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Website: jceps.utq.edu.iq Email: jceps@eps.utq.edu.iq

# EEG Signal Analysis for Epileptic Seizure Detection: Algorithms, Challenges, and Opportunities

**Samar T. Ogaili [1,], Wessam Al-Salman [2,]**

[1]Department of Computer Science, College of Education for Pure Science, Thi-Qar University, Thi-Qar ,64001 Iraq.
[2]1Department of Computer Science, College of Education for Pure Science, Thi-Qar University, Thi-Qar ,64001 Iraq.

[*] Corresponding email: Wessamalsalman.comp@utq.edu.iq

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**Abstract:**

Epilepsy is classified as a chronic, non-communicable disease, but at the same time, it is a serious disease that can lead to death if the necessary measures are not taken on time. Many studies have been presented on how to benefit from machine learning techniques in diagnosing or predicting the disease. However, more studies still need to develop methods and algorithms for better performance and guaranteed results. This article highlights the latest techniques and algorithms that have been used from 2019 - 2024 and which have been published in peer-reviewed scientific journals. This review of the modern literature aims to identify the latest developments in this field and provide work that helps researchers and specialists interested in this disease. Also, in this study, the scope, limitations, and recommendations of previous studies have been discussed.

**Keywords:** Time-Frequency Domain, Cepstral Domain, Short-Time Fourier Transform (STFT), Wavelet Transform, Deep Learning, Machine Learning.

## 1-Introduction

Epilepsy is a chronic, non-contagious neurological disease characterized by recurrent seizures accompanied by involuntary movements affecting a specific part of the entire body [1].Epilepsy is also called "seizure disorder" which has different and multiple causes and types. It occurs as a result of some nerve cells in the brain sending electrical and chemical signals at more than the normal rate at the same time, which leads to the generation of a group of involuntary movements, feelings, sensations, and behaviors[2]. It is one of the oldest known diseases, as written records about this disease date back to 4000 BC[1].The severity of seizures varies from one person to another. There may be a patient who recovers from the symptoms of epilepsy after the seizure ends. In contrast, for another patient, it takes minutes or several hours accompanied by feelings of fatigue, drowsiness, anxiety, and

confusion[2]. Symptoms of epilepsy vary from one person to another. For example, some patients lose consciousness while others do not, or there may be tremors in the hands and feet, or the patient may stare into space for a few seconds during the seizure[3]. Epileptic seizures also vary in frequency, from about once a year to several seizures a day. About 50 million people around the world suffer from epilepsy[1].

Epilepsy has several types depending on the part of the brain in which it originates. Some are called focal epilepsy and others are called generalized epilepsy. Focal epilepsy originates in one part of the brain and affects about 60% of patients. Generalized epilepsy is a nerve activity that arises rapidly on both sides of the brain. Generalized epilepsy has several types, such as absence seizures, tonic seizures, and clonic seizures. Absence epilepsy is a type of epilepsy where the affected person appears to be staring into space and is a common type among children [2]. Epilepsy is evident in the following events:

1. Pre-seizure: It is a neural activity that precedes the seizure.
2. Ictal: is the event when the seizure happens.
3. Postictal: The neurological event that occurs after the seizure has ended.
4. Interictal seizures: Neurological activity between seizures[4].

There are several causes for the occurrence of epileptic seizures, some of which are known and others are unknown. The known causes may be structural, genetic, infectious, metabolic, or immune [5]. Epilepsy is typically diagnosed through manual examination and visual observation by specialists. However, this method is costly, requires significant effort by experts, takes a long time, and is prone to errors[6]. Based on the reasons above, practical and efficient solutions are needed for data analysis, seizure diagnosis, and epilepsy prediction to minimize errors and reduce the burden on experts and doctors. This article aims to provide a comprehensive overview of the most recent techniques for diagnosing or predicting epilepsy, which may assist researchers or specialized doctors interested in this field. It is widely recognized that medicine has greatly benefited from technological advancements, much like other fields. Numerous algorithms and techniques have been utilized and developed to aid in the diagnosis and prediction of diseases such as epilepsy, Parkinson's, Alzheimer's, and more. To diagnose epilepsy, several techniques and methods are used to image the brain condition. For instance, Electroencephalogram EEG is used, as the brain signal contains information that helps in classifying seizures and their places of origin[2].In addition, electrical activity in the brain can be imaged using magnetic resonance imaging (MRI) or computed tomography (CT)[2]. The electroencephalogram was invented by the scientist Hans Burger in 1923[6].The electroencephalogram plays a major and pivotal role in diagnosing epilepsy and its origins, despite the significant progress in other diagnostic techniques since the 1970s[7]. It is a non-invasive technique used to measure the electrical activity in the cortex with high time resolution, measured in milliseconds[8]. Electroencephalography (EEG) is an effective and popular tool that provides important information about brain activity, as shown in Figure 1, which helps experts diagnose the patient's condition and make the appropriate decision for his condition. However, it is not without some drawbacks, such as being complex in terms of analysis and extracting features manually. It is also known that the brain signal is nonstationary and nonlinear[9], which increases the difficulty of analysis even by specialists. Therefore, there is an urgent need to use more practical techniques to facilitate the work and improve accuracy and reliability, such as machine learning, deep learning, and transfer learning. Electrical activity is recorded using electrodes attached to the scalp to transmit brain signals from the depths of the brain to recording devices. This method is one of the oldest, most common, and least expensive techniques in neuroscience[7]. To facilitate the processing process, the EEG signal is analyzed into five frequency bands: delta (up to 4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-26 Hz), and gamma (26-100 Hz)[6] Figure 3. B. The electrodes are positioned on the scalp using the 10-20 system, an internationally recognized non-invasive standard (see Figure 2).

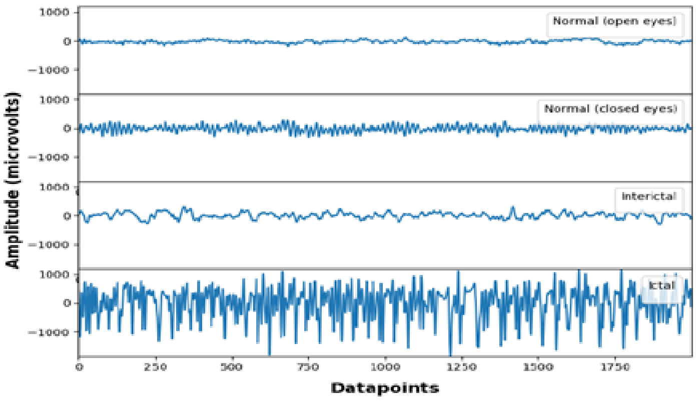


**Figure 1: Electroencephalography (EEG).**

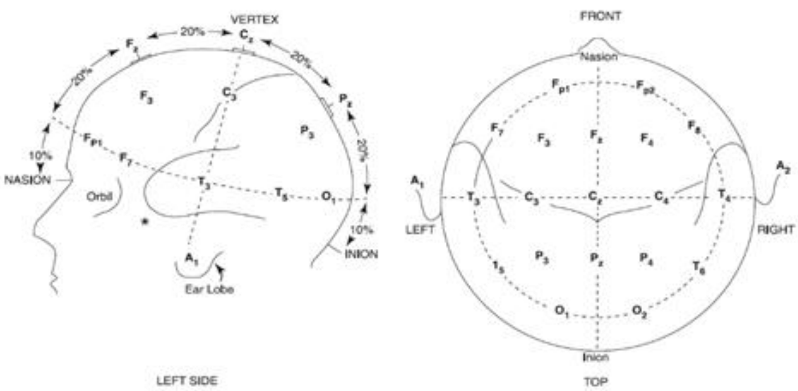


**Figure2: The International 10–20 System for placements of EEG electrodes**

This name means that the distance between the poles is 10% or 20% of the skull's total front-back and right-left parts. The impact of epilepsy extends beyond just seizures. It includes significant economic and social consequences such as healthcare expenses, reduced work productivity, and premature death.

Additionally, there are social implications as patients and their families may feel ashamed and seek isolation. This issue can be more challenging to address than the seizures themselves[1]Moreover, the probability of death for an epilepsy patient is three times the global average [10].Therefore, there is an urgent need to increase efforts, studies, and research on this disease and to provide everything to alleviate the burdens imposed on governments and individuals. Epilepsy represents 0.5% of the global disease burden[1].To accomplish this task requires collaboration across multiple scientific fields, including neuroscience, silicon nanotechnology, micromachinery, electrical engineering, mathematics, and computer science[6]. Classification of epilepsy is crucial for making life-saving decisions. In addition, early prediction of epilepsy provides clinicians and specialists with the time needed to take necessary medical and therapeutic measures to prevent seizures or minimize their impact on the patient's Machine learning techniques offer valuable support to doctors, but they come with their challenges. Machine .life learning: is training a computer to solve problems by training it in advance on relevant data. The benefit of this is to process and analyze huge amounts of data faster than humans and overcome errors. For machine learning to work efficiently, relevant features from the data need to be extracted manually[11].The feature extraction stage is the most important step in efficiently conducting classification methodologies[12]. It is the process of converting signals into meaningful information fed into a classifier model, which may be in the time domain, frequency domain, time-frequency domain, or cepstral domain. This information is used for training and testing classification models to ensure accurate diagnosis and prediction. The extracted features can be classified into univariate and multivariate features. Univariate features are the features that are sampled from each EEG channel separately. Multivariate features are the features that are sampled from two or more channels. Features can be further classified into linear features and nonlinear features [6].There are several benefits to using feature extraction methods:

1-Reducing the data input size for the classification model by extracting important information and excluding unimportant data, thereby saving storage space.

2- Facilitate the classification process.

3- Increasing the speed of the classification model and reducing execution time.

4- Increasing the accuracy and reliability of the classifier, thus making the performance high and efficient.

Therefore, in this work, we will focus on the feature extraction methods used by researchers and discuss the extent Based on the analytical methods used, the following section to which they achieve the abovementioned criteria. discusses the literature. There are different ways to analyze the EEG signal:

1- Time domain.

2- Frequency domain.

3- Time_frequency domain.[6]

4-Cepstral domain.

*1.1 Features extracted by analysis methods*

*1-Time domain analysis*:

It is the amount of change in the signal's amplitude concerning time.[13]It is known that the brain signal is unstable and complex, so we need to use analysis methods to extract useful values. When analyzing the signal in the time domain, we will get multiple features, including standard deviation, mean, median, variance, skewness, flatness, minimum amplitude, and peak.[14].Time domain analysis of the signal is suitable for analyzing patterns and changes that occur rapidly in the brain signal due to internal or external events such as closing or opening the eyes. The use of the time domain is useful in monitoring seizures and determining changes in amplitude over time[13].The time domain is valuable for studies focused on immediate seizure detection, such as real-time patient monitoring applications. However, there are limitations when using the time domain, including the inability to detect frequency information or spectral components and difficulty in analyzing unstable signals. As a result, many researchers in this field turn to more advanced analysis methods, such as the frequency domain or the time-frequency domain.

*2-Frequency domain analysis*

Frequency is the number of cycles of an oscillatory and vibratory waveform per unit time. The unit of frequency is hertz (Hz), which means one cycle per second.[13]The brain signal contains a wide spectrum of frequencies, so it is usually analyzed in the frequency domain (Figure(3B)). There are several methods for frequency analysis, including Fourier transform, short-time Fourier transform (STFT), wavelet transform, Welch's method, and others.[13]Through frequency domain analysis, important signal features are obtained such as power spectrum, spectral density, resonance, frequency response, and signal-to-noise ratio (SNR).[11]To effectively detect different using both time and frequency domains. This seizure patterns, researchers often analyze the signal's details combined approach, known as the time-frequency domain, is considered an advanced analysis method that yields superior results.

*3-Time-Frequency domain :*

provides a better representation of the distribution of signal energy across time and frequency[15]. The features extracted from the time-frequency domain are total power, spectral power, peak frequency, bandwidth, frequency bands, center frequency, and harmonic content. Deep learning is an advanced form of machine learning that automates the process of feature extraction and classification. It consists of a neural network with multiple layers, each performing its operations and passing its outputs as inputs to the next layer. The final layer of the network acts as a classifier for making decisions[11] . Deep Learning has been widely used recently due to its high performance, better data utilization, and automatic feature extraction.[11].

*4-Cepstral Domain:*

It is a domain in which data is represented using cepstrum coefficients, which contain information about the periodicity of the signal or the time patterns. Cepstrum coefficients are features obtained by applying the Fourier transform to the signal, taking the logarithm, and applying the Inverse Fourier transform. The Mel-frequency cepstral coefficients (MFCC) are an advanced version of the cepstral coefficients, which are popular for their use in speech, voice, and earthquake recognition applications. However, they can also be used in the analysis of biometric signals such as EEG and ECG. Figure 3 shows how to extract the MFCC. (Figure 4) shows the applications in which the MFCC has been used[12].

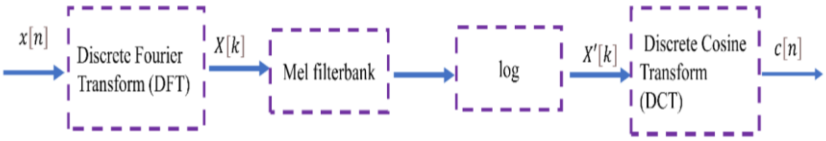


**Figure 3: Show the MFCC framework.**

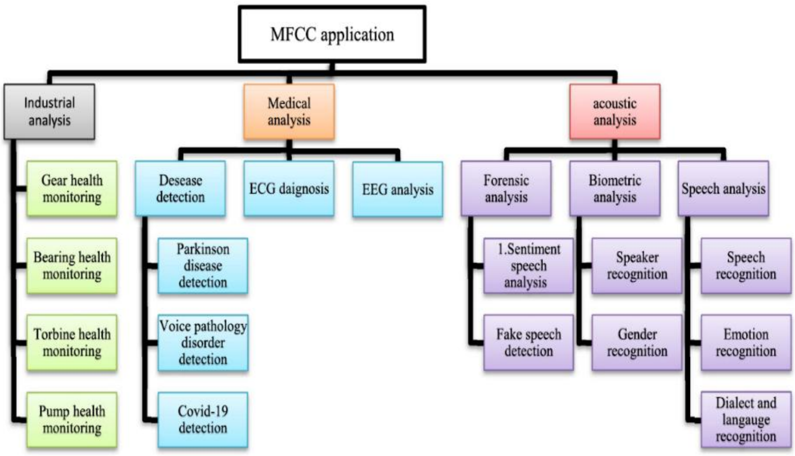

**Figure 4: MFCC application.**

## 2-Literature survey

With this work, we aim to present a study that illuminates the algorithms and methods used by researchers in the past six years to classify seizures and predict the presence or absence of epilepsy. We also aim to discuss the latest scientific advancements in this field. First, we gathered relevant research articles from databases and peer-reviewed scientific journals such as Elsevier, IEEE, Wiley, Springer, MDPI, and others. We then categorized the articles based on the following criteria:

1-Articles with an accuracy rate of less than 90% were excluded.

2-Articles published before 2019 are not included.

3- Articles that were not written in English.

As a result, we have gathered 40 articles for discussion. These articles cover various methodologies, algorithms, analysis methods, and performance measures. Additionally, we will explore the most prominent challenges and their solutions. Ricardo Ramos-Aguilar et al proposed a three-stage approach to extract features: first, relying on the frequency and areas within the spectrogram. Second, using the K-means algorithm, and the third method using the maximum peaks matrix in the spectrogram. The extracted features are passed to three classification models: multi-layer neural network, SVM, and K-Neirest. This approach achieved 100% accuracy on the Boone dataset. However, some drawbacks may appear in this approach, including its application to a limited amount of data, which may lead to changing its performance when applied to large data sizes. In addition, using multiple methods to extract features leads to increased computational complexity, time, and computing resources [16].

In 2022, Sharmila Ashok and colleagues proposed a method for identifying epileptic seizures based on time-frequency domain features. They applied the Discrete Wavelet Transform to the University of Bonn dataset and the Senthil Hospital dataset and obtained the following features: Mean Average Value (MAV), Maximum coefficient, Minimum Coefficient, Average Power, Shannon Entropy, and Approximate Entropy. The classification was performed using SVM, KNN, Naive Bayes, and Decision Tree classifiers[17].

Dinesh Kumar Atal1 and Mukhtiar Singh have introduced a new classification system called Novel Random Forest Classification (NRFC). This system is based on PCA and is designed to automatically detect and classify normal or abnormal (ictal or interictal) signals. The signals are analyzed using Modified Graph Theory (MGT), fractal dimension, and GLCM features. Four features are then extracted for classification: link density, closeness of centrality, graph entropy, and amplitude features. Graph theory is a modern method used in quantitative analysis to visualize the dynamics of signal time series. The MGT technique is robust and resistant to noise. To improve classification accuracy, researchers employed the Gray Level Co-occurrence Matrix (GLCM) technique. Statistical features, such as correlation, entropy, energy, homogeneity, and maximum probability, are also extracted along with the patterns[18].

In 2022, Maokun Lin and colleagues proposed a method for early prediction of epileptic seizures. The method is based on nonlinear features and involves extracting approximate entropy, sample entropy, permutation entropy, spectral entropy, and wavelet entropy. They used the GBDT classifier with random forest as a classification method. This approach achieved an accuracy of 92.00% and a sensitivity of 91.87% according to performance measures. The method is unique in that it aims to address the imbalance in data classes from the CHB-MIT Scalp EEG Database by categorizing brain signals into two classes: signals with seizures and signals without seizures, based on a manually defined period called interval time (InT). However, there are some drawbacks to this approach. It can be challenging to determine the appropriate ( InT ), potentially resulting in the loss of important information. Additionally, the performance ratios are not considered sufficient. Furthermore, the practical application of this approach is difficult, as acknowledged by the researcher, indicating a need for further study and development[19].

In a separate study, Jefferson Tales Oliva et al. introduced a two-part: binary and multiclass classification approach. They extracted 105 metrics from the power spectrum, spectrogram, and bi-spectrogram to use as features.

The study employed eight different machine learning algorithms and achieved an accuracy of 98.75% for binary classification and 96.25% for multiclass classification[10]. Mahajabin Mostafa and colleagues used DWT to extract features. They used DTC, RFC, and KNN classifiers in the classification stage. The data was also divided into binary and multiclass classifications. The results were as follows: 97.22%, 100%, and 83.33% for binary class classification and 91.67%, 91.67%, and 80.56% for multiclass classification respectively[20].In 2020, Fahad Al-Turki and colleagues introduced an approach similar to Muhajibin Mustafa's, based on discrete wavelet transform (DWT) and binary and multiple classification. However, their method relies on statistical features such as logarithmic band power (LBP), standard deviation, variance, kurtosis, and Shannon entropy (SE). In addition, the features are input into four different classifiers: linear discriminant analysis (LDA), support vector machine (SVM), k-nearest neighbor (KNN), and artificial neural networks (ANNs). This method yielded superior results in both binary and multiple classification, with SVM achieving 99.9% accuracy and ANNs achieving 97% accuracy [21]. The above-mentioned studies share one drawback which is not mentioning the time required for classification which is one of the most important requirements required in an efficient classification model, especially in real-time applications. Table 1 summarizes another body of literature.

**Table 1. Comparison of research studies on epilepsy in the time, frequency domain, and machine learning**

| Author | Feature extraction | Data set | Classification | Spe | Sen | Acc |
|---|---|---|---|---|---|---|
| **Wessam Al-Salman et al.**[22] | **dual-tree (DT-CWT) (FFT)** | **Bonn , Bern University** | **(LS-SVM) classifier.** | **98.5** | **97** | **97.7% 96.8%** |
| **Olivera Stojanovic**[23] **et al** | **nonnegative matrix factorization (NMF)** | **Freiburg EPILEPSIAE database** | **(SVM)** | **99** | **95** | **97.22** |
| **Ricardo Buettner**[24] **et al** | **spectral analysis ( Fourier transform** | **University of Bonn,** | **Random Forest** | **98.0** | **100%** | **99.0 %** |
| **Marzieh Savadkoohi**[25] **Et al** | **Butterworth filter, Fourier, and Wavelet respectively** | **university of Bonn** | **SVM** | **100** | **100** | **100** |
| | | | **kNN** | **100** | **99** | **99.5** |
| **Saif Al-jumaili1**[26]**et al** | **FFT** | **TUH** | **SVM** | **98.4** | **95.6** | **96.5** |
| **Itaf Ben Slimen et al**[27] | **MSPCA, DTCWT** | **CHB-MIT database** | **SVM and k-NN** | **_____** | **______** | **100%** |
| **Srinath R et al**[28] | **wavelet packet** | **Bern-Barcelona EEG data set** | **ANFIS classification algorithm** | **99.7%** | **99.7%** | **99.4%** |
| **Hafeez Ullah Amin et al.**[29] | **Discrete Wavelet + Arithmetic coding** | **the University of Bonn** | **k-NN, Naïve Bayes,** | **_____** | **______** | **100%** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | **MLP, and SVM** | | | |
| **Dwi Sunaryono et al.**[30] | **(DFT) and (DWT)** | **University of Bonn** | **gradient boosting machines (GBM),** | _____ | ______ | **100%** |
| **Muhammad Zubair et al.**[31] | **(DWT)** | **University of Bonn** | **SPPCA + Catboost** | ______ | ______ | **97.00** |
| | | | **SUBXPCA + Random forest** | ______ | ______ | **98.00** |
| **Markos G. Tsipouras** [32] | **Frequency sub-bands/energy, total energy, fractional energy, entropy** | **the Bonn EEG database** | **Random forests (three-class)** | ______ | ______ | **98.80%** |
| | | | **Random forests (five-class)** | ______ | ______ | **91.20%** |
| **Ly V. Tran et al.**[33] | **discrete wavelet transform** | **the University of Bonn** | **SVM** | **99.00%** | **96.00%** | **98.40%** |

In the following section, studies conducted by the researchers to classify epilepsy using deep learning are reviewed. In 2020, Theekshana Dissanayake and colleagues presented an approach for the prediction of epileptic seizures that consists of two different CNN architectures. The approach was applied to the CHB-MIT-EEG database and achieved accuracy rates of 88.81% and 91.54%, respectively[34].

Also, M. Shamim Hossain and others used CNN to classify seizures, and the accuracy and sensitivity rates were 98.05% and 90%, respectively[35].Xiaoshuang Wang et al. proposed a CNN-LSTM-based binary and ternary classification method. This hybrid method achieved ternary classification performances of 98%, 97.4%, and 98.3% in accuracy, specificity, and sensitivity, respectively. It achieved 100%, 100%, and 99.8% in binary classification[36].

Omaima Ouichka and colleagues also presented a new classification method. The proposed models are based on the Convolutional Neural Network (CNN) model, the fusion of the two CNNs (2-CNN), the fusion of the three CNNs (3-CNN), the fusion of the four CNNs (4-CNN), and transfer learning with ResNet50. The 3-CNN and 4-CNN models achieved an accuracy of 95%[37] .Syed Muhammad Usman et al. presented a method for predicting seizures. The features were extracted using CNN, and the classification was done using LSTM. This method addressed the problem of class imbalance in the data using GAN. It achieved the following performance rates: 93% sensitivity and 92.5% specificity, with an average prediction time of 32 minutes for the onset of seizures. However, the accuracy rate achieved by this method was not mentioned[38].

Luay Fraiwan also presented an article on the classification of focal and nonfocal epilepsy using the LSTM classifier. Two experts helped extract the features manually and visually and then passed them to the LSTM classifier. This method achieved accuracy, sensitivity, and specificity values of 99.60%, 99.55%, and 99.65%, respectively. Despite the achieved results, this method is expensive in terms of time, effort, and resources[39]. Mustafa Talha Avcu1 and others presented a method for detecting seizure onset using a Convolutional Neural Network for seizure detection. They examined 29 patients with absence epilepsy. They extracted spectrum features and passed them to an SVM classifier to compare them with the proposed SeizNet. The results show that SeizNet outperforms the SVM classifier, which is expected[40]. Chenqi Li and colleagues also used CNN to classify epilepsy and predict seizures. The results were verified using Cross-Validation. The following performance ratios were achieved: in seizure detection, an accuracy of 99.84 was achieved, and in seizure prediction, an accuracy of 99.01 was achieved for the CHB-MIT database and 97.54 for the SWEC-ETHZ database[41].

In some studies, a hybrid approach combining machine learning and deep learning techniques is proposed to fully exploit the advantages of both techniques and overcome the disadvantages. Table 2 mentions a number of these studies.

**Table 2 :presents the hybrid approaches that many researchers use.**

| author | Data set | Feature extraction | Classifier | ACC | Sen | Sep |
|---|---|---|---|---|---|---|
| [42] | **CHBMIT** | **CNN+ handcrafted** | **SVM + CNN+ LSTM+ Bagging** | **94.31%** | **94.73%** | **93.72%** |
| [43] | **CHBMIT** | **DWT + Non-linear** | **CNN-GRU-AM** | **99.35%<br>95.16%** | **99.24%<br>95.47%** | **99.51%<br>94.93%** |
| [4] | **Bonn database** | **Power spectrum** | **BP-MLP(ANN)** | **95.25-98.75%** | _____ | _____ |
| | | **Spectrogram , Bispectrogram** | **1NN, LDA, QDA** | **88.75-96.25%** | | |
| [44] | **TUH** | **DWT** | **LSTM** | **95.92<br>98.08** | _____ | _____ |
| [45] | **CHBMIT** | **statistical features and CNN** | **LSTM** | **94%** | **93.8%** | **91.2%** |
| [46] | **CHBMIT** | **Fourier-based Synchro squeezing Transform (SST)** | **CNN** | **99.63%** | _____ | _____ |
| [47] | **BECTS/Rolandic Dataset<br>Helsinki University** | **Scattering Trans-former + FFA** | **Scattering Transformer** | **96.87%<br>90.55%** | _____ | _____ |

Several researchers have used MFCC to extract frequency features from the brain signal to distinguish patterns that lead to the prediction of seizure occurrence. Inggi Ramadhani et al. presented a new prediction method based on multiple feature extraction techniques including MFCC in addition to Hjorth and ICA. Classification was done using SVM. This method achieved high-performance rates as follows: 90.25%, 97.83%, and 91.4% of average sensitivity, average specificity, and accuracy respectively. Despite the high performance rates, it suffers from some drawbacks, most notably the relatively small data size for training machine learning models and the problem of class imbalance[48].

Delal ŞEKER and colleagues introduced a method for feature extraction based on MFCC. They employed various classifiers including Fine Tree, Quadratic Discriminant Analysis, Logistic Regression, Gaussian Naïve Bayes, Cubic Support Vector Machine, weighted k-nearest neighbors, and Bagged Trees. The method achieved 100% accuracy, specificity, and sensitivity metrics. However, this approach has limitations as it was only tested on a single dataset (Bern-Barcelona) and was not validated on other datasets. Consequently, the method may not be as effective when applied to larger and more diverse datasets. Additionally, utilizing only MFCC as a feature for prediction oversimplifies the signal and may overlook important details[5].

In 2020, Bahar Tajadini and others introduced a method for monitoring and early detection of seizures. This method serves as a warning system by analyzing signal frequencies using Autoregressive (AR), Cystral analysis, and DWT. The method demonstrated accuracy, specificity, and sensitivity rates of 92.6%, 95.6%, and 87.5%, respectively.

However, it relies on thresholding rather than classification algorithms, which may limit its effectiveness with some patients due to the sensitivity of thresholding to changes in the data[49].Also, Fan Zhang et al. used MFCC in their feature extraction method. CNN was applied as a classification model. The results were as follows: accuracy 96%, specificity 84%, and sensitivity 92%[50].

Yixian Wu and colleagues conducted a study where they classified the seizure and non-seizure signals of children with Rolandic epilepsy. They analyzed the signals and extracted both MFCC, LPCC, and features from pre-prepared videos of the signal condition due to limited data size. They then combined all the features using a direct fusion process, which resulted in an accuracy of 98.2%. However, this approach has some challenges, including the complexity of data collection and processing, pattern variability, and potential insufficiencies in the quality of video recordings and environmental influences in children's cases[51]. The methodologies found in the literature can be summarized in Figure 5.

## 3-Challenges and Solutions

1- The brain signal is complex and unstable:

The brain map carries a lot of important information and details, but it is difficult to analyze and process. To overcome this problem, the concept of Signal Engineering can be used. Signal Engineering: It means analyzing the signal using time and frequency analysis techniques such as the wavelet family and Fourier transform.

2- Insufficient data size for training a classification model:

Epilepsy has multiple types and varies in severity and location, so there is an urgent need for diverse and reliable databases, which are not sufficiently available. For example, epilepsy known as absence epilepsy, is common among children, but there is not enough data set. To overcome this obstacle, researchers use the concept of (data augmentation). Data augmentation is the artificially generating data by adding noise, distortions, or time-shifting the signal. One of the techniques that accomplishes this task is GAN. It is a learning technique that consists of two neural networks: the generator and the discriminator. The generator's function is to generate synthetic data, while the discriminator distinguishes the original data from the synthetic data.

3-Data imbalance:

When recording the brain signal of an epilepsy patient, the seizure data is usually less than the seizure count data, so the data is imbalanced, which reduces the efficiency of the classification model and may ignore the minority class. Several techniques address this problem, such as the Synthetic minority oversampling technique (SMOTE). It is a technique that generates new samples based on the nearest neighbors of each sample from the minority class.

4-Computational complexity:

The process of filtering the signal from noise and interference requires computational operations and a long time, which adds more computational complexity to the performance of the models. To speed up the processing, parallel learning techniques are used.

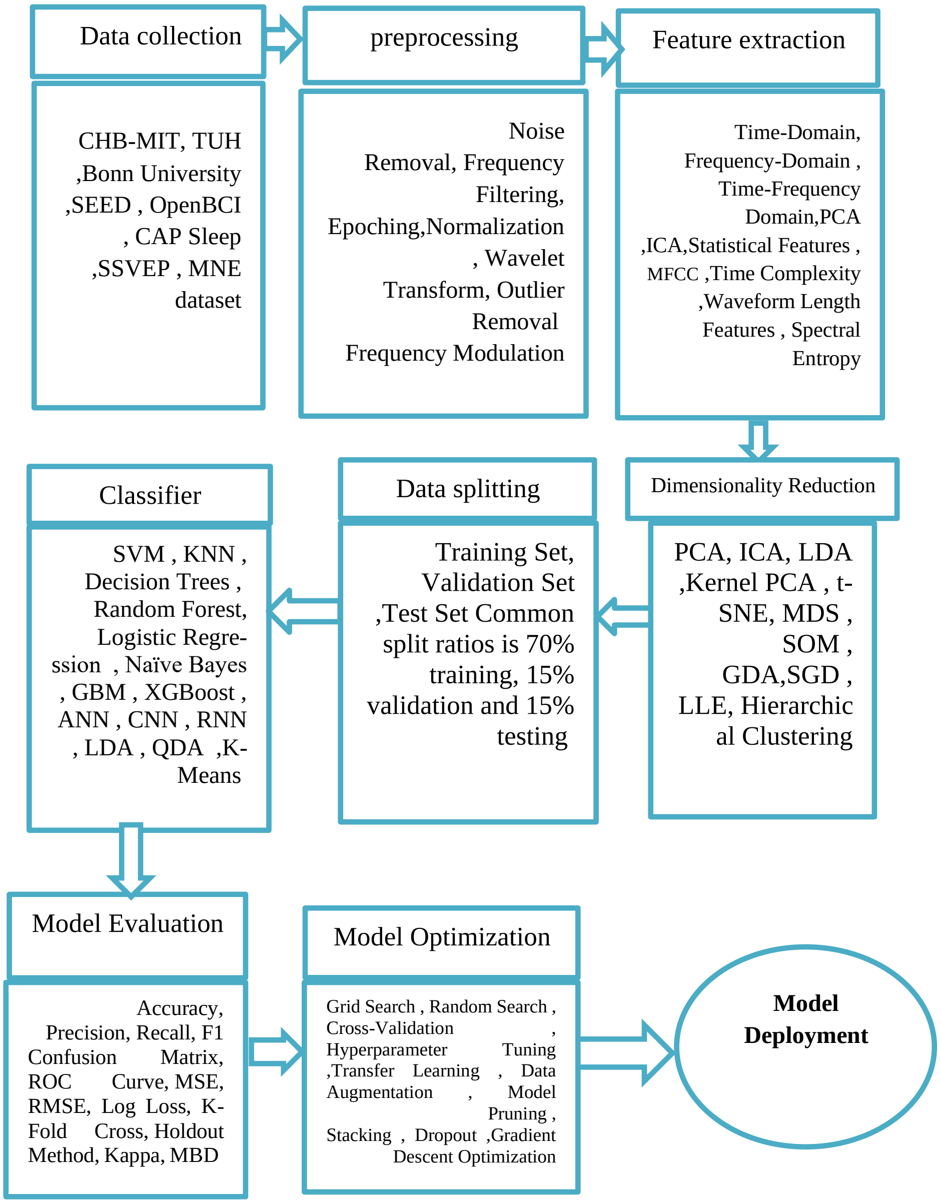


**Figure 5: Show a common and general methodology for classification.**

## 4-Conclusions

In this paper, a wide range of peer-reviewed research on epilepsy classification and prediction methods is presented. This review focuses on feature extraction methods because of their significant impact on the performance of the classification model. Some studies have relied on time-domain signal analysis and some have relied on frequency-domain analysis. The recent trend among researchers is frequency-domain analysis to cover all features, which helps improve classification accuracy. Some have used Cepstral-domain analysis to obtain information from low frequencies, which may lead to the detection of seizure patterns. What distinguishes machine learning techniques is the ease of interpreting the results and it does not require large computational resources. However, there are some limitations such as manually extracting features and it is also suitable for small or medium-sized data. Epilepsy is a disease with diverse types and patterns, so it is sometimes difficult to diagnose accurately. To solve this problem, researchers resort to using deep learning. Deep learning is the most advanced part of machine learning, but it is not without limitations, including that it requires large computing resources (GPUs) and is suitable only for large and complex data. To take full advantage of the advantages of both machine learning and deep learning, researchers have recently resorted to using a hybrid approach that combines them. For example, CNN is used to extract features, while classification is done using one of the machine learning algorithms such as SVM.

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