Chapter 2

Literature Review

2.1 Introduction

Among several nervous system disorders, a disease that affects 50 million people globally is epilepsy. Epilepsy patients experience seizures, which are transient disruptions in brain electrical activity that can result in a lapse in attention or a full-body convulsion. At unpredictable periods, they recur often or without prior notice. Recurrent seizures can be deadly and increase the likelihood of physical injury [11–13]. If a system can identify seizures as soon as they happen and notify the patient or the caregiver, seizures may be lessened. The most frequent test to identify a seizure's beginning before it happens is an EEG. It is a technique for employing several electrodes to capture the electrical activity of the brain. Each patient's EEG recording has different characteristics. The EEG associated with the onset of a seizure in one patient may closely resemble the benign pattern in the EEG of another patient. Patient non-specific classifiers demonstrate low accuracy or lengthy delays in announcing the commencement of a seizure as a result of this cross-patient variability in seizure and non-seizure activity. However, in some circumstances, patient non-specific classifiers might show outstanding performance if they are only allowed to examine seizure forms that differ little between individuals [1]. Also, the development of portable SC-EEG has revolutionized health monitoring and BCI, especially for indoor and non-clinical situations [25].

The vast literature in the field of EEG signals of epilepsy patients illustrates the multifarious techniques used for the different stages in the pipeline of analysis and utilizing these signals for classification and prediction tasks. Each stage has several techniques with advantages that contribute to executing the end task efficiently. The objective of this study is to review such research works and provide an analysis of them.

2.2 Methods

This section reviews the recent methods and techniques utilized in the domain of EEG classification and prediction of ESs. Apart from this, intermediate steps have also been discussed in detail, along with the works that focus on such techniques.

2.2.1 EEG Signal Acquisition

The primary step in the automated epilepsy management system pipeline is the acquisition of EEG signals. There are two main categories of EEG, i.e., sEEG and iEEG. Both these types are used in seizure prediction and classification studies. sEEG has been a crucial tool in the epilepsy workup ever since Hans Berger made the first human recordings in 1924 [26], guiding initial diagnosis, epilepsy categorization, and therapy. The first iEEG recordings were made by Reginald Bickford in 1948 [27] on epilepsy patients, and they showed a startling contrast between sEEGs that seemed to be negative and an abundance of epileptic discharges [28].

2.2.1.1 Scalp EEG

Scalp EEG (sEEG) is used to detect and study epilepsy in a patient. sEEG uses evenly spaced surface electrodes bonded to the skin to record brain activity [29, 30]. However, routine sEEG recordings are thought to miss a sizeable amount of epileptic discharges present within the brain [28].

2.2.1.2 Intracranial EEG

Also known as Invasive EEG, Intracranial EEG (iEEG) uses intracranial electrodes placed in putative epileptogenic regions determined using clinical, anatomical, and functional data available before implantation [23]. iEEG is a common method for pre-operative evaluation in epilepsy procedures and for seizure forecasting. This technique records neuronal electrical activity directly from the patient's brain using implanted electrodes over the cortex underneath the scalp [31, 32].

The practicality of both sEEG and iEEG for seizure classification and prediction has been investigated in various research works [16]. Under these two categories are various types of EEG, such as Sleep EEG, Sleep-deprived EEG, Ambulatory EEG, and Video EEG.

2.2.2 Input Encoding and Preprocessing Methods for EEG Signals

After the data acquisition, the next step is preprocessing the EEG signal and the encoding or representation of data. The preprocessing of the signal is an essential step due to various reasons.

For EEG-based activities to produce appropriate classification and prediction results, EEG data must be preprocessed. Preprocessing EEG waves has the following benefits:

- Noise reduction: Environmental noise, Muscle Artifacts (MA), electrode drift, and other kinds of noise are frequently present in EEG data. These noise sources are reduced by preprocessing methods, including filtering and AR, which also improve the Signal to Noise ratio (SNR) and the EEG data quality [25, 33–35].

- Feature extraction: Preprocessing enables the extraction of pertinent information from the unprocessed EEG data. The raw data is transformed into more meaningful representations that capture significant properties of the underlying brain activity using feature extraction techniques, including spectrum analysis, time-frequency analysis, and statistical metrics. These traits offer useful data for classification and prediction algorithms [32, 36–38].

- Dimensionality reduction: Due to the many electrodes and the continuous time-series structure of the signals, EEG data often has a high dimensional character. The dimensionality of the data can be reduced using preprocessing techniques, including spatial filtering (e.g., frequent spatial patterns) and dimensionality reduction methods (e.g., Principal Component Analysis (PCA)). Consequently, future classification and prediction algorithms may operate more effectively and with more computational traceability [39, 40].

- Artifact removal: A variety of artifacts can affect EEG readings. These artifacts may be successfully identified and eliminated using preprocessing techniques like Independent Component Analysis (ICA) and regression-based approaches, guaranteeing that the analyzed EEG signals predominantly represent the underlying brain activity [41–44].

- Normalization: Preprocessing enables the normalization of EEG data, which is necessary to guarantee comparability across various participants and recording sessions. By adjusting the EEG signals to a single reference point or distribution, normalization techniques like baseline correction and z-score normalization reduce inter-subject and inter-session variability.

- Data augmentation: Preprocessing may comprise approaches that artificially expand the data set's size by transforming or altering the original EEG signals. This method addresses the issue of insufficient training data, possibly enhancing the resilience and generalization of classification and prediction models [45, 46].

Using proper preprocessing techniques, researchers can improve EEG data quality, reliability, and interpretability. This improvement will result in more accurate classification and prediction outcomes in various applications, including BCI, epilepsy diagnosis, sleep analysis, and cognitive workload assessment.

2.2.2.1 Artifact Removal

The EEG, which identifies the electrical activity inside the brain, makes it easier to see any aberrant activity that might result in neurological problems. Every time an EEG recording is captured, it is susceptible to contamination from different artifacts [34, 35, 41]. These "artifacts", often called "noise", can take many forms. Physiological and non-physiological artifacts can distort EEG test results. These can come in a variety of shapes, including background noise from the test instruments and cardiac artifact (CA), MA, Ocular Artifacts (OA), and Motion Artifacts (MoA) [42–44, 47]. The issues with the MoA are brought on by cable instability and electrode displacement as the patient moves [48]. During the examination, the patient could move their limbs or blink, or it might be their cardiac rhythm, which might be detected as an artifact in an EEG recording. Real-time medical observation systems and BCI have been transformed by the development of portable devices that use SC-EEG, particularly in non-clinical and indoor contexts. In these circumstances, the artifacts mentioned earlier might readily enter the EEG signals being recorded [25, 33].

The role of AR is quite essential to the process of EEG signal analysis (ESA). Eliminating noise from EEG signals can boost the quality of the signal and raise the precision with which the data are analyzed and interpreted. The results obtained from such EEG readings may be simpler to comprehend when AR is performed on them. By removing noise, the true underlying brain activity can be seen. It becomes simpler to recognize and understand key aspects of such activity. EEG is frequently employed in clinical settings to identify neurological conditions like epilepsy. Denoising EEG readings can improve diagnosis accuracy by lessening the noise's impact on the signals. Denoising EEG signals can make it possible to classify various forms of brain activity more precisely, which might be crucial for applications like BCIs [49–51]. Various research works focus on denoising while being mindful of the above benefits. To remove OA, MA, and CA from EEG signals, the authors in [52] have developed a Functional Link Neural Network-Radial Basis Function Networks (FLN-RBFN) based filter. In addition, they used adaptive noise cancellation to get rid of artifacts.

2.2.2.1.1 Cardiac Artifacts For the automatic detection and suppression of CA from an SC-EEG, the authors in [53] proposed a hybrid signal denoising methodology that combined adaptable EWTs, adaptive threshold-based non-linear Teager-Kaiser energy operator, and customized morphological filter was proposed. A specialized morphological filter made up of the ideal number of structural elements was used to identify the spikes or R-waves found in the signal. The Particle Swarm Optimisation (PSO) approach optimized structural elements. This technique effectively detected both positive and negative spikes. This approach does not require a reference ECG channel, and the improved EAS approach was used to remove ECG artifacts.

2.2.2.1.2 Muscle Artifacts EMG are artifacts connected to muscular contraction (such as biting, chewing, and frowning) and are generally considered to be more challenging to eliminate than EOG and ECG artifacts [54, 55]. The spectrum range, spatial dispersion, and absence of stereotypy of EMG artifacts are the key challenges in treating them. The work done in [56] presented ReMAE, a user-friendly toolkit that was operated in the MATLAB environment and may be used to remove MA from EEG signals. Many research works have focused on the removal of MoA as well. To filter out MoA from the EEG signal, the authors in [57] proposed methods based on weighted and non-weighted Multiresolution Total Variation. These authors also proposed a Wavelet Domain Optimised Savitzky-Golay filtering strategy to solve the same problem more efficiently in [58]. In [34], the authors proposed a CNN-Autoencoder (CNN-AE) based technique for the removal of MA. The One Dimensional-CNN (1D-CNN) used was fractional and compressed, which reduced the use of main memory. This architecture used orthogonal features such as Tchebichef moments.

These days, a lot of work is focused on real-time AR. One such work is [41] in which a unique Multi-Module Neural Network (MMNN) was proposed for SC-EEG denoising to eliminate MAs and OAs. The MMNN is a parallel architecture that is put together with several denoising modules. The proposed technique has a network flow that can continuously disassemble and reassemble EEG data. By combining Conv1Ds and Fully-Connected (FC) layers, the authors could create denoising modules tailored explicitly to distinguishing OAs or MAs from noisy EEG data using network learning. FC layers were utilized to rebuild the clear signals and artifacts, while Conv1Ds were used to extract and generalize the informative characteristics of brain activity. The proposed technique was highly efficient in terms of signal reconstruction accuracy, which was achieved using a smaller amount of training data than other state-of-the-art techniques.

2.2.2.1.3 Ocular Artifacts The authors in [59] provided a technique to enhance the removal of OA from free viewing experiments using ICA. This study evaluated and improved four ICA-based correction pipeline parameters for natural viewing tasks. With little to no change in brain activity and without the need for subjective experimenter classifications, this technique for training the Infomax ICA could efficiently eradicate OA from EEG signals. This study also examined the relationship between beta and gamma oscillations to facilitate the removal of OAs. In [60], the authors incorporated the information derived from both the temporal and frequency domains into a DL model for OA removal. This is a cross-domain approach used adaptably to enhance the performance of different deep denoising networks. Similarly, in [61], the authors proposed a Stone's Blind Source Separation (BSS) based novel technique hybridized with PSO for separating EOG and PL from SC-EEG in the context of ESA. The proposed method consists of three main steps: centralizing and whitening the input EEG signal, incorporating the processed EEG signal into the iterative PSO algorithm to generate the weight vector parameters' optimal values at random, and applying Stone's BSS using the Generalised Eigenvalue Decomposition method to remove EOG and PL artifacts to obtain a clean EEG.

2.2.2.1.4 Motion Artifacts According to [62], one of the most harmful non-biological artifacts in EEG data is MoA, which is characterized by large amplitude (greater than 100 muV) and low-frequency signals (0.01-10 Hz). It mostly results from disturbances brought on by head or body movement, uneven electrode-tissue contact impedance, or improper electrode contact with the scalp [58, 63]. In [63], for the suppression of MoA from EEG data, a hybrid signal denoising framework that consists of a modified Empirical Mode Decomposition (EMD) and an optimized Laplacian of Gaussian (LoG) filter was presented. The modified EMD broke down the noisy SC-EEG signal into a collection of the ideal number of Intrinsic Mode Functions (IMFs). Additionally, MA, regarded as low-frequency noise expected to be present at low-frequency IMFs, was subjected to the optimized LoG filter. This filter smoothed the EEG signal, eliminating any background noise or artifacts. The denoised signal was rebuilt by including a filtered output signal with high-frequency IMFs.

2.2.2.1.5 Removal of Multiple Artifacts Many research works have identified and proposed techniques capable of removing several artifacts. Such as [64] proposes an approach to removing artifacts from EEG data by combining two established approaches, i.e., the Gray-Level Co-occurrence Matrix (GLCM) and the PCA. The PCA algorithm received its input from the characteristics that the GLCM derived from the EEG data. The ICA technique was then applied to the components to separate the signal from the artifact. This work has reported that the proposed technique successfully eliminates various artifacts, including CA, MA, and OA, and enhances the overall quality of the EEG signal. Another such work is [25], in which the authors tried to overcome existing drawbacks in the literature by eliminating the eye blink artifacts by utilizing VME-DWT for the unsupervised identification and filtering of eye blinks in a brief section (i.e., 3s) of an SC-EEG. The Variational Mode Extraction (VME) first extracted an approximate representation of the eye blink signal to locate the most significant eye blink peaks and identify artifactual periods comprising eye blinks. The discovered periods were then filtered using Discrete Wavelet Transform (DWT) to preserve as much of the eye blink-free EEG as possible. The authors in [65] proposed different Wavelet Transform (WT) modifications for EEG denoising. These different approaches were built on several meta-heuristic algorithms that aid in determining the ideal WT parameters. Three distinct noises — White Gaussian Noise, PL, and EMG — are used to contaminate EEG readings. In all data sets with various forms of noises, the Flower Pollination Algorithm (FPA)-based WT method outperformed the others. The Multi-Objective (MO)-FPA-based WT was proposed by these authors after additional study on this technique. They used this to find the best WT parameter combination to perform EEG signal denoising while meeting the objective of minimal Mean Squared Error (MSE) and maximum SNR.

In [66], a novel Uniform Search PSO-Wide Deep ESN (UPSO-WDESN) denoising model combining width and depth structure made of Echo State Networks (ESN) was proposed. Multiple reservoirs were utilized while being connected in a parallel and stacked configuration. The wide and deep topology and connectivity helped in capturing and integrating the multi-scale dynamical states of temporal data. The UPSO algorithm optimized the WDESN reservoir parameters during the initial stage. Two novel techniques for eliminating EEG artifacts were introduced in [67]. Common Component Rejection (CCR), a technique used in the first method, involved extracting and removing common components shared by EEG channels as artifacts. In the second approach, called Automated Wavelet CCR, the EEG signals were first broken down using wavelet decomposition, and then the CCR method was used to eliminate artifacts in the time-frequency domain. In [68], the authors proposed an innovative heterogeneous-domain DL-based technique that employed hybrid networks to extract multilevel latent characteristics and offered two strategies to reconstruct the EEG signals. A vital component of the suggested solution was the scheme, which considers the intricate relationships between neighboring EEG channels, spatiotemporal connectivity, and signal denoising. Additionally, a novel consistency regularisation technique was put forth to improve information sharing across the multilevel latent features derived from the labeled and unlabeled EEG data, which is advantageous for both the transfer of information and quickening the training. The data analysis done as a part of this technique was based on six sub-bands of the data instead of the raw version to account for the influence of EEG signals' complicated connectivity patterns. A unique consistency regularisation approach was proposed to increase the link between the multilevel features acquired from the signal. This method helped quicken the training process and enhance the generalization of the proposed Neural network (NN). This work focused on developing a reliable DL model for diagnosing schizophrenia. To perform efficient classification, [69] proposed an adaptive optimization strategy based on the Fletcher Reeves (FR) algorithm, and the Sparsity-based EEG Reconstruction (SER) and Three Dimensional-Optimised-CNN (3D-OCNN) classifier was suggested. The different seizure states were classified using a sparsity-based AR method and a 3D-OCNN classifier. The K-Singular Value Decomposition (SVD) approach significantly decreases the length and complexity of the preprocessing stage by substituting PCA for the SVD. This work also proposes a predictor for the Optimal SPH called Phase Transition based Kullback-Leibler Divergence.

Denoising methods based on DWT and Wavelet Packet Transform (WPT) coupled with VMD, namely VMD-DWT and VMD-WPT, was proposed by [70]. The mode selection criterion in these methods will be determined using Detrended Fluctuation Analysis (DFA). VMD deconstructed the signal into multiple components before using DWT and WPT to denoise the artifactual components rather than entirely rejecting them with DFA as the mode selection basis. In [71], the authors presented a novel centroid-based EEG selection method called CenEEGs, which employs a globally optimal centroid strategy to choose valid EEG signals in relation to a similarity threshold after measuring the similarity of EEG signals using a scale-and-shift-invariance similarity metric. Some works have focused on assessing the quality of the obtained denoised signal. Two reliable distortion measures, Weighted SNR and Weighted Correlation Coefficient, were used in [47] to accurately represent the objective reconstruction loss in each band. To quantify the distortion in the application-specific neural activity in each rhythm, weights for these measures were established based on relative wavelet energy and relative wavelet entropy of the subband coefficients of the EEG signal. While developing the suggested distortion metrics, the authors use the wavelet subband energy and entropy of the EEG signal to highlight the distortion of specific neural activity in each cycle. [72] proposed a graph filtering methodology that can better handle the effects of additive and natural impulsive noise on raw EEG recordings. The authors specifically compared the proposed l_p, e -regularised graph filter with well-proven graph-based denoising methods.

2.2.2.2 Generation of Synthetic Data

Because there is a paucity of medical data and it is difficult for potential researchers to acquire the technology, the influence of DL, Artificial Intelligence, and Machine Learning (ML) on healthcare research has been slow and quite challenging. Even if the researcher has access to the data, the legal processes to acquire the data and ensure correct and secure exploitation of the data take a long time, delaying the creation of innovative technologies that may help the healthcare industry. Many owners anonymize data by removing recognizable traits, introducing noise, and classifying persons or factors into wider groups to make medical data accessible. However, the enormous data set makes it impossible to re-identify such anonymized data since it would take too much time and effort [73]. To automate the creation of synthetic biological signals, the authors in [74] proposed the SynSigGAN model, a revolutionary Generative Adversarial Networks (GAN) model. For the generator network of the GAN, the authors employed bidirectional grid LSTM, and they used CNN for the discriminator network model. This technique can generate new biological synthetic signals while utilizing a minimal signal data set from the source. Various works focus on overcoming the problem of less data by generating synthetic EEG data. One such work is [22], in which a Deep Convolutional GAN (DCGAN) model was developed. For creating both iEEG and sEEG data, the suggested DCGAN model demonstrated good generalization. In addition, a generalized Convolutional ES Predictor (CESP), which was suggested to evaluate the synthetic data, is also applicable to both forms of EEG data. The authors used a one-class Support Vector Machine (SVM) and trained and tested the CESP model using four combinations of actual and synthetic data to assess the quality of the synthetic data. Results demonstrate that the synthetic samples accurately captured the link between data attributes and pre-ictal sample labels.

2.2.2.3 Input Encoding and Feature Extraction

In EEG analysis, input encoding refers to representing the raw EEG data in a suitable format that computational models or algorithms can utilize for further analysis. The goal of input encoding is to extract meaningful features or representations from the EEG signals that capture relevant information while reducing noise and irrelevant details [17].

The choice of input encoding technique depends on the specific analysis task and the characteristics of the EEG data. The following are some commonly used input encoding methods in EEG analysis.

2.2.2.3.1 Time-domain Representation: The raw EEG signal, consisting of voltage measurements over time, can be used directly as the input. Each data point represents the amplitude of the electrical activity recorded at a specific time point. Time-domain encoding is simple and straightforward but may not capture the frequency or spectral information present in the signal [75]. In [36], the authors proposed an approach based on EMD and SVM for feature extraction and pattern identification. They used the IMFs acquired from the EEG data to generate time domain features like the coefficient of variation and Fluctuation Index characteristics. Fractal dimension (FD) measures the complexity or irregularity of a signal. In the context of EEG analysis, FD provides information about the self-similarity or scaling properties of the signal across different time scales. The authors in [76] conducted a systematic empirical study of fractal theory, which was used to extract the fractal features of eight different communication modulation signals. Fractal features were box FD, Katz FD, Higuchi FD (HFD), Petrosian FD, and Sevcik FD. Additionally, evaluation methods based on these fractal features were proposed. An anti-noise function analyzed the noise robustness. The data distribution was calculated using box diagrams, and the computational complexity was evaluated using the running time. Finally, Backpropagation NN (BPNN), grey relation analysis, Random Forest (RF), and K-nearest neighbor (KNN) classifiers are used to classify the communication modulation signals.

2.2.2.3.2 Frequency-domain Representation: EEG signals are composed of different frequency components that reflect different neural activities. Frequency-domain encoding techniques, such as Fourier Transform (FT) or WT, convert the EEG signal from the time domain to the frequency domain. This representation provides information about the power or amplitude of different frequency bands in the signal, enabling the analysis of specific frequency-related phenomena [77, 78]. The authors in [79] proposed an EEG-based real-time method to identify ESs by using TQWT and CNN. The time domain and frequency domain patterns in the EEG were revealed using statistical moments and spectral band power, and the resulting imaged-like data was input into CNN. The authors in [80] presented a model-based Field Programmable Gates Array (FPGA) architecture to classify brainwave bands using real-time feature extraction from EEG inputs. Twenty time-frequency feature components were created by a feature extraction subsystem using the Short-Time Fourier Transform (STFT) method and power spectrum density. The FPGA architecture was optimized using fixed-point data formats to raise operating frequency, lower resource utilization, and boost power efficiency.

2.2.2.3.3 Spectrogram: A spectrogram represents the spectral content of the EEG signal over time. It is obtained by calculating the STFT or other time-frequency transforms. Spectrograms provide a visual representation of how the power or intensity of different frequency bands changes over time, allowing for the analysis of dynamic frequency patterns. For instance, [81] coupled convolutional AE with CNN for multi-view spectrogram representations learning based on the STFT approach. This approach is an example of a scalogram-based CNN. Further, the work [82] examined the relationship between time and frequency characteristics derived from multichannel EEG recordings. They used STFT to create spectrograms from the original EEG data, which indicated the signal's time-frequency properties. The authors proposed a dual self-attention residual network that combined a channel attention module that exploits the dependency between channel mappings with a spectrum attention module combining local features with global characteristics to improve forecasting performance. In [83], using CNN, the authors attempted to distinguish different seizure types. The EEG time series were transformed into a spectrogram stack to be fed as input to CNN. The system was assessed using transfer learning, and ten pre-trained networks were used to extract picture attributes.

2.2.2.3.4 Statistical Measures: EEG data can be represented using statistical measures calculated over specific time intervals or frequency bands, such as mean, variance, skewness, or kurtosis. These measures capture different statistical properties of the EEG signal and can be used as input features for further analysis. In [84], the authors developed a novel detection technique to analyze the EEG signal to forecast and categorize ESs. The primary goal of this work was to boost seizure prediction accuracy by effectively extracting the signal's characteristics. The Masking and Check-in-based Feature Extraction Technique was developed to extract the SNR, variance, and Standard Deviation (SD) of the input signal. The check-in function produced the mask for the signals throughout this operation. The upper and lower peaks were computed along with their respective envelopes, and features were retrieved using this value. The signal was then classified as normal, aberrant, inter-ictal, or ictal using an integrated K-Means with a KNN classifier. Here, the signal classification was carried out depending on the value of the minimal distance. The Euclidean distance and the Chebyshev distance were estimated.

2.2.2.3.5 Spatial Representations: EEG data is often recorded from multiple electrode locations placed on the scalp. Spatial encoding involves representing the EEG signals in a spatial domain, such as electrode locations or electrode connectivity. This representation allows for analyzing spatial patterns of brain activity or interactions between different brain regions [85]. In [39], a method of choosing EEG channels based on EEG shapelet transformation was proposed, intended to speed up setup, minimize annoyance to participants, and enhance the performance of BCIs when used. The approach, in further detail, concurrently solved a logistic loss-embedded minimization problem with regard to EEG shapelet learning, hyperplane learning, and EEG channel weight learning to choose the top-k EEG channels. The approach additionally minimizes EEG shapelet similarity by learning distinct EEG shapelets to weigh the contributions of each EEG channel to the logistic loss. Consequently, Shapelet-transformed EEG Channel Selection (StEEGCS) chosen EEG channels have enhanced classification accuracy compared to all other EEG channels, and classification time consumption has decreased. To improve the feature embedding of raw EEG signals throughout seizure and non-seizure periods, the authors in [40] proposed a novel seizure detection model based on a Linear Graph Convolution Network (LGCN). The input graph of the Graph Neural Network was constructed using a Pearson correlation matrix of raw EEG data, where the coefficients of the matrix describe the spatial relationships in the signals to classify seizure from non-seizure. Focused loss was also used to redefine the loss function of LGCN to address the issue of data imbalance during seizure detection. To improve the representational strength of EEG signals during both normal brain activity and seizures, the authors suggested using LGCN to take advantage of the spatial link between EEG electrodes. In [86], three effective frameworks for EEG processing applications were presented. The first one introduced a framework for automatically detecting seizures based on an extraction technique known as scale-invariant feature transform. The second one relied on an NN and the Fast Fourier Transform (FFT) to forecast ESs. Finally, a PS automated framework based on FFT was suggested for channel selection and seizure prediction. The simulation outcomes demonstrated the viability of the suggested frameworks for automated medical diagnosis.

2.2.2.3.6 Representation as Two-dimensional Images: Converting EEG signals into two-dimensional (2D) images opens up opportunities to leverage powerful image analysis methods, such as CNNs or image segmentation algorithms, for feature extraction, pattern recognition, or anomaly detection. These techniques have been extensively developed for image analysis and can be adapted to extract meaningful information from EEG images. [87] is one such work. It proposed a method for predicting ESs, in which the primary step was transforming EEG, i.e., the temporal data into 2D images for multichannel fusion. It proposed a spatiotemporal DL model for predicting ESs using a practical method known as a Long-Term Recurrent Convolutional Network. The convolutional network block automatically retrieved deep features from the data. The LSTM block was utilized to learn a temporal sequence to distinguish the pre-ictal segments. The seizure prediction model recommended new network configurations and a post-processing technique. A study [69] has proposed a method for multichannel EEG seizure prediction based on phase transitions. The authors developed an adaptive optimization strategy with the help of the SER, 3D-OCNN classifier, and the FR method. Seizure states were classified using a 3D-OCNN classifier and a sparsity-based AR method. FR algorithm helps speed up the convergence and lessen the complexity of the proposed non-linear model. In [88], the authors have used images derived from brain signals to perform classification. A pre-trained model, VGG-19, was used in the proposed methodology. They also proposed blockchain-based picture storage to bring privacy awareness to the whole architecture. In [78], Multiscale Radial Basis Function (MRBF) networks and the Fisher vector (FV) encoding were the foundations for the unique automated seizure detection technique presented in this study. In more detail, the Modified PSO (MPSO) method and the Orthogonal Least Squares (OLS) algorithm were used to find the best scales and identify a parsimonious model structure after the MRBF networks were used first to obtain high-resolution time-frequency images for feature extraction. Then, using the FV and GLCM texture descriptors, which helped create high-dimensional vectors, it became possible to extract discriminative features from time-frequency pictures based on five frequency subbands of clinical importance. Additionally, before inputting compact features into the SVM for seizure detection, the t-test statistical technique was used to reduce the dimensionality of the original feature space efficiently.

2.2.2.3.7 Feature Extraction: EEG signals can be further processed to extract specific features that capture relevant information for the analysis task. Feature extraction methods, such as wavelet coefficients, Power Spectral Density (PSD) estimates, or Event-Related Potentials, focus on extracting specific characteristics from the EEG signals. Feature extraction plays a crucial role in EEG analysis by extracting relevant information from the raw EEG signal. EEG signals are complex and contain vast data, making it challenging to interpret and analyze directly. Feature extraction involves transforming the raw EEG signal into a more compact and representative set of features that capture essential characteristics of brain activity. These extracted features can be used for various purposes, such as classification, pattern recognition, correlation analysis, reducing dimensionality, detecting abnormalities, and investigating brain connectivity. It is crucial in extracting relevant information from the raw EEG data, facilitating further analysis and interpretation [38].

In [89], the ability to predict ESs using just one EEG channel was established. A three-level feature extraction approach was utilized to determine the likelihood of an ES. Line length, a feature of the first level, measures the frequency-amplitude fluctuations in the signal. Although the first-level feature can detect the pre-ictal's mild seizures, there were times when this feature picked up a mild seizure without any accompanying intense seizure. The second-level feature, which was integral to the first-level feature, was created to address this issue and lower the false alarm rate. The line length of the retrieved second-level features was used to accomplish third-level feature extraction. This work demonstrated high precision and a low percentage of erroneous predictions. Using features determined by statistical parameters such as anticipated activity measurement, sample entropy, and HFD as input to a classifier, the epileptical signal was retrieved from the EEG signal in [90]. This study used KNN and an NN classifier to divide the healthy, inter-ictal, and ictal EEG signals into three categories based on statistical parameters.

2.3 Task type

2.3.1 Classification

2.3.1.1 Machine Learning for Classification of Epileptic Seizures

The automated detection and diagnosis methodology of ESs in EEG signals consists of three main steps: preprocessing, feature extraction, and classification. For example, in [91], the authors have proposed using arithmetic coding as a compression technique to reduce the size of the feature vector and improve the classification process. The EEG signals were filtered and decomposed in the preprocessing step using the DWT. Statistical features were extracted from the decomposed signals in the feature extraction step. In the classification step, the extracted features were input into an ML algorithm to classify the EEG signals into seizure and non-seizure classes. Additional steps in preprocessing and post-processing can also help improve the classification task's overall performance. Some works combine traditional techniques with

ML techniques to improve seizure classification. Such as [92], which used a newly created time-frequency analytical technique called Local Mean Decomposition (LMD). An arbitrary signal can be divided into several Product Functions (PFs) using LMD. Before calculating the temporal statistical and non-linear properties of the first five PFs, the original EEG signal was first decomposed into several PFs. For each of the five classification cases, the features from each PF were fed into one of five classifiers: BPNN, KNN, Linear Discriminant Analysis, un-optimized SVM, and SVM optimized by Genetic Algorithm (GA). Confluent features from all PFs were further sent to the high-performance GA-SVM for identical classification tasks. Some machine learning techniques extensively used for seizure classification are mentioned below.

2.3.1.1.1 Neural Networks EEG signals were preprocessed using EMD, and the derived IMFs were utilized to generate characteristics like Renly Entropy and Negentropy in [93]. An NN model utilizing this feature collection was employed for classification. Techniques like SVM and logistic regression were utilized to improve such methodologies. In works like [94], two-layer LSTM and four-layer improved NN DL algorithms were proposed to improve the performance in EEG classification. The novelty lies in 1D gradient descent activation functions with radial basis operations used in the initial layers of improved NN, which helped achieve better performance. Statistical features, namely mean, SD, kurtosis, and skewness, were extracted for input EEG. Further feature set enhancement using Hilbert Vibration Decomposition has also been done in works such as [95], which utilized Multilevel Perceptron (MLP) for classification.

2.3.1.1.2 K-Nearest Neighbour ML-based ES detection models are quite prevalent and are used to classify EEG data into ictal and inter-ictal groups accurately. The most distinctive aspects of ictal EEG signals are extracted using a feature extraction technique that uses a temporal and frequency-based statistical analysis of decomposed EEG signals. The appropriate window size was experimentally found to properly analyze long-term EEG recordings by segmenting the EEG signal in [96], which uses KNN for classification.

2.3.1.1.3 Support Vector Machine SVMs play a crucial role in ES classification by effectively separating seizure and non-seizure EEG segments, handling non-linear relationships, robustly generalizing to unseen data, and assisting in feature selection, contributing to the development of accurate and reliable seizure detection and prediction systems. Optimization of SVM parameters using algorithms like PSO or GA [97] enhanced the classifier's performance further. Works like [78] have utilized MRBF networks and the FV encoding as foundations to develop seizure detection methods. The MPSO method and the OLS algorithm were used to find the best scales and identify a parsimonious model structure after the MRBF networks were used first to obtain high-resolution time-frequency images for feature extraction. Then, using the FV and GLCM texture descriptors, which provide high-dimensional vectors, it is possible to extract discriminative features from time-frequency pictures based on five frequency subbands of clinical importance. Additionally, before introducing compact features into the SVM classifier, the t-test statistical technique can efficiently reduce the dimensionality of the original feature space. The effects of smoothing train and test data, post-processing, and Adaptive Median Feature Baseline Correction (AM-FBC) have also been investigated in [98]. AM-FBC was observed to be essential to combat feature distribution variance amongst databases while performing a cross-database evaluation of the classification of ESs using SVM. SVMs have also been used with DL classifiers such as CNN [99] to develop seizure prediction systems. The preprocessing of the EEG signal, followed by automated feature extraction using CNN, was seen to produce improved results. Another work that utilized SVM for classification is [100]. In this work, the authors have proposed tools that utilize recordings from both seizure-free and epileptic EEG signals. These signals can be classified with a high degree of accuracy using the trained SVM-based model. The classifier's great performance is attributable to the computed features' capacity to characterize EEG data, the feature selection method that uses the Information Gain measure, and the model's granularity for the chosen patient. This system enabled channel selection and feature extraction for a single patient. It was proven to be independent of a particular patient and was viable for various patients with various types of epilepsy. SVM and Self Organizing Map (SOM) can process the obtained data to find anomalies that could not be observed through human inspection. The goal of the research in [101] was to estimate the likelihood that using these particular antibiotics may result in negative effects. The suggested data processing systems allowed for statistical analysis of the patient-provided EEG signals, which helped with accurate real-time identification and anomaly warning. The suggested approaches offered online tracking and detection of a patient's propensity for seizure activity, offering a novel clinical connection with regard to seizure risk.

2.3.1.1.4 Random Vector Functional Link Network The Random Vector Functional Link Network (RVFL) network is used in ES classification to map input features, classify seizures using non-linear activation functions, and enable fast inference. It offers efficient training, generalization, regularization, and the potential for ensemble learning, enhancing its effectiveness in seizure classification tasks. Combined with EMD features such as in [102], it gave an improved hybrid model for classifying and diagnosing epileptic EEG signals. A weighted multi-kernel RVFL with the kernel parameters optimized using the effective Water Cycle Algorithm enhanced the performance of the suggested model with the help of the wavelet and Tanh kernel functions. The features produced by EMD in terms of IMFs were modulated to identify significant statistical and entropy-based characteristics. In a reduced form, these features were then used as inputs to the model to categorize epileptic EEG data. To identify and categorize ESs using EEG signals, VMD, Hilbert Transform (HT), and suggested Error-Minimised RVFL

Network (EMRVFLN) was incorporated [103]. The EEG signal was divided into band-limited IMFs using VMD. The feature vector was created by computing the five effective instantaneous features using HT. The ES was classified using the proposed EMRVFLN classifier.

2.3.1.2 Deep Learning Techniques for Classification of Epileptic Seizures

DL uses NNs with several hidden layers to automatically extract detailed patterns and characteristics from EEG data, a crucial step in categorizing ESs. CNNs and Recurrent Neural Networks (RNNs) are examples of DL models that excel in capturing temporal and spatial relationships in the data, allowing for precise seizure detection and categorization. DL's effectiveness in obtaining high performance and resilience in ES classification tasks is attributed mainly to its capacity to build hierarchical representations and manage large-scale data sets. Works such as [104] utilized multichannel EEG representation using multiple hand-crafted features, feature fusion, and transfer learning with multiple pre-trained Deep Neural Networks (DNNs). This approach, along with discriminative feature extraction, was used for classifying epileptic states using a Hierarchical Neural Network (HNN). First, an image feature was developed and combined from the Mean Amplitude Spectrum (MAS), Mean PSD (MPSD), and Wavelet Packet Features (WPFs) for the representation of multichannel EEGs. The fused picture feature was then immediately adopted by five conventional pre-trained DNNs as feature extractors. Finally, for discriminative feature learning and epileptic state classification, a 7-layer FC-HNN was built. The time-scale characteristics (WPFs) and frequency domain features (MAS and MPSD) were integrated for multichannel EEG representation. For feature transfer learning on the fused EEG picture feature, several distinct pre-trained DNNs were employed, and a novel hierarchical NN was created for discriminative feature learning and epileptic state categorization. This approach is a unique technique to categorize various epilepsy states for early seizure warning.

Some of the DL techniques used quite extensively are mentioned below.

2.3.1.2.1 Convolutional Neural Networks Recent DL models do not adequately consider both spectral and temporal domain representations at the same time, which may cause them to overlook the nonstationary or non-linear feature of epileptic EEGs and hence provide a sub-par recognition performance. Using a novel Channel-Embedding Spectral-Temporal Squeeze-and-Excitation Network (CE-stSENet) with a maximum mean discrepancy-based information maximizing loss, an end-to-end EEG seizure detection framework was provided in [105]. In particular, the CE-stSENet first included simultaneous multi-scale temporal analysis as well as multilevel spectral analysis. A variation of the Squeeze-and-Excitation (SE) block was then used to capture hierarchical multi-domain representations cohesively. Based on characteristics derived from earlier subnetworks, the classification network was eventually developed for epileptic EEG identification. Like in [106], within-subject, end-to-end-trained deep ConvNets can decode task-related information from EEG with accuracy levels at least comparable to FBCSP. This study compared a wide range of ConvNet design options on an EEG decoding task. It demonstrated the importance of batch normalization and exponential linear units for achieving high decoding accuracy. This study also demonstrated how cropped training may improve the decoding precision of deep ConvNets. It presented a computationally effective cropped training method for ConvNets that allowed them to be trained on more input crops per EEG session. This study created and used brand-new visualizations that strongly imply that deep ConvNets learn to utilize the band power in frequency bands (alpha, beta, and gamma), which are crucial for motor decoding with meaningful spatial distributions. One of the early works to implement CNN in this domain was [107]. The proposed model was the first to use a DNN for EEG-based seizure identification. A 13-layer DL CNN algorithm was used for the automated EEG analysis. The benefit of the model described in this research is that feature extraction and feature selection can be done together.

Further, [108] proposed EEGNet, a compact CNN for EEG-based BCIs, as a method for classification across and between subjects. This approach constructed an EEG-specific model incorporating well-known EEG feature extraction ideas for BCI using depthwise and separable convolutions in a small CNN structure. Some works integrate multiple domain features derived from EEG signals to perform seizure detection. One such work is [109]. This work proposed a deep multi-view feature learning methodology. Deep features from several perspectives were integrated using the multi-view classifier to improve the detection performance further. This study shows that multi-view learning and deep feature extraction are essential for epilepsy identification with EEG signals. Compared to conventional feature extraction techniques, experimental results demonstrate that the deep features under consideration in this work can improve detection performance. Another such work is [110] in which a multi-view CNN architecture was used to predict when seizures may occur. The proposed framework employed a shared layer to train discriminative feature representations while considering the time and frequency domain in two separate inputs. Adding more layers can also improve the efficiency of the classifier. As in [111], a deep CNN model was employed to detect seizures. The proposed approach extracted spectral and temporal aspects from EEG epilepsy data to understand the overall structure of a seizure that is less sensitive to fluctuations. Even combining CNN with other DL techniques proved advantageous, such as two DL combination models based on CNN-LSTM were proposed by [112]. They integrated two processes of feature extraction and classification of EEG signals into a single model, i.e., by developing parallel and series combiners. Also, [113] proposed a stacked 1-D CNN model for categorizing EEG signals of epileptic patients together with a Random Selection and Data Augmentation (RS-DA) technique for seizure onset detection. The RS-DA approach was used during model training to address the issue of sample imbalance, and the PS model was trained using event-based K-fold cross-validation (CV) to identify all seizures in each patient. Here, K is the average number of seizures per patient.

2.3.1.2.2 Long Short Term Memory LSTM, a type of RNN, plays a crucial role in ES classification. LSTMs are adept at capturing temporal dependencies in EEG signals, enabling accurate seizure detection and classification by effectively modeling the long-range dependencies and temporal dynamics of the data. Their ability to remember and selectively forget information over time makes LSTMs well-suited for analyzing time-series data and achieving high-performance seizure classification results. By developing four LSTM-based models for early and precise seizure prediction while considering real-time operation, a unique PS seizure prediction approach has been proposed in [23]. The finest of them was Deep Convolutional AE + BLSTM. They continued to work on channel selection, which improved the outcomes. Further, in [114] for categorizing seizure and non-seizure EEG, a deep BLSTM model was proposed. This algorithm considered the information before and after the analyzing moment and jointly determined the decision outcome.

2.3.2 Prediction

A systematic prediction approach reduces the risks associated with the sudden occurrence of seizures. Three phases comprise a typical seizure prediction model [115, 116]. The first and most crucial stage is the preprocessing. This step improves the SNR and efficiently eliminates noise. After preprocessing, feature extraction is the next step in the prediction model. To extract useful and sensitive features from EEG data, signal processing techniques including Wavelet Packet Decomposition [117–119], Hilbert-Huang Transform [117], EWT [120], time-frequency analysis [121–124], and others were applied. Following that, SVM [117, 125], NN [121, 123], DT and their variations [120] were employed, as well as more advanced ML and programmed

DL techniques. To learn the characteristics and execute the classification across the many stages of a seizure occurrence, CNN [118, 122, 124], LSTM [119], and others were used [45, 99]. Additionally, DL methods like CNN have been extensively used in several research projects to extract features from unprocessed signals to enhance diagnostic performance and do away with the preprocessing phase of the seizure detection process [20, 23, 118, 126–128].

2.3.2.1 Machine Learning for Prediction of Occurrence of Epileptic Seizures

Combining EMD from a long-term sEEG with a CSP is suggested as a novel seizure initiation detection technique in [129]. First, time-frequency decomposition and filtering preprocessing were applied to EEG data using WT and EMD, respectively. The variance was then extracted as the single feature after CSP was used to minimize the dimension of the multichannel time-frequency representation.

2.3.2.1.1 Support Vector Machine Works such as [130] proposed an efficient ML model for anticipating epileptic episodes. This approach focuses on EEG signal preprocessing and feature extraction. The authors employed EMD to boost the SNR after converting the many channels of EEG data into a surrogate signal. Entropy, estimated entropy, Hjorth parameters (HP), and spectral and statistical moments are only a few of the properties that the authors have retrieved. Statistics and spectral properties improved sensitivity between inter-ictal and pre-ictal phases. The pre- and inter-ictal states were distinguished using the SVM classifier.

2.3.2.2 Deep Learning Techniques for Prediction of Occurrence of Epileptic Seizure

DL techniques, such as RNNs and CNNs, play a vital role in predicting the occurrence of ESs. These models can analyze EEG data, capture temporal and spatial patterns, and learn complex relationships, enabling accurate and timely seizure prediction, which is crucial for early intervention and patient safety.

2.3.2.2.1 Convolutional Neural Networks Creating a DL classifier for ES prediction that is not dependent on the patient is challenging. Models such as in [131] can be applied when the data set has fewer labeled instances (EEG recordings) for the patients. Two distinct CNN designs were suggested to solve this issue. With a one-hour prediction window, the suggested algorithms could reliably identify seizures. Works like [132] consider brain signals from various time periods as separate data domains and learn invariant characteristics across the data domains to protect against signal changes. A CNN model with multi-scale temporal convolutions was first presented to learn useful features from the weak signals in the pre-ictal phase. The ability of features to be represented is enforced by the multi-scale scheme's capacity to capture intricate temporal patterns in pre-ictal signals. Also, minimizing the channels in a CNN to create an effective seizure prediction method can reduce the complexity, comfort, and cost inefficiency of using 22 channels to forecast seizures [133]. In [134], a comprehensive multi-scale framework for predicting ESs was proposed. The geographical multi-scale stage and the temporal multi-scale stage make up the framework. The authors thoroughly examine the data of the related dimension in each stage. The authors specifically employed various kernel sizes to understand the multi-scale properties of EEG signals. The authors then used a dilated convolution block with various dilation rates to systematically gather global information and progressively widen the receptive fields. The authors also employed a feature-weighted fusion technique based on an attention mechanism to improve feature fusion and reduce the duplication in the dilated convolution block.

2.3.2.2.2 Transformer Modern, cutting-edge DL research is incorporated into new architectures. Such as, [135] proposed a new paradigm for detecting seizures using the EEG called

TABS. Achieving a meager FP rate was crucial while designing TABS. The authors created a hybrid architecture using a transformer, FC layers, and convolutional layers. It is important to note that they arrange the data into uniform channels and resample the time steps at a consistent sampling rate as data preprocessing. The authors in [136] proposed measuring the distance between successive sub-band CRVs created utilizing eigenvectors with high spatial frequencies, a revolutionary automated real-time ES detection approach. The suggested method used larger graph Laplacian eigenvalues or spatial frequencies to capture more information about brain states related to seizure and non-seizure segments.

2.4 Task Evaluation: Patient-Specific Studies

PS Studies have many advantages in ESA. For personalized treatment, PS studies allow tailoring treatment plans based on individual EEG characteristics, optimizing therapies for better seizure management and patient outcomes. Such studies can help in precise diagnosis by analyzing EEG data specific to each patient. This approach can enhance the accuracy of seizure diagnosis and classification, leading to more effective medical decisions. Identifying biomarkers becomes more efficient using PS studies, which facilitate the discovery of personalized biomarkers and enable the early detection of epileptic conditions and potential prognostic indicators. However, these studies have disadvantages as well. One of them is data scarcity. Gathering PS EEG data may be challenging due to limited sample sizes, leading to potential generalization issues for rare or unique cases. Also, such studies are quite time-consuming as conducting individualized analysis for each patient requires significant time and effort. This might limit scalability and hinder large-scale studies as well. Further, there is a risk of overfitting as focusing solely on individual patient data might lead to overfitting, where the model performs well on the training data but poorly on new data, reducing generalizability. EEG characteristics and electrode sites for seizure prediction can be chosen using a suggested personalized strategy that focuses on precursors that happen up to ten minutes before the commencement of a seizure. This approach, as implemented in [75], employed an intelligent genetic search strategy for numerous quantitative variables generated from the EEG signals concurrently gathered from several intracranial electrode connections. Each patient's baseline and seizure records were used to train the algorithm, which is tested using split sample validation methods on additional, previously unexplored data. Even this early implementation of a multichannel, multi-feature technique has the potential to be used in prototype implanted devices for treating epilepsy. The characteristics investigated in this study were chosen with an eye toward real-time implementation. Also, using a multiresolution wavelet decomposition to measure the energy of EEG waves at various time scales can help capture their morphology and an SVM classifier can be used to decode the spatial distribution of the energy using a feature vector as done in [137]. Further, identifying EEG synchronization patterns that facilitate the determination of pre-ictal states from inter-ictal states apart is accomplished by utilizing bivariate synchronization measurements, often known as measures involving pairs of EEG channels [3]. The electrode locations where the EEG channels were placed were represented as nodes in a graph model, and the edges connecting nodes were weighted according to the values of one or more synchronization metrics (changing over time) of the signals connected to the two nodes. The fluctuations in the synchronization, as mentioned above, were then captured using simple functions that may be computed over this graph. Lastly, an automatic categorization seeks to pinpoint the pre-ictal condition. [138] utilized point process generalized linear models, a statistical technique used to understand seizures' temporal features in epilepsy patients in a better way. The methodology incorporated cycles of Interictal Epileptiform Activity and provided an accurate but non-causal estimation of instantaneous phases. The results suggested that seizures are not entirely random events.

2.5 EEG Analysis in Domains Other Than Epilepsy

Due to its ability to record brain activity and offer insightful data on cognitive, neurological, and physiological processes, EEG signals have several real-world uses outside epilepsy. EEG signals are also applied in various fields, such as:

1. Motor Imagery Classification: A DL framework called SSD-SE-CNN was suggested for Motor Imagery (MI)-EEG classification in [139]. This framework had three components. A CNN was built to fully utilize the time-frequency features, outperforming conventional classification methods in terms of accuracy and kappa value; 1) Sparse Spectrotemporal Decomposition (SSD) algorithm was proposed for feature extraction; 2) the SE blocks were adopted to recalibrate channel-wise femtosecond timing adaptively; and 3) the CNN was constructed to exploit the time-frequency features. Further, [140] proposed a circular translation data augmentation approach and a discriminative feature learning strategy. The discriminative feature learning technique was first developed for the MI-EEG decoding network to boost the discriminating of distinct classes of samples in the feature space, significantly improving decoding accuracy. After that, a circular translation strategy-based data augmentation technique was suggested to address the overfitting issue.

2. Dementia/Alzheimer's Classification: The authors in [141] explored a routine to gain such biomarkers using the quantitative analysis of EEG. This work proposed a supervised classification framework that uses EEG signals to classify Healthy Controls (HC) and Alzheimer's Disease participants. The framework includes data augmentation, feature extraction, KNN classification, quantitative evaluation, and topographic visualization. Considering the human brain as a stationary or a dynamical system, both the frequency-based and time–frequency-based features were tested in 40 participants.

3. Driver alertness: Based on EEG readings, a novel DL technique was suggested to identify driver distraction [142]. The proposed deep network, i.e., Temporal-Spatial Information Network (TSIN), included spatial and temporal information from EEG data to detect driver distraction. Two other deep networks, i.e., Temporal Information Network and Spatial Information Network, were also employed to investigate the contributions of temporal and geographical information to the detection performance. The findings demonstrate that TSIN beat the other networks in terms of both quality and quantity. The detection performance was maximized by simultaneously using the EEG data's temporal and spatial information. The comparative results of the various approaches revealed that the performance of distraction detection was more significantly influenced by spatial information between EEG channels than by temporal information.

4. Migraine Detection: For the first time, [143] categorized migraine sufferers and their HC controls using a TQWT-based technique. In signal analysis, the signal's stability is necessary for the long-term finding of significant information. Therefore, the EEG signal was separated into subbands using the TQWT technique to analyze its oscillatory structure. Following that, statistical methods were used to determine the characteristics. The Kruskal-Wallis test was used to determine how distinctive certain characteristics are. After that, several ensemble learning classifiers were used to assess the features produced for each subband.

5. Attention-Deficit/Hyperactivity Disorder In 2019, [144] proposed a Hjorth Mobility-based EEG analytic method to identify differences between girls with Attention-Deficit/Hyperactivity Disorder (ADHD) and controls. Compared with the Theta/Beta Ratio (TBR) in this study, significant differences were observed in the selected Hjorth Mobility-related features between the patients with ADHD and the controls.

In 2020, the authors in [145] developed a DL model using a CNN. The authors first preprocessed EEG signals to eliminate noise and artifacts and segmented preprocessed samples into more samples. They extracted the theta, alpha, beta, and gamma frequency bands from each segmented sample and formed a color RGB image with three channels. Eventually, the authors imported the resulting images into a 13-layer CNN for feature extraction and classification.

2.6 Benchmark Datasets and Simulation

Several datasets with different classes and modalities have been considered during the experimental setup. A comprehensive list of datasets used in the work is mentioned below. These datasets are used in this thesis to evaluate the proposed models.

2.6.1 CHB-MIT Scalp EEG Database (DB1) [1, 2]

The Children's Hospital, established in Boston, has supported the construction of DB1. The individuals who participated in DB1 were aged 1.5 to 22 years. The time-series data for them with a sampling rate of 256 Hz was made available through 664 EDF files, each containing a one-hour recording. Among them, 129 files represent the seizure waveform. For the development of DB1, the participants were regularly monitored after the discontinuation of anti-seizure medication.

2.6.2 Siena Scalp EEG Database (DB2) [3]

The University of Siena has supported the construction of DB2. 14 individuals participated in the process. Among them, five females were aged 20 to 58, and nine males were aged 25 to 71. The time-series video data for them has a sampling rate of 512.0 Hz. Each patient has EDF files, averaging 9.17 hrs of recording per patient.

2.6.3 Seizure Recognition Dataset (DB3) [4]

This multivariate time series dataset is frequently used for the classification and clustering of EEG signals of epileptic patients. It has 179 attributes and 11,500 instances where epileptic patients are labeled class-1.

2.6.4 Epileptic EEG Dataset (DB4) [5]

The EEG of six epileptic patients was recorded in this dataset between January 2014 and July 2015 at the Epilepsy Monitoring Unit of the American University of Beirut Medical Center. The data includes readings from 21 scalp electrodes recorded at 500 Hz using the 10-20 electrode system. All channels have undergone a band-pass filtering operation between 1/1.6 Hz and 70 Hz.

2.6.5 CAP Sleep (DB5) [6]

The CAP Sleep Database comprises 108 polysomnographic recordings recorded at the Sleep Disorders Centre at the Ospedale Maggiore in Parma, Italy. The 16 healthy participants in the research had no neurological conditions, and none were taking medicines that would have affected the central nervous system. The 92 pathological recordings contain recordings from 40 individuals with NFLE, 22 with RBD, 10 with PLM, 9 with insomnia, 5 with narcolepsy, 4 with SDB, and 2 with bruxism.

2.6.6 Simulation Environment

The experiments have been performed using Python in IntelliJ IDE and on a Windows operating system with 16GB RAM. For the data sets used in this research work, the approach is multichannel and patient-independent, i.e., the proposed methodology utilizes the data obtained from all the channels and aims to build a generic model for all patients. The experiments have been performed using the 10-fold cross-validation method.

In the next chapter, the challenge of extracting meaningful information from EEG signals affected by artifacts is addressed. This problem can hinder tasks like epilepsy seizure classification and prediction. The chapter introduces a novel architecture that aims to remove artifacts from the EEG signals of epileptic patients.