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Detection of epileptic seizure disorder using EEG signals

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7.1 Introduction

Healthcare has been a source of contention for many decades. Healthcare delivery has evolved from a conventional family doctor delivering the majority of care to a team of healthcare practitioners working across a continuum of care to improve the quality and quantity of life. Before now, healthcare was supposed to be focused on major health problems like epidemics [1]. Furthermore, technology to address the most prevalent health problems is almost nonexistent. As a result of study and progress, more have been found, and they have been identified and assigned to different health care providers. Due to rapid innovations, many health conditions can now be treated, but at a high cost.

Severe neurological and behavioral disorders, such as multiple sclerosis, brain injury, and dementia, can disrupt the brain's ability to communicate with and control its surroundings [2–4]. The inability to communicate any purpose to the external world is often referred to as a locked-in syndrome. A brain-computer interface (BCI) will aid with the renovation of functions and the resolution of cognitive deficits by supplying the brain with a new, nonmotorized processing and control mechanism for communicating signals and instructions to the outside world environment [4,5]. The significance of BCIs is inextricably linked to the development of modern electrophysiological methods for monitoring extracellular electrical impulses triggered by improvements in electric potential transmitted by ions through neuron membranes [6,7]. The techniques for identifying various kinds of brain signals are categorized into invasive and noninvasive [7,8]. Electroencephalogram (EEG) is a complex signal that contains a wealth of information about human brain function and neurological conditions [9]. Electroencephalography (EEG) signals are used in certain noninvasive brain-computer interfaces as they precisely calculate cortical electrical operations with high temporal precision [10–13]. As EEG has remarkable momentary time variations and requires simple, low-cost equipment, EEG-based BCI systems are now used in a variety of disciplines [14–19]. This growth has been aided by a better understanding of neurobiological processes and machine learning algorithms [20,21]. While these are

Artificial Intelligence-Based Brain-Computer Interface. https://doi.org/10.1016/B978-0-323-91197-9.00006-0

major advances with a lot of theoretical and practical potential, there are comparatively low bandwidth devices with maximum data transfer rates. Furthermore, progress is likely to be slow and would necessitate ongoing cautious and laborious investigation [22].

Epilepsy is a neurocognitive affliction marked by uncontrollable and repetitive epilepsy arising from brain trauma [22]. It affects 1% of the world's population, with a frequency ranging from 0.5% to 1% [22–24]. There are several diverse neurological symptoms of epilepsy, including acute sensory disturbances, muscle convulsions, lack of consciousness, behavioral disorders, and so on, due to varying beginning sites and delivery mechanisms of unexplained electrical activities in brains [25]. Seizures might occur regardless of the condition or the characteristics of the patient [26]. Patients with epilepsy have uncontrollable seizures in which they are not able to protect themselves and are at the risk of death or losing control over body movements [26–29]. To date, the condition is frequently treated with medicines and surgery; there is no remedy, and anticonvulsant therapies are not always effective for all cases of epilepsy. The effects of seizures can be reduced by monitoring brain electrical activity, predicting progressing epileptic states, as well as the risk of seizures [23,24]. Electroencephalogram (EEG) signs and patient behavior are used to diagnose epilepsy. Scalp EEG and intracranial EEG are two types of EEG pulse. Scalp EEG signals are normally obtained using electrodes mounted on the cortex and applying liquid electrolyte after moderate deformation of the scalp region to minimize resistance caused by dead skin cells. During iEEG therapy, electrodes are mounted on the brain's surface to detect electrical impulses from the frontal lobe [30,31]. Visual examination of EEG signals can be complex and laborious due to the complexities of keeping a high degree of focus during a comprehensive analysis; this problem raises operator missteps [32,33]. Also visual evaluation of an EEG signal to detect an epileptic seizures takes a long time and can be unreliable, especially for extensive data recordings [34]. As a consequence, artificial intelligence techniques for enhancing epileptic seizure diagnosis have been suggested.

The initiation of a patient seizure and the progression toward preseizure show certain advantages for epileptics [35] in patient-related algorithms in terms of machine learning. Therefore, supervised learning approaches are used to differentiate preictal from interictal data obtained from the patient [36,37]. Artificial characteristics and machine learning classifiers have been the subject of several technical studies [38]. The identification of multiple seizures is split into two parts: feature extraction and another classification. In diagnoses, parameters extracted from EEG recordings are quite useful [39]. There are strategies for extraction of functions such as a study of time-frequency [40], nonlinear dynamics [40], complexity, synchronization [41], and increases in stored energy [42]. Examples of the machine learning classification include Bayesian network, conventional neural network, and support vector machines. For feature-classifier innovation techniques, seizure detection exercises have been successfully used [43]. The functions, on the contrary, are extracted from a small number of operations that have been fine-tuned. Most notably, since convulsion symptoms change over time, it is difficult to immediately extract and interpret insightful features from EEG data [44].

Deep learning is primarily concerned with representation learning, in which the algorithm acquires and discovers the characteristics needed for classification by evaluating several layers of data [45]. Deep learning has demonstrated that it can outperform humans in recognition tasks [45,46]. It is also used in a host of advanced machine learning systems, such as detecting early Alzheimer's disease [46], predicting real estate unit selling prices [36], and calculating concrete compressive strength [47,48]. In the last decade, deep learning has sparked a huge interest, especially in the research of detective and predictive data, particularly in the health services and clinical professions [48,49]. The potential of deep learning to generate highly accurate findings has influenced researchers to tackle a wide range of real-world applications using DL techniques with a variety of approaches [50]. The deep multilayer structural backpropagation network has previously outperformed standard methods like regression models [51] and aided the neural network [51]. A recurrent convolution network, superior to previous cross-patient classification findings [52], was used to train the general spectrally invariant representation of a seizure. Additional methodologies can also be used for seizure prediction such as deep neural networks and transfer training [53,54]. These deep learning algorithms serve as the foundation for seizure detection techniques [44,55].

Fig. 7.1 shows the traditional ML approach for epilepsy detection, as well as the key differences in the operation of ML and DL techniques. In general, unprocessed info or marginally polished data (i.e., raw data without feature extraction) can be fed into a DL model for pattern recognition. Sections 7.3 and 7.4 provide a brief explanation of these techniques.

In Section 7.2, a brief introduction of EEG signals, their analysis techniques, and signal analysis methods are explained. Section 7.3 comprises ML and DL approaches for detecting epileptic seizures. Related work and comparative analysis are discussed in Section 7.4. We have also outlined potential future job paths and issues that need to be investigated further.

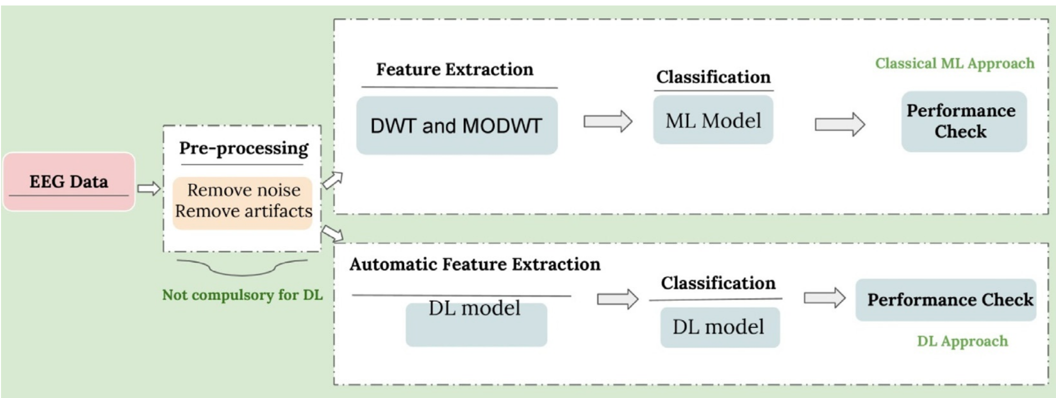

FIG. 7.1 Classification of approaches in ML and DL techniques.

7.2 Background on EEG signals

When it comes to epileptic seizure detection, the electroencephalogram (EEG) is a useful instrument for assessing brain activity using electrodes mounted on the cerebral cortex [56]. It basically measures the nerve impulses of dendrites of neurons near the cerebral cortex [57]. A standard EEG signal has an amplitude of around 10 V to 100 V and a frequency of 1 Hz to about 100 Hz when measured from the scalp. To establish electrode positions, the International Federation Societies for EEG recommends using the 10–20 electrode positioning system. The 10–20 scheme is focused on the relationship between an electrode's position and the cerebral cortex's surrounding area. Various interfering waves or artifacts are introduced into the EEG signals during the recording process. Artifacts are extra electric capacities that come from anywhere other than the brain. Objects are very common in EEG signals with small amplitudes. Electrogalvanic signals (slow artifacts), frequency artifacts, and motion artifacts are all examples of this. Objects must be detected and eliminated to improve EEG signal analysis [58].

EEG waveforms are categorized based on their wavelength, amplitude, frequency, and location of electrodes on the scalp. Frequency bands are used to classify the constant rhythms of the brain. Five frequency bands are investigated when analyzing EEG signals [59]:

(1) Delta (0–4 Hz): It has prevailing rhythms in children and is rarely detected by expertise mediators because it has the greatest amplitude. It is rare for awake adults, and it also stimulates growth hormones.
(2) Theta (4–8 Hz): It is unusual in adults, but it is very common in children under the age of 13. These sleep patterns can be seen during deep meditation and relaxation.
(3) Alpha (8–12 Hz): Alpha waves are seen in people of all ages, but they are most prevalent in adults who are active but comfortable, with their eyes closed.
(4) Beta (12–26 Hz): It is concerned with our attitudes and actions and is linked to what we see, touch, hear, smell, and taste. These waves occur during cognitive states such as talking and eating.
(5) Gamma (26–100 Hz): These waves are generated during hyperalertness and sensory integration. It integrates the senses and memory to create an incredible experience.

EEG recording can be done in two ways depending on the location of the working electrode:

Unipolar Montage/Monopolar Montage: A monopolar montage involves placing a single electrode on an area that is electrically active and a counterelectrode on an electrically inactive region [60]. The differential amplifier rejects all that is common to both electrodes, including any common EEG operation, which is much less prevalent in monopolar recordings. In general, the monopolar recording contains more details and has less distortion [61]. Bipolar Montage: A bipolar montage involves placing two electrodes on an electric-powered intrinsic area on the brain and measuring the voltage difference of both the electrodes [50]. Viewing the captured data using both monopolar and bipolar montages has advantages for study, as switching between the two will show several clues, such as generator positions or event classifications.

EEG studies can help with a variety of epilepsy diagnoses, including whether the seizure is focal or generalized, idiopathic or simply a symptom, or a section of complex epilepsy disorder. Focused and generalized epilepsy conditions have psychiatric and electrographic overlap, and the entity of unihemispheric epilepsies only blurs the lines. The distinction between partial and generalized seizures/epilepsy forms, on the contrary, remains true and clinically beneficial [62].

EEG has many characteristics that make it an excellent choice for ES prediction analysis. Including the potential to regulate the changes that occur during epilepsy in the brain, a major benefit it gives is the comparatively low cost of hardware, which is being used by a large number of patients as well as to monitor over a longer period of time. EEG signals from epileptic patients are automatically analyzed by considering Fourier transform interpretation and parameterized approaches [63]. Other methods, such as fMRI or MEG, necessitate large, immobile equipment, which can cost thousands of dollars [50]. The use of the EEG signal is often favored because it is easy to obtain with wearable devices and contains important data [38,64,65]. Wearable technologies are a significant technological development because they enable subjects to track their health data conveniently in their family environment [65,66].

7.2.1 Analysis techniques

Electroencephalography (EEG) signals are analyzed using computational signal methods and modern technology. EEG analysis is used to aid researchers in learning more about the brain, doctors in making diagnostic and therapy decisions, and to advance BCI technology [67]. EEG analytical processes can be divided into the following methods: time domain, time-frequency domain, frequency domain, linear or nonlinear, and ANN methods [68].

7.2.1.1 Time-domain analysis

EEG signal features can be extracted using linear prediction (LP) and independent component analysis (ICA). Linear prediction creates a direct combination of the previous output values and the new and previous input values, resulting in an approximation. EEG signals can be generated, stored, and transmitted using LP [69]. It can also be used to analyze and present spectral array information, which allows for a more accurate visualization of background EEG behavior [58,70].

Component analysis is a technique for mapping a set of data to a variety of features that is unsupervised [57]. Independent component analysis (ICA), linear discriminant analysis (LDA), and principal component analysis are examples of unsupervised time-domain approaches for analyzing EEG results. ICA's aim is to logically disintegrate a distributed data vector into statistically individual components. Each transfer mechanism is thought to be a linear combination of individual signals [70]. PCA reduces high-dimensional data to a low-dimensional orthogonal function subspace, resulting in a projection that is as similar to optimal as possible in terms of sum-squared error. LDA reduces dimensionality by locating a linear combination of factors that can distinguish between two or more groups. This combination is suitable for use as a linear classifier [57].

Importantly, the time-domain system parameters can be extracted from the mathematical instances of the power variety, despite the fact that they are entirely dependent on time. This establishes a connection between physical perception of the time-domain and normal spectrum studies [69].

7.2.1.2 Frequency-domain analysis and time-frequency-domain analysis

The frequency-domain Fourier evaluation is used to translate EEG signals into distinct frequency domains. Epileptic EEG recordings will detect the frequency-domain difference between the data of epileptic and normal data [68,71]. A slow wave occurs in recordings of epileptic patients in most cases, but the use of frequency analysis reveals epileptic abnormality that cannot be observed in the temporal domain. The downside of the frequency analysis is that the signals received are of their full spectrum through the Fourier analysis and cannot be used for further analysis. Moreover, Fourier-based approaches cannot include significant EEG dynamic data in the time and frequency domains; at the corresponding time, they cannot be used to test signals from time series, like EEG signals with ambiguity and randomness [72].

Time-frequency-domain processing is now commonly used to derive features from EEG. The most commonly used function extraction technique is the wavelet transform [72–75]. The wavelet transform can be used to selectively analyze signals in various sub-bands, which is ideal for the extraction of epilepsy and enhances the device detection efficiency. Unlike the Fourier transform, the wavelet transform uses analysis windows of various sizes to provide a more versatile approach to signal representation. At higher frequency, wavelet transformations provide precise statistics, while at lower frequency, they provide specific frequency components. This function is critical in biological applications since signals normally produce short-frequency information with a prolonged time and high-frequency information with a short duration [72].

7.2.1.3 Nonlinear analysis

The fundamental theory of nonlinear analysis is to analyze a system's dynamics in phase space; a point in this region at any time characterizes the system's state [60]. A nonlinear examination can derive spatiotemporal changes from the electric brain before the epileptic seizures [76]. The coupling between harmonics is detected in the signal spectrum by nonlinear analytical methods. The most common nonlinear parameters for EEG analysis are higher cognitive spectra (HCS), different entropy measures, e.g., estimated entropy, entropically Kolmogorov, and largest Lyapunov exponent (LLE). Entropy and LLE are generally used for the identification of epilepsy. Entropy provides insights into information saved in the distribution of signal probability distributions and measures the insecurity or randomness of data patterns. Strongly alleged data patterns lead to higher entropy values [50].

7.2.1.4 ANN analysis

Artificial neural networks are used to classify EEG signals. Until EEG data are put in neural networks, it is usually essential to perform a prewavelet transformation [60,76]. Recurrent neural networks (RNNs) are commonly used in the analyses of ANN applications for EEG analysis [60,77]. Furthermore, due to the large amount of EEG data used as a source for ANN, secure handling and fast computational power are needed for real-time analysis. A cloud-based deep learning approach for real-time processing of large amounts of EEG data has been proposed and released to overcome these concerns [78].

7.2.2 Signal analysis for epilepsy

EEG measures the electrical processes of the cerebral cortex directly using electrodes mounted on the scalp. The dendrites of nerve cells near the cortical surface measure their electrical potential. The primary tool for detecting ES events in the brain is to analyze EEG signals. EEG recordings are a reliable way to tell the difference between ES and non-ES patients in a clinical setting. EEG symptoms can be used to distinguish between the different stages of epilepsy, as well as the preseizure and postseizure periods that occur before and after a seizure. The following is a brief description of these phases [73].

- **(a)** Pre-ictal State: A pre-ictal condition occurs for a period of time before a seizure begins, although it does not always happen. At first glance, it might not be visible. However, it reflects changes in the signals at the end of the line and predicts many seizures [73,79].
- **(b)** Pro-ictal State: In this case, seizures are more probably, but not confirmed [73].
- **(c)** Interictal and Ictal State: The ictal state is the time between two seizure onsets, and the interictal phase is the change of EEG signals that occurs throughout an epilepsy seizure. The number of epileptic cells, cerebral area, and seizure duration can be altered in the same person [73].
- **(d)** Post-ictal State: This condition occurs following a seizure [73].

It is crucial to distinguish the preictal state when predicting epileptic seizures from the three states. The preictal condition is a difference between the interictal and preictal states that are important for seizure prediction [36]. It is the transition from the interictal to the ictal state.

The wave pattern can reveal useful data regarding brain activity. Expert neurologists can observe EEG signs and diagnose disorders. This procedure, however, takes a long time and is susceptible to faulty detection because of the high time and space aspect of the nonlinear dynamic EEG data. Thus, the diagnostics can be profoundly advantageous through computerized methods, EEG signals, and analyses [73].

7.3 Machine learning approaches for epilepsy

7.3.1 Signal preprocessing

Noise and artifact identification in actual biomedical parameter is a crucial step. Filtering these objects is needed to reduce their effect on feature extraction. Filtering options abound such as band-pass filters, wavelet filters, finite impulse response filters, and adaptive filters have been applied [50]. A finite impulse response (FIR) filter has a finite length, since it is zero to finite time, with its impulse response (or answer to a finite input). An infinite impulse response (IIR) filter can have internal feedback and can react forever [80]. This analysis is often performed to normalize the information so that it becomes similar to most of the patients' recordings. Owing to the drawbacks of embedded electrodes, there are a lot of data dropouts or distorted data in EEG recordings, which causes algorithms to perform poorly. There are several outliers in the results due to muscle artifacts and background noises. These outliers harm the extracted functionality [50].

7.3.2 Feature extraction

Feature extraction is the most crucial step in classifying EEG signal data in order to identify epileptic seizures [81]. The extraction of characteristics is a critical step in integrating machine learning and seizure recognition classification techniques. It necessitates the creation of an optimal feature set capable of effectively distinguishing the subjects. The extraction of features is entirely problem-specific. Direct extraction methods are difficult to use when trying to extract the properties of a signal [82]. EEG feature extraction is essential in diagnosing the majority of brain disorders. Obtaining necessary and discriminant features has a significant impact on the feature extraction method used [83]. The analysis is performed using both the maximal overlap discrete wavelet transform (MODWT) and the discrete wavelet transform (DWT) [84]. The EEG signal consists of several waves of varying frequency ranges, and the DWT is used to quantify and represent nonstationary signals on various scales to satisfy our needs [85]. In both analyses, a Haar wavelet, a fourth-order Daubechies (Db4) wavelet, and a second-order Daubechies (Db2) wavelet are used. The wavelet should be chosen based on the real characteristics. To put in other terms, the wavelet must be well matched to the behaviors being examined. Wavelet families vary in terms of symmetry and the precision with which ideal high-pass filters are calculated (i.e., frequency response functions). The degree of wavelet symmetry is significant because it requires wavelet decomposition to reduce feature phase shift. When the phase change is high, the position of attributes in transform coefficients can be skewed [80,84]. For the breach of EEG signals in various frequency bands, DWT utilizes multiresolution wavelet analysis technology. MODWT is used for obtaining the EEG sub-band alpha (8–12 Hz) and delta (0–4 Hz) from a healthy person (Db2). The six-component function vector built from the median, mean, and variance of both the alpha and the delta sub-strips is expressed in each EEG segment [80]. As a result, these EEG signal sub-bands can be used [80,86,87].

7.3.3 Classification

After extracting features from EEG signals using the aforementioned signal processing methods, various pattern recognition techniques for classifying the feature vectors obtained are created. To select the best classification model for a given number of features, the characteristics of the appropriate classification algorithms must be recognized. Various classification methods for estimating epileptic seizures using EEG signals have been developed in recent years, with support vector machines and neural network-based approaches being the most widely used classification principles [72].

7.3.3.1 Support vector machine (SVM)

The support vector machine is a machine learning algorithm that can solve linear, nonlinear, and regression problems [88]. It has been commonly seen in EEG signal detection and diagnosis of epileptic seizures because of its accuracy and capacity to handle a high proportion of predictor variables [89–93]. In continuous or high-dimensional space, SVM creates a hyperplane or group of hyperplanes that can be used for classification. This hyperplane with the greatest length to the nearest training position in each class is used to achieve a good separation, and the greater the margin indicates, the lower the classifier's generalization error. The hyperplane with the shortest minimum distance to the training instance is sought by SVM. This term is also defined as a margin in SVM theory. The maximal margin is considered for the maximized hyperplane. Another significant aspect of SVM contributes to its superior generalization ability. SVM is a two-category classification algorithm that uses variational training data or larger dimensions to transform data into a hyperplane [94]. Furthermore, SVM outperforms other classification models in terms of efficiency. One drawback with SVM is that it associates the complexity of the system with the sequence of number patterns instead of the sequence of pattern dimensions. The standard quadratic programming algorithm would almost always fail, necessitating the use of special-purpose optimization methods including problem-specific diagnosis [72]. A variety of factors affects the efficiency of the SVM classification. By defining the grid array and phase size, the matrix search method is used to locate the corresponding parameter value. The limitation infringement costs associated with the data point that falls on either side of the decision function [95] are defined by the only parameter of the linear kernel (the soft-margin constant "c"). The SVM including RBF and Gaussian kernel function has two variables: cost (C) and sigma (S). Cost regulates the model's fitting problem and sigma regulates the model's nonlinearity. The regular cost function and sigma values are employed.

7.3.3.2 Naive Bayes (NB)

The Naive Bayes (NB) is an analytical method. It is a simplified Bayes' theorem-based probabilistic model. The NB approach is based on the premise that the NB classifiers can be calculated more quickly than the exponential complexity. For classification, the NB classifier needs fewer training data. Simply stated, it works on the assumption that the existence of some class characteristics has no bearing on the appearance of other forms. The classifier examines every function separately to determine the feature components that contribute to a particular class being the classification result. To prevent high encounters with zero probability, it uses Laplace correction as the default configuration [96–98].

7.3.3.3 K-nearest neighbor (KNN)

In machine learning, pattern recognition, and a number of different fields, the k-nearest neighbor classifier is the most widely used [94]. It is a nonlinear, nonparametric, and straightforward classifier [99,100]. The lazy learning (instance-based) algorithm is another name for this technique. Since a model or classifier is not created right away, all dataset samples are stored and held before new results require classification. This feature distinguishes the lazy learning algorithm from eager learning, which constructs a classification model before each new instance to be classified [94]. This approach is especially effective for larger training sets. It works by calculating how close the instruction and test sets are. The datasets categorize the “n” attributes. The training sets make up the n-dimensional pattern space, and each set is an n-dimensional point. Based on the adjacent datasets, an undefined dataset is allocated to the class [100]. When complex data must be modified and updated often, this algorithm becomes much more important. KNN was employed with different distance metrics [94,101].

7.3.3.4 Artificial neural network (ANN)

An artificial neural network is a mathematical concept that focuses on the configuration and function of biological neural networks [83]. ANN is a nonlinear, adaptive process that learns to perform a function (a knowledge map) from the input. The theory of ANN was inspired by the structure of complex networks found in human brains [56]. The three layers of an ANN are input, secret, and output [102]. A network of interconnected units known as nodes or neurons makes up an ANN. These neurons, like biological neurons in the brain, integrate feedback signals and transfer them to a large number of other cells. The neurons’ output is exposed to a summation dependent on the performance of the neurons preceding them [47]. ANN can estimate posterior probabilities to define classification rules and perform statistical analysis [60,83,103,104]. The component properties and the weights associated with their linkages are used to assess the transformation’s effect. The network can be adapted to the expected output by changing the links between the nodes [105,106]. The concussion areas of the brain could be precisely identified after the recorded EEG signals are trained using Artificial Neural Net artificial neural networks works [107]. The ANN model, on the contrary, is prone to transition and translation distortion, which can lead to a low accuracy rate [108].

The techniques for detecting epileptic seizures described earlier have their individual characteristics; the efficiency of identifying epileptic seizures using all these existing systems is enhanced if these methods could be combined to enhance their self-adaptability [72]. Several signal classification approaches have been established in order to obtain force spectra in persons with seizures [109]. It was proposed that methods based on k-nearest neighbor clustering, statistical analysis, and chaos theory can be used [110]. Although several epileptic seizure detections using EEG signals approaches have recently been introduced and shown to have promising scientific efficacy, a few problems must also be solved before they can be used in clinical settings. Many proposed strategies in the study of EEG-based epileptic diagnosis were developed only using databases with a limited number of experiments, and it is conceivable that they are not applicable in actual cases, making an analysis of suitable methods challenging [72]. This is attributed to the shortage of clinical evidence samples and the lack of freely accessible EEG databases.

7.4 Deep learning approaches for epilepsy

Although machine learning classification algorithms have high precision and practice with feature vectors derived from conventional spectral analysis, they cannot predict a widespread pattern. For seizure prediction using an ML method, scriptwriting necessitates a lengthy feature extraction step. Feature extraction is extremely difficult to handle due to the existence of noise and particles in the data. Consequently, creating a generalized automatic system with a consistent performance is difficult, particularly when training samples' data are small. DL algorithms, on the contrary, learn the pattern's features automatically and provide promising ES estimation outcomes. Handcrafted features are less distinct and stable than DL model-learned features [111].

7.4.1 Recurrent neural networks (RNNs)

Text, signals, and images are examples of sequential data that have complex and long lengths, making them unsuitable for basic deep learning methods [112,113]. These records, however, make up a considerable portion of the world's knowledge, as a result, deep learning-based techniques must be used to analyze them. RNNs are the suggested approach for overcoming the challenges listed, and they are commonly used in biomedical processing.

Long Short-term Memory (LSTM): The problem for a simple recurring neural network is short-term memory. Since it has a tough time getting data from earlier period measures toward the next measures in a complex sequence, RNN can forget important details. The vanishing gradient dilemma is another disadvantage of RNN [112,114–117]. As it backpropagates, the dilemma occurs due to the shrinking of gradients. LSTMs are a form of RNN that can acquire long-term requirements [118,119]. By storing the error and propagating it back across layers and time, LSTMs solve the issue of bursting and dwindling trends [118]. LSTM gates were used to solve the short-term memory dilemma [112,114]. Gates may be used to control the flow of information. The gates would save a lengthy list of necessary data while discarding unnecessary data. The cell state and its gates are the foundation of LSTM [112]. Any other secret layer, unlike multilayer perceptron ANNs, is described by an LSTM cell, which is proportional to the number of neurons in that cell and can contain many LSTM cells [118].

The bidirectional-LSTM (Bi-LSTM) structure is used, with two blocks processing temporal information in multiple separate locations at the same time in each layer [118,120]. In comparison with the aforementioned context in the conventional LSTM architecture, this architecture improves prediction outcomes by gaining access to the potential context.

The forward transfer block processes the function map of the EEG segments from start to finish, while the backward relay block processes the same parts in the opposite direction. The output of the network is formed by combining the outputs of these two layers. Every block has 20 LSTM cells and is classified using a single bidirectional layer based on the Bi-LSTM network's last output after it has processed every one of the EEG segments. To avoid overfitting, the dropout regularization strategy is used. Root-mean-squared propagation (RMSProp) and the sigmoid activation mechanism are used to refine the proposed model for predicting the EEG segment's identity [118].

7.4.2 Convolutional neural networks (CNNs)

Convolutional neural networks have shown to be highly functional for large-scale image and video recognition [29,121,122] due to the establishment of massive public imagery servers, like ImageNet [29,123], including high-performance computer networks, such as highly distributed arrays [29,124,125]. Several researchers have recently begun implementing CNNs to EEG signals [29,126], and there has been a surge of interest in using CNNs to forecast seizures, owing to the fact that these methods are used widely and therefore are more well known and popular in the research field [29]. A CNN has an input/output layer including other hidden layers. Usually, the cached layers of a CNN are comprised of convolutions, bundling, and completely linked layers. The input is processed via convolutional layers, which are then passed on to the next layer. The convolution articulates a neuron's response to visual stimulation. Neuron cluster outputs can currently be combined into a single input neuron using local and global pooling lays. The average value of each of the neuron clusters in the preceding example is determined using mean pooling. In completely related layers, each neuron in one layer is bound to a neuron in the layer above it. CNN is theoretically equivalent to a multilayer perceptron biological system [29].

The CNNs have clear advantages over conventional classifiers when it comes to processing the high-dimensional data. CNN uses a parameter sharing system to monitor and reduce the parameters in convolutional layers. To monitor overfitting, a pooling layer progressively decreases the representation spatial scale as well as the parameters and calculations in the system [29].

The CNN templates used had three major layers. In CNNs, convolutional layers are interlaced with pooling layers before being replaced by entirely connected layers. The convolution layer contains kernels, which run through the EEG signals and have six function maps linked through 5*5 kernels to the input layers. A kernel includes an input EEG signal and step matrix (stride = 1) that can also be combined with the input signal and regulates the magnitude of the filter's overall stiffness. The second layer consists of a framework for pooling layers of 2 to 2 and is primarily used to delete essential components and minimize the computational complexity of the network. The classification effect with sigmoid activation (e.g., ictal, interictal, or preictal) is the output by the final fully connected layer [29].

For ES detection and a variety of factors, CNN with a maximum of three layers is used. On the one hand, the amount of data collected during ictal and preictal recordings is typically much lower than the amount gathered during the interictal phase, resulting in a large sample imbalance; on the other hand, a simplistic arrangement satisfies the need for fewer samples. Furthermore, the network's number of layers is reduced to some extent due to the limited number of interfaces. A basic instructional system, on the contrary, is more helpful to online patient reviews of epileptic symptoms [29]. The identification method was put through the paces on all of the patients. To ensure that the results were correct and interpretable for new research forecasts, the study was randomly partitioned across test sets and 6-fold crank validation was used. The model trained in the other five subassemblies is tested separately in each of six subassemblies [127]. Each run uses five subsets, with the other subset being used for analysis, and helps to keep all datasets independent [29,128].

7.5 Related work and comparative analysis

Using ApEn and the discrete wavelet transform, Ocak [129] proposed a technique for epileptic seizure detection. The classification precision was 96% when ApEn values were determined from discrete wavelet-transformed signals. The percentage of ApEn that was analyzed using raw EEG data was 73%. Principal component analysis, linear discriminant analysis, and independent component analysis were used to divide the DWT functions of the EEG signals into two groups, regular and epilepsy EEG signals, to minimize the dimensionality of the DWT features. When these components are fed into the SVM, the accuracy is 98.85%, 98.5%, and 99.0% and PCA is 99.0%, 99.5%, 99%, and 99% is sensitive and 100% precise with the ICA method as well as 100% classification precision, sensitivity, and species with the LDA method.

Sharmila et al. [100] proposed suggested an approach for detecting epileptic seizures using EEG signals. This method focuses on using linear and nonlinear classifiers to analyze EEG signals using discrete wavelet transformations (DWTs). Using naive Bayes and k-NN classifiers for the DWT-derived sample statistics, the contribution of 14 two distinct epilepsy recognition combinations is investigated. Specific and cumulative statistical functionality derived from the University of Bonn's DWT data of normal and epileptic EEG data outperforms the NB classifier, which has a 100% accuracy score. It has been discovered that the NB classifier takes less time to compute than the k-NN classifier, resulting in higher precision. As a result, using NB classifiers based on DWT, predictive functionality to diagnose an epileptic seizures in real time is more suited for a safe, automated epileptic seizure management device to intensify the patient's treatment and standard of life.

Hussian [94] suggested multidomain features focused on epileptic EEG signal properties ranging from the time domain to the frequency domain, as well as mathematical, probability, and wavelet-based entropy metrics. To reach better precision and deeper learning for predicting epileptic seizures, the most efficient machine learning techniques, such as support vector machine kernels, K-nearest neighbors, decision trees, and ensemble classifiers with enhanced approximation, were used. This automated system could be used by clinicians for medical purposes, potentially saving millions of lives per year. For classification and identification, the integrated hybrid feature set was used. With an overall accuracy of 99.5%, SVM classifiers deliver better and optimal results at a range of kernel sizes, parameterization, and strategy rates, while KNN produces superior results by using various distance metrics and differing neighbors.

Khan et al. [130] investigate whether scalp electroencephalogram (EEG) data can be used to forecast focal seizures. The first objective is to determine what distinguishes the interictal and preictal regions. In comparison with the first goal, the next goal is to create a forecast horizon in which the measurement is as accurate and timely as possible. Convolutional filters were applied to the wavelet transformation of the EEG signal in order to identify and understand numerical signatures for each of the three periods: interictal, preictal, and ictal. The optimization problem's computational solutions propose a seizure forecast horizon of 10 min. To confirm this result, the Kullback–Leibler difference is used in the distribution of the automatically extracted function. The observations from the 204 EEG database records show that the pre-ictal phase transition occurs about 10 min prior to the onset of the seizure, and the test set prediction results of 87.8% sensitivity and 0.142 fps/h are promising. These results exceed a random forecast and a wide margin of other convulsion forecast algorithms.

Lasefr et al. [131] propose a seizure monitoring method for epileptic patients that can be integrated into a hardware program. The thesis made use of an EEG dataset that had previously been used in epilepsy identification research. The EEG signal was preprocessed with a Chebyshev filter before being analyzed in time domain and frequency domain. The filtered signal was disintegrated into five sub-bands using wavelet analysis. However, the delta sub-band was used for further evaluation. The DWT was used to extract the characteristics, and thresholding was used to assess the signal's noisy portion. Decomposing, filtering, feature extraction, quantization, and characterizing EEG signals are some of the most effective and informative approaches, with SVM and ANN achieving 96 and 98% accuracy, respectively. It is concluded from the study that extending the research to an integrated approach for tracking epileptic patients may be quite appealing.

Juarez-Guerra et al. [80] have suggested a system focused on neural networks and wavelet processing for detecting epilepsy with EEG signals [4]. Firstly, the signals have been filtered using the finite reaction impulse filter and the infinite impulse reaction filter (IIR). The EEG signal was then divided into five sub-bands. Only alpha and delta were used in the analysis, with feature extraction including DWT and MODWT to achieve three aspects on the delta ribbon and three features on the alpha band, which included average values, unique values, and variations. The classification algorithm was then trained to differentiate between normal and abnormal patterns using a feed-forward artificial neural network. They experimented with the use of the sections (93.23% precise) and subsegments while practicing the FF-ANN classifier (99.26% precise).

Yinxa Liu et al. [132] have discussed a novel wavelet-based automated seizure detection process. Using wavelet decomposition, a multichannel intracranial EEG signal was disintegrated into five sub-bands in this process. A total of 87 seizures were reported from 21 patients over a 24- to 26-h nonseizure period and a 2- to 5-h seizure period. They then used (DWT) for function extraction process of relative amplitude, relative entropy, coefficient of variance, and index of fluctuation on three of the sub-bands. The data were then categorized using a SVM called the radial basis function. The classification results were then subjected to postprocessing techniques such as regularization, multichannel, and decision function collar. They were able to achieve 94.46% sensitivity and 95.26% accuracy with a false detection rate of 0.58 per hour after using this tool.

Shanir and Khan [133] suggest an automated seizure detection system based on the mean and minimum energy values per epoch. One second was chosen as the window size. The classifier is linear in this situation. Using the CHB-MIT database, the algorithm was evaluated on three separate topics, with 60% and 40% of the results being used for testing and 40% being used for test data, respectively. They achieved 99.81% identification precision, 100% sensitivity, and 99.81% specificity. Seizure epochs have higher mean and less energy values than nonseizure epochs, making them easily distinguishable. The scale of the function vector is high due to feature extraction from the resulting epoch, which may cause the device to slow down. To minimize the size of this large vector, use the half-wave and histogram techniques.

Guangyi Chen et al. [134] defined a technique for detecting EEG seizures by disintegrating EEG signals with up to six wavelet scales without sampling. The Fourier swift transformation then takes place using wavelets of 3, 4, 5, and 6 and is applied to seizure detection with the magnitude of the Fourier coefficients. The closest neighbor classification is used to determine whether the receiving EEG signal is an attack. Experiments in EEG databases from the University of Bonn show that the approach proposed is similar, if not stronger, to the Fourier method of our preceding dual-tree complex wavelet. The suggested technique is also highly consistent with an existing number of EEG seizure identification procedures. For EEG seizure detection, we discovered that wavelet filters of various types had perfect detection rates (100%).

U. Orhan et al. [135] proposed using the equal frequency discretization (EFD)-based probability density approach to evaluate seizures from electroencephalogram (EEG) signals in this paper. EEG signals were disintegrated into subcarriers by using a discrete wavelet discretization (DWT) technique, the coefficients in every subcarrier were formulated to multiple intervals using the EFD method, and the probability density of every EEG segment's subcarriers was estimated depending on the number of parameters in various ranges. Two probability density functions were then defined using gradient descent over the probability densities of both healthy subjects and epilepsy survivors. The mean square error (MSE) criterion was applied to these functions to classify EEG signals. The ROC method was used to analyze the classifier performance, which revealed an 82.50% progress rate in epilepsy diagnosis.

Dattaprasad A. Torse et al. [136] defined a new approach for extracting and identifying EEG signal characteristics for neurofeedback mechanisms. The first objective is to extract signal parameters using empirical mode decomposition (EMD), and the second phase is to segment the signals using an ANN to decide whether it is seizure or nonseizure. The EEG signal is decomposed into intrinsic mode functions for such retrieval of immediate frequencies (IMFs). The Hilbert transform is then used to produce function coefficients that display the frequency information for each one of these collected IMFs. The ANN classifier is trained using these attributes, and the EEG signal is classified into two categories: seizure and nonseizure signals. The EEG signals were graded with 96% precision by the ANN classifier.

Faust et al. [137] tested three classifiers for detecting epileptic seizures and used three parametric methods for maximum power continuum estimation. Four local maxima and four local minima parameters were collected from the power density set using Burg's method [57] and fed into the classifiers. The SVM classifier was the most accurate, with a classification precision of 93.33%, a sensitivity of 98.33%, and a specificity of 96.67%. Acharya et al. [138] conducted several trials to detect epileptic seizures. Higher order statistics (HOS) cumulative compounds derived from WPD coefficients have been integrated into the SVM classifier, giving 98.5% precise, 100% sensitive, and 100% specification. In the SVM classification, the same group [139] used recurrence quantification analysis (RQA) parameters and acquired 95.6% accuracy, 98.9% sensitivity, and 97.8% accuracy.

For detecting seizures, Chua et al. [140] used HOS-based features in GMM and SVM classifiers and obtained an accuracy of 93.11% and 92.67%, respectively. When Chua et al. [141] compared HOS features to power spectrum-based features, they discovered that HOS features had a classification accuracy of 93.11%, whereas power spectrum-based features had an accuracy of 88.78%, all for the GMM classifier. In another analysis, Acharya et al. [142] used nonlinear parameters in SVM and GMM classifiers: CD, FD, H, and ApEn. With an overall classification accuracy of 95% and a precision of 100%, the GMM classifier outperformed the others.

Table 7.1 gives a description of the normal and epileptic groups for automated detection. It can be shown that EEG is studied using a variety of methods to differentiate between epileptic and normal states, including FFT, time-frequency, DWT, mathematical analyses, nonlinear, and entropy scales. These methods had higher accuracies when using nonlinear methods and time-and frequency-dependent techniques, especially methods based on DWT.

7.5.1 Challenges

As each pathway or electrode implanted in the brain generates a unique scientific measurement, selecting appropriate statistical features is one of the most important and key steps. Previous scholars, without a doubt, made good attempts to find the right features. When analyzing statistical characteristics of features like entropy, strength, and skewness, it is critical to consider the various statistical perspectives of each brain signal. We should also avoid depending on nonessential components, as this will increase the dataset's size

Table 7.1 Summary of techniques that show different approaches to epilepsy detection using features extracted from EEG signals.

Authors	Features	Classifier	Accuracy (%)
Rivero et al. [143]	Relative wavelet energy	ANN	95.20
Orhan et al. [144]	DWT	ANN	100
Ubeyli [145]	AR	SVM	99.56
Coelho et al. [146]	Wavelet transform (WT)	SVM	100
Rivero et al. [147]	Genetic programming	KNN	99
Miao et al. [85]	Wavelet packet entropy (WPE)	KNN	100
Polat et al. [71]	Fast Fourier transform (FFT)	Decision tree	98.72
Polat et al. [148]	Wavelet transform and FFT and autoregressive model	Decision tree	99.32
Vinitha sree et al. [149]	Entropies + HOS + Higuchi FD + Hurst	Fuzzy	99.70
Molinari et al. [150]	Entropies	Fuzzy	98.10
Nigam and Graupe [103]	Nonlinear preprocessing filter	Diagnostic neural network	97.20
Sadati et al. [151]	DWT	Adaptive neural fuzzy network	85.90
Sriraam et al. [152]	Time- and frequency-domain features	Elman network	99.60
Guler et al. [153]	Lyapunov exponents	Recurrent neural network	96.79
Adeli et al. [154]	Mixed-band feature space	Backpropagation neural network	96.70

unnecessarily. As a result, machine learning classifiers will face an obstacle rather than an advantage, as the dataset of lower dimensionality will be useless for an efficient information development cycle. Consequently, we can prioritize future features that can produce rational outcomes. It is best to choose a subset of features to prevent overloading machine learning classifiers and to gain assistance with relevant information discovery. Based on the dataset characteristics and parameters, each classifier has its own range of advantages and drawbacks. In general, determining which classifier was the most efficient for datasets is complicated. Several classifiers have been tested to ascertain which is the most capable, and the one that works best will be used to solve seizure detection and information discovery. To train the algorithm, all deep learning technologies require a huge volume of data, and network architecture is much more complex to ensure whether it is optimal. Maybe fine-tuning the small parameters in future experiments would yield better results. Finding a larger EEG dataset with a larger number of patients is beneficial for allowing our deep learning network model and understanding the diverse dynamics of epileptic seizures among multiple patients, thus improving its generalizability. The performance of deep neural networks is well understood to improve as the volume of training data grows. The procedures can be tested on a broad dataset to achieve more generalizable clinical validation. The aim of ongoing research is to create a detection algorithm that takes these additional inputs and data types into account. The ultimate aim in this case is to monitor preseizure EEG activity and alert epileptic patients of possible seizures.

7.5.2 Future scope

After reading a number of articles, we discovered that there has been a lot of research done in the time-domain features, and we believe that it is needed to find certain functionalities that quantify differences in EEG patterns. In order to predict seizures, rising and reliable algorithms must be designed and integrated into various hardware systems. Furthermore, integrating the techniques with different datasets is very difficult, necessitating a significant amount of effort and analysis in this area, as well as a focus on developing new technologies to derive features from signals. The use of a sensible, realistic approach to remove functionality from EEG signals in order to identify seizures is a recent field that requires further research. Researchers could be forced to try a free parametric orthogonal framework after P. Kovacs et al. tried something similar and got positive results with much less simulations. The amount of EEG data obtained daily is increasing; researchers must develop algorithms that have promising results when working with massive quantities of data. The role of channel selection is also difficult, and there is still work to be done in this field. It is impossible to pinpoint the exact start and finish of a seizure cycle. As spectral analysis is a very useful function of extraction techniques such as wavelet, it is worth experimenting with. A separate methodology can be needed for parameter optimization. Many studies used a single-channel system to diagnosis seizures, but multichannel methods perform exceptionally well, so further research is needed in this area. On discrete biomedical signs, other transformations, such as piecewise linear transformations, must be tested.

7.6 Conclusion

Epilepsy is the most prevalent psychiatric condition, with millions of people dying from it each year. As these signals are extremely complex, multivariable, and nonstationary, diagnostic and prognostic analyses require multidomain attribute extraction strategies as well as the most efficient machine learning and deep learning classifiers. EEG signals are highly contextual and can be described as chaotic. Any of the most effective and informative techniques used in EEG signal analysis are filtering, decomposing, attribute selection, thresholding, and classification. We suggested multidomain features ranging from the time domain to the frequency domain, as well as numerical, ambiguity, and wavelet-dependent entropy indicators, depending on the existence of epileptic EEG signals. We used the most versatile machine learning classifiers, such as support vector machine kernels, K-nearest neighbors, naive Bayes, and artificial neural networks, to achieve high precision and deeper learning for predicting epileptic seizures. Various deep learning algorithms, such as CNN and RNN, are discussed for automated feature extraction, resulting in quick and stable performance. Clinicians may use this automated method for diagnostic purposes, potentially saving millions of lives per year. These methods with multidomain features produce better results in distinguishing between safe and epileptic subjects than conventional approaches.

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