**Review**

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# A review on the pattern detection methods for epilepsy seizure detection from EEG signals

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**Abstract:** Over several years, research had been conducted for the detection of epileptic seizures to support an automatic diagnosis system to comfort the clinicians' encumbrance. In this regard, a number of research papers have been published for the identification of epileptic seizures. A thorough review of all these papers is required. So, an attempt has been made to review on the pattern detection methods for epilepsy seizure detection from EEG signals. More than 150 research papers have been discussed to determine the techniques for detecting epileptic seizures. Further, the literature review confirms that the pattern recognition techniques required to detect epileptic seizures varies across the electroencephalogram (EEG) datasets of different conditions. This is mostly owing to the fact that EEG detected under different conditions have different characteristics. This consecutively necessitates the identification of the pattern recognition technique to efficiently differentiate EEG epileptic data from the EEG data of various conditions.

**Keywords:** classification; feature extraction; feature selection; mutual information; seizure.

## Introduction to epileptic seizure detection

Electroencephalogram (EEG) is an effective, low-cost, non-invasive technique used in clinical studies to examine the electrical activity of the brain. EEG is one of the techniques to identify abnormalities of the brain. One of the chronic, non-communicable, neurological disorders that can be studied by EEG is epilepsy. Epileptic seizure is the transient occurrence of signs and/or symptoms due to abnormal, excessive or synchronous neuronal activity in the brain. Epilepsy is a disorder of the brain characterized by an enduring predisposition to generate epileptic seizures, and is characterized by the neurobiology, cognitive, psychological and social consequences of this condition. Epilepsy is defined as the occurrence of at least one epileptic seizure [1].

The neurological condition of epilepsy is characterized by recurrent seizures, which are momentary electrical disruptions in the brain. These seizures may cause a disturbance in movement, control of bowel or bladder function, loss of consciousness or other disturbances in cognitive functions.

A seizure can be realized by an infinitesimal muscle jerk to severe, generalized and prolonged convulsions. Seizures which occur recurrently and suddenly are hazardous and lead to serious states. In clinical terms, if two or more motiveless seizures occur, it is suspected that the cause might be epilepsy. If the seizure is due to epilepsy, then the detection of epilepsy at its onset is very useful for initial treatment with anti-epileptics for improving the quality of life and care of epileptic persons. Epileptic seizures generally begin and end unexpectedly without any external intrusion. If seizures are unpredicted, it generally causes physical risks due to accidents, such as falling down and head injuries. The most common, effective diagnostic method for the detection of epilepsy is based on the analysis of EEG signals. EEG analyses not only distinguish epileptic data from normal data, but also differentiate epileptic seizures or ictal from pre-ictal or inter-ictal data. Skilled neurophysiologists visually examine the EEG signals and detect epilepsy. However, epilepsy can be detected from a long recording of EEG data, which is difficult and also requires human expertise.

In the early 1970s, the diagnosis of epilepsy started to provide support for the automated analysis of EEG recordings. An automatic detection system based on seizure patterns was presented by Gotman [2]. Two main techniques have been developed for the automated analysis of epileptic EEG recordings from the early days. They are as follows:

– analysis of spike detection or inter-ictal spike detection and
– analysis of epileptic seizure.

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The problem related to automatic spike detection can be transferred to the detection of the presence of inter-ictal spikes with high selectivity and sensitivity in multi-channel EEG recordings [3, 4]. It means that great proportions of true events need to be detected with a lesser number of false detections. Numerous studies have assessed this problem by extracting the features of raw EEG recordings that best describe the spike morphology. Spikes can also be detected using machine-learning techniques [4]. In machine-learning techniques, the spike detection problems are divided into feature extraction and classification. Apart from the single channel itself, other contextual information such as spatial and temporal data are vital to neurophysiologists for recognizing spikes [5, 6].

In [7], a system which is used for the detection of seizures in intracranial EEG based on a combination of generative, discriminative and hybrid methods was presented. The system took part in the UPenn and Mayo Clinic's Seizure Detection Challenge using the Kaggle platform and the solutions of the winners were ranked fifth. A general idea of seizure detection and the relevant prediction methods, and their potential use in closed-loop warning systems in epilepsy were presented [8]. Further, the methods established to detect seizures using scalp and intracranial EEG, electrocardiography, accelerometer and motion sensors, electro-dermal activity, and audio/video captures were presented. A robust and fast algorithm for the offline detection of epileptic seizures of scalp EEG have been described [9]. The algorithm provides high sensitivity and a low number of false detections in long-term EEG data without any prior information. A method for an automatic epileptic seizure detection system with 205 patients from long-term scalp EEG recordings called EpiScan was presented [10]. In the case of a seizure, EpiScan can be used as an alarm device to alert the medical supervision of epilepsy monitoring units (EMUs).

The abnormality in neuron synchronization plays a vital part in the generation of epileptic seizures. So, multivariate time series analysis techniques examining the relations between the dynamics of different neural populations might be beneficial to epileptic seizure prediction [11]. Responsive cortical stimulation reduces the frequency of disabling partial seizures and it is related to enhancements in the quality of life and is well-tolerated with no mood or cognitive effects [12]. Further, responsive stimulation might afford an alternative adjunctive treatment preference for adults with clinically intractable partial seizures.

In [13], the researchers have studied the seizure detection algorithm that is quite modest to implement on a microcontroller. As a result, it could be used for an implantable closed loop stimulation device. The researchers proposed a set of 11 time-domain and power band features which were worked out from one intracranial EEG contact located in the seizure onset zone. The classification of the features is executed by means of a random forest classifier. The three-stage seizure detection approach is based on 339 h of data collected from 10 patients in an EMU [14]. The study intended to develop a wearable system that would detect seizures, alert a caregiver and record the time of the seizure in an electronic diary for the patient's doctor. In this work, stage I detects concurrent activity in heart rate, arterial oxygenation and electro-dermal activity, all of which can be monitored by a wrist-worn device and which in combination produce a very low false-positive rate. Further, stage II detects a specific pattern created by these three bio-signals. For patients whose seizures cannot be detected by stage II, stage III detects seizures using limited-channel EEG monitoring with at most three electrodes.

Pattern recognition is one of the techniques used for detecting epileptic seizures from EEG signals by extracting the hidden patterns of EEG.

# Methods of pattern recognition

The pattern recognition system for epileptic seizure detection consists of different stages such as EEG signal acquisition, pre-processing, feature extraction, dimensional reduction and classification as shown in Figure 1.

All the pattern recognition approaches focused on improving classification accuracy with varying combinations of feature extraction and classification techniques [15–17]. The disadvantage of this technique is the requirement of a conventional visual examination of the patterns and a careful inspection by an expert.

## Pre-processing

Raw EEG data have low signal-to-noise ratio and poor spatial resolution. So, the signals are pre-processed to get a better spatial resolution and an improved signal-to-noise ratio. The data may be pre-processed using a (i) Butterworth band-pass filter and (ii) a discrete wavelet transform (DWT).

## Feature extraction

The next step after pre-processing is the feature extraction. Potentially useful information hidden in the characteristics of the signal can be extracted from this stage. Feature extraction involves extracting hidden information from a signal. In biomedical signal processing, these features or measurements are important in the process of data analysis. These features establish a new procedure for expressing the data, and it could be categorical, continuous or binary, and

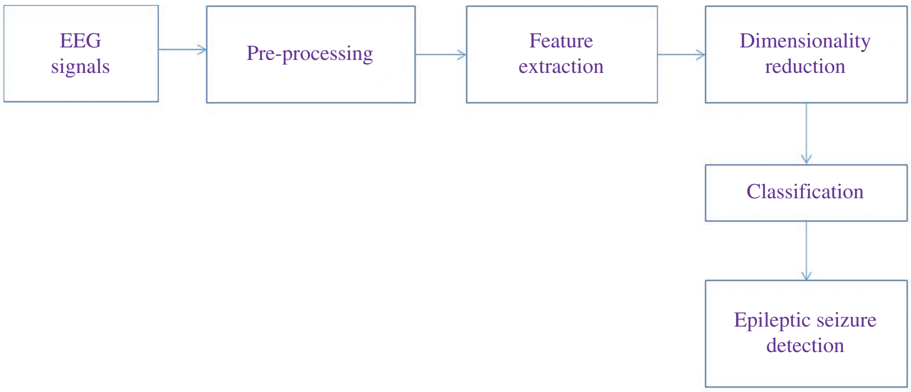


**Figure 1:** Pattern recognition system for the detection of epileptic seizure from EEG signals.

moreover, denote direct measurements or attributes to the signal. For instance, the features might be power spectral density (PSD), Lyapunov exponents, etc.

The researchers used linear and non-linear methods for EEG analysis. The analysis is performed in the time domain, frequency domain and time-frequency domain. The concept of seizure prediction was originally stated for the EEG data collected from two electrodes based on spectral analysis [18]. In [19], pole trajectories of an autoregressive model were used to study the pre-ictal periods. The rates of inter-ictal spiking as indicators of forthcoming seizures were examined in [20]. The scored autocorrelation moment analysis was used for distinguishing EEG epochs containing seizures [21].

Linear methods have been broadly used in epilepsy detection mostly due to their ease and adaptability. In order to detect the pre-ictal state, the statistical moment of the EEG amplitudes and Hjorth parameters among others were used as features of seizure prediction [22]. The other linear features such as power and signal variance are also used to predict seizure onset [23, 24]. In various studies of seizure prediction, accumulated energies were used [25–27]. Also, seizure onset and offset determination might be successful in using linear prediction filters [28]. Another linear feature, the relative fluctuation index, can be used to measure the intensity of the fluctuation of EEG signals [29]. For the period of a seizure, there exists higher fluctuation in the EEG signals than an ictal-free period. Hence, values of the fluctuation index for the period of a seizure are generally higher than other EEGs. In [30], the epileptic seizure from EEG signals was detected using linear least squares (LS) pre-processing.

Several methods for the detection of seizure onset and nonlinear feature analysis motivated by the correlation dimension have been presented [31]. Researchers have extracted several nonlinear features such as entropies [32], energy and correlation dimension [33], fractal dimension [33, 34], the Lyapunov exponent [33] and higher-order spectra (HOS) [35, 36] from both detailed and approximate coefficients of the wavelet transform by employing non-linear dynamics and chaos theory [37, 38].

Currently, EEG epileptic detection has developed with various methods such as non-linear models, neural networks, Bayesian methods, independent component analysis (ICA), variance-based methods and support vector machines (SVMs) [39]. For detecting and analyzing non-stationary signals, other groups of techniques that are potentially useful are time-frequency distributions [40]. These techniques permit us to visualize the progression of frequency activities for the period of certain non-stationary occurrence by mapping a one-dimensional time signal into a two-dimensional function of time and frequency.

The quantifiable valuation of epilepsy by using the methods of nonlinear dynamics with intracranial EEG signals as input has been shown [41]. The correlation dimension methods to study the different neurological conditions of epilepsy from EEG signals have been applied [42]. A new measure to distinguish between linear stochastic and nonlinear deterministic systems have been used [43]. It was observed that EEG signals which were recorded from epileptic regions showed durable nonlinear determinism whereas non-epileptic zones could be categorized as linear stochastic systems. Nonlinear features and discriminant analysis have been applied to detect epileptic seizures along with time and frequency domain methods [44]. Sample entropy which is a nonlinear parameter has been used for analyzing epileptic EEG signals [45].

In epileptic seizure detection from EEG signals, ICA has been applied to eliminate artifacts and it has also been used for decomposing the recorded signals of EEG into distinct component signals originating from different sources [46]. The spectral characteristics of time-varying epileptic signals were studied and the statistical parameters were calculated in a time domain [47]. Researchers also used principal component analysis (PCA) for detecting an epileptic seizure [48–50].

In [51], frequency domain analysis was performed using Welch's method to differentiate epilepsy from normal data. In [52], PSD was used for classifying the three-class problems of EEG signals.

EEG signals contain low-frequency information about long time periods and high-frequency information with short time periods [53]. Raw EEG data suffer from low signal-to-noise ratio and poor spatial resolution. Pre-processing is a de-noising step which improves the signal-to-noise ratio and provides a better spatial resolution of the EEG data. The wavelet transform is one such technique based on multi-resolution analysis to capture the relevant frequency information on low frequencies along with the relevant time information on high frequencies. Therefore, the wavelet transform is useful in analyzing epileptic seizure signals.

DWT decomposes the signal to different levels using a filter bank consisting of a group of filters. In the literature, various statistical time-domain features were extracted from the DWT subbands of the publicly available database of the University of Bonn, Germany, to identify epileptic seizures. In order to analyze the effect of DWT on EEG pre-processing, in that study the widely used features such as the mean absolute value (MAV), standard deviation

(SD) and average power (AVP) were derived with and without DWT pre-processing from raw as well as filtered EEG data to identify epileptic seizures [16].

In the automatic detection of an epileptic seizure using time-frequency analysis, DWT has been used [54–59]. Further, DWT has been used for analyzing and characterizing epileptiform discharges [53]. To detect seizures, time-frequency patterns as signatures were used [60]. In [61–63], time-frequency distributions extracting features of PSD have been used. In order to reveal seizure patterns, a time-frequency-matched filter was introduced [64]. In [65], normal and seizure signals were classified using DWT and SVM classifiers. Numerous researchers have worked with time-frequency features for epileptic seizure detection [65]. Dual-tree complex wavelet transform has been used for detecting epileptic seizures [66]. In [59], a double-density DWT (DD-DWT)-based Hurst exponent and fuzzy entropy have been used in epileptic detection.

HOS parameters have been applied for automated epileptic detection [34, 67]. Furthermore, for detecting epileptic seizures, recurrent quantification analysis features have been used in the classification of a three-class problem [68]. Approximate entropy (ApEn) has been used for distinguishing the epileptic states [68, 69]. Permutation entropy has been used to differentiate the epileptic states [70]. In [71], the Hilbert weighted frequency was used to distinguish normal from seizure activities. In [72], empirical mode decomposition (EMD) was used for classifying the time series of three states. EMD and intrinsic mode functions were used to distinguish inter-ictal from ictal states [73]. In [73, 74], EMD and intrinsic mode functions were used to distinguish interictal from ictal states. In [75], EMD was applied to differentiate a non-seizure and a seizure. Further, to distinguish seizure from seizure-free states, fractional linear prediction (FLP) has been attempted [76].

In the literature, it has been found that most of the researchers attempted to use features derived from DWT sub-bands as shown in Table 1.

In most of the literature, statistical features derived from the DWT coefficients were used, and Table 1 shows the research attempts for DWT-derived features and these features may be redundant and, therefore, increase the computational burden of the classifier despite not providing any useful information.

## Dimensionality reduction

It is essential to know the relevance of features to solve the problem considered. Feature selection techniques play a vital role. Dimensional reduction reduces the information to a lower dimensional space to reduce the computational burden and memory requirement. Feature selection might be outlined in two key tasks as follows: (i) choosing the significant features, and (ii) searching for the best subset of a feature. The use of feature reduction reduces the data dimension, known as dimensional reduction. Further, it is essential to select the feature subset that describes better performance and is utmost beneficial for problems such as regression, classification or detection. Feature selection techniques lead to a better understanding of data visualization composed of reduction in data storage and measurement. Therefore, feature selection methods aim to attain a (i) reduction in the size of the feature matrix and (ii) improve both the computational cost and the performance of the classifier [88].

The selection of feature has become more crucial to biomedical engineering for which a large volume of datasets are available. In order to avoid taking redundant features to the classifier, a feature selection is preferred. A total of 55 features derived from the time domain, frequency domain and information theory have been used for attaining notable results [89]. In [90], surface EEG recordings were assessed using non-linear features and features derived from the information theory. The application of feature selection methods based on the information theory to minimize the complication and computation costs of LS-SVM has been investigated and distinguishes nocturnal motor seizures of children from normal nocturnal movements using accelerometer signals [91]. Dimensional reduction for EEG classification using mutual information (MI) for improving the performance of SVM has been used [39].

Numerous algorithms have been proposed to feature ranking for selecting the optimal feature subset. A common measure of significance of several feature selection algorithms is based on the MI of the input feature and the target variable [92]. The probability density functions (pdfs) of the input and output variables are integrated to compute the MI between continuous variables. Researchers have

**Table 1:** Literature survey on the classification of features derived from DWT.

| Author/year | Features from DWT | Classifiers |
|---|---|---|
| [77] | SD and average value | Logistic regression and multilayer perception neural networks |
| [78] | Autoregressive parameter estimation and maximum likelihood estimation | Wavelet neural networks and back propagation |
| [63] | Lyapunov exponent | Recurrent neural networks |
| [56] | SD, mean value and average value | ANN |
| [79] | Maximum value, minimum value, mean value and SD | Combined neural networks |
| [80] | SD | ANN |
| [81] | Line length | ANN |
| [82] | SD and average value | SVM, LS-SVM |
| [83] | Maximum value, minimum value, mean value and SD | k-NN |
| [84] | Energy | ANN |
| [85] | Energy, entropy, maximum value, minimum value, mean value and SD | Linear classifiers |
| [86] | Mean value, power, average value, SD and median value | Fuzzy neural network |
| [87] | Maximum value, minimum value and SD | SVM |

ANN, artificial neural network; k-NN, k-nearest neighbor; LS, least squares; SD, standard deviation; SVM, support vector machine.

used histogram estimators [93, 94], kernel estimators [95] and parametric methods to estimate MI. The histogram method might be used in the estimation of the pdfs if appropriate data are specified [92, 96].

The MI method is based on scoring and ranking of features. The advantage of the algorithm is simplicity, but it only considers the MI between individual features and the class, and the MI between each pair of individual features.

Dimensional reduction using the feature selection technique based on the estimation of MI has been applied to identify the significant features required for the classifiers. The MI technique measures the values of a feature reliant on the related class labels. Each feature value is first quantized into one of the quantization ($Q_S$) levels in which the feature-specific quantization scale is determined such that each bin will contain approximately an equivalent quantity of samples of the complete dataset. The bins are chosen in this manner, instead of a conventional uniform quantization scale, so as to provide some statistical validity of the occurrence of the different quantization levels. The MI between the discretized feature values "$a$" and the class labels "$b$" is assessed according to the following equation (1):

$$\mathrm{MI} = \int_{a\in A}\int_{b\in B} p(a,\, b)\log\frac{p(a,\, b)}{p(a)p(b)} \tag{1}$$

where $p(a, b)$, $p(a)$ and $p(b)$ are probability density functions.

The higher the MI, the higher is the dependency on the feature values and the class labels. Higher MI values show extra information about the target and therefore a higher significance. The MI method results in the ranking of features to select the number of features having the highest values [97].

The dimensions of the features are reduced using transformation techniques such as distance-based data reduction [98], PCA [65, 99], ICA and linear discriminant analysis (LDA) [65]. Further, the dimension of the features is reduced using selection techniques such as the genetic algorithm (GA) [100] and MI [97, 101].

### Classification

The features obtained from the feature extraction/feature selection stage should be given to the classifier. The main purpose of using a classifier is to identify a set of features required to characterize the epileptic seizure data from other data.

Researchers have used k-nearest neighbor (k-NN) [38, 59], naïve Bayes (NB) [63, 102], probabilistic neural network [77], decision trees [51], artificial neural networks (ANNs) [58, 61, 63, 69], SVMs [58, 65, 103], LS-SVM [76], GA SVM [59], Fisher's linear discriminant (FLD) [104], optimum path forest [105], PCA [106], enhanced probabilistic neural network [107] and other various classification algorithms for detecting epileptic seizures.

## Seizure prediction

Literature on seizure prediction has reported various difficulties and drawbacks in the testing and designing of seizure-prediction algorithms [108]. The influences of long prediction horizons with respect to the clinical requirements and the strain on patients were discussed and analyzed by long-term continuous intracranial EEG data [109].

Seizure prediction possibly has more advantages compared with the detection of seizure. Seizure prediction devices may be suitable both in stopping accidents and in enlightening effects, eventually permitting primary treatment or even avoidance of seizures. The prediction approaches must be capable of recognizing the pre-ictal changes that – if they exist – take place within minutes, hours or days preceding seizures [8].

In seizure prediction in ambulatory patients, intracranial electroencephalography in patients with refractory epilepsy has been developed as a feasible tool. In 15 patients with an implanted seizure advisory device, high rates of sensitivity were found, ranging from 65 to 100%, with no significant impact on the quality of life, rigorousness of seizures, and processes for angst and depression disorders [110].

## Databases

The role of high-quality EEG databases in the enhancement and valuation of seizure prediction approaches was presented [111]. In that study, the researchers used a long-term EEG recording of 275 patients from a European Union-funded database which is publicly available from 2012. Further, the researchers used the EPILEPSIAE database, a widespread electroencephalography database of epilepsy patients [112].

Advanced epilepsy research through data sharing and increased collaboration between international research communities was discussed [113]. A kaggle.com competition to crowdsource introduced the development of seizure detection algorithms using intracranial EEG from canines and humans with epilepsy. Further, researchers shared a "plug and play" pipeline to allow other researchers to easily use these algorithms on their own datasets. The success of this competition demonstrates how sharing code and high-quality data results in the creation of powerful translational tools with significant potential to impact patient care [114].

From the literature, it is found that in two-class classification, most of the researchers used the University of Bonn dataset, which consists of five datasets A, B, C, D and E. These datasets are used for developing a pattern recognition technique to detect epileptic seizures from EEG signals.

## Methods of spike detection

There are various methods of EEG spike detection. Spike detection techniques such as mimetic techniques, morphological analysis, template matching algorithms, parametric methods, ICA, ANNs, clustering techniques, knowledge-based rules, data mining and classification techniques have been discussed [61, 115].

Mimetic techniques are based on the hypothesis and the process of recognizing a spike in the transient waveform in EEG recordings uses the typical features of spikes such as height, slope, sharpness and duration [2, 116–119]. The EEG signals have been decomposed into two half-waves [116]. Many other researchers decomposed the EEG waveform into half-waves in the spike detection [120–122]. Waveform decomposition with physical coordinates, curvatures and angles were used, and it provides a better representation of the expertise [123]. Researchers have proved that the correlation between expert human readers could be low on certain records and might complicate the testing of seizure detection algorithms [124]. Further, researchers studied and validated the Reveal algorithm. In both the EMU and the intensive care unit, the algorithm improves seizure detection as well as patient care [125].

In morphological analysis, raw EEG signals are decomposed into a number of physical parts. Morphological analysis is based on the frequency bands, waveforms or time-frequency representations of the spikes [20, 61, 126]. Further, using this analysis, the spike and background activities are separated and the foremost morphological characteristic of the spikes is retained. In [127], a detection method based on the morphological filter and second-order polynomial functions was used to designate the general structure elements. Further, to confine the background activity completely, a morphological filter with an appropriate morphological operation and structure elements has been used. Bi-directional spikes have been used in epileptic EEG recordings to detect a selected circular structure element and employed the mathematical morphology and wavelet transform [128]. An enhanced morphological filter had been developed for automatic spike detection to differentiate the spikes and their background activity [129].

In template matching algorithms, the spikes from a set of test EEG recordings are averaged to create a template [130, 131]. Many researchers have used the wavelet features of the signal for spike detection and template building [132–135].

In the parametric methods, local stationary of the noise in the EEG signal has been assumed, and spikes are detected as a deviation from the stationary [136, 137]. In [6], a time-varying autoregressive model was used, which assessed autoregressive parameters using a Kalman filter. Also, to determine spike locations, initially the signal was processed to emphasize the spikes and attenuate the background activity, and was finally passed over a threshold function.

In addition to these techniques, various spike detection techniques have also been proposed using ICA. ICA has been applied to the spatiotemporal data and components resembling abnormal epileptic activities selected by visual inspection and then inferred by a neurophysiologist [138, 139]. Further, researchers used ICA to isolate spikes from multichannel EEG data and demonstrated a model based on real EEG data [140]. The recursively applied and projected multiple signal classification (RAP-MUSIC) source localization approaches together with ICA decomposition have been used to detect epileptic discharges [141].

In the spike detection problem, ANNs have been trained either using raw data or features [6, 142–144]. In ANN training, windows of the data/feature such as slope, duration, amplitude, slope, sharpness and the context features extracted from the EEG activity surrounding the spikes such as baseline crossings and EEG variance were used [6, 122, 144–147].

In clustering techniques, self-organizing maps have been used for clustering EEG segments [148]. In order to cluster the spikes, the nearest mean algorithm [149], fuzzy $C$-means algorithm [150, 151] and ant $K$-means algorithm have also been used by researchers [6, 152, 153].

Furthermore, knowledge-based rules are generally used to incorporate the spatial and temporal rules [6]. The knowledge-based system with a high degree of success has been developed and has benefitted from both temporal and spatial information [147, 154, 155]. Further, the spatial information has been used to identify the common spatial distribution of spikes [156]. In order to incorporate the spatial information on the multichannel EEG recordings, a spatial-combiner stage has been used with the outputs of a self-organizing ANN to a fuzzy logic scheme [5]. To confirm the existence of spikes across two or more channels of the EEG recordings, researchers have combined the classification outputs of each channel in the final stage of spike detection [6, 146].

## Conclusions

This review illustrates the introduction to epileptic detection emphasizing the primary factor limiting the detection, i.e. the technique that can detect epileptic data among various conditions of EEG data and also the spike detection methods. A brief background of the pattern recognition of epileptic detection has been given with the intention of populating the importance of various modules of the pattern recognition scheme. This review also discusses and analyzes the work carried out by other authors in the field of epileptic detection. In this literature review, the influence of DWT to improve the accuracy of the detection of epileptic seizures using different pattern recognition schemes has been discussed. Several pattern recognition approaches have been attempted with various features. It is clear that most of the researchers have the quest to identify efficient and effective pattern recognition-based epileptic seizure detection techniques. It has been concluded that the accuracy of pattern recognition depends on feature extraction, feature selection and classification.

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