afflicted by stigma and discrimination. Epilepsy is characterized by means of surprising bursts of extra energy in the mind, manifesting as recurrent seizures. Epilepsy continues to be now not properly understood whilst compared with other neurological disorders. This paper provides an overview of detection and classification era for the reason of EEG seizure. Time frequency transforms and system learning plays an important function in extracting meaningful facts. The overall performance of detection and classification techniques of the researchers is the primary focus of the paper.

Key words: Electroencephalogram (EEG); Epileptic Seizures; Epileptic Seizure prediction;, feature extraction; Similarity Measure ;Time frequency techniques.

1. INTRODUCTION

Epilepsy is a continual neuron disordered related situation that influences about fifty million peoples throughout the world, which makes Epilepsy a usual neurological illnesses globally in step with the report of WHO(World Health Organization),June,2019[1]. EEG is a controlling technique that uses more than one electrodes located alongside the brain scalp to degree electric interest of mind generated by means of the neocortex nerve cells. The prognosis of detection of seizure is analyzed by a neurologist, however can be hard to identify in the early stages. Epileptic seizure detection manually sports from EEG quantification could be time ingesting in particular within lengthy observations. Therefore, computer aided epileptic seizure detection has been considered as a completely appropriate generation for the seizure hobby [2], [3]. Seizures are manifested inside the EEG as paroxysmal events characterized through stereotyped perpetual waveforms that boost in amplitude and frequency afore decaying ultimately. Nevertheless, seizures must be detected as early as viable in order that the medicine can be furnished right away to control the seizure without further effects. In the current literatures, a huge quantity of research work had been achieved with diverse signal processing strategies to extract functions for evaluation and reputation of epileptic seizure. In these specific methods, the main employed strategies include transforming techniques (wavelet transform, Fourier transform, etc.), nonlinear dynamic analysis (various entropies, and many others.), and information-structured time-frequency decomposition techniques empirical mode decomposition (EMD) [4-6]. Copious quantity of researches has been achieved to ameliorate the detection, prognostication and knowledge of epilepsy. Up gradations and implicative insinuations at the subsisting methods as a result of arguments are but in discussion term.

One of the most exhilarating methods in epileptic seizures presage and detection is the procedure of growing computational techniques termed as classifiers. The primary objective of these research is to precisely decide the epileptic EEG states by the processing of extracted EEG features. In this article, we have offered an in depth assessment of the last ten years research findings of eminent researches cognate with the detection and prognostication of seizures. The essential contribution is a path for developing technology that support epilepsy treatment in the course of development[7]. Along with this, an in depth description approximately Electroencephalographic alerts, Epileptic seizures, are supplied.

The paper is organized as follows: Section-2 presents the details of EEG signal, section-3 presents seizure detection and classification process, section-4 presents the review of Seizure detection and prediction technique, section -5 presents conclusion and reference.

2. EEG SIGNAL DETAILS

EEG signal contains an intricate facts provided for perpetual seizures. EEG evolve into an immense areas of the encephalon seizure [8]. The electrical activity from the cerebrum and termed them as EEG signals [9]. The EEG signal betokens the superposition of encephalon activities which are taken as variation of electrical activities over the scalp. The EEG signals absorb a consequential amount of information concerned with the function of the encephalon. Genuinely, the greatest challenges in EEG signals are considered to be the nonlinear quandaries, which inhibition the relegation prosperity rates, always.

However, with the fast development of signal processing techniques, the signal-processing technique based method named local mean decomposition (LMD) assumed as the most suitable method to solve the nonlinear problem [10].Signal processing is employed to handle issues related to EEG analysis such as data compression, detection and relegation, reduction of noise, signal disseverment. Seizure prognostication predicated on analysis of EEG signals [11].

3. PROCESS OF DETECTION AND CLASSIFICATION OF SEIZURE

For the management of epilepsy, the system provides clinicians with specified seizure data [12]. Seizures can be either from a selected location or from the complete brain [13]. In standard, as seizures are discovered from time to time and unpredictably, automated seizures detection can be achieved through signal processing transforms. Since EEG signals are having widespread strategies of frequency evaluation for clinical functions. An abundant of researches is to be had in the literature worried with automatic identification of epileptic seizures. Here, we've carried out an intensive overview of a number of those noteworthy researches. The steps for identifying and relegating the activities of epileptic seizures are described in Fig.1 and mentioned in Appendix-1.

3.1 Preprocessing

It lets in eliminating noise from the EEG signal generated at some point of the data acquisition. The procedure of 10-20 EEG recording gadget can suffer from contaminations and accordingly generate ambiguous scheme an apt recording of sign approaches will capable of minimize the noise generated. The preprocessing level depend on the software dataset type used and complexity of the algorithm in phrases of computation time [14].

3.2 Feature extraction

Feature extraction from the EEG signals have mostly amplitude-based capabilities in time domain, time-frequency distribution provides Instantaneous Frequency based functions [15]. The overall performance of seizure detection and classification system relies upon especially at the high-quality of the extracted features

3.3Feature Selection

The extracted features from the EEG indicators which might be accumulated from distinctive patients. The feature reduction may be carried out the use of ICA (Independent thing analysis) to lessen the computational time of the classifier. The statistical extracted features are provided as input to the classifier for categorization. This permits choosing informative features for desirable relegation.

3.4 Training phase

The training phase follows the steps such as preprocessing or filtering, feature reduction or feature extraction [8]. During this phase, the model parameters determine the existences of seizures. This step entails sizable computation and is carried out offline earlier than implementation for seizure detection. It also can be up to date as more statistics are accumulated.

3.5 Classification

The relegation step receives features and identifying germane class of either seizure or non-seizure utilizing a relegation process. Different relegation methods often used are Artificial Neural Network (ANN), Least Square Support Vector Machine (LS-SVM) and K-Nearest Neighbor (k-NN), Multilayer perceptron neural network (MLPNN), Naive Bayes. The efficiency of seizure detection and relegation depends on features extracted from different signal processing transforms. This paper reviews some of ANN based classification whose details are mentioned in the following section.

3.5.1 Multilayer Perceptron Neural Network (MLPNN)

The MLPNNs with the ability to learn and generalize are most commonly used classifiers in EEG analysis and seizure detection. They need smaller training set and work fast with less complexity in implementation. In the MLPNN, the signal xi and the strengths of the individual correlation weights w_{pq} are multiplied at hidden layer units. The output y_q is then computed as a function of the summation as:

$$Yq = WqpXp \tag{1}$$

The output is given by

$$sum = \frac{1}{2}\Sigma_q\left((y_{dq} - y_q)^2\right) \tag{2}$$

Where y_dq is the desired output and y_q is the actual output. Each weight w_{qp} is tuned to decrease Sum as fast as possible. Depending on the training algorithm employed the w_{qp} value is set for the computation. The ANN model development primarily focuses on the training algorithms. A suitable training algorithm can result in the better model for prediction. An optimized training algorithm can also reduce the training time. The back propagation algorithm is relatively easy to implement in which a search of an error using gradient descent is carried out. However, the error remaining in the local minima for indefinite time is a major challenge in the back propagation algorithm. The long training sessions is another major concern in the back propagation algorithm.

3.5.2 Least Square Vector Machine (LS-SVM)

The SVM classifier reduces error and increases the boundary to classify data. The LS-SVM method is based on using a quadratic error criterion with equality constraints as an alternative to a quadratic programming for SVM. The. The least squares formulation of SVM and contains the equality constraints. For two-class SVM, decision function is as follows:

$$f(x) = \text{sign}\,[W^T f(x) + b1] \tag{3}$$

Where b1-bias, and f(x) is a function which maps x. To get w and b values, we can write

$$J(W, b1, E) = \frac{1}{2}W^TW + \frac{y}{2}\sum_{i=0}^{n} E_i^2 \tag{4}$$

Minimize

Subject to equality constraints

$$y_i\,[W^T f(x_i) + b1] = 1 - E, i = 1, 2, 3, \ldots, N \tag{5}$$

Where x_i and y_i are N input output pairs.

3.5.3 Nearest Neighbor

It is a non-parametric Supervised learning method in which magnificence labels can be saved. The data may be classified also. The KNNs are an instance of example primarily based supervised getting to know wherein nearest neighbor value *k* is used to make class. The classifier takes the selection about the elegance label.

3.5.4 Native Bayes

The Bayesian classifier is a statistical method for classification.. This classifier uses Bayes theorem, and naively presupposes that the predictors are conditionally independent for the given class of data [52].

The naive Bayes assumption is given the class label:

$$p(x|y = c) = \prod_{i=1}^{D} p(x_i|y = c) \tag{6}$$

These classifiers allocate observations to the most probable class. The algorithm works as:

1. An estimation of the densities of predictors inside each class.

2. Modeling subsequent probabilities according to Bayes theorem, i.e., for all k = 1,...,K,

$$\hat{p}(Y = k|x_1, \ldots, x_p) = \frac{\Pi(y=k)\prod_{j=1}^{p}(x_i|y = k)}{\sum_{k=1}^{k}\Pi(y = k)\prod_{j=1}^{p}(x_j|y = k)} \tag{7}$$

Where Y is the random variable equivalent to the class index of a sample set, $X_1,\ldots,X_P$ are the random predictors, and π(Y=k) is the former probability for a class index k.

4. REVIEW OF CLASSIFICATION AND SIMILARITY MEASURE BASED APPROACHES

Temko et al. (2011) proposed a support vector machine classifier which is a multi-channel patient-independent seizure detection procedure to differentiate between seizure and non-seizure signals and achieves89%detection [15].Sorrensen et al. (2010) proposed a completely unique approach exploitation the matching Pursuit formula for feature extraction. The extracted features are combined with the SVM classifier and achieved a sensitivity of 78% [16]. Luigi Chiski et al. (2010) planned an answer depends on autoregressive modeling with SVM for binary relegation. [17].

Petersen EB et.al (2011) projected a long monitoring system for EEG that mechanically detects seizures, that is beneficial for designation and treatment of brain disease. The analysis work investigates the spike-and-wave behavior throughout absence of seizures. The seizure characteristics are captured and classified by employing a SVM. This work was given a brand new graphical image supported by the topographic distribution on the scalp. The proposed seizure detection technique shows result of sensitivity of 99.1 %, positive prognostic price of 94.8 %. [18]. Acharya UR et al. (2011) presented an automatic system which utilizes HOS (Higher order statistics) features to use in classifiers for the detection of classes. It was found that the SVM achieves 98.5% [19]. Kharbouch A et al. (2011) presents the quandary of authentic-time seizure detection from intracranial EEG (IEEG). The research work presented and evaluated utilizing a machine-learning approach and detected 97% and sensitivity was 100% [20].Liu Y et al.,(2012) presented a new wavelet-predicated automatic seizure detection technique and achieve a sensitivity of 94.46% and a specificity of 95.26% with an erroneous 0.58/h detection rate is achieved[21]..Xie S et al,(2012) developed a novel model to capture discriminative desultory states of EEG signals by utilizing wavelet components and engenders a 100% relegation precision for sundry relegation tasks. The proposed relegation model performs 99% overall relegation precision University of Freiburg dataset [22].

Direito B et al.,(2012) proposes a consummately unique procedure to spot the sundry states of the epileptic encephalon using Hidden Markov Model (HMM). This method applied to ten patients plagued bifocal seizures, and achieves precision of 89.31% [23]. Rabbi AF et al., (2012) presented a multistage fuzzy rule-predicated rule for convulsion onset detection. Fuzzy rules strategy made on iEEG datasets of twenty patients having 56 seizures and achieves95.8% sensitivity with 0.26 per hour detection rate [24]. Roshan Ecstasy Martis et al (2012) presents a live of neural electrical activity in encephalon recorded on scalp and features are extracted by employing EMD decomposition. The performance of relegation of 95.33%, 98%sensitivity, and 97%specificity is achieved utilizing C4.5 call tree classifier [25]. Ardalan Aarabi et al. (2012) developed a consummately unique patient-categorical rule-predicated seizure presage system for focal cerebral mantle encephalopathy. Five uni-variate measures together with correlation entropy and dimension, amplitude, Lempel-Ziv complexness, and most immensely colossal Lyapunov exponent still joined measure quantity, interdependency, extracted from iEEG. The system was tested on eleven patients with medically incompliant focal cerebral mantle encephalopathy and achieved sensitivity of 79.9% and 90.2% with a median mendacious presage rate of 0.17 and 0.11/h, severally [26].

Kris Cuppens, et al.in 2012 provided a completely unique approach of detection myoclonic jerks throughout sleep employing a video rather than ancient graphical record primarily based systems. This sort of approach is useful because it assists in up the standard of sleep of patient because it permits them to sleep with none electrodes connected. The rule accustomed notice seizure is predicated on spatiotemporal interest points (STIPs), projected by Ivan Laptev. The classification is completed via SVM and provides a sensitivity of over seventy fifth and a PPV of over eighty fifth.[27]. AS Zandi et al., (2013) utilized a moving window analysis with variational Bayesian Gaussian coalescence model for relegation and achieves a 88.34%sensitivity, rate of 0.155 h-1 erroneous presage, and a 2.5 min median presage time [28].Li et al. (2013) provided a time-domain technique for seizure prognostication that is primarily predicated on spike price estimation. The envelope detection has been done by utilizing Morphological operations and averaging. This approach achieves rate of 0.09/h fake-alarm prognostication and a sensitivity of 75.8% [29].

Wang et al. (2013) provided a wavelet-predicated thoroughly on-line adaptive seizure presage contrivance [30]. The author proposed KNN classifier achieves a sensitivity of 73% and 67% specificity. Haiping Lu, et al. (2013) recommended a gadget to detect epilepsy using color based video evaluation. This is a unique technique which makes use of neither any electrode nor any sensor. It analyses colored pajamas to analyze limb movement. It deploys Gaussian fashions in historical background modeling and detects limbs with graph-cut-based segmentation. The consequences of this technique are akin to EEG primarily based structures [31]. Daou and Labeau(2014) proposed a wavelet-predicated approach for seizure detection from EEG signal [32].Sahar Nesaei et al. (2014) proposed a unique technique utilizing wavelet packet transform (DWPT) approach for detection of epileptic seizures in intracranial EEG. In this research work, the Lyapunov exponent of the DWPT is taken into consideration with (SVM) classifier to discover epileptic seizure. The proposed scheme utilized the Freiburg dataset and gets the results of sensitivity of a 100% [33]. Ram Bilas Pachori et al.(2014) supplied a pristinely incipient technique for relegation. The proposed method utilized (EMD) and the second one-order difference plot (SODP). It has been identified from SODP that the characteristic area of first and 2d IMFs shows experimental results on EEG database [34].Oliver Faust et al., (2015) reviewed wavelet techniques for automated analysis of seizure detection. A multi paradigm technique based totally on the combinations of wavelets, nonlinear dynamics and chaos principle, and ANN which achieves a totally prognosis of epilepsy[35].

Noha S.Tawfik et al.(2015), introduces a novel automatic seizure detection by utilizing Weighted Permutation Entropy (WPE) and a SVM classifier model. The proposed technique is applied on loads authentic EEG alerts and the ability is compared primarily predicated on sensitivity, specificity and precision which withal manifests high robustness towards noise assets [36]. Sharmila et al., (2016), proposed discrete wavelet rework utilizing linear and nonlinear relegation models. The detection is analyzed by utilizing naïve Bayes (NB) and K-NN classifiers with features of DWT. NB classifier performs a precision of 100% by utilizing the University of Bonn, Germany dataset. [37].

Enamul Kabir et al. (2016) presented a singular evaluation system which makes utilization of mathematical functions predicated consummately on finest allocation technique with logistic model trees. The EEG features obtained is alimented into the relegation model to discover seizure events. The effects exhibit very exorbitant performances for each magnificence, and adscititiously shows the consistency of the technique in the reiterating flow. The results of the mentioned technique outperform EEG signal detection utilizing the equal EEG dataset [38]. Bashivan et al. (2016) proposed a novel approach for mastering such representations from multichannel EEG time-amassment, and exhibit its advantages in relegation task. In 1st phase the EEG activities converted into a series of multi-spectral features and in the next phase the deep recurrent convolutional network has been trained for classification which upgrades classification precision over modern methods on this field [39]. In 2017, Snehal V. Tonpe, et al. Proposed a Micro Sensor based method for detection of EEG seizure. This technique is used a wearable tracking tool which consisted of an accelerometer and a microcontroller. The accelerometer detected movement even as the microcontroller anticipated the seizure and if a seizure prevalence changed into showed then the microcontroller brought on an audio-video alarm [40]. QiYuan et al., (2017) proposed a unique technique predicated on the weighted ELM for seizure detection. (i)To get time and frequency visualization of EEG data, the wavelet packet transform is employed.(ii)To quantify the intricacy of the EEG time amassment, sample fit regularity statistic is utilized as the nonlinear characteristic. The G-mean is utilized to evaluate the overall performance and achieves G-implicatively insinuate of 93.96%, occasion-primarily predicated 97.73% sensitivity and fake alarm charge of 0.37/h are achieved [41].

TurkyN.Alotaiby et al., (2017) provided seizure predication approach counting on the common spatial pattern primarily based on feature extraction of scalp EEG signals. Multichannel EEG indicators are identified and divided into overlapping segments for both preictal and interictal periods. The common spatial pattern are used for classification. A LDA classifier, that's then used within the checking out phase. A go away-one-outcross-validation approach is followed in the experiments. The experimental effects for seizure prediction obtained from the information of 24 sufferers from the CHB-MIT database display that the proposed predictor can reap 0.89median sensitivity, 0.39 mean false prediction charge and an average prediction time of 68.71 minutes using a120-minute prediction horizon [42]. Bhattacharyya et al.(2017a) proposed empirical wavelet transform with random forest classifier and accomplished 99.4% accuracy, 97.9% sensitivity and 99.5% specificity [43]. Further Bhattacharyya et al. (2017b) proposed Tunable-Q wavelet transform based on multiscale entropy degree for computerized category of epileptic EEG indicators with SVM classifier and performed accuracy of 98.6% [44]. Sharma et al.(2017) proposed an incipient approach of analytic time-frequency flexible wavelet remodel and LS-SVM and accomplished sensitivity of 100%[45].U. Rajendra Acharya et al. (2017) developed a computer aided design contrivance to distinguish the magnificence of EEG signals automatically by the utilization of system studying techniques. For evaluation of EEG signals, convolutional neural network has been employed. This work proposed a thirteen-layer deep convolutional neural network (CNN) and achieves 88.67% precision, 90.00% specificity, and 95.00% sensitivity respectively [46].

B. AL-Bokhity et al. (2017) proposed a Short-Time Fourier Transform (STFT) and WTfor denoising and features extraction. Four different EEG types (i.e. Salubrious human beings, Epileptic people throughout the seizure-unfastened c program language period (Interictal), Epileptic humans in the course of seizure c language (Focal) and Epileptic humans at some stage in seizure interval (Nonfocal)) are classified via the utilization of a (MLPNN) classifier. The integration of STFT and WT achieves 94.4 % which significantly outperforms the preceding [47].Arijit Ghosh, Anasua Sarkar et al. In 2017 got here up with a technique to hit upon epilepsy the utilization of ECG signal acquired at the preictal level of length spanning to five minutes. The approach utilized a transmuted Pan-Tompkins set of rules to stumble on epilepsy. They had done analysis on time area, frequency area, and non-linear functions [48]. Baumgartner C et al., (2018) proposed scalp EEG predicated seizure-detection algorithm and achieves 90% sensitivity. The application of scalp-EEG-primarily predicated seizure event detection systems which is restrained due to the fact patients might not abide sporting great electrode arrays for lengthy periods in mundane subsistence. [49].Ahmed I. Sharaf et al. (2018), provided a singular technique to apprehend and relegate the seizure events automatically by utilizing a keenly intellective computer-availed method. The proposed technique uses a tunable Q-wavelet to extract chaotic, statistical, and electricity spectrum features. An arbitrary classifier is inculcated for the category and presage of the different seizures. The firefly optimization is employed to reduce the authentic set of functions and engenders a reduced compact set [50]. Yanli Yang et al.,(2018) defined the unconventional software of permutation entropy to make the dynamical adjustments of the brain interest from intracranial electroencephalogram for the prediction of seizure. After preprocessing EEG data, permutation entropy was obtained and SVM has been employed and achieves94%mean sensitivity (SS) and fake prediction prices (FPR) of0.111 h^{-1} and achieved 61.93min average prediction. The performance results indicated that making use of PE as a characteristic to extract records and classification by SVM ought to are expecting seizures, and the supplied method indicates superb ability in medical seizure prediction for human [51]. Most these days, in 2018, Isabell Kiral-Kornek, Subhrajit Roy, Ewan Nurse et al. finished a examine to lay out a machine to expect epileptic seizures the use of two powerhouse technologies; i.e Big Data and Deep Learning. IEEG facts of 10 patients were obtained from a seizure advisory system. A machine changed into then designed which had 4 steps: step (i) involved a deep getting to know classifier to distinguish among preictal and interictal indicators; step (ii) was testing of classifier performance on held-out iEEG facts of sufferers. The statistics turned into additionally benchmarked in opposition to the overall performance of a random predictor. Step (iii) changed into a prediction system for sensitivity and time in a caution by the patient. Last step (iv) became the deployment of the wearable tool device on a neuro based chip for impartial operation. The prediction machine offers 69% mean sensitivity and 27%time warning [52].

Xiashuang Wang et al. (2019) proposed on this research together with Fourth-order Symlet wavelet, grid search optimizer and gradient boosting. Symlet wavelets are employed for feature extraction and grid search optimizer is utilized for training the classifier. The type precision of the gradient boosting system become in comparison with that of a conventional avail vector system and an arbitrary wooded area classifier constructed consistent with antecedent descriptions. Different indices have been used to assess the performance of proposed relegation scheme, which provided higher relegation precision and detection efficacy that was reported in different research on 3-elegance category of EEG statistics [53]. Dattaprasad et al. (2019) proposed a nonlinear method of EEG characteristic extraction predicated at the RP, and RQA analysis. These features had been labeled the utilization of (ANN), (PNN) and (SVM). The SVM relegates EEG alerts with precision of 91.2 % is culled for relegation [54].Sheoran et al. (2019) proposed a (TT- Transform) for a fine-tuned of involute time-axis spectrum. With the TT-Transform, the visual inspection on the time axis has been optically discerned to show potent in seizure event. TT-Transform is suggests frequency filtering noise reduction inside the time domain. The quadratic discriminant analysis utilized for classification and the impeccable class precision achieved as 100%.[55]. Umar Asif et al. (2019), presented a deep learning using multiple CNN model architecture for correct seizure identification. The experiments produces a weighted f1 rating of 0.98 for seizure detection for the benchmarks dataset [56].

Liu, J. et al.(2019) implemented deep learning method by the utilization of a convolutional neural network. The approach achieves high precision by utilizing handiest one channel. The experimentation on a trendy check statistics set betokens a 90% or better precision on prevalent aspect [57]. Roozbeh Zarei et al. (2019) evolved a pristinely incipient scheme primarily predicated on Douglas-Peucker algorithm (DP) and predominant factor based on for extraction from seizure events. To analyze the performance of the proposed method, there are four system getting acquainted with strategies, K-NN, SVM, are applied. The proposed approach achieves the copacetic overall performance of 99.85% [58-59]. M. Shamim Hossain et al. (2019) used a deep CNN model for detection purpose. This approach engendered a mundane sensitivity of 90.00%, 91.65% specificity and macrocosmic precision of 98.05%. The model can identify seizures with a precision of 99.46% and ecumenical precision of 99.65%. [60-61]. Harshit Bhardwaj et al. (2019) proposed a modern GP where EMD approach is utilized for the characteristic extraction followed by genetic programming which is liable for the boom in class precision and a decrementation in time complexness. This classifier has a capability for as it should presage the seizure events for constructing a seizure event detection algorithm [62].

Seizure detection structures are able to detecting perpetual events and provide clinicians with concrete event information utilizable for the utilization of epilepsy. Different algorithms with detection methods are given in (Table-1) which is presented in Appendix-1. The sizably voluminous researches reviewed on the strategies applied for detection and presage, like neural networks, kindred attribute quantification, correlation and more.

5. CONCLUSION

In this paper, we have reviewed feature extraction techniques proposed to betoken the functionality of epileptic seizure for the purport of seizure type and detection. An epileptic seizure is a prognosticable event and an epileptic seizure prognostication machine can avail the patient in managing their situation more preponderant correctly. Identification of seizure and prognostication make adequate preparation for incipient and independently centered possibilities for the analysis of epilepsy. This overview offered a survey of cutting edge technology for relegation and detection to assist the clinical records wishes all through epilepsy treatment. In our review process we have analyzed and presented different types of classification techniques and feature extraction techniques. Some of the ANN based classifiers are presented with short description. The table-1 provided for quick reference of classification techniques and related accuracy, sensitivity and specificity from the year 2010 to 2019 research work. Also the table depicts the type feature extraction techniques based on time frequency transform. From the review of research work it is observed that the deep CNN classifiers are presenting proven results for detection and classification of elliptic seizures. Most of the researchers use University of Bonn, Germany and CHB-MIT dataset for the classification work. In some research it is observed that the researchers use hybrid transform technology for the purpose of detection and classification. Further studies can focus on optimizing the weights of deep CNN with hybrid soft computing technologies to decrease error rates and improve the performance of algorithms to maximize the prediction rate.

REFERENCES

1. https://www.who.int/news-room/fact-sheets/detail/epilepsy,June,2019.
2. Dazi Li, Qianwen Xie,Qibing Jin, Kotaro Hirasawa, A sequential method using multiplicative extreme learning machine for epileptic seizure detection, Neurocomputing 214:692–707, 2016. https://doi.org/10.1016/j.neucom.2016.06.056
3. Zhang T, Chen W, LMD based features for the automatic seizure detection of EEG signals using SVM,IEEE Trans Neural Syst Rehabil Eng25:1100–1108, 2017. https://doi.org/10.1109/TNSRE.2016.2611601
4. U. Rajendra Acharya, S.Vinitha Sree, G.Swapna,Roshan Joy, Martisa Jasjit S.Suri, Automated EEG analysis of epilepsy: A review, Knowl-Based Syst,Vol.45:147–165, 2013. https://doi.org/10.1016/j.knosys.2013.02.014
5. Farhan Riaz , Ali Hassan, Saad Rehman, Imran Khan Niazi , Kim Dremstrup, EMD-based temporal and spectral features for the classification of EEG signals

using supervised learning, IEEE Trans Neural Syst Rehabilitation Eng 24:28–35, 2016.

6. Sharma R, Pachori RB, Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions, Expert Syst Appl42:1106–1117,2015 https://doi.org/10.1016/j.eswa.2014.08.030
7. Jonathan Bidwell, Thanin Khuwatsamrit, Brittain Askew, Joshua Andrew Ehrenberg,Sandra Helmers , Seizure reporting technologies for epilepsy treatment: A review of clinical information needs and supporting technologies, Seizure 32 (2015) 109–117 https://doi.org/10.1016/j.seizure.2015.09.006
8. Sriram Ramgopal,, Sigride Thome-Souza, Michele Jackson, Navah Ester Kadish,Iván Sánchez Fernández, Jacquelyn Klehm, William Bosl, Claus Reinsberger,Steven Schachter, Tobias Lodden kemper,Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy.Epilepsy & Behavior 37 (2014) 291–307. https://doi.org/10.1016/j.yebeh.2014.06.023
9. Lee M. Hively and Vladimir A. Protopopescu, "Channel-Consistent Forewarning of Epileptic Events from Scalp EEG", IEEE Transactions On Biomedical Engineering, vol. 50, no. 5, pp. 584-593, May 2003. https://doi.org/10.1109/TBME.2003.810693
10. Ren Het al., An adaptive unsupervised classification of seizure method based on LMD-MSSE with EEG signals, Biomed Res28:3151–3158, 2017.
11. Simone Carreiro Vieira, Paulo Breno Noronha Liberalesso, Mônica Jaques Spinosa, Adriana Banzzatto Ortega, Alaídes Suzana Fojo Olmos, and Alfredo Löhr Júnior, "First Unprovoked Seizure: Clinical and Electrographic Aspects", Journal of Epilepsy and Clinical Neurophysiology, vol. 12, no. 2, pp. 69-72, 2006.
12. R. Acharya, and P. K. Sadasivan, Entropies for detection of epilepsy in EEG, Computer Methods and Programs in Biomedicine, vol. 80, no. 3, pp. 187–19, 2005 https://doi.org/10.1016/j.cmpb.2005.06.012
13. A. Aarabi, F. Wallois, and R. Grebe, Automated neonatal seizuredetection: A multistage classification system through feature selection based on relevance and redundancy analysis, Journal of Clinical Neu-rophysiology, vol. 147, no. 2, pp. 328–340, 2006. https://doi.org/10.1016/j.clinph.2005.10.006
14. Liu Y, Zhou W, Yuan Q, Chen S. Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG. IEEE Trans Neural Syst Rehabil Eng 2012; 20(6):749–55. https://doi.org/10.1109/TNSRE.2012.2206054
15. TemkoA, Thomas E, MarnaneW, LightbodyG, BoylanG. , EEG-based neonatal seizure detection with Support Vector Machines. Clin Neurophysiol 2011;122:464–73 https://doi.org/10.1016/j.clinph.2010.06.034
16. Sorensen TL, Olsen UL, Conradsen I, Henriksen J, Kjaer TW, Thomsen CE, et al. Automatic epileptic seizure onset detection using matching pursuit: a case study. Conf Proc IEEE Eng Med Biol Soc 2010; 2010:3277–80.
17. Chisci L, Mavino A, Perferi G, Sciandrone M, Anile C, Colicchio G, et al. Real-time epileptic seizure prediction using AR models and support vector machines. IEEE TransBiomed Eng 2010; 57:1124–32. https://doi.org/10.1109/TBME.2009.2038990
18. Petersen EB, Duun-Henriksen J, Mazzaretto A, Kjaer TW, Thomsen CE, Sorensen HB.Generic single-channel detection of absence seizures. Conf Proc IEEE Eng Med Biol Soc 2011;2011:4820–3 https://doi.org/10.1109/IEMBS.2011.6091194
19. Acharya UR, Sree SV, Suri JS. Automatic detection of epileptic EEG signals using higher order cumulant features. Int J Neural Syst 2011;21:403–14 https://doi.org/10.1142/S0129065711002912
20. Kharbouch A, Shoeb A, Guttag J, Cash SS. An algorithm for seizure onset detection using intracranial EEG. Epilepsy Behav 2011; 22(Suppl. 1):S29–35. https://doi.org/10.1016/j.yebeh.2011.08.031
21. Liu Y, Zhou W, Yuan Q, Chen S. Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG. IEEE Trans Neural Syst Rehabil Eng 2012; 20(6):749–55. https://doi.org/10.1109/TNSRE.2012.2206054
22. Xie S, Krishnan S. Wavelet-based sparse functional linear model with applications to EEGs seizure detection and epilepsy diagnosis. Med Biol Eng Comput 2012; 51(1–2):49–60. https://doi.org/10.1007/s11517-012-0967-8
23. Direito B, Teixeira C, Ribeiro B, Castelo-Branco M, Sales F, Dourado A. Modeling epileptic brain states using EEG spectral analysis and topographic mapping. J Neurosci Methods 2012; 210:220–9. https://doi.org/10.1016/j.jneumeth.2012.07.006
24. Rabbi AF, Fazel-Rezai R. A fuzzy logic system for seizure onset detection in intracranial EEG. Comput Intell Neurosci 2012; 2012:705140. https://doi.org/10.1155/2012/705140
25. Roshan Joy Martis , U. Rajendra Acharya ,Jen Hong Tan,Andrea Petznick Ratna Yanti, Chua Kuang Chua ,Louis Tong ,Application of empirical mode decomposition (EMD) for automated detection of epilepsy using EEG signalsInternational Journal of Neural Systems,2012, 22(6):1250027 DOI: 10.1142/S012906571250027X
26. A Aarabi, B He, A rule-based seizure prediction method for focal neocortical epilepsy. Clin.Neurophysiol. 123(6), 1111–1122 (2012) https://doi.org/10.1016/j.clinph.2012.01.014
27. Cuppens K, Chen CW, Wong KB, Van de Vel A, Lagae L, Ceulemans B, et al. Using spatiotemporal interest points (STIP) for myoclonic jerk detection in nocturnal video. Conf Proc IEEE Eng Med Biol Soc 2012; 2012:4454–7.

https://doi.org/10.1109/EMBC.2012.6346955
28. AS Zandi, R Tafreshi, M Javidan, GA Dumont, Predicting epileptic seizures in scalp EEG based on a variational Bayesian Gaussian mixture model of zero-crossing intervals. IEEE Trans. Biomed. Eng. 60(5), 1401–1413(2013) https://doi.org/10.1109/TBME.2012.2237399
29. S Li, W Zhou, Q Yuan, Y Liu, Seizure prediction using spike rate of intracranial EEG.IEEE Trans. Neural Syst. Rehabil. Eng. 21(6), 880–886 (2013)
30. S Wang, WA Chaovalitwongse, S Wong, Online seizure prediction using an adaptive learning approach. IEEE Trans. Knowl. Data Eng. 25(12), 2854–2866(2013) https://doi.org/10.1109/TKDE.2013.151
31. H. Lu, Y. Pan, B. Mandal, H. L. Eng, C. Guan, and D. W. S. Chan, “Quantifying Limb Movements in Epileptic Seizures Through Color-Based Video Analysis,” in IEEE Transactions on Biomedical Engineering, vol. 60, no. 2, pp. 461–469, Feb. 2013.
32. H Daou, F Labeau, Dynamic dictionary for combined eeg compression and seizure detection. IEEE J. Biomed Health Inform. 18(1), 247–256 (2014) https://doi.org/10.1109/JBHI.2013.2263198
33. Sahar Nesaei and Ahmad R. Sharafat, Real-time Detection of Precursors to Epileptic Seizures: Non-Linear Analysis of System Dynamics,J Med Signals Sens. 2014 Apr-Jun; 4(2): 103–112. https://doi.org/10.4103/2228-7477.130467
34. R. B. Pachori and S. Patidar, “Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions,” Computer Methods and Programs in Biomedicine,vol.113,no.2,pp.494–502,2014 https://doi.org/10.1016/j.cmpb.2013.11.014
35. Oliver Faust, U. Rajendra Acharya, Hojjat Adeli, Amir Adeli, Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis,Seizure 26 (2015) 56–64. https://doi.org/10.1016/j.seizure.2015.01.012
36. Noha S.Tawfika Sherin M.Youssef, Mohamed Kholief, A hybrid automated detection of epileptic seizures in EEG records, Computers & Electrical Engineering ,Volume 53, July 2016, Pages 177-190 https://doi.org/10.1016/j.compeleceng.2015.09.001
37. A. Sharmila, And P. Geethanjali, DWT Based Detection of Epileptic Seizure From EEG Signals Using Naive Bayes and k-NN Classifiers, IEEE Access,2016, Digital Object Identifier 10.1109/ACCESS.2016.2585661.
38. Enamul Kabir . Siuly . Yanchun Zhang,Epileptic seizure detection from EEG signals using logistic model trees,Brain Informatics (2016) 3:93–100 DOI 10.1007/s40708-015-0030-2.
39. Pouya Bashivan, MohammedYeasin NoelCodella,,Irina Rush, Learning Representations From EEG With Deep Recurrent-Convolutional Neural Networks ,Published as a conference paper at ICLR 2016
40. S. V. Tonpe, Y. G. Adhav and A. K. Joshi, “Epileptic seizure detection using microsensor,” 2017 International Conference on Communication and Signal Processing (ICCSP), Chennai, 2017, pp. 0660–0662.
41. Qi Yuan, Weidong Zhou,Liren Zhang, Fan Zhang, Fangzhou Xu, Yan Leng, Dongmei Wei, Meina Chen, Epileptic seizure detection based on imbalanced classification and wavelet packet transform, Seizure 50(2017),99-108
42. Turky N. Alotaiby, Saleh A. Alshebeili, Faisal M. Alotaibi and Saud R. Alrshoud, Epileptic Seizure Prediction Using CSP and LDA for Scalp EEG Signals, Hindawi Computational Intelligence and Neuroscience Volume 2017, Article ID 1240323, 11 pages https://doi.org/10.1155/2017/1240323
43. Bhattacharyya, A., Pachori, R. B., 2017a, A multivariate approach for patient-specific EEG seizure detection using empirical wavelet transform, IEEE Transactions on Biomedical Engineering, 64(9):2003-2015.
44. Bhattacharyya A., Pachori R. B., Upadhyay A., Acharya, U. R., 2017b, Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals, Application of Signal Processing Methods for Systematic Analysis of Physiological Health, 7(4):385.
45. Sharma, M., Pachori, R. B., Acharya, U. R., 2017. A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension, Pattern Recognition Letters, 94:172-179.
46. U. Rajendra Acharya , Shu Lih Oh , Yuki Hagiwara , Jen Hong Tan , Hojjat Adeli,Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signalsComputers in Biology and Medicine, · September 2017 DOI: 10.1016/j.compbiomed.2017.09.017
47. B. AL-Bokhity, Dalia Nashat, and T. M. Nazmy, Accuracy Enhancement of the Epileptic Seizure Detection in EEG Signals,Appl. Math. Inf. Sci. 11, No. 6, 1693-1702 (2017). https://doi.org/10.18576/amis/110616
48. A. Ghosh, A. Sarkar, T. Das, and P. Basak, “Pre-ictal epileptic seizure prediction based on ECG signal analysis,” 2017 2nd International Conference for Convergence in Technology (I2CT), Mumbai, 2017, pp. 920–925. https://doi.org/10.1109/I2CT.2017.8226263
49. Baumgartner C, Koren JP, Seizure detection using scalp-EEG. Epilepsia. 2018 Jun;59 Suppl 1:14-22. doi: 10.1111/epi.14052
50. Ahmed I. Sharaf, Mohamed Abu El-Soud, and Ibrahim M. El-Henawy,An Automated Approach for Epilepsy Detection Based on Tunable Q-Wavelet and Firefly Feature Selection Algorithm International Journal of Biomedical Imaging Volume 2018, Article ID 5812872, 12 pages, https://doi.org/10.1155/2018/5812872.

51. Yang Y, Zhou M, Niu Y, Li C, Cao R, Wang B, Yan P, Ma Y and Xiang J (2018) Epileptic Seizure Prediction Based on Permutation Entropy. Front. Comput. Neurosci. 12:55. doi: 10.3389/fncom.2018.00055
52. Isabell Kiral-Kornek, Subhrajit Roy, Ewan Nurse, Benjamin Mashford, Philippa Karoly, Thomas Carroll, Daniel Payne, Susmita Saha, Steven Baldassano, Terence O'Brien, David Grayden, Mark Cook, Dean Freestone, Stefan Harrer, Epileptic Seizure Prediction Using Big Data and Deep Learning: Toward a Mobile System, EBioMedicine,Volume 27, 2018, Pages 103–111. https://doi.org/10.1016/j.ebiom.2017.11.032
53. Xiashuang Wang , Guanghong Gong and Ni Li ,Automated Recognition of Epileptic EEG States Using a Combination of Symlet Wavelet Processing, Gradient Boosting Machine, and Grid Search Optimizer,Sensors 2019, 19, 219; doi:10.3390/s19020219.
54. Dattaprasad A. Torse, Rajashri Khanai, Veena V. Desai,Classification of Epileptic Seizures using Recurrence Plots and Machine Learning Techniques,2019 International Conference on Communication and Signal Processing (ICCSP),April 2019.
55. Poonam Sheoran, J.S. Saini,Time-time analysis of electroencephalogram signals for epileptic seizure detection,International Journal of Biomedical Engineering and Technology, 2019 Vol.30 No.2, pp.113 – 131.DOI: 10.1504/IJBET.2019.100554.
56. Umar Asif, Subhrajit Roy, Jianbin Tang, and Stefan Harrer, Seizure Net: Multi-Spectral Deep Feature Learning for Seizure Type Classification, arXiv: 1903.03232v3 [cs.LG] 12 Nov 2019.
57. Liu, J., & Woodson, B. (2019). Deep Learning Classification for Epilepsy Detection Using a Single Channel Electroencephalography (EEG). Proceedings of the 2019 3rd International Conference on Deep Learning Technologies - ICDLT 2019. doi:10.1145/3342999.3343008.
58. Roozbeh Zarei, Jing He, Siuly Siuly, Guangyan Huang, and Yanchun Zhang, Exploring Douglas-Peucker Algorithm in the Detection of Epileptic Seizure from Multicategory EEG Signals,Hindawi BioMed Research International Volume 2019, Article ID 5173589, 19 pages https://doi.org/10.1155/2019/5173589.
59. Munya A. Arasi, Sangita babu, Survey of Machine Learning Munya A. Arasi, Sangita babu, Survey of Machine Learning Techniques in Medical Imaging, International Journal of Advanced Trends in Computer Science and Engineering, 8(5), September - October 2019, 2107 – 2116. https://doi.org/10.30534/ijatcse/2019/39852019
60. M. Shamim Hossain, Syed Umar Amin, Mansour Alsulaiman, and Ghulam Muhammad. 2019. Applying Deep Learning for Epilepsy Seizure Detection and Brain Mapping Visualization. ACM Trans. Multimedia Comput. Commun. Appl. 15, 1s, Article 10 (February 2019), 17 pages. https://doi.org/10.1145/3241056.
61. Sheetal S. Pandya, Nilesh B. Kalani, Review on Text Sequence Processing with use of different Deep Neural Network Model, International Journal of Advanced Trends in Computer Science and Engineering, 8(5),September - October 2019, 2224 – 2230 https://doi.org/10.30534/ijatcse/2019/56852019
62. Harshit Bhardwaj, Aditi Sakalle,Arpit Bhardwaj, Aruna Tiwari, Classification of electroencephalogram signal for the detection of epilepsy using Innovative Genetic Programming, Expert Systems. 2019; 36:e12338. https://doi.org/10.1111/exsy.12338 wileyonlinelibrary.com/journal/exsy.

APPENDIX-1

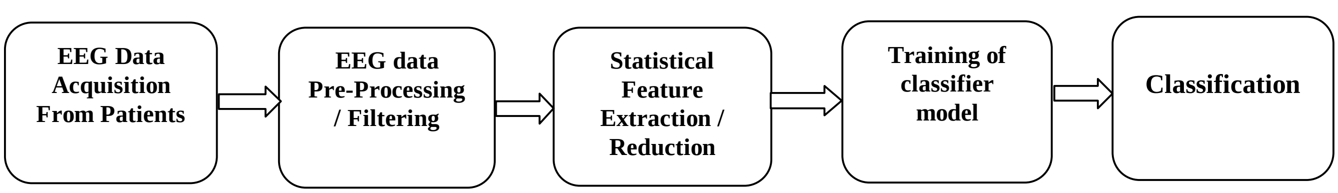

Figure1: Classification of seizure detection prediction steps

Table 1: Year wise research work on classification and detection of Elliptic seizure

Sl No.	Author/Year	Seizure Detection method	Detection Algorithm	Results
1	Sorrensen et al,2010[16]	EEG-3channels	SVM	SEN-78%, FPR -0.16 to 5.31 events/hr
2	Chiski et al,2010[17]	EEG multichannel	Least Square Estimator and SVM classification	SEN-100 %
3	Peterson et al,2011[18]	EEG-1-channel	WT+ SVM	SEN-99.1 % & PPV of 94.8 %
4	Temko et al,2011[15]	EEG (8 bipolar) neonatal Seizures	FFT+ SVM classification	SEN-89 %
5	Acharya et al,2011[19]	EEG seizures /not stated	Higher order spectra + SVM	Detection accuracy 98.5%
6	Kharbouch et al,2011[22]	Intracranial EEG/Social epilepsy	SVM classifier	ACC-97%
7	Liu et al,2012[21]	CPS	WT+ SVM classification.	SEN-94.8 % & SPEC of 95.3%
8	Xie et al,2012[22]	EEG (6 channel).	Wavelet + 1-NN classification method.	ACC-99%
9	Direito et al,2012[23]	EEG-multichannel	Markov modeling	ACC-89.3%
10	Rabbi et al,2012[24]	Intracranial GTCS	Fuzzy	SEN-95.8 % & FPR of 0.26 events/hr
11	Roshan Joy Martis et al (2012)[25]	EMD	Classification + regression tree (CART)	ACC: 95.33%,SEN: 98%,SPEC: 97%
12	AS Zandi et al.,(2013)[28]	moving window analysis	Variational Bayesian Gaussian mixture model	SEN-91-100% & SPEC of 100%
13	Bhattavharyya et al., (2017a) [43]	EMD	Random forest	ACC: 99.4%,SEN: 97.9%,SPEC: 99.5%
14	Bhattavharyya et al., (2017b) [44]	Tunable Q-wavelet transform	SVM	ACC: 100%
15	Sharma et al., (2017) [45]	Analytic time frequency flexible wavelet transform	LS-SVM	SEN: 100%
16	Rajendra(2017)[46]	deep CNN Structure	CNN	ACC: 88.7%,SEN: 95%,SPEC: 90%
17	Yanli Yang et al.,(2018)[51]	permutation entropy	SVM	ACC: 100%,SEN: 94%,SPEC: 99%
18	Xiashuang Wang et al., (2019)[53]	Symlets wavelets,	SVM	ACC: 100%
19	Sheoran et al., (2019)[55]	TT-Transform	Quadratic Discriminant Analysis	ACC:100%
20	M. Shamim Hossain et al., (2019)[59]	correlation maps	Deep CNN	ACC: 99.46%,SEN: 90%,SPEC: 91.65%