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# Prediction of Epileptic Seizures Using Deep Learning: A Brief Review of Current Methods and Emerging Trends

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## ABSTRACT

Epilepsy is a chronic neurological disorder characterized by abnormal neuronal activity, leading to sudden seizures that can cause loss of consciousness, convulsions, involuntary movements, and communication difficulties in patients. The unpredictability of when and where these seizures will occur can result in accidents, deaths, and negatively affect a patient's quality of life and social relationships. Therefore, it is crucial to take preventive measures against potential adverse events by predicting epileptic attacks in advance. For more accurate and sensitive forecasts, advanced computer-based algorithms have become an indispensable tool in seizure prediction. Epileptic seizures can be predicted using EEG data through various methods developed over time. This study provides an overview of epileptic seizure prediction methods and explains current and emerging deep learning techniques.

## 1. INTRODUCTION

Today, epilepsy is treated with methods such as medication and surgical procedures that remove the part of the brain causing seizures. However, surgery is only an option for a small number of patients. Approximately 30%-40% of epilepsy patients cannot be treated with medication because they have a drug-resistant form of epilepsy [1]. The global prevalence of epilepsy is estimated to be around 1%, and a significant proportion of these patients are classified as untreatable. The prediction of uncontrolled epileptic seizures has been a focus of research for many years due to the potential risks associated with such seizures. EEG data is commonly used for predicting epileptic seizures, with studies in this area dating back to the early 1970s [2]. Although signal analysis methods were frequently used in the early stages of research, faster and more efficient results have been achieved over time with advanced machine learning techniques. In recent years, deep learning methods have gained significant popularity and have been extensively utilized due to their ability to efficiently process vast amounts of data, including EEG data, which is crucial for the accurate prediction of epileptic seizures.

**Table 1.** EEG datasets

| Dataset | Number of Channels | Type of Signal | Number of Subjects | Subject Type | Recording Length Per Segment | Numbers | Frequency (Hz) |
|---|---|---|---|---|---|---|---|
| University of Bonn | 1 | Scalp/Intrac. EEG | 10 | Human | 23.6 s | 500 segments | 173.86 |
| CHB-MIT Scalp EEG | 18 | Scalp EEG | 23 | Human | 1h | 198 events | 256 |
| Melbourne-NeuroVista | 16 | Intracranial EEG | 12 | Human | Av. 107 s | 2979 segments | 400 |
| Kaggle American Epilepsy Society | 16 | Intracranial EEG | 7 | Human Canine | 10min | 111 events | 400–5000 |
| Neurology and Sleep Centre Hauz Khas | 1 | Scalp EEG | 10 | Human | 5.12 s | 100 segments | 200 |
| TUH EEG Seizure Corpus (TUSZ) | 23-31 | Scalp EEG | 642 | Human | 1h | 3050 events | Min 250 |
| Helsinki University Hospital EEG | 19 | Scalp EEG | 79 | Human | 74m | 460 events | 256 |
| Siena Scalp EEG | 20/29 | Scalp EEG | 14 | Human | varied | 47 events | 512 |

| | |
|---|---|
| University of Bonn 24 | https://www.ukbonn.de/en/epileptology/workgroups/lehnertz-workgroup-neurophysics/downloads/ |
| CHB-MIT Scalp EEG 53 | https://physionet.org/content/chbmit/1.0.0/ |
| Melbourne-NeuroVista seizure trial | https://melbourne.figshare.com/articles/dataset/Seizure_Data/6939809 |
| Kaggle American Epilepsy Society | https://www.kaggle.com/competitions/seizure-prediction/data |
| Neurology and Sleep Centre Hauz Khas | https://www.researchgate.net/publication/308719109_EEG_Epilepsy_Datasets |
| TUH EEG Seizure Corpus (TUSZ) 21 | https://isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml |
| Helsinki University Hospital EEG 23 | https://zenodo.org/record/2547147#.Y7eU5uxBwlI |
| Siena Scalp EEG 22 | https://physionet.org/content/siena-scalp-eeg/1.0.0/ |

This study aims to provide a detailed description of epileptic seizure prediction methods and to compare the techniques used at each step of the process. Currently, there is no single study that comprehensively combines and describes all these methods in detail. By reviewing both past and present studies, this research offers an overview of the evolution of seizure prediction. Table 1 presented highlight various rates and criteria, with the goal that the advantages and disadvantages of the methods will serve as a guide for future research.

## 2. INFORMATION ON EPILEPSY, EEG, AND EEG DATASET

### 2.1 Epilepsy

Epilepsy is a physiological anomaly characterized by abnormal electrical activity caused by temporary asynchrony in brain neuron activities. These abnormalities, known as seizures, can occur at any time and last for several minutes, leading to uncontrollable involuntary movements, and loss of emotion and consciousness in the patient. Epilepsy can present in two forms based on its symptoms: focal and generalized. Focal epilepsy is further divided into two types: *simple focal*, where consciousness is not lost but communication becomes difficult, and *complex focal*, where consciousness is lost, and abnormal behavior is exhibited. Generalized epilepsy, on the other hand, affects the entire nervous system because it involves the whole brain. In prediction studies, generalized epilepsy is used more frequently.

### 2.2 EEG

Electroencephalography (EEG), which measures and records the electrical waves in the brain, is used to diagnose neurological issues and detect any functional disorders in the brain. These electrical waves are obtained by placing thin wires, called electrodes, on the scalp. The EEG signals are generated by the electrical activity in the brain, which is caused by the movement potential of neurons within the brain structure. The most influential type of neuron responsible for generating EEG signals is the pyramidal cell. The summation of postsynaptic potentials in these cells produces the electrical signals measurable by EEG.

In 1929, Hans Berger demonstrated that the electrical activity of the human brain could be recorded, coining his system the Electroencephalogram (EEG). The method proposed by Herbert Jasper in 1958 for obtaining EEG signals was later accepted as a standard by the International Federation of EEG Societies, known as the "International 10-20 System". EEG measurements can be made using single-channel or multi-channel techniques. Mormann et al. [3] compared studies using these techniques and found that studies employing the single-channel measurement technique were less successful.

### 2.3 EEG dataset

One of the most important factors when selecting a dataset is its size. Since deep learning algorithms require a larger number of examples, large-scale, comprehensive, and consistent datasets are crucial for developing seizure prediction algorithms. While early studies on epileptic seizure prediction were limited to EEG data from local databases with a small number of patients nowadays, the availability of larger datasets are relatively easy. The most commonly used ones in studies are shown in Table 1. These datasets are long-term and include daily activities such as sleep, wakefulness, and physical activity are generally used in studies by categorizing periods as ictal, interictal, preictal, and postictal. Among these periods, the preictal period can be easily confused with physiological signals, so proper time adjustment through testing will affect the results. As a result, although the databases used today are sufficiently large, the lack of detailed information and data imbalance remains a challenge. It should also be noted that periodic changes in individuals and their activities can cause variations in the signals.

In an analysis of studies on epilepsy conducted over the past five years, the CHB-MIT dataset is found to be the most commonly utilized resource. This dataset provides 1-D data obtained from channels placed according to the 10-20 system. In the CHB-MIT dataset, interictal data significantly outnumbers preictal data. To mitigate this imbalance, researchers frequently use overlapping window techniques. Additionally, generating synthetic data, such as through the use of Generative Adversarial Networks (GAN), is another method employed to address this issue.

## 3. THE PREDICTION OF EPILEPTIC SEIZURE

When examining studies on epilepsy, it is evident that most research focuses on diagnosing epilepsy to provide the necessary treatment. In contrast, there are fewer studies on seizure prediction, which aims to alert the patient a certain time before an upcoming seizure. The expectation for a seizure prediction study is that it functions in a way that minimizes interruption of the patient's life, provides sufficient time for medical intervention, and has the lowest possible number of false predictions. One of the most critical aspects of seizure prediction is the selection of the appropriate approach. Two different approaches are used to predict epileptic seizures. The first approach, known as preictal-interictal classification, involves labeling a specific periods preictal and interictal. A specific period before the onset of a seizure, such as 15, 30, 60, or 120 minutes, is considered preictal, while the period before the preictal phase and after the end of the seizure is considered interictal. Typically, a moving window is used to temporarily characterize these interictal and preictal stages, where a linear or nonlinear measure is calculated and ranges from 5 to 50 seconds. These windows may overlap to a certain extent. Classifier is then applied to distinguish between these phases. The second approach, which is rarely studied, involves the threshold methodology. In this method, increasing and decreasing values are detected during the preictal period, and an alarm is activated when a certain threshold is reached. An example of the second approach is Usman and Hassan's research [4]. He worked exclusively with seizure data and determined threshold values based on various statistical calculations, such as variance, entropy, skewness, complexity, and kurtosis. Using these values, he performed classification by applying machine learning algorithms. However, this method is not preferred because preictal signals are often unclear and may overlap with artifacts. Another important consideration in predicting epileptic seizures is whether the study is patient-specific or patient-independent. Although patient-specific studies often achieve high success rates, the limited number of samples can pose challenges. In such studies, each patient is classified according to their own data. Patient-independent studies, on the other hand, are more applicable to real-world scenarios but have a lower success rate and a more complex classification structure, as EEG data vary significantly from patient to patient. In these studies, data from all patients are used for training and testing is conducted on any individual patient. Upon reviewing the studies for the prediction of epilepsy attacks, it was observed that the process shown in Figure 1 was generally applied.

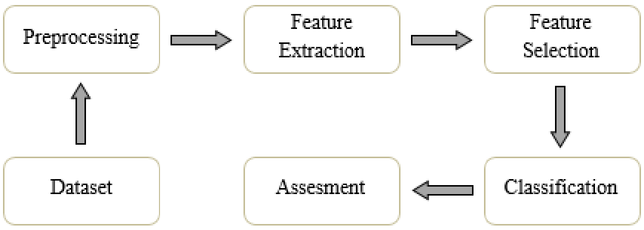


**Figure 1.** A common process in the prediction of epileptic seizures

In reviewing the literature, it would be logical to examine epileptic seizure prediction studies in two distinct periods:

(1) The early period and traditional machine learning: Until the 1990s, linear methods were frequently used, especially in the feature extraction phase. While these approaches offer computational advantages, they have low sensitivity to artifacts. Since EEG signals are multidimensional and chaotic, these methods have yielded limited success. From the 1990s onward, methods based on nonlinear dynamics theory started to be employed. Studies conducted in the early 1990s initially focused only on the preictal period; however, Lehnertz and Elger [5] compared the preictal and interictal periods using the correlation dimension method, a nonlinear approach for time series analysis. This method enables the prediction of epileptic seizures minutes before they occur by detecting signal deterioration during the preictal stage.

Given the uncertainty and irregularity of EEG signals, nonlinear methods, which are chaotic and dynamic, offer higher accuracy in predicting seizures and are relatively preferred despite requiring more computational costs than linear methods [6]. As chaotic methods, the Large Lyapunov Exponent [7] and Correlation Intensity [8], which are time-domain analyses providing information about the brain's dynamic stability, have been used. Iasemidis et al. [7] analyzed the chaotic state before the onset of an epileptic seizure using the moving window method and reported that it decreased. In their later work, Iasemidis et al. [9] developed a real-time statistical algorithm that continuously calculates the maximum Lyapunov exponent and monitors the T-index curves of this calculation. The measurement calculated by the algorithm generated a warning when it exceeded a specified threshold. The study, which predicted seizures 45.3 minutes in advance, achieved an average sensitivity of 81% and a specificity of 78%. However, these methods cannot provide fast analysis due to their computational complexity on a long time scale.

Since the EEG signal is not static and linear, EEG signal analysis of some mathematical models in the time domain is difficult. To overcome this difficulty, some studies have used frequency domain methods. Frequency Domain, also known as Spectral Analysis, which is more sensitive to the presence of artifacts than Time Domain statistical methods, is another method used in the feature extraction phase in the traditional method. The most commonly used frequency domain property is the Power Spectral Density (PSD). Bandarabadi et al. [10], Direito et al. [11] and Zhang and Parhi [12], used Spectral Power Analysis as their feature extraction method. They windowed the EEG data and calculated the spectral power property of the data in each window. They reported that this method is very cost-effective in terms of calculation and therefore suitable for portable warning systems. They also found that Spectral Power Analysis could show promising results for seizure prediction, especially in high gamma frequency bands.

An example of the use of Time-Frequency (TF) techniques is the research by Gadhoumi et al. [13]. They used the Continuous Wavelet Transformation (CWT) analysis method for preictal and interictal periods. In this method, wavelet energy and entropy in different frequency bands were calculated using a two-second non-overlapping sliding window. They used LDA for classification and achieved an average sensitivity of 85% in the data of seventeen patients. However, CWT conversion increases file size, and therefore working with large files can lead to hardware and time issues.

In this period, in 2002, the first international workshop on epileptic seizure prediction took place. In 2007 and 2009, the International Workshop on Seizure Prediction (IWSP3) organized two competitions using iEEG datasets from dogs and humans. Although these competitions contributed to significant progress in seizure prediction, the overall performance remained low, and no standardized methods were established.

A small number of data sets were used in the Early Stage and these data sets were of low quality and short time. There is no controlled and standardized evaluation method. The transition to nonlinear chaotic feature extraction methods and the classification process by comparing preictal-interictal periods instead of preictal period analysis alone is noteworthy. in the Early Stage, linear approaches that are frequently used have a computational advantage, but on the other hand, the artifact sensitivity is low. They are also able to identify certain changes that occur before the seizure. Although it was stated in early studies that epilepsy attacks could be predicted between 20-90 minutes before, the performance of these methods was not evaluated in long and high-quality data. Although traditional signal processing methods with phases such as pre-processing, feature extraction, and feature selection provide good accuracy in Machine Learning-based studies conducted in the following years, process complexity, length of time, lack of a generalized model, and constraint in big data can be listed as disadvantages. Since most of the operations are done manually, it can cause data loss.

(2) Deep learning: Due to the development of technology for fully automated systems to overcome the constraints of traditional methods, Deep Learning techniques have been used in the prediction of epileptic seizures since the second half of the 2010s. Deep Learning, a subset of Machine Learning, models human learning ability in computer science and is the multi-layered version of Artificial Neural Networks (ANN) consisting of neurons. In seizure prediction studies, CNN and RNN models, along with their derivatives, are commonly utilized as deep learning algorithms. CNN was the first method employed due to its success in image processing and automatic feature extraction, as proposed by Troung et al. [14]. Troung and colleagues initially transformed the Freiburg and CHB-MIT datasets using STFT and achieved a sensitivity of 89.8%, FPR of 0.17 with CNN classification. Subsequent studies applied various CNN models, such as 1D, 2D, and 3D. Ra and

Li [15] utilized a 1D CNN model for feature extraction. However, while this model demonstrates high performance in certain datasets, it can be restrictive in some application areas. The LSTM model, derived from RNN, was first employed by Tsiouris et al. [16], where they developed different LSTM models, addressed the overfitting problem, and achieved a 15–120-minute early alert with a sensitivity of 99.37% and specificity of 99.6%. Liu et al. [17] proposed the Bi-LSTM model, which captures contextual information from both past and future sequences, for a patient-independent model. Their performance reaching 99.37% and 99.6% for sensitivity and specificity. However, since this model operates bidirectionally, it is inefficient in terms of time consumption and computational efficiency. Additionally, it may pose challenges for real-time applications with continuous data flow. Bhattacharya et al. [18] were the first to propose the use of transformers for epileptic seizure prediction, achieving a sensitivity and false-positive rate per hour (FPR/h) as 98.46%, 94.83% and 0.12439, 0, respectively in their study. Deep learning methods are explained in detail in Chapter 4.

With automatic feature extraction, data loss can be minimized, and model complexity can be reduced. However, the drawbacks include the requirement for large datasets, the need for powerful hardware to support automatic feature extraction, and consequently, increased energy consumption.

### 3.1 Preprocessing

This phase involves cleaning the raw EEG data by removing artifacts and organizing the data. High-amplitude signals are typically identified as artifacts. The pre-processing stage aims to reduce noise by detecting and eliminating these artifacts, thereby enhancing the accuracy of the classification process. Although the filtering techniques used may vary based on the type of artifacts present, the methods frequently employed for predicting epileptic seizures are generally divided into two categories:

(1) Use of Simple Filters: This method involves applying uncomplicated digital filters, such as band-pass, high-pass, and low-pass filters, by selecting a specific frequency range. Among these, the band-pass filter is the most commonly used in EEG signal analysis. An example of a band-pass filter that allows signals within a defined frequency range is the 'Butterworth' filter. As the filter's order increases, it offers a wider transition zone compared to other band-pass filters.

(2) Use of Signal Analysis Methods: Simple digital filters become ineffective when signal frequency bands overlap with artifact frequencies. To address this, various techniques from Signal Analysis are employed for filtering. These methods are also used for decomposing data and reducing its size. In signal analysis methods used for preprocessing, PCA, which is a linear transformation, is used to rotate the coordinate system to obtain lower dimensional components. ICA, generally utilized to remove artifacts, the first axis, which corresponds to the first component, that is, the main component, is selected according to the maximum variance of the data in a given direction and rotated in the direction in which the variance of the data is maximum. The next component, the secondary axis, is perpendicular to the first component and shows the next highest data variance. Other components are selected in this way and so on [19].

### 3.2 Feature extraction

The feature extraction phase involves applying methods to the filtered EEG data. In traditional methods, signal analysis techniques are generally used, while in some cases, studies may employ deep learning approaches that utilize automatic feature extraction. Feature extraction is the process of identifying significant properties from the recorded EEG data and obtaining a feature vector. This step reduces the size of the feature vector while selecting the most relevant features for the classifier [20]. Feature extraction methods for the prediction of epileptic seizures are based on various approaches, including multichannel, single-channel, linear, and nonlinear (chaotic) analysis. As shown in Figure 2, feature extraction methods used in studies can be categorized into four groups: time domain, frequency domain, time-frequency domain (signal analysis), and automatic feature extraction (deep learning techniques).

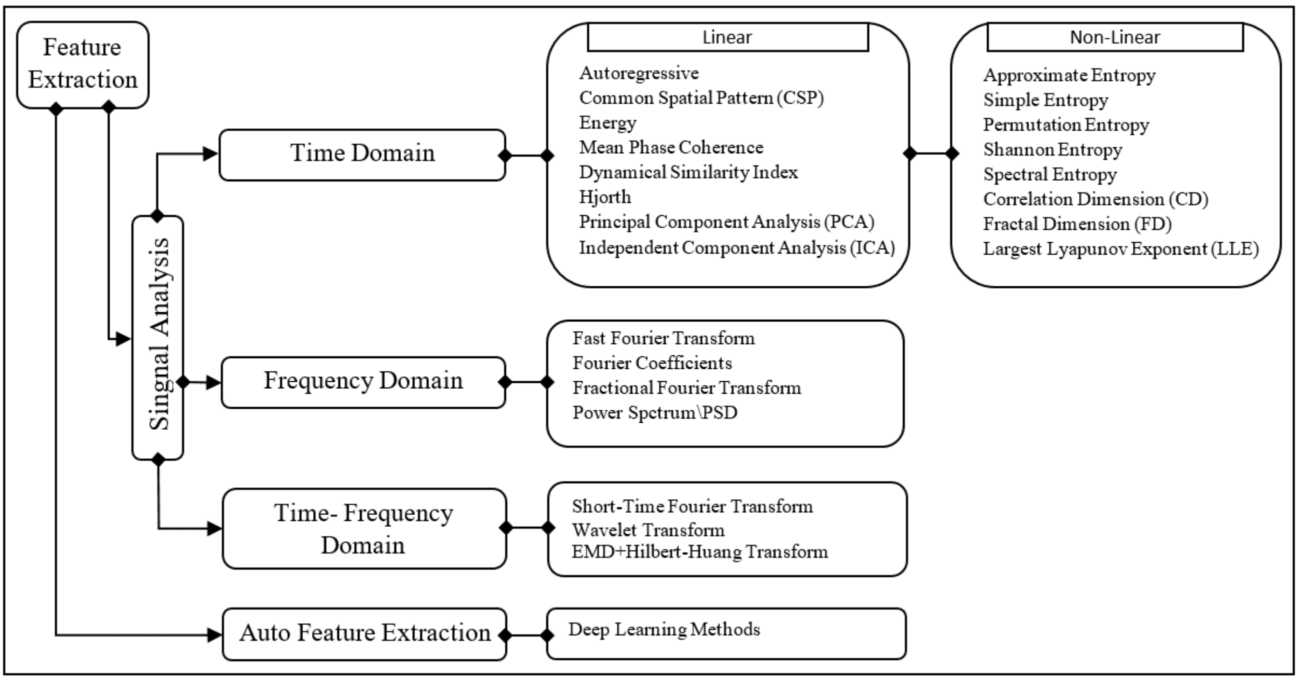


**Figure 2.** Feature extraction methods

In the Time Domain, signal analysis is usually performed with statistical calculations. Unlike the time domain, frequency domain relates to the spectral component of a signal and it does not contain any information about time. Time-frequency domain analysis is the method that characterizes the energy of EEG and other signals over time and frequency and decomposes the signal in a two-dimensional level, one dimension in time and the other in frequency.

### 3.3 Feature selection

One of the important phases for the correct and effective classification of EEG data is feature selection. The feature selection approach falls into two categories: (1) Feature order-based approach; each feature is ranked according to a specific selection criterion, and the top-ranked features are selected as relevant based on a predefined threshold value. (2) Feature subset selection approach; this method evaluates an independent subset of features using a measure of feature selection, such as correlation, consistency, and so on. It generates possible combinations of subsets using various search methods, such as the Greedy algorithm. The feature ranking method is less computationally expensive and has lower complexity. Although it is not commonly used in deep learning algorithms, it can be preferred by most machine learning algorithms to enhance performance.

### 3.4 Classification

In the general process for predicting epileptic seizures, classification is performed by making a preictal-interictal comparison at this stage. Classification, a type of learning used in statistics, data analysis, pattern recognition, and machine learning, involves determining the class to which the data belongs based on its characteristics, using information about the input dataset. In classification, each test identifies the class of its instance by combining features and finding patterns from the training data that are common to each class. Classification is simply conducted in two stages: first, a classification algorithm is applied to the training dataset, and then the extracted model is validated against a labeled test dataset to evaluate model performance and accuracy.

Algorithms called 'non-black box' classifiers in the studies of the Machine Learning Period in which each process step can be interpreted because it is visible and understandable and methods that do not offer explanations called 'black boxes' have been used. Examples of Non-Black Box methods are 'Decision Trees', 'Random Forest', 'Naive Bayes', and Black Box methods are 'SVM', 'ANN', 'KNN', and 'LDA'. Although there is a wide range of machine learning methods, from simple to extremely complex computational approaches, SVM is the most popular technique used in the classification of epileptic seizure prediction.

In deep learning methods, while filtering or signal analysis techniques can be used for preprocessing, this step can also be skipped, allowing the raw EEG data to be processed directly with deep learning techniques. Additionally, these techniques can automatically extract features. In deep learning applications, EEG data can generally be processed in two ways: as images or time series. For instance, the Convolutional Neural Network (CNN) technique is used for image processing, while derivatives of Recurrent Neural Networks (RNNs) are used for processing time series data. Upon reviewing recent studies, it is evident that, in addition to those employing the transfer and transformer models, various deep learning algorithms can be utilized in hybrid forms, transfer learning and multiple methods can be integrated through fusion techniques.

### 3.5 Assessment

The results obtained after classification are evaluated using some criteria. Various methods are used to evaluate these prediction results. The assessments are shown Figure 3.

| | | Actual Value: Pozitif (1) | Actual Value: Negatif (0) | | | |
|---|---|---|---|---|---|---|
| Prediction Value | Pozitif (1) | TP | FP | Accuracy | Sensitivity | Specificity |
| | Negatif (0) | FN | TN | $\frac{TP+TN}{TP+TN+FP+FN}$ | $\frac{TP}{TP+FN}$ | $\frac{TN}{TN+FP}$ |

*TP: The number of '1' in the test and prediction. FP: The number of '0' on the test and '1' on the prediction.*
*FN: The number of '1' on the test and '0' on the prediction. TN: The number of '0' on the test and prediction.*

**Figure 3.** Performance evaluation

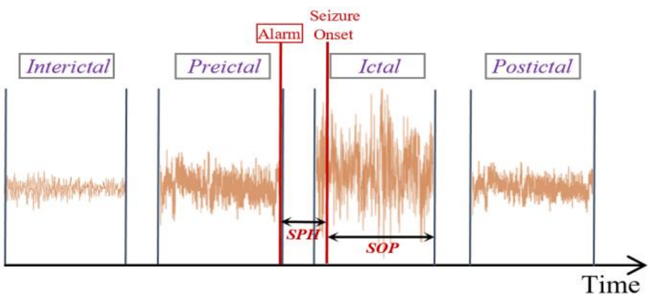


**Figure 4.** SPH/SOP evaluation

The prediction period before the seizure occurs is another criterion. This involves determining the Seizure Prediction Horizon (SPH) and the Seizure Occurrence Period (SOP). As shown in Figure 4, SOP represents the interval in which the seizure is expected to occur, while SPH indicates the time between the alarm and the start of the SOP.

Predicting a seizure too early can cause discomfort for the patient, and there must be sufficient time for preparation before a seizure occurs; thus, determining the optimal SPH/SOP is crucial. In their study on the optimal SPH/SOP duration, Alaei et al. [21] found that the best times are 7 minutes for SPH and 27 minutes for SOP. The k-of-n method is used in SPH/SOP evaluation, where an alarm is triggered if k out of n predictions are identified as preictal within the specified period.

## 4. CURRENT DEEP LEARNING METHODS AND EMERGING TRENDS

Epileptic seizure prediction studies, which initially relied on classical machine learning methods, have now largely shifted towards deep learning algorithms. As shown in Figure 5, the reviewed studies used deep learning methods with three different approaches.

(1) Following the classical process in machine learning methods, signal analysis techniques were employed for feature extraction after filtering, and more advanced deep learning methods were utilized for classification due to their effectiveness in handling large datasets. This approach assumes that effective signal processing will enhance classification accuracy, given that the EEG dataset is composed of signal data. An example of this approach is the study by Liu et al. [22]. In their preprocessing phase, they segmented the raw EEG data into 30-second intervals without overlap. They then applied PCA to reduce the data size and used the FFT method to convert the segmented dataset into the frequency domain during the feature extraction phase. For classification, they implemented the CNN technique from deep learning methods.

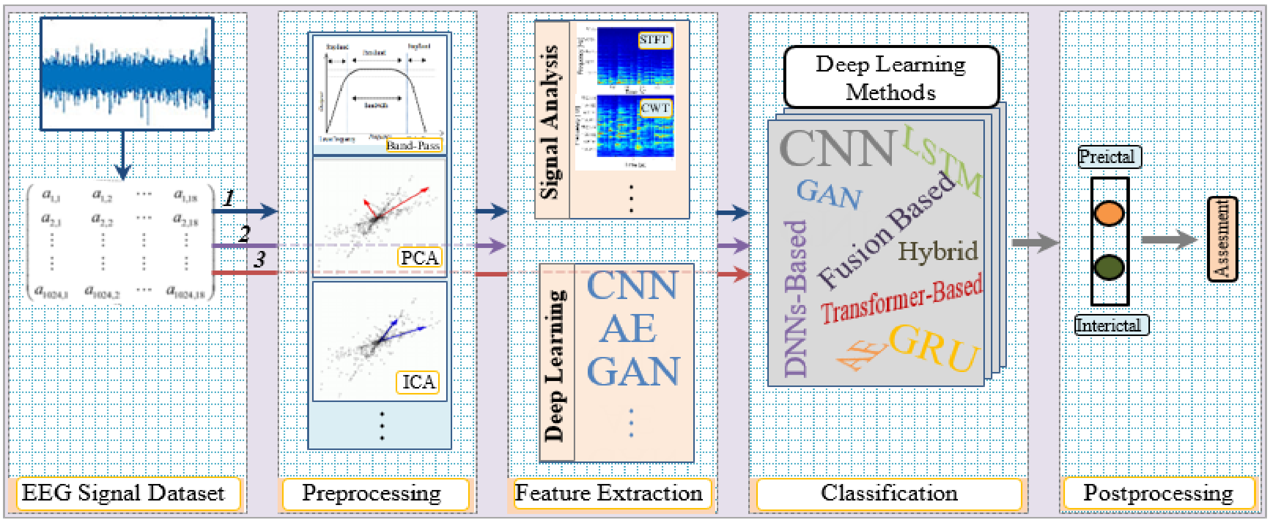


**Figure 5.** The deep learning process for predicting

(2) In this approach, the pre-processing step is applied in some studies, and alongside simple filtration methods like band-pass filtering, signal analysis techniques commonly used in classical methods are also employed during the feature extraction stage. Deep learning is utilized for both feature extraction and classification stages. At this point, feature extraction and classification can be performed using the same method, or a separate deep learning technique can be applied specifically for feature extraction, taking advantage of deep learning's capability for automatic feature extraction. In other words, different deep learning techniques may be used separately for feature extraction and classification. Assuming that manual feature extraction in classical methods may lead to data loss, Daoud and Bayoumi [23] used CNN for automatic feature extraction and then classified the features with LSTM. Other studies, such as those by Daoud et al. [24] and Avcu et al. [25], applied a less stepwise approach by using deep learning for both automatic feature extraction and classification directly after the filtering phase.

(3) Another approach is end-to-end deep learning, which is applied directly to the raw EEG dataset. In this method, with the aim of fully automating all stages, the pre-processing step is omitted, and feature extraction and classification are combined into a single integrated stage. For example, Daoud and Bayoumi [26] utilized the CNN technique on the raw EEG signals without requiring any additional processing steps in their study. The deep learning methods used for predicting epileptic seizures can be categorized into five groups:

**Supervised / Semi-Supervised Learning**

These methods use labeled data for classification. The key difference in the semi-supervised approach compared to supervised learning is the lower proportion of labeled data during the training process. With this trained data set, effective predictions are made of the data set whose results are unknown.

•Convolutional Neural Network (CNN): If the data is converted into image format during the pre-processing phase, the CNN deep learning technique is typically used. CNN, developed based on artificial neural networks, is one of the most widely utilized methods in recent years for predicting seizures from EEG data. Owing to its effectiveness in image recognition and classification, the CNN method is applied to EEG data by converting signals into image formats, such as spectrograms.

Various studies have applied the CNN technique for both feature extraction and classification. For instance, Wei et al. [27] utilized CNN during the feature extraction phase, while Hussein et al. [28] employed it in the classification stage. Zhao et al. [29] noted the limitations of image processing when applied to EEG signals; therefore, they implemented the Binary Single-dimensional Convolutional Neural Network (BSDCNN) technique directly on the raw EEG data without a separate feature extraction stage, achieving a sensitivity of 94.69%. In some studies, ready-made DNN-based architectures namely transfer learning, such as AddNet [30], RepNet [31], and ResNet50, were used to prevent overfitting.

Using the European database, Sarvi Zargar et al. [32] divided the EEG signals into 5-second segments and converted them into tensors. By utilizing ImageNet convolutional networks and MobileNet-V2 models, they achieved sensitivity rates of 98.47% and 98.39%, respectively. As mentioned earlier, CNN has been applied with significant success in image processing. However, when reducing the size of the pooling layer, some information may be lost, and the training time is long due to the large amount of training data required. Additionally, CNN struggles to maintain the spatial relationships between components within an image. For example, while it may make a correct classification when the components of an object change position, it does not recognize that the component's position has shifted. Hinton et al. addressed these shortcomings with the "CapsNets" technique, which they proposed in 2017, preserving the spatial relationships of object features. In their study, Toraman [33] used the CapsNets technique to overcome the limitations of CNN. By selecting channels from the raw EEG data and applying windowing, they achieved an accuracy rate of 97.74% using CapsNets. Capsule Networks are structures that learn various attributes of objects, such as posture, position, angle, and orientation. Despite their successful performance, image processing-based studies have disadvantages, such as high computational and memory bandwidth requirements. Considering these limitations and the time series nature of EEG data, researchers have increasingly turned to RNN and its derivative models.

•Recurrent Neural Network (RNN): Due to its effectiveness in processing time series data, this structure has been increasingly used in recent years for predicting epileptic seizures. Recurrent neural networks (RNNs) are designed to utilize sequential information and retain historical data, effectively using memory within the input data. In this network architecture, the hidden layer feeds its output back to its input, making the network recurrent. This type of neural network can maintain its state across sequential inputs, processing temporary sequences of data based on operations performed in previous sequences. This characteristic makes RNNs well-suited for applications like time series prediction. The RNN, which links previous information to the current task and is structured as a chain of recurrent connections, typically has a simple design with only the tanh activation layer. Models such as LSTM and GRU as RNN derivatives are frequently used in seizure prediction.

**Unsupervised Learning**

When training data is unclassified and unlabeled, unsupervised learning techniques are applied. These techniques analyze how the system can develop a function to identify hidden patterns within unlabeled data. Unsupervised learning algorithms do not require an explanation to define the relationship between input and output. Clustering and dimensionality reduction are commonly used methods in unsupervised learning approaches. Examples of deep learning models used in seizure prediction include GANs and AutoEncoders (AEs).

•Generative Adversarial Networks (GAN): GANs were developed based on the principle that a high number of examples contribute to the performance of deep learning algorithms. Introduced by Goodfellow in 2014, GAN is an unsupervised deep learning algorithm consisting of two networks: the 'Generator', which creates artificial outputs similar to the original data, and the 'Discriminator', which differentiates between the generated outputs and real ones. The discriminator network calculates the probability that the input images are real, assigning values between '0' and '1'. The network's values are updated in each iteration to minimize the loss value, which is the difference between the probability assigned by the discriminator and the true value, aiming to bring it as close to '0' as possible. Conversely, the generator network aims to have the fake images it produces evaluated as '1'. In their study, Usman et al. [34] utilized GAN to address the class imbalance problem that limits classification performance. Similarly, Rasheed et al. [35] used GAN to compensate for the lack of data in their study. After evaluating the effectiveness of the newly created dataset using SVM and CNN, they applied transfer learning and CNN methods for classification, achieving a sensitivity rate of 96%.

GAN generates synthetic data, making it useful for replicating preictal data in epileptic seizure prediction studies. Since interictal data is typically more abundant in EEG datasets, it is important to balance these two datasets before classification.

•Auto Encoder (AE): As an unsupervised neural network model, the Autoencoder (AE) compresses the multidimensional data it receives into a layer called the "Hidden Space" and then reconstructs it. AE has numerous applications, such as noise removal, data compression, dimensionality reduction, and feature extraction. It is composed of two parts: an encoder and a decoder. The encoder compresses high-dimensional input data into a lower-dimensional representation known as the latent space, while the decoder restores the data back to its original size. Deep AE models can be created by extending both the encoder and decoder with multiple hidden layers. However, the gradient vanishing problem, where the gradient becomes very small as it propagates through the layers, is a significant challenge in deep AE models. Despite the utility of GANs, certain limitations have led to the prominence of Variational Autoencoders (VAE). These limitations include difficulty in generating specific images and distinguishing clearly between real and fake objects. VAE addresses these challenges using the latent space layer. In their study, Abdelhameed and Bayoumi [36] developed a convolutional Variational Autoencoder model based on AE to create a low-dimensional representative dataset and classify this dataset. They utilized a CNN structure in both the encoder and decoder stages, achieving a sensitivity of 94.45%. In their study, Gözütok and Ademoülu [37] used a convolutional AE for both feature extraction and dimensionality reduction. In the subsequent stage, they classified the data using LSTM, achieving an accuracy of 87.6%.

**Hybrid Methods**

These methods involve the integral use of multiple deep learning techniques. One of the most efficient combinations for predicting epileptic seizures from EEG signals is the CNN-RNN architecture. LSTM, an enhancement of the RNN method suited for time series data, is often paired with CNN. In the context of hybrid methods, Daoud and Bayoumi [26] conducted a comprehensive study. They compared patient-dependent models, including DCNN+MLP, DCNN+Bi-LSTM, DCAE+Bi-LSTM, and DCAE+Bi-LSTM+CS, and found that the DCAE+Bi-LSTM method was the most successful, achieving a training time of 4.25 minutes and an accuracy rate of 99.6%. Another study, conducted by Affes et al. [38], applied the CNN-GRU model and achieved a 75% accuracy rate. In this study, a 30-second sliding window technique was used, where CNN was employed for feature extraction, and GRU was utilized for making predictions based on these features.

**Transformer-Based Deep Learning Models**

Today, classification studies using image processing can achieve high accuracy. However, these classifications often lack the simplicity needed to generalize well with training, testing, and a limited set of parameters. The transformer architecture, created by Vaswani et al. [39]. To address this issue, a neural network model based on the 'self-attention' mechanism, which assigns different weights to each part of the input data, was developed. Although the Transformer was initially designed for Natural Language Processing (NLP), as mentioned earlier, it has also been adapted for image processing with models like ViT and DETR. The Transformer handles dependencies between input and output using 'Attention' and 'Recurrent' mechanisms. In image processing, they are generally preferred over LSTM models. Unlike RNN-based sequential and recurrent models such as LSTM, the Transformer processes input sequences using the self-attention mechanism without requiring data labeling.

In studies focused on predicting epileptic seizures, transformer-based models have gained significant popularity recently. Li et al. [40] used a transformer-based model in their study, specifically a Transformer-guided CNN. Their method first applies the Short-Time Fourier Transform (STFT) to extract features from EEG signals. The proposed method achieves a sensitivity of 91.5% and an Area Under the Curve (AUC) of 93.5% using the CHB-MIT database. Similarly, Yan et al. [41] leveraged the advantages of the transformer architecture. In their proposed method, EEG signals were processed using STFT, followed by classification with the transformer model. Experiments conducted with the CHB-MIT database achieved a sensitivity of 92.11%. Another example of this model is the research by Zhang and Li [42]. In their method, the raw EEG signal from the CHB-MIT dataset was filtered, and the preictal and interictal periods were labeled. The EEG signal was then transformed into spectrograms using STFT. They employed the Vision Transformer model for feature extraction and classification, achieving an accuracy of 94.6%.

Power consumption and computational costs pose significant challenges for transformer methods.

**Fusion-Based Models**

It involves combining different machine learning or deep learning models to overcome the limitations of a single model in machine learning/deep learning and achieve better performance. This approach is applied to build more robust models. The fusion process can be carried out in three stages. A notable example of a fusion model is the study conducted by Ma et al. [43], where they achieved 94.83% accuracy. However, fusion models can sometimes increase computational load due to their complexity.

**Data Level Fusion:** This involves combining various interrelated data from multiple sources and merging them into a single dataset.

**Feature Extraction Level Fusion:** It is the integration of different features extracted from various methods and sources at the neural network level.

**Decision Level Fusion:** This process combines the outputs obtained from different classifiers and merges them into a unified decision.

Wang et al. [44] achieved an accuracy of 98.4% by using feature fusion and a transformer with multi-domain dynamic changes in a deep graph structure specifically designed for the patient, which they referred to as a 'multi-branch dynamic multi-graph convolution-based channel-weighted transformer feature fusion network.' In their study, Kapoor and Nagpal [45] combined features such as logarithmic band power, statistical features, wavelet features, spectral features, common spatial pattern, and entropy-based features extracted from the frequency bands at the feature fusion level. In their patient-specific study, Yang et al. [46] extracted features from EEG and ECG datasets using Bi-LSTM and CWT methods, respectively. After classifying both branches, they achieved an accuracy of 99.70% using decision-level fusion. Sun et al. [47] combined spatiotemporal features extracted with STFT and raw EEG signals for further feature extraction. The combination of two inputs from different domains allows for the representation of distinct and distinguishable features of EEG signals, enhancing the ability to utilize temporal, spectral, and spatial information. After applying the attention mechanism to the two distinct feature domains, feature-level fusion was performed. They achieved an accuracy of 91.7% following simple CNN classification. While fusion can create stronger models, it also presents challenges such as computational cost and an increase in parameters.

Table 2 provides an overview of the deep learning models preferred in studies conducted over the last five years.

**Table 2.** Studies using deep learning techniques

| CHB-MIT Dataset | | | | |
|---|---|---|---|---|
| **Ref. No.** | **Preprocessing** | **Deep Learning Techniques** | **Pred. Time** | **Achievement** |
| [48] | Raw Data | CNN | - | Spec 92.5%<br>Acc 97.7%<br>Sens 95.6% |
| [49] | Raw Data | CNN | 30 min | Sen 96.1%<br>ROC 0.918%<br>FPR 0.096 |
| [50] | Raw Data | CNN | 10 min | Acc 99.47%<br>Sens 97.83 %<br>Spec 92.36% |
| [29] | Raw Data | BSDCNN | 5 min | Sens 89.26%<br>FPR 0.117 |
| [30] | Raw Data | AddNet-SCL | 30 min | Auc 94.2%<br>Sens 94.9%<br>FPR 0.077 |
| [31] | Raw Data | RepNet | 30 min | Sens 93.1%<br>FPR 0.033<br>Auc 0.950 |

| | | | | |
|---|---|---|---|---|
| [51] | Raw Data | CapsNet | 30 min | Acc 95.7%<br>Sens 88.6%<br>FPR 0.127 |
| [33] | Raw Data | CapsNets | 30 min | Acc 97.74% |
| [52] | STFT | RDANet | 50 min | Acc 91%<br>Sens 89.33%<br>Spec 93% |
| [53] | STFT | ResNet | - | Auc 0.877 |
| [54] | STFT | Hybrid CNN + SVM | - | Acc above 90% |
| [41] | STFT | Transformer-Based | 5 min | Sens 96.01%<br>FPR 0.047 |
| [42] | STFT | Transformer-Based | 10 min | Acc 94.6%<br>Spec 90.5%<br>AUC 0.989 |
| [4] | EMD+STFT<br>Band-Pass+ GAN<br>Statistical, Spectral | CNN<br>Hybrid SVM+CNN+LSTM | 34 min | Acc 97.07%<br>Sens 88.89%<br>Spec 97.49% |
| [55] | CWT | CNN | 44 min | Sens 98.9% |
| [56] | CWT | Transformer-Based | - | Sens 99.8% |
| [57] | DWT | SVM | 25.1 min | Acc 96.38%<br>FPR 0.19 |
| [58] | DWT | Hybrid AE+ CNN | - | Acc 94.54%<br>Auc 92.15% |
| [59] | WPT | Bi-LSTM | - | Acc 99.47%<br>Sens 99.34%<br>Spec 99.60% |
| [26] | N/M | Hybrid<br>DCAE + Bi-LSTM | 60 min | Acc 99.6%<br>Sens 99.72% |
| [24] | AE | LSTM | | Acc 96.1% |
| [36] | Sample Entropy | Bi-LSTM | - | Sens 94.45%<br>FPR 0.06 |
| [6] | Two-Dimensional Segments of Five Sec. | Hybrid DCNN + Bi-LSTM | - | Acc 91.50%<br>Sens 94% |
| [16] | Time and Frecansy Features | LSTM | 30 min | Sens 99.37%<br>Spec 99.6% |
| [22] | FFT<br>PCA | CNN | - | N/M |
| [44] | STFT and Raw Data | Fusion-Based | 5-9 min | Sens 97.8%<br>Auc 0.935<br>FPR 0.059 |
| [45] | Statistical-Spectral | Fusion-Based | - | Acc 97.76%<br>Sens 95.6%<br>Spec 92.5% |
| **Otrher EEG Datasets** | | | | |
| [46] | Bi-LSTM<br>CWT | Fusion-Based | 5 min | Acc 99.7%<br>Sens 99.76%<br>Spec 99.61% |
| [28] | Band-Pass<br>STFT | CNN | - | Sens 87.85%<br>AUC 0.84 |
| [60] | Power Spectrum | Transformer-Based | 30 min | Sens 0.86<br>FPR 0.18 |
| [32] | Linear<br>Features | ImageNet<br>MobileNet-V2 | 40 min | Sens 98.47%<br>FPR 0.031 |
| [61] | STFT | Transformer-Based | 29 min | Sens 82%<br>FPR 0.38<br>AUC 0.746 |
| [27] | Band-Pass ICA | Hybrid LSTM + CNN | 21 min | Acc 93.4%<br>Sens 91.88%<br>Spec 86.13 |

## 5. DISCUSSION AND FUTURE DIRECTION

Research on the prediction of epileptic seizures, which began in the early 1970s with linear approaches such as spectral analysis and pattern recognition using spike rates, later solved many problems through the development of machine learning techniques; however, these efforts were still not sufficient. With an increase in the availability of sample data, machine learning approaches gradually gave way to deep learning methods. Recently, the rise of transformer-based models and the use of deep learning models in hybrid and fusion forms have led to significant progress in addressing existing challenges. Nevertheless, despite these advancements, several issues remain unresolved. These persistent challenges can be outlined as follows:

•It remains unclear which model performs best under specific conditions.

•The most critical issue appears to be related to datasets.

The EEG datasets used for seizure prediction are not sufficiently descriptive and suffer from artifacts, data deficiencies, and imbalances.

•Single-channel EEG systems, which are typically used to collect data, negatively impact performance, while multi-channel EEG systems are impractical for widespread application.

•While traditional methods demonstrate low performance, advanced algorithms come with high hardware and computational costs. • In addition to brain signals, seizures are often accompanied by changes in heart rate, muscle contractions, tremors, and blood values. However, most studies focus primarily on EEG signals, neglecting these other symptoms.

•Many of the methods used so far have not been evaluated on real patients.

Precise and effective seizure prediction methods are necessary to improve the quality of life for epilepsy patients who do not respond to medication or surgery. Although current studies have made significant progress, there is still no definitive solution. However, the pursuit of more effective models using new deep learning algorithms continues. It seems that we will encounter algorithms like Transformers more frequently. Similarly, methods such as GANs will be preferred, especially to address the dataset problem. First of all, for adaptation to real life, there is a need for a system that is more practical for obtaining EEG signals, can be applied at any time, and is capable of acquiring artifact-free signals that can be easily utilized in practice. This will facilitate the clinical application of future studies. Additionally, we will likely see that it will incorporate not only EEG signals but also different sensor information through fusion models, which are now frequently used in deep learning. In the future, there will be an increased focus on designing real-time alert systems, particularly within the realm of wearable technologies. For this, models that require less hardware will be needed.

## 6. CONCLUSIONS

Not knowing when and where epileptic seizures will start can negatively affect the lives of people with this disease and even cause fatal accidents. Therefore, the prediction of epileptic seizures is a critical issue. In this article, the existing literature on seizure prediction has been analyzed comprehensively and especially the most preferred methods have been included as much as possible. In this context, starting from the methods used in the first studies, signal analysis, machine learning and finally how deep learning algorithms are used are explained and the results of the studies are given. Finally, the discussion section focuses on the problems that still remain unsolved and the possibilities that will be focused on more in the future.

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