An overview of deep learning techniques for epileptic seizures detection and prediction based on neuroimaging modalities: Methods, challenges, and future works

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Abstract

Epilepsy is a disorder of the brain denoted by frequent seizures. The symptoms of seizure include confusion, abnormal staring, and rapid, sudden, and uncontrollable hand movements. Epileptic seizure detection methods involve neurological exams, blood tests, neuropsychological tests, and neuroimaging modalities. Among these, neuroimaging modalities have received considerable attention from specialist physicians. One method to facilitate the accurate and fast diagnosis of epileptic seizures is to employ computer-aided diagnosis systems

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(CADS) based on deep learning (DL) and neuroimaging modalities. This paper has studied a comprehensive overview of DL methods employed for epileptic seizures detection and prediction using neuroimaging modalities. First, DL-based CADS for epileptic seizures detection and prediction using neuroimaging modalities are discussed. Also, descriptions of various datasets, preprocessing algorithms, and DL models which have been used for epileptic seizures detection and prediction have been included. Then, research on rehabilitation tools has been presented, which contains brain-computer interface (BCI), cloud computing, internet of things (IoT), hardware implementation of DL techniques on field-programmable gate array (FPGA), etc. In the discussion section, a comparison has been carried out between research on epileptic seizure detection and prediction. The challenges in epileptic seizures detection and prediction using neuroimaging modalities and DL models have been described. In addition, possible directions for future works in this field, specifically for solving challenges in datasets, DL, rehabilitation, and hardware models, have been proposed. The final section is dedicated to the conclusion which summarizes the significant findings of the paper.

Keywords: Epileptic Seizures, Neuroimaging, Deep Learning, Detection, Prediction, Rehabilitation, Cloud-Computing.

1. Introduction

Epileptic seizures are a non-communicable disease and are one of the most prevalent disorders of the nervous system. Epileptic disorders usually occur with sudden attacks that result from abnormal activity of the cortical or membrane nerve in the brain (Iasemidis, 2003; Shoeb and Guttag, 2010; Tzallas et al., 2012; Subasi, 2005; Shoeb, 2009a). More than 60 million people worldwide have various types of epileptic seizures and suffer from them (Pachori and Bajaj, 2011; Siddiqui et al., 2020; Wong and Kuhlmann, 2020). Figure 1 displays the number of people with epileptic seizures in various parts of the world (Abramovici and Bagić, 2016). As shown in the figure, the number of people with this type of neurological disorder is greater in underdeveloped countries than in other countries (Abramovici and Bagić, 2016).

Epilepsy is a rapid and early abnormality in the brain's electrical activity,

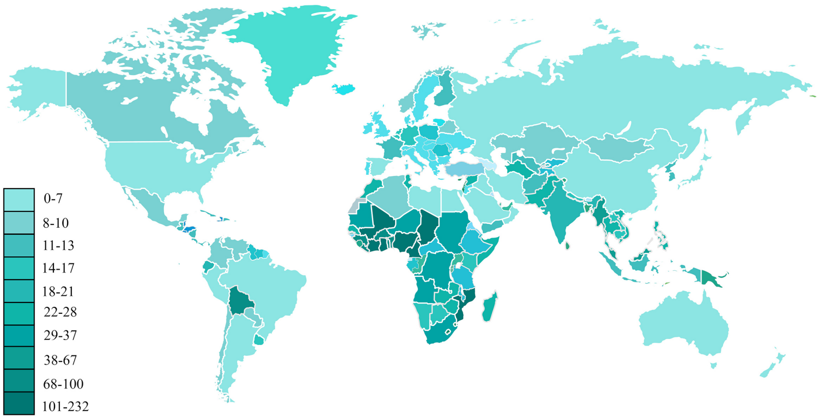


Figure 1: Graph of the number of people with epileptic seizures worldwide (Abramovici and Bagić, 2016).

disrupting part or all of the human body (Duncan et al., 2006; Noachtar and Peters, 2009). Medical researchers have divided epileptic seizures into three categories: generalized (Hussein et al., 2018a; Gloor and Fariello, 1988), focal (Nair et al., 2020; Frauscher and Gotman, 2019), and epilepsy with unknown onset (Ngoh and Parker, 2017), each of which has various types.

General epilepsy involves the whole brain and causes disruption of the activity of all neurons in the brain, eventually may lead to the impairment of all parts of the brain (Cerulli Irelli et al., 2020; Liu et al., 2017; Clarke et al., 2019). In partial epilepsy, a small group of neurons form a focal epilepsy and are confined to a hemisphere of the brain. 60% of patients with epilepsy have focal seizures that are mostly drug-resistant (Misiūnas et al., 2019; Boran et al., 2019; Pellegrino et al., 2018). The classification of epileptic seizure types is shown in Figure 2. In this figure, the classification of epileptic seizures before 2011 is depicted in darker color, and the classification of epileptic seizures from 2016 onwards is highlighted in lighter color. More information is available in reference (Ngoh and Parker, 2017).

People with epileptic seizures may sometimes experience severe psychological trauma due to embarrassment and lack of proper social status (Sharma

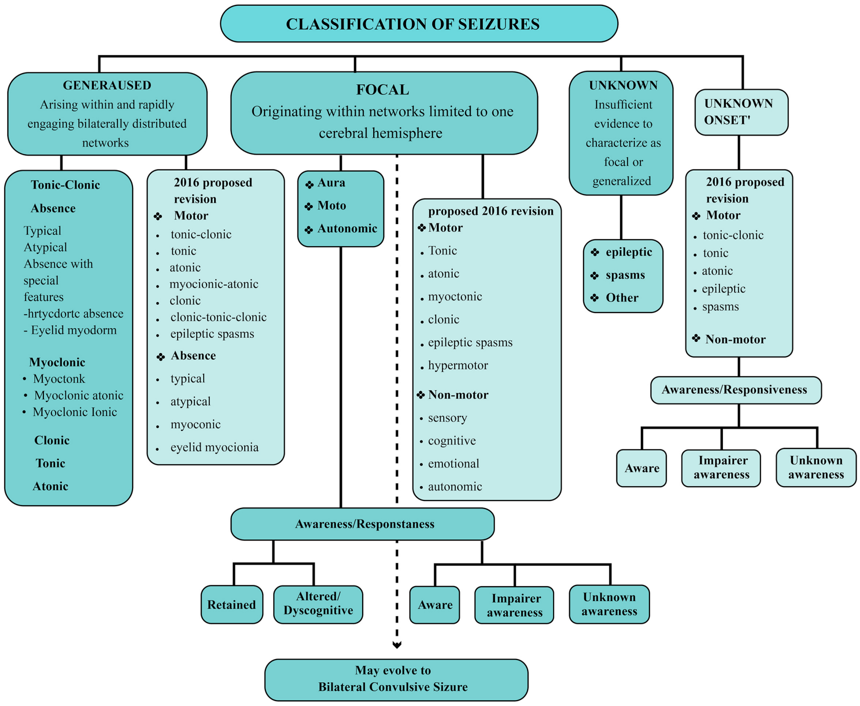
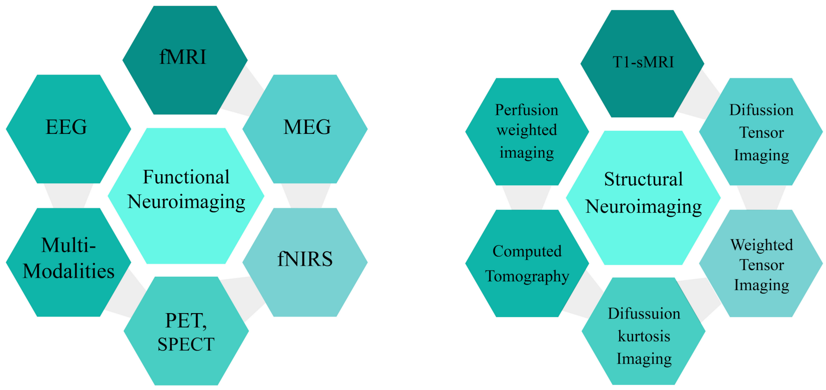


Figure 2: Showing different types of general and focal epileptic seizures (Ngoh and Parker, 2017).

and Pachori, 2015; Gupta et al., 2020). Given the above, accurate and rapid diagnosis of these neurological disorders in the early stages is crucially pivotal.

Specialist physicians usually use functional and structural neuroimaging techniques to diagnose epileptic seizures. Electroencephalogram (EEG) (Yuan et al., 2018a; Fan and Chou, 2018), functional magnetic resonance imaging (fMRI) (Vaughan and Jackson, 2020; Garner et al., 2019), magnetoencephalography (MEG) (Colon et al., 2018; Rampp et al., 2019), electrocorticography (ECoG) (Mohammadpoory et al., 2019; Siddiqui et al., 2019), functional near-infrared spectroscopy (fNIRS) (Rosas-Romero et al., 2019; Guevara et al., 2020), positron emission tomography (PET) (Oldan et al., 2018; Wang et al., 2019), and SPECT (El Tahry et al., 2018) are the most substantial functional neuroimaging modalities. In contrast, structural MRI (sMRI) (Rüber et al., 2018; Xu et al., 2020b) and diffusion tensor imaging (DTI) (Bao et al., 2018; Chapman et al., 2005) are in the category of structural neuroimaging modalities. In figure 3, neuroimaging modalities for epileptic seizures detection are described.



(a) (b)

Figure 3: Neuroimaging modalities for epileptic seizures detection.

As shown in Figure 3, structural neuroimaging modalities include sMRI and DTI approaches. By using the sMRI modality, structural abnormalities and brain lesions caused by epileptic seizures can be identified (Woermann and Vollmar, 2009; Bell et al., 2009). Additionally, this modality can be used to identify the anatomical zone of the epileptogenic region that is responsible for the seizure, which is a pivotally significant step for presurgical evaluations of epilepsy (Woermann and Vollmar, 2009; Bell et al., 2009). sMRI is also employed after surgery to evaluate the success or failure of the epileptic region removal and to assess the need for reoperation (Woermann and Vollmar, 2009; Bell et al., 2009). Disadvantages of sMRI include its widespread unavailability, high cost, and the necessity for long-term scans.

The DTI modality provides information on the structural anatomy of the white matter tracts and makes it possible to investigate the microstructural status of the white matter. Although the advantages of applying DTI in the diagnosis of the lesions for epilepsy are still being examined, modeling and reconstructing hidden pathways in white matter is of utmost importance as a presurgical evaluation step (Zhang et al., 2020d).

In EEG modality, the measurement of voltage fluctuations produced by the ionic current of neurons in the brain is performed, indicating the bioelectric activity of the brain and containing the physiological information of people with epileptic seizures (Acharya et al., 2013; Sharmila, 2018). The investigations reviewed in this paper demonstrates the effectiveness of EEG modality performance in diagnosing epileptic seizures. EEG incorporates two methods of non-invasive scalp (sEEG) (Saab and Gotman, 2005; Fergus et al., 2015) and intracranial (IEEG) recording (Liu et al., 2012; Aarabi et al., 2009). The sEEG method is widely used by specialist physicians and neurologists compared to IEEG due to its lower risks and more straightforward recording. Additionally, considering that these signal recordings are economically inexpensive and the fact that the frequency and rhythm of brain activity vary during seizures, EEG has become one of the foremost epileptic seizures diagnostic methods (Birjandtalab et al., 2017; Weng and Khorasani, 1996). Compared to EEG, ECoG, fNIRS, and MEG functional modalities are less effective in diagnosing epileptic seizures.

fMRI modality is another neuroimaging technique for epileptic seizures detection and includes two methods based on task (T-fMRI) (Gaillard et al., 2002) and resting state (rs-fMRI) (Centeno and Carmichael, 2014). fMRI is adapted to detect changes in regional blood flow and metabolism due to the activation of brain regions (Gaillard et al., 2002; Centeno and Carmichael, 2014). One of the fMRI applications in epilepsy is identifying ictal and interictal phenomena given rise to the localization of the focal seizures (Gaillard et al., 2002; Centeno and Carmichael, 2014). During seizures, brain function changes in the epileptogenic region, which can be detected using fMRI (Gaillard et al., 2002; Centeno and Carmichael, 2014). fMRI can also be exploited to assess brain function before surgery in patients with drug-resistant epilepsy (Gaillard et al., 2002; Centeno and Carmichael, 2014). One of the drawbacks of fMRI is that the patient has to be in the scanner for a long period to seizure occur and the scan to be completed.

Detecting epileptic seizures from neuroimaging modalities with all the benefits that are sometimes challenging. Epileptic seizure detection using neuroimaging modalities requires a considerable amount of recording data in order for the specialist doctors to make the appropriate decisions. Big data analysis of neuroimaging modalities in most cases beget incorrect epileptic seizures diagnosis by physicians. This is due to eye fatigue when interpreting many structural or functional imaging modalities. Additionally, the presence of diverse noises in neuroimaging modalities is another cause of misdiagnosis. In order to conquer these dilemmas, CADS for epileptic seizures detection using neuroimaging modalities and AI are of considerable help to specialists in the epileptic seizures detection field.

So far, many research works have been conducted to diagnose epileptic seizures using AI. Until quite a few years ago, most examinations were performed in the field of conventional machine learning (Abbasi and Goldenholz, 2019; Rasheed et al., 2020). In traditional machine learning, the selection of the feature extraction, reduction and classification techniques is dependent on the characteristics of the data (Dey, 2016; Naik et al., 2020). However, in DL approaches, all these steps are fulfilled via integrated layers and automatically (Dash et al., 2020; Goodfellow et al., 2016). Various DL methods have promptly received a tremendous amount of attention from numerous experts in the brain signal processing domain (Wainberg et al., 2018). This has made the diagnosis of epileptic seizures based on functional and structural brain modalities along with DL techniques one of the most novel areas of research. In this paper, a complete review of conducted research in the epileptic seizures field from neuroimaging modalities along with DL methods, along with challenges and future work in this field has been presented.

In order to search for papers in the scope of diagnosis of epileptic seizures, various citation databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Wiley have been exploited. In addition, Google Scholar has been used to find papers with the keywords "Epileptic Seizure," "EEG," "fMRI," "ECoG', "MEG," "fNIRS," "MRI," "PET" and "Deep Learning." The latest articles were reviewed by the authors on December 30th, 2020. The number of papers accepted each year in different citation sites for the diagnosis of epileptic seizures is illustrated in Figure 4.

In the following, the outline of this investigation is introduced. The second section concisely presents the DL networks exploited in diagnosing epileptic seizures. Recent CADS for epileptic seizures using DL techniques are examined in Section three. Several research works in the field of rehabilitation systems, cloud computing, and diagnostic epilepsy procedures using non-neural modalities are presented in the fourth section. The discussion is introduced in Section

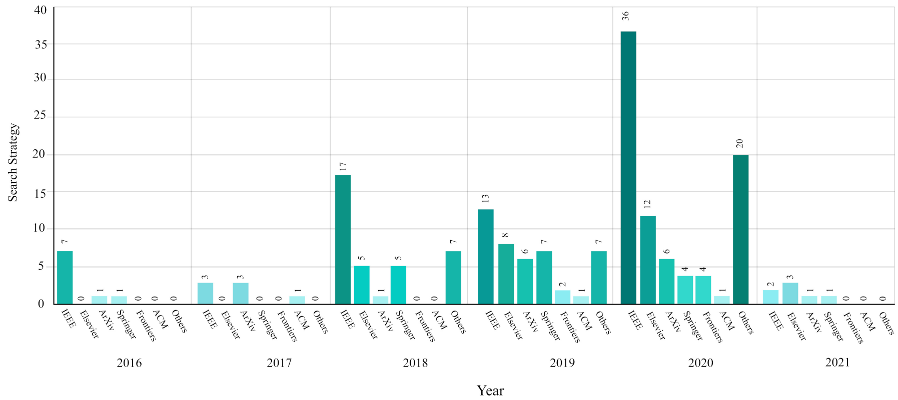


Figure 4: Number of papers published for automated detection of epileptic seizures using DL techniques.

five. In the sixth section, the challenges in diagnosing epileptic seizures are fully described. Finally, conclusions and recommendations for future work are provided in the seventh section.

2. Epileptic Seizures Detection Using DL Techniques

In this section, DL networks used in the diagnosis of epileptic seizures are presented. Convolutional neural networks (CNNs) are the first category of DL architectures involving a variety of one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) models (Goodfellow et al., 2016; Sadeghi et al., 2021). These networks follow supervised learning and have three main layers: convolutional, pooling, and fully connected (FC) layers (Goodfellow et al., 2016). Recurrent neural networks (RNNs) are another paradigm of DL networks that are based on supervised learning widely applied in time series tasks (Goodfellow et al., 2016; Shoeibi et al., 2020). Autoencoders (AEs) models (Goodfellow et al., 2016; Burda et al., 2015) and deep belief networks (DBNs) (Goodfellow et al., 2016; Hinton, 2009) are other types of DL networks based on unsupervised learning. In addition to these models, improved methods from CNN named generative adversarial networks (GANs) (Goodfellow et al., 2014) architectures have been proposed for various applications that are based on unsupervised learning. It should be pointed out that generative adversarial networks (GANs) architectures are adopted as supervised techniques in some issues (Goodfellow et al., 2014; Yi et al., 2019; Alizadehsani et al., 2021; Ghassemi et al., 2020). CNN-RNN and CNN-AE are two other categories of DL systems created by combining two different architectures (Chen et al., 2017a). The CNN-RNN and CNN-AE architectures follow supervised and unsupervised learning, respectively (Keren and Schuller, 2016). Details of the types of DL networks in the diagnosis of epileptic seizures are manifested in Figure 5.

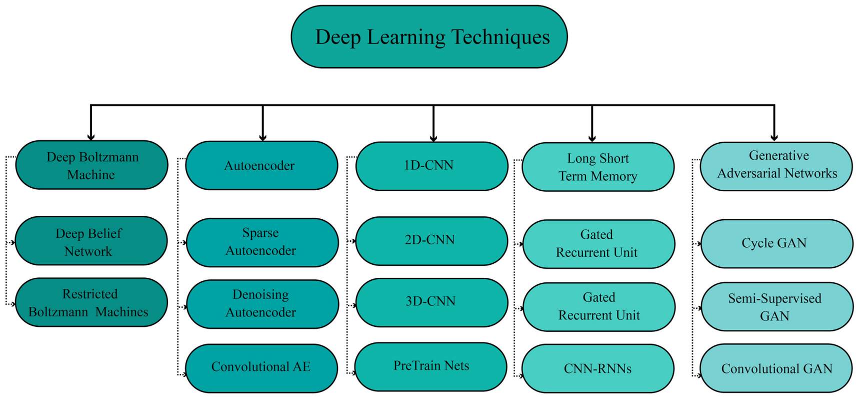


Figure 5: Illustration of various DL methods used for epileptic seizures detection.

3. CAD Based on DL techniques for Epileptic Seizures using Neuroimaging Modalities

Diagnosis of epileptic seizures from functional and structural neuroimaging modalities of the brain along with AI algorithms has a long history. Until recently, the diagnosis of epileptic seizures using CADS was based on conventional machine learning techniques that have been the subject of much research (Paul, 2018; Boonyakitanont et al., 2020a; Dhull et al., 2021; Mei et al., 2018). The most significant weaknesses of these systems were the process of selecting the best feature extraction and dimensional reduction algorithms (feature selection or reduction) using trial and error that required a considerable amount of knowledge in the AI fields (Mohammadpoor et al., 2016). To resolve these issues, from 2016 onwards, DL methods in CADS for epileptic seizures detection were considered and quickly replaced the conventional machine learning approaches. In

CADS based-DL, the feature extraction and selection steps are accomplished entirely automatically. The CADS for epileptic seizures detection based on DL techniques are represented in figure 6.

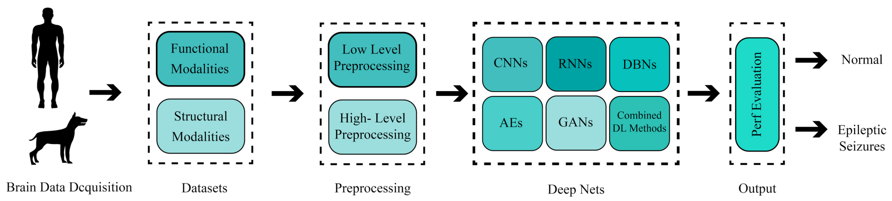


Figure 6: Illustration of block diagram for epileptic seizures detection using DL methods.

According to figure 6, a variety of structural and functional neuroimaging modalities are first considered as DL input. In the following, low-level and high-level preprocessing methods are applied to the input data. Then, feature extraction up to classification steps are performed by the desired DL networks (DL networks for epileptic seizures detection research papers are displayed in Appendix A). Finally, various evaluation parameters such as accuracy, sensitivity, and precision are calculated.

3.1. Epileptic Seizures Datasets

In this section, the most notable datasets on diagnosing epileptic seizures are reviewed, all of which are freely accessible. Without proper datasets, developing accurate and robust CADS is not possible. Several EEG datasets and an ECoG dataset are currently available to researchers freely; however, datasets on other neuroimaging modalities such as MRI have not yet been made freely available. Multiple EEG datasets, namely Freiburg (Ihle et al., 2012), CHB-MIT (Shoeb, 2009b), Kaggle (George et al., 2020), Bonn (Andrzejak et al., 2001), Flint-Hills (Assi et al., 2017), Bern-Barcelona (Andrzejak et al., 2012), Hauz Khas (Assi et al., 2017), and Zenodo (Stevenson et al., 2019) are the main ones for developing automatic systems for epileptic seizure detection. The signals forming each datapoint of these datasets are recorded either intracranial or from the scalp of humans or animals. Table 1 provides the supplementary information on each dataset, and also, the types of EEG datasets for epileptic seizures diagnosis using DL are listed in table 2.

Table 1: List of popular epileptic seizure datasets.

Dataset	Number of Patient	Number of Seizures	Recording	Total Duration (hour)	Sampling Frequency (Hz)
Flint-Hills (Assi et al., 2017)	10	59	Continues intracranial ling term ECoG	1419	249
Hauz Khas (Assi et al., 2017)	10	NA	Scalp EEG (sEEG)	NA	200
Freiburg (Ihle et al., 2012)	21	87	Intracranial Electroencephalography (IEEG)	708	256
CHB-MIT (Shoeb, 2009b)	22	163	sEEG	844	256
Kaggle (George et al., 2020)	5 Dogs / 2 Patients	48	IEEG	622	400 / 5000
Bonn (Andrzejak et al., 2001)	10	NA	Surface and IEEG	39m	173.61
Bern Barcelona (Andrzejak et al., 2012)	5	3750	IEEG	83	512
Zenodo (Stevenson et al., 2019)	79 Neonatal	460	sEEG	74m	256

3.2. Preprocessing

3.2.1. EEG Preprocessing

Preprocessing is the first step in DL-based CADS for epileptic seizures detection. The presence of different artifacts in EEG signals always poses a severe challenge to physicians and neurologists in accurately diagnosing epileptic seizures. Artifacts from eye blinks, eye movements, muscle expansion and contraction, and municipal electricity noise are among the most important EEG data noises that should be eliminated from the signals in the preprocessing step (Shoka et al., 2019; Kim, 2018; Peng, 2019; Jiang et al., 2019b). In some cases, the presence of multiple artifacts begets loss of EEG signals' substantial information between various noises and makes it challenging to diagnose epileptic seizures. EEG signal preprocessing in the diagnosis of epileptic seizures is divided into two types of low-level and high-level approaches, which are explained following. Table 2 shows the low-level and high-level preprocessing techniques of EEG signals in epileptic diagnostic research.

A. Low Level EEG Preprocessing

In this section, low-level preprocessing methods are presented in the DL-based CADS for epileptic seizure detection. Low-level preprocessing in EEG signals involves noise removal, normalization, down-sampling, and segmentation. In order to remove noise from EEG signals, various types of low-pass, high-pass, and band-pass based Butterworth and or Chebyshev filters with different orders are widely employed (these filters are of finite impulse response (FIR) or Infinite impulse response (IIR) types) (Gao et al., 2009; Lai et al., 2018; Patro and Sahu, 2015). Raw EEG signals have variable voltage amplitude degrading the efficiency of CADS in diagnosing epileptic seizures. To obviate this problem, it is recommended to utilize different normalization methods such as Z-Score (Sayem et al., 2021). Storing and processing EEG signals requires a lot of memory space. By using down-sampling, EEG signals sampling frequency is decreased by half, which halves the storage space of EEG signals. Windowing or segmentation of EEG signals is the last part of low-level preprocessing. Segmentation assists in decomposing EEG data into more detailed sections to extract more significant information from each signal frame (Tuncer et al., 2020).

B. High Level EEG Preprocessing

High-level preprocessing techniques play a pivotal role in enhancing the efficiency of CADS in diagnosing epileptic seizures. In this section, Data augmentation (DA) models are stated as the first category of high-level preprocessing (Lashgari et al., 2020; Hartmann et al., 2018). The deficiency of EEG signals usually causes overfitting of DL networks during training, and the exploiting of DA techniques is a proper approach to address this problem. Discrete wavelet transform (DWT) (Ocak, 2009), continues wavelet transform (CWT) (Abibullaev et al., 2010), fast Fourier transform (FFT) (Polat and Güneş, 2007), and empirical mode decomposition (EMD) (Alam and Bhuiyan, 2013) are other high-level preprocessing techniques employed to eliminate noise and extract meaningful frequency bands from EEG signals. In addition, some improved FFT techniques such as short-time Fourier transform (STFT) to transform EEG signals to 2D images for application to CNNs have been investigated in research (Samiee et al., 2014). Also, some studies have selected independent component analysis (ICA)-based techniques to preprocess the EEG signals of epileptic seizures and have achieved satisfactory results (LeVan et al., 2006). Feature extraction procedures have also been considered in research as a crucial step in high-level preprocessing (Shoeibi et al., 2021).

C. Medical Imaging Modalities Preprocessing

Medical imaging modalities are another method of diagnosing epileptic seizures that possesses a special place among specialist physicians. In imaging techniques, applying preprocessing techniques is of great significance. According to Table 3, epileptic seizure detection using MRI modalities is more significant than other techniques. MRI neuroimaging modalities contain structural (sMRI) and functional (fMRI) techniques (Khodatars et al., 2020a). In sMRI modalities, the most important low-level preprocessing techniques include denoising, inhomogeneity correction, brain extraction, registration, intensity standardization, and re-orientation (Manjón, 2017; Park et al., 2019). Also, slice timing correction, motion correction, normalization, smoothing, and filtering are the most important low-level fMRI preprocessing methods (Jaber et al., 2019; Behroozi et al., 2011). Some of the high-level preprocessing methods that have been surveyed in investigations for sMRI and fMRI modalities are segmentation (Makropoulos et al., 2018) and functional connectivity matrix (FCM) (Luo et al., 2011), respectively. Other research has focused on using PET imaging modality for diagnosis (Jiang et al., 2019a; Shiri et al., 2019). ROI, normalization, Ordered subset expectation maximization (OSEM), and down-sampling are some of the PET modality preprocessing methods (Jiang et al., 2019a; Shiri et al., 2019).

D. Other Modalities Preprocessing

fNIRS and ECoG are two other modalities for functional neuroimaging of the brain employed by researchers for epileptic seizures detection (Modir et al., 2017; Sirpal et al., 2019; Chen et al., 2017b). Essential preprocessing steps in these modalities are similar to those of EEG signals and include noise reduction, normalization, and windowing of signals.

3.2.2. Review of Deep Learning Techniques

In recent years, with the increased availability of large datasets, methodologies rooted in DL techniques are poised for making a significant improvement in the diagnosis of various neurological disorders, including epileptic seizures. The DL-based CAD systems enable physicians to make better-informed decisions based on the recorded patient neuroimaging modalities. Figure 5 illustrates different types of DL architecture. It shows that CNNs (Goodfellow et al., 2016), GANs (Goodfellow et al., 2014), RNNs (Goodfellow et al., 2016), AEs (Goodfellow et al., 2016), DBNs (Hinton, 2009), CNN-AE (Chen et al., 2017a), and CNN-RNN (Keren and Schuller, 2016) are the main DL architectures used for epileptic seizures detection. Among those, 2D-CNN and 1D-CNN are the most widely used DL architecture in the field of epileptic seizures (Tables 2 and 3). This is due to the impressive achievements of CNNs architectures in other fields, including biomedical signal processing and medical imaging. In the rest of this section, we review the major DL network architectures and their variants.

A. 1D and 2D-CNNs

The idea of using neural net like algorithms has been around for decades, yet many limitations have stopped them from being useful in machine learning. With the famous AlexNet paper (Goodfellow et al., 2016), neural nets have resurfaced once again in the past decade. Adding some knowledge to the network structure, i.e., the fact that patterns are presented in spatial localities, led to convolutional layers, and by fixing the convolutional filters, the decrement in parameters made it possible for networks to train properly (Goodfellow et al., 2016; Khodatars et al., 2020b; Sharifrazi et al., 2021). 2D-CNNs have been widely used since their first introduction, and their variant, 1D-CNNs, have also been applied vastly for signal processing tasks (Giudice et al., 2020; Bird et al., 2021). Figure 7 shows a general form of a 2D-CNN used for epileptic seizure detection.

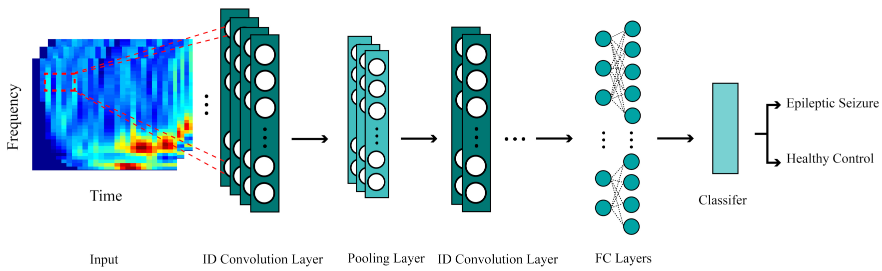


Figure 7: A typical 1D-CNN for epileptic seizure detection.

B. Generative Adversarial Networks (GANs)

In 2014, Goodfellow et al. (Goodfellow et al., 2016) revolutionized the field of generative models by introducing Generative Adversarial Nets (GANs). The main contribution of GANs is their capability of generating high-quality images similar to the training dataset; GANs have been applied to signal (Hazra and Byun, 2020; Abdelfattah et al., 2018), image (Schlegl et al., 2019; Yang et al., 2017), and many other data types in the past years (Ghassemi et al., 2020). Given the quality of generated data, GANs can be used for data augmentation and model pre-training (Goodfellow et al., 2016), helping to overcome one of the main issues in biomedical machine learning, the limited size of datasets. The general GAN architecture is shown in Figure 8.

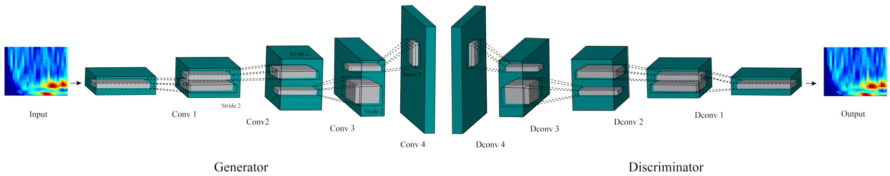


Figure 8: A typical GAN architecture for epileptic seizure detection.

C. Pre-Train Networks

Deep neural nets usually have a tremendous amount of parameters; thus, they require enormous datasets for proper training. This is generally challenging in biomedical data processing due to small dataset sizes. However, one method used commonly to overcome this issue is to fine-tune previously trained networks. In this method, first, a DNN is trained on a big dataset, such as ImageNet, then the last layer, classifier, is removed. After that, as illustrated in figure 9, its weights are fine-tuned using the primary dataset, or it is merely used as a feature extractor (Goodfellow et al., 2016).

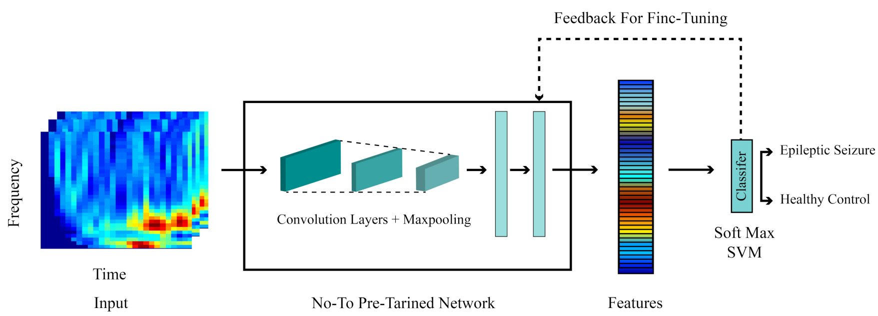


Figure 9: A typical deep pre-train network for epileptic seizure detection.

AlexNet

As the first famous DL network, AlexNet is still the center of attention in many studies (Iandola et al., 2016). In this network, two new perspectives dropout, and local response normalization (LRN), are used to help the network learn better. Dropout is applied in two FC layers employed in the end. On the other hand, LRN, utilized in convolutional layers, can be employed in two different ways: Firstly, applying single channel or feature maps, where the same feature map normalizes depending on the neighborhood values and selects the N×N patch. Secondly, LRN can be exploited across the channels or feature maps (Goodfellow et al., 2016; Iandola et al., 2016).

VGG

Created by Visual Geometry Group in 2014, VGG is one of the pioneers of deep neural net structures; however, this famous structure is still extensively used and popular among researchers (Wang et al., 2015). Many argue that this is due to its straight forward design and also ease of applying this network for transfer learning (Wang et al., 2015). Two variants of VGG are mostly used for transfer learning, namely, VGG-16 and VGG-19 (number stands for the number of layers); also, they are applied in various fields, ranging from face recognition (Sun et al., 2015) to brain tumor classification (Sajjad et al., 2019).

GoogleNet

Different receptive fields, generated by various kernel sizes, form layers called "Inception layers," which are the building block of these networks. Operations generated by these receptive fields find correlation patterns in the novel feature map stack (Ballester and Araujo, 2016). In GoogLeNet, a stack of inception layers is used to enhance recognition accuracy. The difference between the final inception layer and the naïve inception layer is the inclusion of 1x1 convolution kernels, which performs a dimensionality reduction, consequently reducing the computational cost. Another idea in GoogleNet is the gradient injection, which aims to overcome the gradient vanishing problem. GoogLeNet comprises a total of 22 layers that is greater than any previous network. However, GoogLeNet uses much fewer parameters compared to its predecessors VGG or AlexNet (Ballester and Araujo, 2016; Goodfellow et al., 2016).

ResNet

The idea behind ResNet was to overcome the issue of vanishing gradient by utilizing skip connections between blocks. This allowed the Residual nets to go deeper than regular networks; many varieties of these networks, with various sizes, such as 34, 50, and 152 have been created and applied in many tasks (Targ et al., 2016). ResNet's main contribution was not the network or its state-of-the-art performance, but the network's building blocks, and similar blocks have been widely used in many other deep NN structures; as an example, Res2Net is an image segmentation network with a similar design to ResNet.

D. 3D-CNN

To overcome this, 3D-CNN was introduced. In 2D-CNN, many well-known structures such as VGG and GoogLeNet are available as a great starting point to construct the new structure upon them. However, creating 3D-CNNs can be challenging, considering there are not many famous 3D-CNN structures (Zhao et al., 2019; Kwak et al., 2020). Nevertheless, designed and trained properly, 3D-CNNs can find 3D patterns and achieve state-of-the-art performances. A typical 3D-CNN for epileptic seizure detection is shown in figure 10.

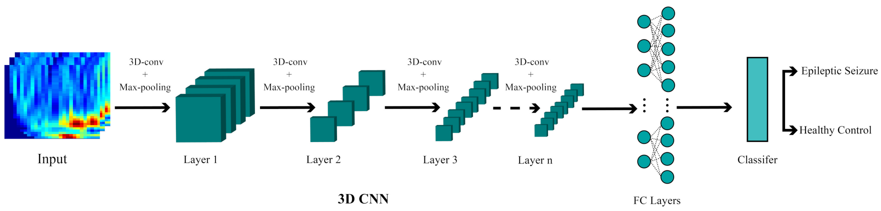


Figure 10: A typical 3D-CNN for epileptic seizure detection.

E. Recurrent Neural Networks (RNNs)

Many data forms, such as signal, have embedded patterns that cannot be characterized by local or spatial patterns. To create a model suitable for these datasets, researchers have created recurrent neural nets that, as stressed by the name, use the same group of neurons with a recurring scheme to process these data properly. Few variants of these networks, such as LSTM (long short term memory) and GRU, are created to find local and global patterns efficiently (Li et al., 2018; Hsu et al., 1990). The standard type of these networks is usually used as a baseline for creating models on signal processing and time-dependent datasets (Khalifa et al., 2020; Zihlmann et al., 2017). However, a combination of these networks with convolutional layers is popular among researchers aiming to reach high performances with more complex models. A typical RNN for epileptic seizure detection is shown in figure 11.

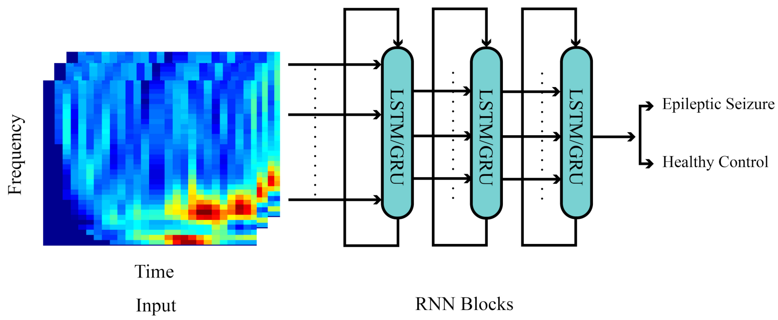


Figure 11: A typical RNN for epileptic seizure detection.

F. Deep Belief Networks (DBNs)

Restricted Boltzmann Machine (RBM), the building block of Deep Boltzmann Machine (DBM), is an undirected graphical model (Hinton, 2009). The unrestricted Boltzmann machines are also similar; however, they may also have connections between the hidden units. DBNs are unsupervised probabilistic hybrid generative DL models comprising of latent and stochastic variables in multiple layers (Hinton, 2009). Moreover, a variation of DBN is called Convolutional DBN (CDBN), which is more suitable for images and signals, as it uses the spatial information of data (Krizhevsky and Hinton, 2010).

G. Autoencoders

AEs were one of the first groups of neural networks with practical use in machine learning (Goodfellow et al., 2016). Even with new advancements in DL, AEs have never lost researchers' attention and are widely used for dimensionality reduction and representation learning. The main idea behind AE is to map data to a smaller latent space and then back to the starting space with a minimum loss, thus reaching a mechanism to preserve essential aspects of data while reducing its dimensionality. Nowadays, many variations of AEs have been introduced with the goal of improving the base AE performance, such as stacked AE (SAE), denoising AE (DAE), and sparse AE (SpAE) (Sønderby et al., 2016; Bank et al., 2020; Holden et al., 2015). A typical AE for epileptic seizure detection is shown in figure 12.

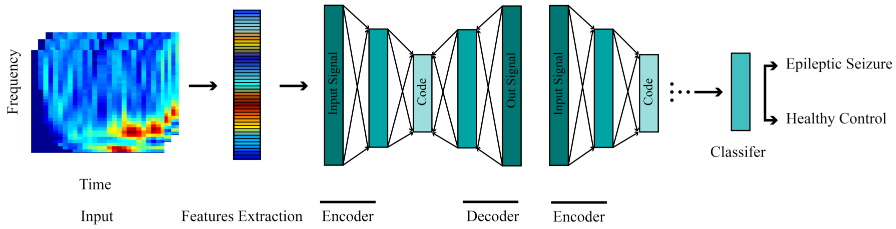


Figure 12: A typical AE for epileptic seizure detection.

H. CNN-RNN

To combine RNNs and CNNs, researchers usually use convolutional layers in the first layers of the model to extract features and find local patterns, and they feed the output of these layers to RNNs to use their superiority for global pattern recognition (Keren and Schuller, 2016). The reasoning behind the noble performances of these models is a two-fold. First, convolutional layers empirically find local and spatial patterns considerably better than RNNs in signals. Second, adding convolutional layers allows RNN to see data with stride, hence finding more distanced patterns. By combining the output of convolutional layers and handcrafted features, CNN-RNNs are allowed to reach a state-of-the-art performance, in addition to learning a representation of data that overcomes handcrafted features' deficiencies (Keren and Schuller, 2016). A typical CNN-RNN for epileptic seizure detection is shown in figure 13.

I. CNN-AE

Convolutional Autoencoder, or CNN-AE, is a DL based model that uses superiorities of convolutional layers to learn a representation of input unsupervised (Chen et al., 2017a). Base AEs are not suitable for raw representation learning, i.e., learn a representation of data without any added knowledge. This is due to the large number of learnable parameters that stops the network from learning anything useful. However, using convolutional layers, parameters are

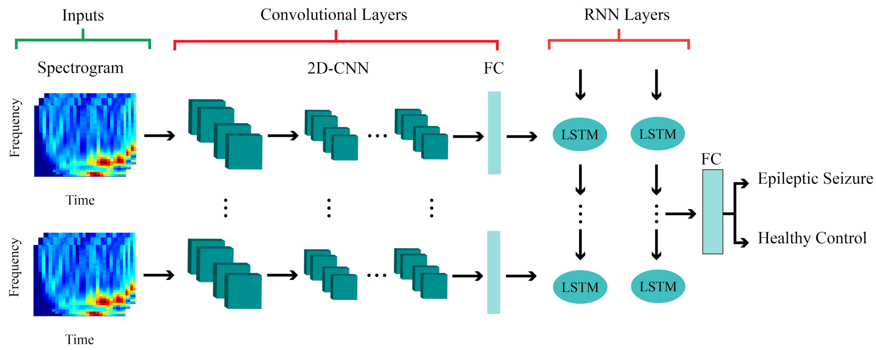


Figure 13: A typical CNN-RNN for epileptic seizure detection.

reduced dramatically, and networks can be appropriately trained (Chen et al., 2017a). A combination of this model with other ones, such as DAE, can lead to complex models with state-of-the-art performances (Li et al., 2015; Makhzani et al., 2015). A typical CNN-AE for epileptic seizure detection is shown in figure 14.

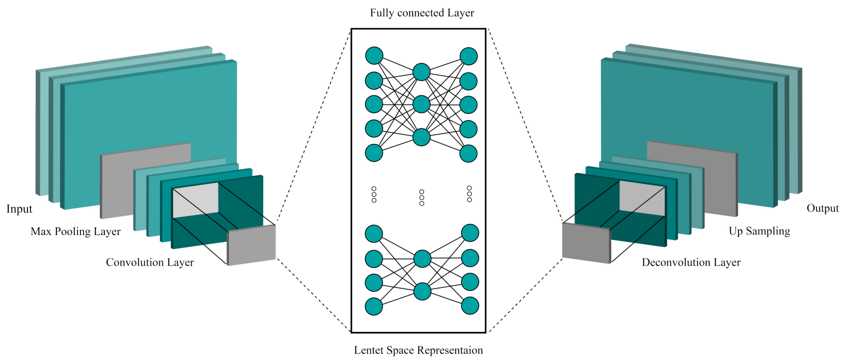


Figure 14: A typical CNN-AE for epileptic seizure detection.

3.2.3. Other Neuroimaging Modalities for Epileptic Seizure Detection

A. Medical Imaging

In the medical imaging literature, many researchers have focused on the application of fMRI, sMRI, and PET modalities for epileptic seizure detection using DL methods. sMRI and fMRI neuroimaging modalities are more popular than PET among physicians and neurologists for detecting epileptic seizures (van Lanen et al., 2021; Ma et al., 2020). This has led to more research papers be conducted on fMRI and sMRI modalities for epileptic seizures detection. Therefore, we summarize the relevant works that leverage various PET and MRI-based modalities in table 3.

B. EEG-fMRI

Multimodal neuroimaging techniques give physicians very detailed information about the type of neurological disorders and their location on the brain. As such, it is essential to use these modalities to identify the central location (focus) of epilepsy in the brain. EEG-fMRI is one of the best multimodal techniques for epileptic seizures detection (Gotman, 2008; Ebrahimzadeh et al., 2019). The modality of EEG-fMRI along with the ResNet network was investigated for epileptic seizures detection in (Hao et al., 2018). In the proposed ResNet architecture, the Softmax and Triplet functions are used for supervised classification, achieving 84.40% specificity.

C. EEG - fNIRS

fNIRS uses infrared waves to monitor changes in blood oxygen levels in the brain, allowing imaging and analysis of active brain areas (Pouliot et al., 2012). In this method, using special electrodes on the scalp, variations in oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) are measured, which can be helpful in diagnosing a variety of brain diseases. In (Mao et al., 2020), EEG-fNIRS combination modalities have been employed to detect epileptic seizures. The proposed LSTM-based based approach, with a Softmax classifier as the last layer, achieved 98.30% accuracy in their case study.

D. ECoG

RaviPrakash et al. (RaviPrakash et al., 2020) introduced an algorithm based on DL for Electrocorticography based functional mapping (ECoG-FM) for eloquent language cortex identification. ECoG-FM's success rate is low compared to Electro-cortical Stimulation Mapping (ESM). The algorithm showed an improvement of 34% over the existing ECoG-FM method with an accuracy of approximately 89%. ECoG-FM method coupled with DL has the potential for state-of-the-art performances. This method can help the surgeons performing epilepsy surgery by removing the ESM hazards. Also, in part of the (Hosseini et al., 2017), an ECoG modality has been considered for the detection of epileptic seizures. 2D-CNN and SVM were used for feature extraction and classification steps, respectively.

E. MEG

MEG is a functional neuroimaging technique used to evaluate and analyze the structure of the brain to diagnose a variety of brain disorders. Due to its high operational costs, it is only used in exceptional cases. (Zheng et al., 2019) Proposed a new technique, EMS-Net, for detecting epileptic spikes from MEG modality, with satisfactory results.

4. Rehabilitation Systems Based DL Techniques

In recent years, research in the field of design and construction of rehabilitation systems aimed at assisting people with a variety of neurological disorders has advanced significantly. Rehabilitation systems are of particular significance to assist patients. The major objective of these systems is to achieve real and accessible tools for different patients. These systems are important in two aspects: First, they continuously monitor the patient's condition and, in the occurrence of disease, perform some necessary work to improve the disease. In the second case, there is another category of these systems that constantly report the patient's vital signs to the specialist so that the patient is at lower risk of disease. In this section, various rehabilitation systems are presented to help patients with epileptic seizures. These tools include programs to diagnose epileptic seizures from non-medical modalities (Ahmedt-Aristizabal et al., 2018a; Achilles et al., 2018), Brain Computer Interface (BCI) systems (Hosseini et al., 2016), Implantable (Kiral-Kornek et al., 2018), and Cloud-Computing (Singh and Malhotra, 2018; Ali et al., 2020; Amin et al., 2019; Alhussein et al., 2018) are discussed below.

4.1. Non Neuroimaging Modality for Epileptic Seizure Detection

In a study by Ahmedt et al. (Ahmedt-Aristizabal et al., 2018a), facial images have been used to diagnose epileptic seizures. To collect the dataset, epileptic patients were monitored for 2 to 7 days, and eventually, 16 patients with MTLE were randomly selected from the general data set by default. The DL architecture in this investigation is CNN-RNN and, the results reveal that they have achieved promising results.

4.2. Brain Computer Interface

BCI based on DL to detect epileptic seizures has been recommended in Hosseini et al.'s study (Hosseini et al., 2016). In the proposed technique, SSAE and Softmax methods have been exploited to perform feature extraction and classification steps, respectively. In this study, they achieved 94% accuracy.

4.3. Implantable Based DL

Kiral-Kornek et al. (Kiral-Kornek et al., 2018) proposed an online and wearable system in the body for epileptic seizures detection based on DL. The proposed system has low power consumption, long life, and high reliability. In the proposed approach system, the DL method is trained to distinguish pre-ictal signals from ictal and has a sensitivity of 69%.

4.4. Cloud Computing Based DL for Epileptic Seizures Detection

With the advancement of information technology, performing heavy computational tasks at different times and places becomes a necessity. There is also a need for people to be able to easily fulfill their heavy computing tasks without owning expensive hardware and software. Cloud computing plays an important role in allowing users to process various data and store information outside of personal computers. The advantages of cloud computing have led to its accelerated application in various medical fields. An overview of cloud computing to help diagnose epileptic seizures is exhibited in Figure 15. In the epileptic seizure detection field, research has been carried out using cloud computing, which we will describe below (Singh and Malhotra, 2018; Ali et al., 2020; Amin et al., 2019; Alhussein et al., 2018; Muhammad et al., 2018).

4.4.1. Cloud System Design Based DL and Smartphone

Singh et al. (Singh and Malhotra, 2018) developed a commercial product for epileptic seizures detection, which involves user and cloud sections. The user section includes EEG headset, smartphone, WiFi system or, 4G network. The cloud segment also contains the dataset and the SAE algorithm for classifying EEG signals. EEG signals are recorded via a 14-channel Bluetooth headset and then transmitted to the patient's smartphone. Then, Android-based software transmits the recorded data to the cloud via WiFi or 4G internet connection. If

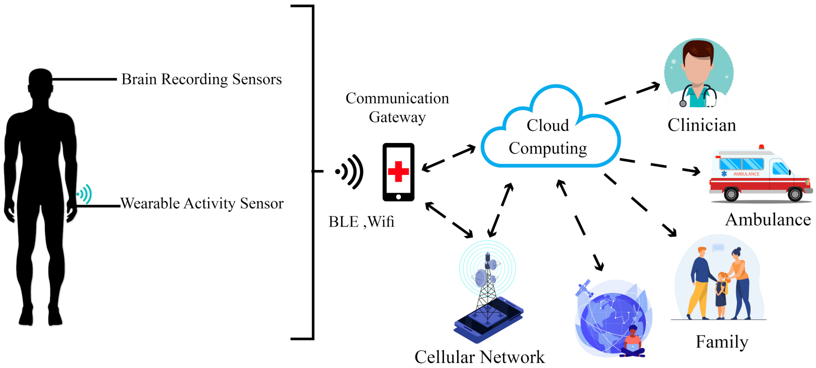


Figure 15: Cloud computing in helping patients with epileptic seizures.

the output of the classifier is pre-ictal, an alarm message containing the patient's geographical location is sent by the alarm system to the patient's telephone, family members' telephone, and the nearest hospital.

4.4.2. Cloud System Based DL and Mobile Edge Computing

Ali et al. (Ali et al., 2020) used the combination of DL with mobile edge computing to detect epileptic seizures. The objective of Edge Computing is to lessen the communication load of the cloud server and the edge device, which is specifically the main focus of this article. The proposed design assumes that the data has already been recorded and provided to the edge device, which is mobile. Next, receiving the raw data by mobile phone, they are partially processed and then sent to the cloud. Other processes continue to epileptic seizures detection in the cloud, and then the result is sent to the mobile phone.

4.4.3. IoT Based Healthcare

An IoT-based healthcare framework and DL to help patients with epileptic seizures are introduced in (Amin et al., 2019; Alhussein et al., 2018). In (Amin et al., 2019), the function of two adopted cloud systems is employed, one of which sends EEG signals, and the other sends other vital information such as movements and emotions. With the cognitive module, the patient's vital signs are supervised online and then fed to the CNN network input. Finally, patient status and EEG signal analysis results are shared with medical providers. In the recommended approach, emergency help is provided if the patient is in critical condition.

4.4.4. Mobile Multimedia Framework

In a study by Muhammad et al. (Muhammad et al., 2018), a technique based on mobile multimedia healthcare was proposed to help patients with epileptic seizures. In the proposed method, DL and the CHB-MIT dataset are utilized to detect epileptic seizures. Finally, the algorithms adopted are implemented on a module. Experimental results show the achievement of 99.02% accuracy and 92.35% sensitivity parameters.

5. Discussion

Today, many people worldwide suffer from epileptic seizures, and their daily activities are faced with serious challenges. So far, numerous clinical and screening procedures have been proposed to treat and diagnose epileptic seizures. Among the screening methods, EEG, fMRI, sMRI, and PET modalities are more important for epileptic seizures detection for physicians than other techniques. Applying DL techniques and neuroimaging modalities are crucially significant in epileptic seizure detection. In this paper, conducted researches on the diagnosis of epileptic seizures using DL methods are studied. Also, in the papers reviewed, practical applications in this field have been mentioned.

Diagnosis of epileptic seizures based on EEG modalities as well as medical imaging techniques are summarized in Tables 2 and 3. These tables provide each research information, including dataset, modality, preprocessing techniques, DL network input, DL network, classification algorithm, K-Fold evaluation, and finally, various evaluation parameters.

The most important datasets available used for diagnosing epileptic seizures are provided in Table 1. It is observable that the majority of them take advantage of EEG modalities. The total number of datasets utilized in epileptic seizure investigations is shown in Figure 16. As can be observed, the Bonn dataset is the most widely used by researchers. This is because this database is preprocessed and can be easily employed for research.

Different neuroimaging modalities are applied to diagnose epileptic seizures. Detailed information on the types of neural modalities for diagnosing epilep-

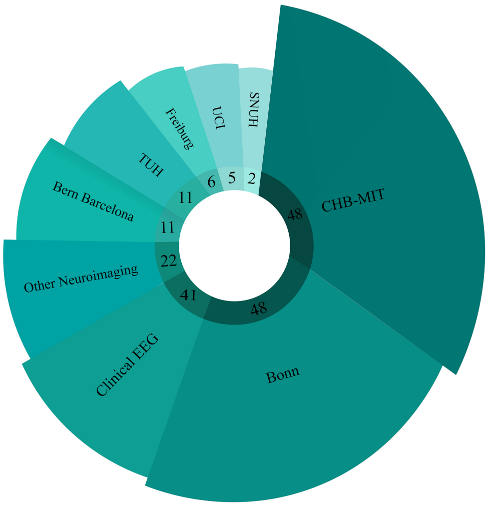


Figure 16: Number of studies published for epileptic seizures detection using different datasets.

tic seizures is given in the diagram 17. According to diagram 17, the sEEG modality has dedicated to itself the highest use in the research. This is due to the non-invasive nature of the sEEG modality, which exposes patients to fewer risks. Moreover, according to Figure 17, IEEG modality is considered the second epileptic seizures detection approach.

Numerous tools have been proposed to implement a variety of DL architectures, the main objective of which is to facilitate the simulation of these networks. Matlab, Keras, TensorFlow, PyTorch, Caffe, and Theano are the most well-known tools for the implementation of DL networks (Peng et al., 2016; Nguyen et al., 2012). The number of times each DL tool is used for epileptic seizure detection is illustrated in Figure 18. The TensorFlow and Keras libraries are widely applied due to their continuous updating, high flexibility, and ease of use in implementing CADS epileptic seizures.

In tables 2 and 3, the DL network types are discussed for epileptic seizures detection based on neuroimaging modalities. A variety of CNN models in various medical applications, especially the diagnosis of epileptic seizures, have reached promising results. Figure 19 display the total number of DL techniques for epileptic seizures detection.

Also, figure 19 shows the number of annual researches on the utilization of DL networks for epileptic seizures detection. Based on Figure 19, the researchers

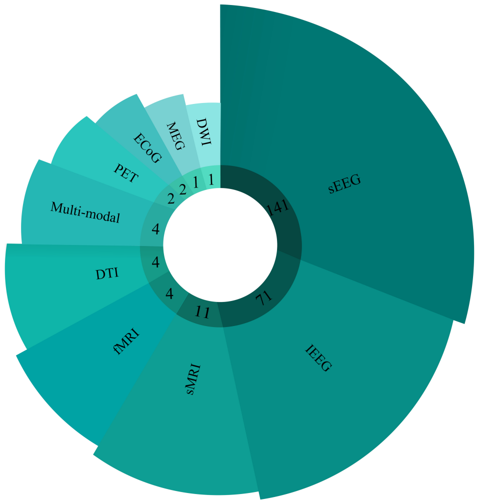


Figure 17: Number of studies published for epileptic seizures detection using different neuroimaging modalities.

have concentrated on different models of 2D-CNN and 1D-CNN. CNN architectures discover local spatial dependencies well; thus, these networks can be used to extract the necessary patterns from various modalities, including EEG signals. Furthermore, the patterns that CNNs learn are unchanged from relocation, and on the other hand, they can well train the hierarchy of feature space. In this article, not only the type of DL network in each research is discussed, but also in the table 4, the implementation details of DL networks in each research are mentioned.

Classification algorithms are the last part of the DL network. Figure 20 shows the number of classification algorithms used in DL networks based on Tables 2 and 3. As can be seen, the Softmax algorithm (Zeng et al., 2014) is the most popular in DL applications as a classification approach. Regarding the superiority of Softmax compared to other classifiers such as SVM (Noble, 2006), we can remark its easy derivability, which makes it possible to apply it in the backpropagation algorithm. Also, compared to gradient descent methods, such as exploiting Sigmoid for classification purposes, Softmax provides better performance due to the weights normalization between different classes.

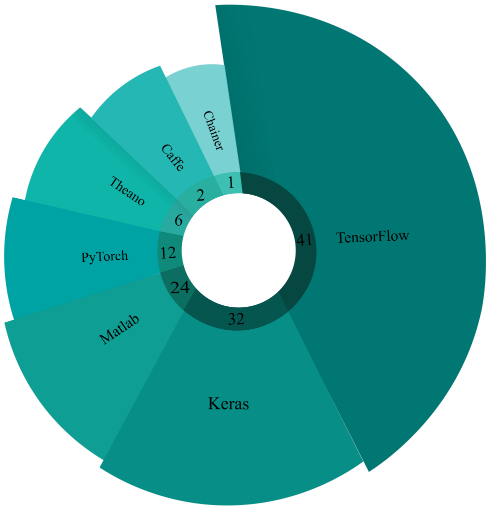


Figure 18: Number of DL tools used for epileptic seizures detection based on the published papers.

6. Challenges

In this section, the challenges in epileptic seizures diagnosis using DL techniques have been described. The most important challenges concerning datasets, DL methods, and hardware resources are explained in detail below.

Available datasets for diagnosing epileptic seizures are mostly EEG type. However, available datasets from other functional and structural neural modalities have not been provided for investigations until now. For example, the fNIRS modality is one of the most inexpensive and most accurate procedures to diagnose a variety of neurological disorders (Tak and Ye, 2014; Peng et al., 2014). The lack of available fNIRS datasets for the diagnosis of epileptic seizures has given rise to confined research in this field. Additionally, sMRI and fMRI modalities are recognized as some of the most significant and accurate tools for diagnosing brain disorders (Del Gaizo et al., 2017; Bharath et al., 2019). So far, no dataset on sMRI or fMRI modalities has been made freely available to researchers for epileptic seizures detection. Multimodality techniques such as EEG-fMRI or EEG-fNIRS have been investigated in the diagnosis of mental and neural disorders and, noteworthy results have been achieved (Zijlmans et al., 2007; Kowalczyk et al., 2020; Peng et al., 2016; Nguyen et al., 2012). In

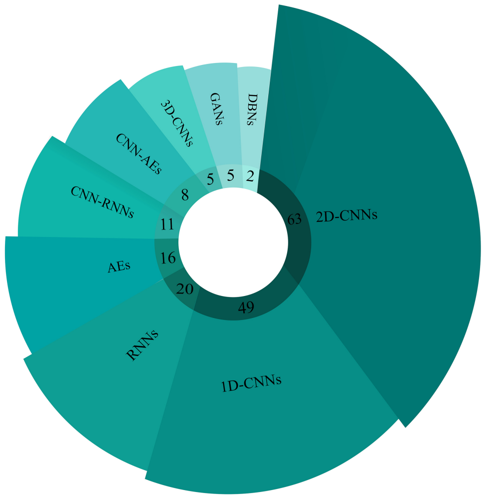


Figure 19: Number of DL architectures used for epileptic seizures detection based on published papers.

order to diagnose epileptic seizures using multimodality approaches, insufficient research has been performed, the main reason being the deficiency of available and free datasets.

Available EEG datasets commonly follow two approaches to distinguishing seizures from normal or when they occur. However, there are different types of epileptic seizures, and diagnosing their type is a troublesome task for physicians. Therefore, contributing datasets with functional or structural neuronal modalities to diagnose different types of epileptic seizures is profoundly felt.

Regarding the utilization of DL models for epileptic seizures detection, several challenges must be examined before implementing these models for clinical applications. The first challenge of this category is the extensiveness and differences of seizure patterns in signals. This issue leads to collect very large datasets to make these models more robust to new patterns or a more feasible solution to apply few-shot learning techniques to improve these models' robustness. Another challenge is to investigate the transferability of the model implemented on various datasets. Various studies have succeeded in achieving very high accuracy on particular datasets, but before adopting these models in real-world applications, their performance requires to be evaluated with a different distribution of the training data. The final challenge in this scope is the lack of

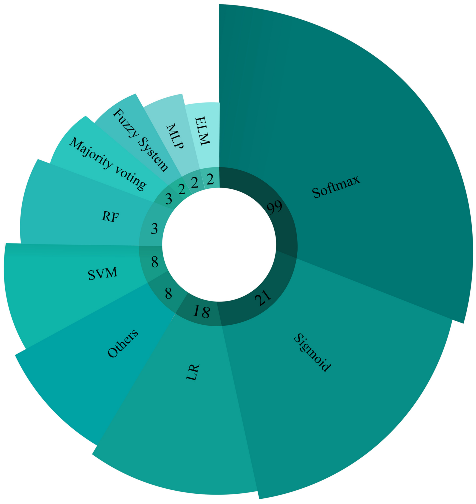


Figure 20: Illustration of the number of various classifier algorithms used in DL networks for automated detection of epileptic seizures.

networks with a dedicated structure for diagnosing epileptic seizures performing as a benchmark. In the image processing field, networks such as VGG and AlexNet have served as benchmarks and, in addition to providing researchers with a highly effective evaluation tool, allowing them to easily track their work to evolve and improve on previous work, while most of the networks used in this field are modified derivatives of networks presented for ImageNet and not specifically designed to diagnose epileptic seizures.

The following challenges category refers to the presentation of rehabilitation systems in the diagnosis of epileptic seizures with the help of DL. Unfortunately, much concentration has not been carried out on designing rehabilitation systems like BCI. In some research papers, cloud computing technologies, IoT and, Healthcare have been studied to address the difficulties of patients with epileptic seizures using neuroimaging modalities. The most substantial research challenges in this field are the deficiency of multimodality datasets for these systems' better performance.

Furthermore, dedicated hardware design platforms for this research have not been yielded till then, which is another challenge. To date, most researchers have developed the hardware implementation of conventional machine learning algorithms to detect epileptic seizures timely. This issue has led to these hardware circuits can not be employed for epileptic seizures detection seriously. Hardware implementation of DL algorithms to diagnose epileptic seizures can give specialist physicians the hope that they can accurately and real-time diagnose epileptic seizures and their type. Hardware implementation of DL algorithms on field-programmable gate array (FPGA), application-specific integrated circuit (ASIC), etc. can address many difficulties and challenges for medical professionals. However, when designing hardware based on DL, a number of existing challenges can be addressed, such as reducing hardware resources, minimizing power consumption, and so on.

7. Conclusion and Future Works

Early detection of epileptic seizures is of particular importance to specialist physicians, and research in this field has grown significantly in recent years. In this paper, a comprehensive review of the diagnosis of epileptic seizures using neuroimaging modalities coupled with DL methods has been performed. In the discussion section, it was observed that sEEG datasets are most applied in epileptic seizures detection. In another section, it was perceived that different models of DL have been employed to diagnose this type of neurological disorder, among which CNNs have the highest number of studies. In most investigations, small datasets have often been used to diagnose epileptic seizures alongside pre-train deep networks. To improve the performance of these DL networks, it is better to provide a comprehensive dataset of medical signals. This enhances the performance of pre-train deep networks for diagnosing epileptic seizures. Increasing the efficiency and accuracy of CAD systems in epileptic seizures detection is of particular significance, but aforementioned, the data deficiency is a serious challenge. Another novel field for research is applying Zero-Shot learning techniques, which can result in promising results for the implementation of real epileptic seizure detection systems.

In another part of the paper, the types of hardware and applied programs for detecting epileptic seizures were presented. Cloud Computing, IoT, Healthcare, and wearable implants have recently been introduced coupled with DL techniques to aid people with epileptic seizures, and it is encouraging that more applied research will be conducted in the near future. Lack of adequate hardware resources is another reason hardening the practical implementation of these systems. For future work, it is expected that CADS based on DL will be implemented on a variety of dedicated hardware such as FPGA and ASIC for epileptic seizures detection.

Responsive neurostimulation (RNS) and vagus nerve stimulation (VNS) diagnostic systems are a type of invasive implants that can be implanted in the human body and are programmed to detect and neutralize the onset of epileptic seizures (Fisher, 2012; Skarpaas et al., 2019). These systems still have open problems in accurately diagnosing epileptic seizures. Enhancing the accuracy of RNS and VNS based diagnosis and treatment systems based on DL techniques can be noteworthy as one of the future tasks.

Another procedure of diagnosis and prediction is from other vital human signals such as the heart. Designing and manufacturing invasive and non-invasive implants based on other vital signals of the human body along with DL methods is another recommendation for future work.

In addition to other future directions, the use of more sophisticated methods in deep neural networks can itself be a path for future works. The use of deep metric (Schroff et al., 2015) methods to increase the informativeness of learned representations, few-shot learning (Sung et al., 2018) methods and scalable networks (Tan and Le, 2019) for small dataset tasks, and newer data augmentation methods such as simple copy-paste (Ghiasi et al., 2020) can all be investigated.

Table 2: Summary of DL methods employed for automated detection of epileptic seizures.

Work	Dataset	Modality	Preprocessing		Input Network	Deep Tools	Network	K-fold	Classifier	Performance Criteria (%)			
			Low Level	High Level						ACC	Sens	Spec	F1-S
(Antoniades et al., 2016)	Clinical	IEEG	Standard Preprocessing	Spectrogram	2D Spectrograms	NA	2D-CNN	–	LR	87.51	–	–	–
(Qin et al., 2020b)	CHB-MIT	sEEG	Segmentation	STFT	2D Spectrograms	PyTorch	2D-CNN	–	ELM	95.65	95.85	–	–
(Park et al., 2018)	SNUH CHB-MIT	sEEG sEEG	Segmentation, Filtering	DA	Preprocessed Data	NA	1D with 2D-CNN	–	Sigmoid	90.58	89.20	91.90	–
(Tjepkema-Cloostermans et al., 2018)	Clinical	sEEG	Filtering, Down-Sampling	–	the preprocessed 2 s epochs	Keras Theano	2D-CNN	–	Softmax	–	47.40	98.00	–
(Avcu et al., 2019)	Clinical	sEEG	Down Sampling, Z-Normalization	DA	Preprocessed Data	Keras	SeizNet	–	NA	–	95.80	–	–
(Zhan and Hu, 2020)	Freiburg	IEEG	–	Fourier Transform (FT), Wavelet Transform (DWT)	Spectrograms, Time Domain Signal, and Time Frequency Signal	NA	DCNN	NA	Multi-view Fuzzy Clustering	97.38	96.26	–	–
(Nejedly et al., 2019)	Clinical	IEEG	Z-Normalization	STFT	Raw IEEG Signals Spectrogram Images	PyTorch	CNN	–	Softmax	–	79.00	–	–
(Hossain et al., 2019)	CHB-MIT	sEEG	–	Visualization	Raw EEG as 2D Array	PyTorch	2D-CNN	–	Softmax	98.05	90	91.65	–
(Mao et al., 2020)	UCI	sEEG	–	CWT	2D Scalograms	MATLAB	2D-CNN	–	Softmax	72.49	–	–	–
(Zuo et al., 2019)	Clinical	IEEG	Filtering, Normalization	Visualization	Input Images 4*1,024 Pixels in Size	NA	2D-CNN	10	Softmax	87.65	83.23	79.36	–
										90.83	77.04	72.27	–
(Asif et al., 2019)	TUH	sEEG	–	DivSpec	3D Visual Representation	PyTorch	SeizureNet	5	Softmax	–	–	–	90
(Iešmantas and Alzbutas, 2020)	TUH	sEEG	Feature Extraction		Pattern Matrices	TensorFlow	2D-CNN	10	Softmax	74	68	67	–
(Zeng et al., 2021)	Bonn	sEEG and IEEG	Filtering, Segmentation using FNSW	Conversion Module (GRP Transformation)	2D-GRPs	TensorFlow	GRP-DNet	10	Majority Voting	100	–	–	–
(San-Segundo et al., 2019)	Bern Barcelona Clinical	IEEG sEEG	Filtering	EMD, FWT, FT	Raw IEEG Signals IMFs Wavelet Coefficients Module Values	Keras	2D-CNN	5	Sigmoid Softmax	99.80	–	–	–
(Sui et al., 2019)	Bern Barcelona	IEEG	Z-Normalization	STFT	2D Spectrograms	TensorFlow	2D-CNN	10	Softmax	91.80	–	–	–
(Chatzichristos et al., 2020)	TUH	sEEG	Multi-Channel Subspace Filters	IC Label	Raw EEG Signals Subspace Filtering ICLabel	NA	Multiple Attention-Gated U-Net	10	Bi-LSTM + FC Layer	–	–	–	–
(Covert et al., 2019)	Clinical	sEEG	–	STFT	2D Spectrograms	NA	TGCN	–	Sigmoid	92.80	–	–	–
(Akut, 2019)	Bonn	sEEG and IEEG	–	DWT	Wavelet Coefficients	NA	2D-CNN	–	Sigmoid	100	100	100	–

(Türk and Özerdem, 2019)	Bonn	sEEG and IEEG	–	CWT	2D Scalograms	Keras	2D-CNN	10	Softmax	100	100	100	–
(Liu and Woodson, 2019)	Bonn	sEEG and IEEG	Filtering	–	Black and White Plots of The Amplitude Scaled Wave Files	MATLAB	2D-CNN	–	Softmax	99.60	–	–	–
(Tian et al., 2019)	CHB-MIT	sEEG	Over Sampling Method	FFT, WPD	Time Domain Frequency Domain	MATLAB TensorFlow	2D-CNN 3D-CNN	5	MV-TSK-FS	98.33	96.66	99.14	–
(Bouaziz et al., 2019)	CHB-MIT	sEEG	Segmentation	Spatial Representation by Producing A Set of Intensity Images	2D Data	NA	2D-CNN	–	Softmax	99.49	–	–	99.49
(Prasanth et al., 2020)	Clinical	sEEG	Down-Sampling, Filtering, Artifact Rejection Based on Noise Statistics, Decomposition, Segmentation	–	Combination of Raw EEG and Frequency Sub-Bands	NA	1D-CNN, 2D-CNN	5	NA				
(Ansari et al., 2019)	Clinical	sEEG	–	Different Methods	2D Data	MATLAB	2D-CNN	10	Sigmoid RF	89.00	82.00	90.00	–
(Cao et al., 2019)	CHB-MIT	sEEG	–	Sub-band Mean Amplitude of Spectrum (MAS) Map of Multi-channel EEGs	MAS Map Image	NA	SCNN (4 CNNs)	5	AWF fusion scheme, KELM classification	99.33	–	–	–
	Clinical									98.86	–	–	–
(Taqi et al., 2017)	Bern Barcelona	IEEG	NA	–	2D Data	Caffe	AlexNet GoogleNet LeNet	–	Softmax	100	–	–	–
(Emami et al., 2019b)	Clinical	sEEG	Filtering, Segmentation	Visualization	2D Data	Chainer	2D-CNN	–	Softmax	80	–	–	–
(Bizopoulos et al., 2019)	UCI	sEEG	–	Signal2Image	2D Data	PyTorch	2D one-layer CNN	–	DenseNet	85.30	–	–	–
(Thanaraj et al., 2020)	Bern Barcelona	IEEG	Segmentation	GASF, DA	GASF Images	MATLAB	Different Pre-Train Networks	–	Softmax	92.00	–	–	–
			–	Textural Features Extraction from the GASF Images, PSO Feature Selection	Different Features	Keras TensorFlow	Deep ANN						

(Zhang et al., 2020a)	CHB-MIT	sEEG	Segmentation, Resizing	STFT	2D Spectrograms	NA	VGG-16 VGG-19 ResNet-50	–	Softmax	98.26	–	–	–
(Cho and Jang, 2020)	Clinical Kaggle	IEEG	Segmentation, Down-Sampling, Raw EEG time series	Periodogram, STFT Gray Image, Black and White Image of Raw EEG Waveform, Concatenation of 3 Black and White images	Raw EEG Signals Periodogram 2D Spectrograms 40 X 250 Image of EEG Signals 40 X 750 Image of EEG Signals	TensorFlow	2D-CNN FCNN, 1D-CNN LSTM	10	NA	99.90	96.70	99.90	–
(Liu et al., 2020a)	Freiburg	IEEG	Segmentation, Normalization	DWT, S-Transform Spectrogram	2D Spectrograms	MATLAB	2D-CNN	10	Softmax	98.12	97.01	98.12	–
(Bouallegue et al., 2020)	Bonn, CHB-MIT	sEEG IEEG	Segmentation	Filter EEG using FastICA Network, Feature Extraction using GRU	Matrix of Size 16 x 400	Keras, TensorFlow	2D-CNN	10	Softmax	100	–	–	–
(Raghu et al., 2020)	TUH	sEEG	Filtering	STFT	2D Spectrograms	MATLAB	Inception-V3	10	SVM	88.3	–	–	–
(Li et al., 2020a)	Bonn TUSZ CHB-MIT	sEEG and IEEG sEEG sEEG	Segmentation, Resampling, Transformation into 20 Common Channels, Baseline Removal and Detrending, Filtering	–	Spectral-Temporal Features	PyTorch	CE-stSENet	5	MLP	99.80	–	–	–
(Usman et al., 2020)	CHB-MIT	sEEG	Filtering, Segmentation	STFT	2D Spectrograms	MATLAB	2D-CNN	–	SVM	–	92.7	90.8	–
(Ilakiyaselvan et al., 2020)	Bonn	sEEG and IEEG	Filtering, Segmentation	RPS representation	RPS Images	Caffe	AlexNet	10	Softmax	98.5	100	97.83	–
(Bhagat et al., 2020)	CHB-MIT	sEEG	–	Converting 1D EEG Data into 2D EEG Images	224×224 Images	NA	ResNet-50	–	Softmax	94.98	–	–	–
(George et al., 2020)	CHB-MIT	sEEG	–	Backpropagation Auto Stack Encoder (BP-ASE)	–	NA	ResNet	–	Softmax	99.4	99	96	96.8

(Gao et al., 2020b)	CHB-MIT	sEEG	Segmentation	DWT Threshold Denoising Method, PSD Analysis, PSDED	PSDED	NA	Inception-ResNet-v2 Inception-v3 ResNet152	–	Softmax	92.60	92.60	97.10	–
(Singh et al., 2020)	Bonn	sEEG and IEEG	Filtering, Segmentation	DWT	Features from 2D Data	NA	2D-CNN	–	Softmax	97.74	–	–	–
(Bhattacherjee, 2020)	Bonn	sEEG and IEEG	–	Bi-Linear Interpolation, Concatenation of DWT and Power Spectrum Band	2D Data	NA	Multi Column CNN	–	Softmax	99.99	–	–	–
(Lian et al., 2020)	Bonn	sEEG and IEEG	Filtering	–	Raw EEG Signals	NA	Combination of 1D-CNN and 2D-CNN	10	Softmax	99.3	99.5	99.6	–
(Madhavan et al., 2019)	Bern-Barcelona	IEEG	–	FSST, WSST	Time-Frequency Matrix	PyTorch	2D-CNN	5	Softmax	99.94	99.94	99.94	–
(Sakai et al., 2020)	Clinical	sEEG	Filtering, Segmentation	–	EEG Signals Segment	Keras	ScalpNet	–	Sigmoid	99.9	–	–	94.4
(Hussein et al., 2020)	Clinical	IEEG	Segmentation	CWT	2D Scalograms	NA	SDCN	–	Sigmoid	92.80	88.45	–	–
	Clinical	IEEG								88.30	89.52	–	–
(Kaya, 2020)	Bonn	sEEG and IEEG	Normalization	CWT, mRMR Algorithm	2D Scalograms	NA	Combination of AlexNet and VGG16	10	KNN	98.78	99.15	–	98.46
(Shankar et al., 2020)	Bonn	sEEG and IEEG	Noise Removal, Instantaneous Power Calculation, Segmentation	Gramian Angular Summation Field (GASF) and Gramian Angular Difference field (GADF)	2D Data	NA	2D-CNN	–	Sigmoid	98	99	98.9	–
(Rashed-Al-Mahfuz et al., 2021)	Bonn	sEEG and IEEG	Segmentation	STFT and CWT, RGB Representation, DA	2D Data (Spectrogram, Scalogram)	Keras	FT-VGG16	–	Softmax	99.21	99.04	99.38	–

(Hu et al., 2020a)	CHB-MIT and the iNeuro	sEEG	Filtering, Segmentation	Mean Amplitude Spectrum (MAS), Mean Power Spectral Density (MPSD), and Wavelet Packet Features (WPFs)	Fused into a Single Image	–	AlexNet, VGG-19, Inception-v3, ResNet152, Inception-ResNet-v2 Hierarchical Neural Network (HNN)	–	Softmax	98.97	–	–	–
(Glory et al., 2020)	Bonn Bern CHB-MIT	sEEG and IEEG IEEG sEEG	–	DWT, Nonlinear, and Entropy-based features	Different Features	Keras, TensorFlow	Hybridizes Adaptive Haar Wavelet-based Binary Grasshopper Optimization Algorithm and Deep Neural Network (AHW-BGOA-DNN)	10	Softmax	–	–	–	–
(MohanBabu et al., 2020)	CHB-MIT	sEEG	Filtering, Differentiating	Hilbert Transform, Segmentation, Phase-Synchronization Measures, Graph Model	643 × 5 and up to 643 × 50	Keras, TensorFlow	Optimized Deep Learning Network Model (ODLN)	–	Softmax	–	100	–	–
(You et al., 2020)	Clinical	sEEG	Reviewed Separately by 2 Epileptologists, Filtering	Segmentation, STFT, Normalization, Rescaling, Stack 3 Images to form a Data Structure	2D Spectrograms	TensorFlow	AnoGAN	–	Combination of Anomaly Loss and a Gram Matrix	–	96.6	–	–
(Truong et al., 2019)	CHB-MIT EPILEPSIAE Freiburg	sEEG sEEG IEEG	Segmentation	STFT	2D Spectrograms	TensorFlow	DCGAN	–	Softmax	77.68	–	–	–

(Pascual et al., 2019)	EPILEPSIAE	sEEG	Segmentation	DWT, Power and Non-Linearity per Electrode Features Extraction	Non-Seizure (inter-ictal) EEG Samples	NA	Conditional GAN	–	RF	–	–	–	–
(Torfi and Fox, 2020)	UCI	sEEG	NA	Different Methods	Matrix	NA	CorGAN	–	Softmax	–	–	–	21
(Sharan and Berkovsky, 2020)	CHB-MIT	sEEG	Segmentation, Filtering	FFT and WT	135×1×54 with FFT and 132×1×54 with WT	NA	1D-CNN	10	Softmax	97.25	97.25	97.25	–
(Hu et al., 2020b)	CHB-MIT and iNeuro	sEEG	Filtering, Decomposition	Feature Extraction (MAS, MPSD, WPFs)	Multiple Fused EEG Features	NA	Different Pre-Train Nets	NA	Hierarchical Neural Network (HNN)	98.97	–	–	–
(Ullah et al., 2018)	Bonn	sEEG and IEEG	–	DA	EEG Signals Segment	TensorFlow	P-1D-CNN	10	Majority Voting	99.1	–	–	–
(Acharya et al., 2018)	Bonn	sEEG and IEEG	Z- Normalization	–	Normalized EEG Signals	MATLAB	1D-CNN	10	Softmax	88.67	95	90	–
(Wang et al., 2020b)	Berne-Barcelona	EEG	NA	–	Raw EEG Signals	NA	Time-ResNeXt	–	Softmax	91.5	–	–	–
(Page et al., 2016)	CHB-MIT	sEEG	Filtering	DA	EEG Signals Segment	NA	MPCNN	–	Softmax	96	100	–	–
(Zhang et al., 2020b)	Bonn	sEEG and IEEG	Normalization	–	Raw EEG Signals	Keras	Multi-Scale Non-Local (MNL) Network	10	Softmax				
(O'Shea et al., 2017a)	Clinical	sEEG	Down-Sampling, Filtering	–	EEG Signals Segment	Keras	1D-FCNN	5	Softmax	97.1	–	–	–
(Thomas et al., 2020b)	Clinical	sEEG	Filtering, Down Sampling, Artifact Rejection Based on Noise Statistics, Segmentation	–	EEG Signals Segment	TensorFlow	1D-CNN	5	Softmax	–	80	–	–
(O'Shea et al., 2017b)	Clinical	sEEG	Filtering	–	Raw EEG Signals	Theano Lasagne	1D-CNN	–	Binary LR	94.70	–	–	–
(Yıldırım et al., 2018)	TUH	EEG	Segmentation, Normalization, and Standardization	–	EEG Signals Segment	Keras	1D-CNN	–	Softmax	79.34	–	79.64	78.92
(Zhao and Wang, 2020)	Bonn	sEEG and IEEG	Normalization	–	Raw EEG Signals	Keras, TensorFlow	SeizureNet	10	Softmax	98.5	97	100	–

(Akyol, 2020)	Bonn	sEEG and IEEG	Normalization	–	Raw EEG Signals	Keras, TensorFlow	Stacked Ensemble based DNN Modeling	10	Meta Learner	97.17	93.11	98.18	–
(Thomas et al., 2018)	MGH Epileptic Dataset	sEEG	Filtering, Down Sampling	CAR montage	Raw EEG Signals	TensorFlow	1D-CNN	4	SVM	83.86	–	–	–
(Uyttenhove et al., 2020)	TUH	sEEG	Filtering, Segmentation	–	EEG Signals Segment	NA	Tiny-Visual Geometry Group (T-VGG)	5	NA	70.38		82.98	
(Boonyakitanont et al., 2019)	CHB-MIT	sEEG	Segmentation, Normalization	–	Raw Multi-Channel EEG Signals	NA	1D-CNN	10	NA	99.07	66.76	99.63	65.69
(Chen et al., 2018)	Bonn	sEEG and IEEG	DWT, Segmentation, Normalization		Preprocessed EEG Signals	NA	1D-CNN	5	Sigmoid	97.27	–	–	–
(Zhang et al., 2020e)	TUSZ	sEEG	Montage Selection, Segmentation	Denoising, Normalization, DWT, SMOTE	4 Wavelet Coefficient Packages	PyTorch	DWT-Net	5	Softmax	–	25.24	97.05	–
(Zhang et al., 2018)	Bonn	sEEG and IEEG	Normalization	–	Raw EEG Signals	NA	1D-TCNN	–	NA	100	100	100	100
(Zhao et al., 2020a)	CHB-MIT and Another Dataset	sEEG	NA	–	Raw EEG Signals	Keras, TensorFlow	Binary Single-Dimensional Convolutional Neural Network (BSDCNN)	–	Sigmoid	–	94.69	–	–
(Daoud et al., 2018)	Bonn	sEEG and IEEG	–	EMD Feature Extraction	IMFs of EMD	NA	1D-CNN	10	Softmax	100	100	100	100
(Daoud et al., 2020)	CHB-MIT	sEEG	EEG Channel Selection	–	Raw EEG signals	NA	DCNN	–	NA	96.1	97.41	94.8	–
(Lu and Triesch, 2019)	Bonn	sEEG and IEEG	Filtering, Z-Normalization	–	Raw EEG signals	TensorFlow	1D-CNN	–	Softmax	99.00	–	–	–
										91.80	–	–	–
(Craley et al., 2019)	CHB-MIT	sEEG	Filtering	–	Raw EEG signals	PyTorch	1D-PGM-CNN	5	Softmax	80.00	–	–	67.00
	JHH	sEEG											
(Wei et al., 2019)	CHB-MIT	sEEG	–	MIDS, WGANs	5s length EEG Signals	NA	1D-CNN	–	Softmax	–	74.08	92.46	–
(Qin et al., 2020a)	Bonn	sEEG and IEEG	NA	–	Raw EEG signals	TensorFlow	1D-CNN	10	Softmax	98.67	99	98	–
(Meisel et al., 2019)	Clinical	Multi Modal Wristband Sensor Data	Segmentation Down Sampling	–	Raw EEG signals	NA	1D-CNN	4	Sigmoid	71.4	–	–	–

(Zhang et al., 2020c)	TUH	sEEG	EEG Decomposition to Seizure and Patient Components	–	Latten Seizure and Patient Representation	NA	CNN	14	Sigmoid	80.5	97.4	88.1	–
(Yuvaraj et al., 2018)	CHB-MIT	sEEG	Filtering, Segmentation	–	EEG Signals Segment	TensorFlow	1D-CNN	4	Softmax	–	86.29	–	–
(Abou Jaoude et al., 2020)	Clinical	IEEG	Down Sampling, Filtering	DA	1 Second Epoch from a Single FO-EEG Bipolar Channel	Keras TensorFlow MATLAB	CNN-BP	5	Sigmoid	99.60	84.00	–	–
(Fukumori et al., 2019)	Clinical	sEEG	Filtering	DWT	Raw EEG signals Coefficients Sub-bands D6, D5, D4	NA	1D-CNN LSTM GRU	–	Sigmoid RF SVM	96.10	–	–	–
(Guha et al., 2020)	UC Irvine Machine Learning Repository Bonn	sEEG sEEG and IEEG	Normalization	Feature Extraction, Data Cleaning	NA	TensorFlow	DNN	–	NA	80.00	–	–	71.00
(Kaziha and Bonny, 2020)	CHB-MIT	sEEG	Segmentation		EEG Signals Segment	Keras	1D-CNN	5	Sigmoid	96.74	82.35	100	–
(Truong et al., 2020)	EPILEPSIAE	sEEG	NA	–	n×59×114	NA	Bayesian Convolutional Neural Network (BCNN)	–	Softmax	–	–	–	–
(Zhao et al., 2020c)	Bern-Barcelona	IEEG	Filtering	DA	Augmented EEG Signals	NA	1D-CNN	10	NA	89.28	–	–	–
(Boonyakitanont et al., 2020b)	CHB-MIT	sEEG	Segmentation	–	EEG Signals Segment	NA	1D-CNN	–	Onset-offset Detection Method	99.72	72.78	99.82	64.4
(Khalilpour et al., 2020)	CHB-MIT	sEEG	Segmentation, Normalization	–	EEG Signals Segment	NA	1D-CNN	–	Softmax	97	98.5	98.47	–
(Zhao et al., 2020b)	Bonn	sEEG and IEEG	Segmentation, Normalization	–	EEG Signals Segment	Keras TensorFlow	1D-CNN	10	Softmax	99.52 98.06	– –	– –	– –
(Abiyev et al., 2020)	Bonn	sEEG and IEEG	Normalization	–	Raw EEG signals	Keras TensorFlow	1D-CNN	10	Softmax	98.67	97.67	98.83	–
(Pisano et al., 2020)	Clinical	sEEG	Segmentation, Standard Thresholding, Filtering	DA	Augmented EEG Signals	MATLAB	1D-CNN	–	Softmax	96.39	93.2	96.81	–
(Lu et al., 2020)	Clinical (Mice)	IEEG	Filtering, Segmentation	CAM	EEG Signals Segment	MATLAB TensorFlow	DNN	7	Softmax	73.00	–	–	78.00

(Xu et al., 2020c)	Kaggle CHB-MIT	IEEG sEEG	Segmentation	–	EEG Signals Segment	Keras TensorFlow	CNN	–	Softmax	98.80	98.80	–	–
(Lin et al., 2020)	Clinical	sEEG	Filtering, Normalization, Segmentation, Resampling Strategies	–	EEG Signals Segment	NA	Deep ConvNet	10	Softmax	80	70	90	77.77
(Jana et al., 2020)	CHB-MIT	sEEG	Filtering, Segmentation	Spectrogram Generation	2D Spectrograms	Keras TensorFlow	1D-CNN	–	Softmax	77.57	75.59	79.54	–
(Gao et al., 2020a)	Bonn	sEEG and IEEG	Segmentation	ApEn and RQA Features	Feature Vectors	MATLAB	1D-CNN	–	Softmax	99.26	98.84	99.35	–
(Thomas et al., 2020a)	CHB-MIT	sEEG	Segmentation, Resample, Rescale	–	Raw EEG signals	TensorFlow, Keras	1D-CNN	–	NA	84.1	–	–	–
(Vance et al., 2020)	Clinical	sEEG	Sequence Generation, Resampling	Online Augmentations	Sequence Length of 10 Seconds	TensorFlow, Keras	1D-CNN	–	Sigmoid	77	60.6	82.8	–
(Liu and Richardson, 2020)	CHB-MIT	sEEG	Segmentation	–	Raw EEG signals	TensorFlow	1D-CNN	10	Weighted Majority Voting (WMV)	89.21	89.50	94.86	–
							LSTM			90.94	91.53	95.75	–
(Vidyaratne et al., 2016)	CHB-MIT	sEEG	Filtering	Montage Mapping	2D Grid	MATLAB	DRNN	–	MLP	–	100	–	–
(Hussein et al., 2018c)	Bonn	sEEG and IEEG	Filtering, Segmentation	–	EEG Signals Segment	Keras TensorFlow MATLAB	LSTM	10	Softmax	100	100	100	–
(Ahmedt-Aristizabal et al., 2018b)	Bonn	sEEG and IEEG	Segmentation	–	Raw EEG signals	Keras	LSTM	10	Sigmoid	95.54	–	–	–
(Yao et al., 2019b)	CHB-MIT	sEEG	Segmentation	–	EEG Signals Segment	NA	IndRNN	10	NA	87	87.3	86.7	87.07
(Verma and Janghel, 2021)	Bonn	sEEG and IEEG	–	DWT	Wavelet Coefficients	Keras	RNN	NA	LR	98.5	–	–	–
(Hussein et al., 2019)	Bonn	sEEG and IEEG	Filtering, Segmentation	DA	Augmented EEG Signals	TensorFlow Keras	LSTM	10	Softmax	100	100	100	–
(Jaafar and Mohammadi, 2019)	Freiburg	IEEG	Normalization, Filtering, Shuffling, Segmenting and Reshaping	–	EEG Signals Segment	NA	LSTM	5	Softmax	97.75	–	–	–
(Hu et al., 2020c)	CHB-MIT	sEEG	Segmentation	Local Mean Decomposition (LMD), 10 Statistical Features Extraction	Feature Vectors	Python	Bi-LSTM	NA	Softmax	–	93.61	91.85	–
(Yao et al., 2019a)	CHB-MIT	sEEG	Segmentation	–	EEG Signals Segment	NA	ADIndRNN	10	NA	88.7	88.8	88.6	88.71

(Talathi, 2017)	Bonn	sEEG and IEEG	–	Auto-Correlation	EEG Signals Segment	Keras	GRU	–	LR	98	–	–	–
(Roy et al., 2019)	TUH	EEG	–	TCP	Raw EEG signals	NA	ChronoNet	–	Softmax	86.57	–	–	–
(Hussein et al., 2018b)	Bonn	sEEG and IEEG	Filtering	–	EEG Signals Segment	NA	LSTM	–	Softmax	100	100	100	–
(Geng et al., 2020)	Freiburg	IEEG	Segmentation	DA, Stockwell Transform	2D Spectrograms	TensorFlow MATLAB	Bi-LSTM	–	Softmax	98.91	98.08	98.91	–
(Fraiwan and Alkhodari, 2020)	Bern-Barcelona	IEEG	Normalization, Filtering	–	EEG Signals Segment	MATLAB	Bi-LSTM	10	Softmax	99.6	99.55	99.65	–
(Hu and Yuan, 2019)	Bonn	sEEG and IEEG	Filtering	Linear Feature Extraction	Linear Features	MATLAB	Bi-LSTM	–	Softmax	98.56	100	97.14	–
(Abbasi et al., 2019)	Bonn	sEEG and IEEG	Segmentation, Normalization, Standardization	DCT, Hurst Exponent and ARMA Features Extraction	Feature Vectors	NA	LSTM	–	Softmax	99.17	98.88	99.45	–
(Yao et al., 2021)	CHB-MIT	sEEG	Segmentation	–	EEG Signals Segment	–	Attention Bi-LSTM	10	Softmax	87.8	87.3	88.3	87.74
(Patan and Rutkowski, 2021)	Clinical	sEEG	Segmentation	–	EEG Signals Segment	MATLAB	LSTM	–	Softmax	97.9	–	–	–
(Rajaguru and Prabhakar, 2018)	Clinical	EEG	Segmentation	–	EEG Signals Segment	NA	AE with EM-PCA	–	GA	93.92	96.11	91.73	–
(Sharathappriyaa et al., 2018)	Bonn	sEEG and IEEG	Filtering	HWPT, FD	Feature Vectors	MATLAB	AE	–	Softmax	98.67	98.18	100	–
(Emami et al., 2019a)	Clinical	sEEG	Down Sampling, Filtering, Normalization	–	EEG Signals Segment	TensorFlow	AE	–	Sigmoid	–	100	–	–
(Yuan et al., 2017)	CHB-MIT	sEEG	–	STFT	2D Spectrograms	NA	SSDA	–	Softmax	93.82	–	–	
(Qiu et al., 2018)	Bonn	sEEG and IEEG	Segmentation, Z-Normalization, Standardization	–	EEG Signals Segment	MATLAB	DSAE	–	LR	100	100	100	–
(Golmohammadi et al., 2019)	TUH	sEEG	–	Different Methods	A Vector of 6 Posterior Probabilities	Theano	SDA	–	LR	–	90	–	–
(Yan et al., 2016)	Bonn	sEEG and IEEG	Filtering	–	Raw EEG signals	NA	SAE	–	SVM	100	100	100	–
(Lin et al., 2016)	Bonn	sEEG and IEEG	Segmentation, Normalization	–	EEG Signals Segment	NA	SSAE	–	Softmax	100	100	100	–
(Yuan et al., 2019)	CHB-MIT	sEEG	Segmentation	Scalogram	2D Scalograms	Theano	Wave2Vec	–	Softmax	93.92	–	–	96.05
(Gasparini et al., 2018)	Clinical	EEG	Filtering	CWT, Feature Extraction	Feature Vectors	NA	SAE	–	Softmax	86.5	88.8	90.7	–

(Karim et al., 2018a)	Bonn	sEEG and IEEG	–	Taguchi Method	Raw EEG signals	NA	SSAE	–	Softmax	99.8	–	–	–
(Karim et al., 2019)	Clinical	EEG	–	Dimension Reduction, ESD	Feature Vectors	NA	DSAEs	–	Softmax	100	–	–	–
(Karim et al., 2018b)	Bonn	sEEG and IEEG	–	DWT	Feature Vectors	NA	SAE	–	Softmax	96	–	–	–
(Yuan et al., 2018c)	CHB-MIT	sEEG	–	Different Methods	2D Spectrograms	NA	SAEs	–	Softmax	96.61	–	–	97.85
(Sharma et al., 2020)	Bonn	sEEG and IEEG	–	Raw EEG Signals in to 2D Space using the Third-Order Cumulant	ToC Coefficients	NA	SAE	–	Softmax	100	100	100	–
(Siddharth et al., 2020)	Bern-Barcelona	IEEG	Standard Preprocessing	FBSE-EWT	Raw EEG signals	NA	SAE	5	SVM	100	100	100	–
(Le et al., 2018)	Clinical	EEG	–	DWT	Waveform Features	MATLAB	DBN	–	NA	–	87.35	97.89	–
(Turner et al., 2017)	Clinical	EEG	Normalization, Standardization	Feature Extraction	Feature Vectors	Theano	DBN	–	LR	85	–	–	–
(Tang et al., 2020)	CHB-MIT	sEEG	Segmentation	Decomposition, Multi-View Feature Extraction	3 Feature Sets (Local Fractal Spectrum, Relative Band Energy, Synchronization Modularity)	NA	Multi-View CNN-GRU	–	Softmax	–	94.5	–	–
(Thodoroff et al., 2016)	CHB-MIT	sEEG	–	Image Based Representation	2D Data	NA	2D CNN-LSTM	–	NA	–	–	–	–
(Saqib et al., 2020)	TUSZ		Resampling, Filtering, Segmentation	DA	1000×21	NA	2D CNN-LSTM	–	Softmax	–	86	–	65.1
(Choi et al., 2019)	CHB-MIT SNUH	sEEG	–	STFT, 2D-mapping	2D Spectrograms	NA	3D-CNN_ Bi GRU	–	NA	99.40	89.00	99.50	–
(Liang et al., 2020)	CHB-MIT	sEEG	–	Converted Into a Series of Two Seconds Waveform Images	EEG Signals Segment	NA	LRCN	–	Softmax	99	84	99	–
(Roy et al., 2018)	TUH	sEEG	Various Preprocessing Technique	–	EEG Signals Segment	NA	1D-CNN-RNN	–	Softmax	70.39	–	–	–
(Golmohammadi et al., 2017)	TUH Clinical	sEEG	Segmentation, Filtering	Feature Extraction, left to right channel independent GMM-HMM, PCA, IPCA	EEG Signals Segment (210 frames of EEGs)	NA	CNN-LSTM	–	Different Activation Functions	–	39.09	76.84	–

(Li et al., 2020b)	Bonn Freiburg CHB–MIT	sEEG and IEEG IEEG sEEG	Segmentation, Resizing	–	EEG Signals Segment	Keras TensorFlow	FC-NLSTM	10	Softmax	100	100	100	–
(Liu et al., 2020b)	UCI	sEEG	Segmentation	–	EEG Signals Segment	NA	C-LSTM	–	Softmax	98.8	100	–	100
(Yang et al., 2021)	Clinical	Long-Term Video-EEG Monitoring	Segmentation, Resizing	–	224 x 224-Pixel Resolutions	Keras, TensorFlow	CNN-LSTM	–	Sigmoid	–	88	92	–
(Xu et al., 2020a)	UCI	sEEG	Normalization	–	Raw EEG signals	–	1D CNN-LSTM	–	Softmax	99.39	–	–	98.59
(Yuan et al., 2018b)	CHB-MIT	sEEG	–	DA, STFT	2D Spectrograms	PyTorch	CNN-AE	5	Softmax	94.37	–	–	85.34
(Wen and Zhang, 2018)	Bonn CHB-MIT	sEEG and IEEG sEEG	Channel Selection	–	Raw EEG signals	NA	CNN-AE	10 5	Different Methods	92.00	–	–	–
(Abdelhameed et al., 2018)	Bonn	sEEG and IEEG	Segmentation	–	EEG Signals Segment	NA	1D-CNN-AE	–	MLP/LSTM/ Bi-LSTM	100	100	100	–
(Antoniades et al., 2018)	Clinical	sEEG	–	Mapping	EEG Signals Segment	Theano	ASAE-CNN AAE-CNN	–	LR	68.00	67.00	68.00	68.00
(Yuan and Jia, 2019)	CHB-MIT	sEEG	–	STFT	2D Spectrograms	PyTorch	CNN-AE	5	Softmax	96.22	–	–	89.53
(Daoud and Bayoumi, 2019)	Bonn Bern Barcelona	sEEG and IEEG IEEG	Segmentation, Filtering, Normalization	DA	EEG Signals Segment	NA	DCAE DCVAE	10	MLP K-means clustering	96.00	93.00	99.00	–
(Shoeibi et al., 2021)	Bonn	sEEG and IEEG	Filtering, Segmentation	Feature Extraction (Time, Statistical, Non-Linear), Feature Selection (Fisher Feature Scoring Algorithm)	Feature Vectors (20 Most Important Features)	TensorFlow	CNN-AE	–	Softmax	99.53	–	–	–
(Takahashi et al., 2020)	Clinical	sEEG	Filtering, Segmentation	–	EEG Signals Segment	–	CNN-AE	–	Softmax	99.6	–	–	52.6

Table 3: Summary of related works done using medical imaging methods and DL.

Work	**Dataset**	**Modalities**	**Preprocessing**	**Preprocessing Toolbox**	Input Network	DNN	**DNN toolbox**	Classifier	K-fold	Performance criteria (%)			
										Acc	**Sens**	**Spec**	**F1-S**
(Dev et al., 2019)	SCTIMST	MRI	Noise Reduction with BM3D Algorithm, Skull-Stripping, FCD Lesion Segmentation	FSL	256 × 256 Image Size	FCN	Keras TensorFlow	Sigmoid	5	–	–	–	–
(Gill et al., 2018)	Clinical	MRI	Different Methods	NA	3D Patches	Two-Stage CNNx Cascade	NA	Softmax	5	–	87	90	–
(Hao et al., 2018)	Clinical	EEG-fMRI	Filtering, ICA, BCG, GLM, MCS	Brain Vision Analyzer Software	IEDs	ResNet	NA	Triplet	– Softmax	–	–	84.40	–
(Hosseini et al., 2017)	Clinical	EEG/ECoG rs-fMRI	Different Methods	NA	Preprocessed EEG and fMRI Data	2D-CNN	NA	SVM	–	–	–	–	–
(Yan et al., 2018)	Clinical	MRI	Scaling Down	NA	Raw MRI Data	3D-CNN	NA	Softmax	5	98.8	–	–	–
(Gleichgerrcht et al., 2018)	Clinical	MRI	Preprocessing the Connectivity Matrix, Construction of The SZ And SZF Binary Masks, Applying Masks to Reduce Dimensionality of Input Connectivity Matrix	NA	SZ and SZF Binary Masks	2D-CNN	NA	Softmax	–	–	–	–	–
(Jiang et al., 2019a)	Clinical	PET	ROI, Normalization, AAL, CNNI, Down-sampling, NNI (3D images)	NA	2D ROI 3D ROI	2D-ResNet 50 2D-VGG 16 2D-Inception V3 3D-SVGG-C3D	TensorFlow Keras	Sigmoid	–	98.22	97.27	98.86	–
(Shiri et al., 2019)	Clinical	PET	OSEM, DA Radionics Features	NA	Non-Attenuation-Corrected (NAC) 2D PET Image Slices	Deep-DAC	TensorFlow	Tanh	–	–	–	–	–
(Wang et al., 2020a)	Clinical	MRI	Bias Field Correction, Skull-Stripping, Intensity Normalization, Patch Extraction, DA	NA	Patches	CNN	MATLAB	Softmax	–	88	90	85	–
(Shakeri et al., 2016)	a Rolandic Epilepsy (RE) study	MRI	Resizing, DA	NA	Single 2D Slice	FCN	MATLAB	Softmax	–	–	–	–	–
(Figini et al., 2020)	HCP Dataset	MRI	Simulated LF Images from HF References	NA	Paired HF and Simulated LF Images	Aniso-U-Net	NA	–	–	–	–	–	–
(Pominova et al., 2018)	Clinical	sMRI, rs-fMRI	Resizing, Denoising	SPM, FSL	3D Scans	VoxCNN-B	NA	Softmax	5	–	–	–	–

(Xu et al., 2019)	Clinical	DWI, fMRI	Different Methods	SPM, FSL	DWI Streamline Coordinate	DCNN-CL-ATT	PyTorch	Softmax	–	–	–	–	–
(Torres-Velázquez et al., 2020)	ECP Project	sMRI, rs-fMRI and task-fMRI, PDC data	Minimal Pre-Processing Pipelines For The Human Connectome Project (HCP) Version 3.4.0	FSL	sMRI Features, rs-fMRI and task-fMRI Based ROI Correlation Matrices, and PDC	Multi-Channel Deep Neural Network (mDNN)	Keras	Output Layer	10	72.86	–	–	–
(Rebsamen et al., 2020)	Inselspital	MRI	Ground Truth Generation using FreeSurfer, Skull-Stripping, Re-Sampled and Cropped, Re-Scaled, DA	FreeSurfer	Preprocessed MRI	3D-CNN	TensorFlow	–	–	–	–	–	–
(Si et al., 2020)	Clinical	Diffusion MRI	Standard Preprocessing, Generate The Connectivity Matrix using HARDI and (NODDI) Methods	MRIcro, MRtrix3, DSI studio, NODDI toolbox	Connectivity-Strength Based Weight ICVF	Inception_ResNet_v2	NA	Softmax	–	75.2	–	–	–
(Huang et al., 2020)	Clinical	MRI	Series of Standard Preprocessing Procedures, Hippocampus Mask, FA, MD, and MK of Hippocampus	SPM8, MATLAB R2017a	FA, MD, and MK Slice-Level	VGG16	–	SVM	5	90.8	89.29	93.5	–
(Lee et al., 2020)	Clinical	DWI	Series of Different Preprocessing Procedures	FreeSurfer, FSL, MRtrix3 package, ANTs package, QuickBundles package	14 ESM	DCNN	PyTorch	Softmax	–	92	–	–	99.3

Table 4: Details for DL Networks for Epileptic Seizures Detection.

Work	**Networks**	**Network Details**	**Classifier**	**Optimizer**	**Loss Function**
(Antoniades et al., 2016)	2D-CNN	1 Conv Layer + 1 FC Layer 2 Conv Layers + 1 FC Layer	LR	NA	NA
(Qin et al., 2020b)	2D-CNN	3 Conv Layers + 3 Max Pooling Layers + 3 BN Layers + 1 FC Layer + ReLU activation function	ELM	NA	NA
(Park et al., 2018)	Combination of 1D-CNN and 2D-CNN	6 1D Conv Layers + 3 2D Conv Layers + 3 Max Pooling Layers + 2 FC Layers	Sigmoid	Sum-Squared Error	Proposed Loss Function
(Tjepkema-Cloostermans et al., 2018)	2D-CNN	6 Conv Layers + 6 Dropout Layers + 3 Max Pooling Layers + 2 FC Layers	Softmax	Adam	Categorical Cross Entropy (CCE)

(Avcu et al., 2019)	SeizNet	4 Conv Layers + 4 Max Pooling Layers + 5 Dropout Layers + 4 BN Layers + 1 FC Layer	Dense Layer	Adam	Binary Cross Entropy (BCE)
(Zhan and Hu, 2020)	DCNN	4 Conv Layers + 4 FC Layers	Multiview Fuzzy Clustering Method	NA	NA
(Nejedly et al., 2019)	CNN	6 Conv Layers + 6 BN Layers + 3 Dropout Layers + 3 FC Layers	Softmax	Adam	CE
(Hossain et al., 2019)	2D-CNN	4 Conv layers + 2 Max Pooling Layers + 4 BN Layers + 1 Dropout Layer	Softmax	Minibatch SGD	NA
(Mao et al., 2020)	2D-CNN	3 Conv layers + 3 pooling layers + ReLU activation function	Softmax	NA	NA
(Zuo et al., 2019)	2D-CNN	4 Conv Layers + 4 BN Layers + 3 Max Pooling Layers + 1 Dropout Layer + 2 FC Layers	Softmax	Minibatch SGD	CE
(Asif et al., 2019)	SeizureNet	52 Conv Layers + 5 Pooling Layers + 51 BN Layers + 24 Dropout Layers	Softmax	Adam	Proposed Loss Function
(Iešmantas and Alzbutas, 2020)	2D-CNN	1 Conv Layer + 1 subsampling Layer+ 1 FC layer	Softmax	Adam	CE
(Zeng et al., 2021)	GRP-DNet	DenseNet: 1 Conv Layer + 3 Dense Blocks + 2 Transition Layers + 3 Global Average Pooling Layers + 1 FC Layer	Softmax	Adam	CE
(San-Segundo et al., 2019)	2D-CNN	2 Conv Layers + 1 Max Pooling Layer +4 Dropout Layers + 2 FC Layers	Softmax	Root-Mean Square Propagation Method	CCE
			Sigmoid		
(Sui et al., 2019)	2D-CNN	5 Conv Layers + 5 Max Pooling Layers + 5 FC Layers	Softmax	NA	NA
(Chatzichristos et al., 2020)	Attention-Gated U-Net	15 Conv Layers + 6 Max Pooling Layers + 5 Average Pooling Layers + 6 Up Sampling Layers + 5 Gating Signals + 5 Attention Gates	Bi-LSTM + FC Layer		Regular Cross-Entropy, Weighted Cross-Entropy
(Covert et al., 2019)	TGCN	4 STC Layers + 5 Pooling Layers + 4 BN Layers + 2 FC Layers + 1 Dropout Layer	Sigmoid	SGD	CE
		8 STC Layers + 5 Pooling Layers + 4 BN Layers + 2 FC Layers + 1 Dropout Layer			
		12 STC Layers + 5 Pooling Layers + 4 BN Layers + 2 FC Layers + 1 Dropout Layer			
		16 STC Layers + 5 Pooling Layers + 4 BN Layers + 2 FC Layers + 1 Dropout Layer			
(Akut, 2019)	2D-CNN	4 Conv Layers + 2 Max Pooling Layers+ 8 BN Layers + 4 Dropout Layers + 4 FC Layers	Softmax	NA	NA
(Türk and Özerdem, 2019)	2D-CNN	2 Conv Layers + 2 Max Pooling Layers	Softmax	Adadelta	NA
(Liu and Woodson, 2019)	2D-CNN	3 Conv Layers + 3 BN Layers + 2 Max Pooling Layers + 1 FC Layer	Softmax	NA	NA
(Tian et al., 2019)	2D-CNN	4 Conv Layers + 3 FC Layers	MV-TSK-FS	NA	CE
		2 Conv Layers + 3 FC Layers			
	3D-CNN	4 Conv Layers + 4 FC Layers			
(Bouaziz et al., 2019)	2D-CNN	3 Conv Layers + 2 Max Pooling Layers + 1 FC Layer	Softmax	SGD	
(Prasanth et al., 2020)	1D-CNN, 2D-CNN	NA	NA	NA	NA
(Ansari et al., 2019)	2D-CNN	7 Conv Layers + 8 Pooling Layers + 2 FC Layers	Sigmoid	NA	NA
		5 Conv Layers + 8 Pooling Layers	RF		
(Cao et al., 2019)	SCNN	2 Conv Layers + 2 Max Pooling Layers + 1 Dropout Layer + 2 FC Layers	KELM	SGD	NA

(Taqi et al., 2017)	GoogleNet AlexNet LeNet	Standard Network	Softmax	NA	CE
(Emami et al., 2019b)	2D-CNN	VGG-16	Softmax	Adam	NA
(Bizopoulos et al., 2019)	2D-CNN 1D-CNN	Standard Networks	Softmax	NA	NA
(Thanaraj et al., 2020)	AlexNet, VGG-16, VGG-19	Standard Network	Softmax	NA	NA
	Custom CNN	3 Conv Layers, 1 BN Layer + 1 Max-Pooling Layer + 2 FC Layers	Softmax		
(Zhang et al., 2020a)	VGG-16 VGG-19 ResNet-50	Standard Network + 2 Trainable FC Layers	Softmax	SGD	Softmax Cross Entropy (SCE)
(Cho and Jang, 2020)	2D-CNN	2 Conv Layers + 2 Max Pooling Layers + 2 FC Layers + 2 Dropout Layers	Output Layer	Adam	NA
	1D-CNN	2 Conv Layers + 2 Max Pooling Layers + 2 FC Layers + 2 Dropout Layers			
	LSTM	1 LSTM Layer + 1 Pooling Layer + 1 FC Layer			
(Liu et al., 2020a)	2D-CNN	4 Conv Layers + 4 BN Layers + 3 Max Pooling Layers + 1 FC Layer + 2 Dropout Layers	Softmax	Adam	CE
(Bouallegue et al., 2020)	2D-CNN	Conv Layers + Max Pooling Layers + FC Layers + Dropout Layer + ReLU Activation Function	Softmax	Adam	MSE
	RNN-GRU	2 GRU Layers + 1 FC Layer + ReLU Activation Function	NA		
(Raghu et al., 2020)	Inception-V3	Standard Network + Final Three Layers Replaced	SVM	SGDM, RMSProp, Adam	NA
(Li et al., 2020a)	CE-stSENet	Proposed Architecture	MLP	Adam	CE
(Usman et al., 2020)	2D-CNN	3 Conv Layers + 3 BN Layers + 3 Max Pooling Layers + 1 Dropout Layer	SVM	NA	NA
(Ilakiyaselvan et al., 2020)	AlexNet	Standard Network	Softmax	SGD	CE
(Bhagat et al., 2020)	ResNet-50	Modified	Softmax	Adam	Categorical CE
(George et al., 2020)	ResNet	Standard Network	Softmax	NA	NA
(Gao et al., 2020b)	Inception-ResNet-v2 Inception-v3 ResNet152	Standard Network + 2 FC Layers	Softmax	NA	OHEM
(Singh et al., 2020)	2D-CNN	2 Conv Layers + 2 BN Layers + 1 Max-Pooling Layer + 1 FC Layer	Softmax	SGD	NA
(Bhattacherjee, 2020)	Multi Column CNN	–	Softmax	NA	NA
(Lian et al., 2020)	Combination of 1D-CNN and 2D-CNN	2 1D-Conv Layers + 3 2D-Conv Layers + 1 FC Layer	Softmax	NA	SLF

(Madhavan et al., 2019)	2D-CNN	5 Conv Layers + 5 Pooling Layers + 5 FC Layers	Softmax	SGD	CE
(Sakai et al., 2020)	ScalpNet	11 Conv Layers + 10 Dropout Layers + 1 FC Layer	Sigmoid	NA	Focal Loss
(Hussein et al., 2020)	SDCN	6 SDC Blocks+ 2 FC Layers	Sigmoid	Adam	BCE
(Kaya, 2020)	Combination of AlexNet and VGG16	Standard Networks	KNN	NA	NA
(Shankar et al., 2020)	2D-CNN	3 Conv Layers + 4 BN Layers + 1 Dropout Layer + 3 Max Pooling Layers + 1 FC Layer	Sigmoid	SGD	BCE
(Rashed-Al-Mahfuz et al., 2021)	FT-VGG16	Fine-tuning VGG16	Softmax	RMSprop	–
(Hu et al., 2020a)	Different Pre-Train Nets	Standard Versions	Softmax	Mini-Batch Gradient Descent (MBGD)	CE
	HNN	3 Cascaded Learning Blocks			
(Glory et al., 2020)	AHW-BGOA-DNN	NA	Softmax	Adaptive Optimization, SGD with CLRA	CCE
(MohanBabu et al., 2020)	ODLN	2 ODLN Layers + 2 Dropout Layers + Avg Pooling Layer	Softmax	Adam	CCE
(You et al., 2020)	AnoGAN	Generator: 4 Transposed Conv Layers + 4 BN layers, Discriminator: 4 Conv Layers+ 4 BN Layers	Combination of Anomaly Loss and a Gram matrix	SGD	Sigmoid Cross Entropy (SCE)
				Adam	
(Truong et al., 2019)	DCGAN	Generator: FC Layer+ Reshape Layer+ 3 de-Conv Layers, Discriminator: 3 Conv Layers + Flatten Layer+ FC Layer, Classifier: 2 FC Layers + 2 Dropout Layers	Softmax	Adam	NA
(Pascual et al., 2019)	conditional GAN	Generator: 8 Conv Layers + 8 Max Pooling Layers + 8 de-Conv Layers + 8 Dilations Layers, Discriminator: 8 Conv Layers + 8 Max Pooling Layers + 8 de-Conv Layers + 8 Dilations Layers + 1 FC Layer	RF	Adam	LSGAN
(Torfi and Fox, 2020)	CorGAN	CorGAN with Proposed Layers		NA	BCE
(Sharan and Berkovsky, 2020)	1D-CNN	3 Conv Layers + 3 Max Pooling Layers + 1 FC Layer + ReLU Activation Function	Softmax	Adam	
(Hu et al., 2020b)	Different Pre-Train Nets	Modified models		7-Layer HNN	Mini-Batch Gradient Descent (MBGD)
(Ullah et al., 2018)	P-1D-CNN	3 Conv Layers + 3 BN Layers + 1 Dropout Layer + 2 FC Layers	majority voting	Adam	CE
(Acharya et al., 2018)	1D-CNN	5 Conv Layers + 5 Max Pooling Layers + 2 FC Layers	Softmax	NA	NA
(Wang et al., 2020b)	Time-ResNeXt	Not Reported	Softmax	Adam	CE
(Page et al., 2016)	MPCNN	1-3 pairs of Conv and Max Pooling Layers + 1-3 FC Layers + Dropout	Softmax	NA	NA
(Zhang et al., 2020b)	MNLN	3 Conv Layers + 3 BN Layers + 2 Max Pooling Layers + 1 Signal Pooling Layer + 1 Multi-Scale Non-Local Layer + 2 FC Layers + RELU Activation Function	Softmax	Adam	CE
(O'Shea et al., 2017a)	1D-FCNN	6 Conv Layers + 1 BN Layer + 3 Pooling Layers	Softmax	SGD	CCE

(Thomas et al., 2020b)	1D-CNN	2 Conv Layers + Max Pooling Layer + 2 FC Layers + Dropout Layer + ReLU Activation Function	Softmax	Adam	CE
(O'Shea et al., 2017b)	1D-CNN	3 Conv Layers + 1 FC Layer + 1 Dropout Layer	Binary LR	SGD	BCE
(Yıldırım et al., 2018)	1D-CNN	10 Conv Layers + 5 Max Pooling Layers + 2 Dropout Layers + 1 BN Layer + 1 FC Layer	Softmax	Adam	CCE
(Zhao and Wang, 2020)	SeizureNet	10 Conv Layers + 10 BN Layers + 6 Max Pooling Layers + 1 FC Layer + 1 Dropout Layer + ReLU Activation Function	Softmax	Adam	Binary CE
(Akyol, 2020)	Stacked Ensemble based DNN modeling	3 Hidden Layers + ReLU Activation Function	Meta Learner	Adam	NA
(Thomas et al., 2018)	1D-CNN	1 Conv Layer + 1 Pooling Layer + 1 FC Layer + 1 Dropout Layer	SVM	Adam	NA
(Uyttenhove et al., 2020)	T-VGG	6 Conv Layers + 6 BN Layers + 3 Max Pooling Layers + 1 FC Layer + ReLU Activation Function	Output Layer	Adam	Binary Cross-Entropy
(Boonyakitanont et al., 2019)	1D-CNN	11 Conv Layers + 5 BN Layers + 5 Max Pooling Layers + 3 Dropout Layers + 8 FC Layers	NA	NA	NA
(Chen et al., 2018)	1D-CNN	1 Conv Layer+ 1 Max Pooling Layer + 1 FC Layer	Sigmoid	Adam	CE
(Zhang et al., 2020e)	DWT-Net	8 2D-Conv Layers + 8 1D-Conv Layers + 4 Max Pooling Layers + 4 Dropout Layers + Concatenation + 3D- Conv Layer + Max Pooling Layer + 2 FC Layers + ReLu Activation Function	Softmax	Adam	Weighted Cross-Entropy
(Zhang et al., 2018)	1D-TCNN	NA	NA	NA	NA
(Zhao et al., 2020a)	BSDCNN	5 Conv Blocks + 5 BN Layers + 2 FC Layers	Sigmoid	NA	NA
(Daoud et al., 2018)	1D-CNN	5 Conv Layers + 5 Max Pooling Layers + 1 FC Layer	Softmax	Gradient Descent Algorithm	BCE
(Daoud et al., 2020)	DCNN	4 Conv Layers + 3 Max Pooling Layers + 4 BN Layers + RELU Activation Function	NA	NA	NA
(Lu and Triesch, 2019)	1D-CNN with Residual connections	5 Conv Layers + 3 Max Pooling Layers + 3 BN Layers + 4 Dropout Layers + 1 FC Layer	Softmax	Adam	NA
(Craley et al., 2019)	1D-PGM-CNN	4 Conv Layers + 4 Max Pooling Layers + 1 FC Layer	Softmax	Adam	CE
(Wei et al., 2019)	1D-CNN	5 Conv Layers + 5 Max Pooling Layers + 3 Dropout Layers + 1 FC Layer	Softmax	Adam	NA
(Qin et al., 2020a)	1D-CNN	3 Conv Layers + 2 Dilated Conv Layers + 3 Max Pooling Layers + 3 FC Layers + 3 Dropout Layers + ReLU Activation Function	Softmax	Adam	CE
(Meisel et al., 2019)	1D-CNN	4 Conv Layers + 2 Pooling Layers + 3 Dropout Layers	Sigmoid	NA	NA

(Zhang et al., 2020c)	CNN	1 Conv Layer + 1 Max Pooling Layer + ReLU Activation Function + de-Conv Layer	–	Adam	MSE
		4 Conv Layers + 4 Max Pooling Layers + 2 FC Layers + 1 Dropout Layer + Attention Mechanism	Sigmoid		CE Multi-Class CE
(Yuvaraj et al., 2018)	1D-CNN	5 Conv Layers + 5 Pooling Layers + 1 FC Layer	Softmax	Adam	CE
(Abou Jaoude et al., 2020)	CNN-BP	3 Conv Layers + 3 Max Pooling Layers + 3 Dropout Layers + 1 GC Layers	Sigmoid	Adam	Log (CE)
(Fukumori et al., 2019)	LSTM GRU	Reshape Layer + 4 LSTM/GRU + 1 FC Layer	Sigmoid	NA	NA
	1D-CNN	Primary Conv Layer + 4 Conv Layers + 4 Max Pooling Layers + 1 FC Layer	Sigmoid	NA	NA
(Guha et al., 2020)	DNN	5 Hidden Layers	NA	NA	NA
(Kaziha and Bonny, 2020)	1D-CNN	5 Conv Layers + 5 BN Layers + 5 Avg Pooling Layers + 2 FC Layers	Sigmoid	RMSprop	NA
(Truong et al., 2020)	BCNN	3 Conv Blocks + 2 FC Layers	Softmax	ELBO	Negative of ELBO
(Zhao et al., 2020c)	1D-CNN	4 Conv Layers + 3 Max Pooling Layers + 1 FC Layer	NA	NA	NA
(Boonyakitanont et al., 2020b)	1D-CNN	14 Conv Layers + 7 BN Layers + 7 Max Pooling Layers + 2 Dropout Layers + 2 FC Layers	Onset-offset Detection Method	NA	NA
(Khalilpour et al., 2020)	1D-CNN	2 Conv Layers + 2 Pooling Layers + 1 Dropout Layer + 1 FC Layer	Softmax	NA	NA
(Zhao et al., 2020b)	1D-CNN	3 Conv Layers + 3 BN Layers + 5 Dropout Layers + 3 Max Pooling Layers + 2 FC Layers	Softmax	Adam	CE
(Abiyev et al., 2020)	1D-CNN	8 Conv Layers + 4 Pooling Layers + 1 Dropout Layer + 2 FC Layers	Softmax	RMSprop	Proposed Loss Function
(Pisano et al., 2020)	1D-CNN	4 Convolutional Units + 2 Pooling Layers + 1 FC Layer	Softmax	SGD	NA
(Lu et al., 2020)	DNN	16 Blocks with Residual Connections	Softmax	NA	NA
(Xu et al., 2020c)	CNN	5 Conv Layers + 5 Max Pooling Layers + 1 Dropout Layer + 2 FC Layers	Softmax	Adam	BCE
(Lin et al., 2020)	Deep ConvNet	5 Conv Layers + 5 Max Pooling Layers + 2 BN Layers + 2 FC Layers	Softmax	NA	NA
(Jana et al., 2020)	1D-CNN	3 Conv Layers + 3 BN Layers + 2 Pooling Layers + 1 Dropout Layer	Softmax	NA	NA
(Gao et al., 2020a)	1D-CNN	2 Conv Layers + 2 Subsampling Layers + 2 FC Layers	Gaussian Connection	Adam	BCE
(Thomas et al., 2020a)	1D-CNN	2 Conv Layers + 1 Max Pooling Layer+ 2 FC Layers	NA	Adam	NA
(Vance et al., 2020)	1D-CNN	2 Conv Layers + 1 BN Layer + 1 DownSampling Layer + 5 Pre-Activation Residual Blocks + 1 MaxGlobal Pooling Layer	Sigmoid	SGD	BCE
(Liu and Richardson, 2020)	LSTM	1 Conv Layer + 1 Max Pooling Layer + 1 Dropout Layer + Bi LSTM Layer + 3 FC Layers	Sliding WMV	NA	NA
	1D-CNN	3 Conv Layers + 3 Max Pooling Layers + 2 Dropout Layers + 3 FC Layers			

(Vidyaratne et al., 2016)	DRNN	DRNN Layers	MLP with 2 Layers	Jacobian free Unscented Kalman filer-based parameter optimization method	NA
(Hussein et al., 2018c)	LSTM	1 LSTM Layer + 1 Time Distributed Dense Layer + 1 Average Pooling Layer	Softmax	Adam	CCE
(Ahmedt-Aristizabal et al., 2018b)	LSTM	1 LSTM Layer + 1 Dropout Layer + 1 FC Layer	Sigmoid	Adam	BCE
		2 LSTM Layers + 2 Dropout Layers + 2 FC Layers			
(Yao et al., 2019b)	1D-CNN	5 Conv Layers + 5 Max Pooling Layers + 3 FC Layers	NA	Adam	NA
	IndRNN	15 IndRNN Layers+ 15 BN Layers + 15 Max Pooling Layers + 1 Average Pooling + 2 FC Layers	NA	Adam	NA
	LSTM	1 LSTM Layer + 1 Time Distributed Computing Layer + 1 Average Pooling layer + 1 FC Layer	NA	Adam	NA
(Verma and Janghel, 2021)	RNN	2 GRU Layers + 1 FC Layer	LR	NA	NA
(Hussein et al., 2019)	LSTM	1 LSTM Layer + 1 Time Distributed FC Layer + 1 Average Pooling Layer	Softmax	Adam	CCE
(Jaafar and Mohammadi, 2019)	LSTM	1 LSTM Layer + 1 Time Distributed FC Layer	Softmax	NA	NA
(Hu et al., 2020c)	Bi-LSTM	Bi-LSTM Layer + dropout Layer	Softmax	Adam	Cross Entropy
(Yao et al., 2019a)	ADIndRNN	Attention Layer + 9 IndRNN Layers + 9 BN Layers+3 Max Pooling Layers+ 1 Avg Pooling Layers + 2 FC Layers	NA	Adam	NA
(Talathi, 2017)	GRU	2 GRU Layers + 1 Time Distributed FC Layer	LR	Adam	NA
(Roy et al., 2019)	GRU	4 GRU Layers	Softmax	Adam	NA
	C-RNN	3 Conv Layers + 4 GRU Layers			
	IC-RNN	9 Conv Layers + 4 GRU Layers			
	C-DRNN	3 Conv Layers + 4 GRU Layers			
	ChronoNet	9 Conv Layers + 4 GRU Layers			
(Hussein et al., 2018b)	LSTM	1 LSTM Layer + 1 FC Layer + 1 Max Pooling Layer	Softmax	SGD	CE
(Geng et al., 2020)	Bi-LSTM	1 Bi-LSTM Layer	Softmax	Adam	NA
(Fraiwan and Alkhodari, 2020)	Bi-LSTM	1 LSTM Layer + 2 FC Layers	Softmax	Adam	NA
(Hu and Yuan, 2019)	Bi-LSTM	Bi-LSTM Layer	Softmax	Adagrad	NA
(Abbasi et al., 2019)	LSTM	2 LSTM Layers + 2 Dropout Layers + FC Layer	Softmax	Adam	NA
(Yao et al., 2021)	Attention Bi-LSTM	Attention Layer + Bi LSTM Layer + Time-Distributed Fully-Connected Layer + Global Average Pooling Layer + Fully Connected Layer	Softmax	RMSprop	NA
(Patan and Rutkowski, 2021)	LSTM	4 LSTM layers + 4 dropout layers + 1 FC Layer	Softmax	Adam	NA
(Rajaguru and Prabhakar, 2018)	MAE	NA	GA	NA	NA
(Sharathappriyaa et al., 2018)	AE	2 Hidden Layers	Softmax	NA	MSE

(Emami et al., 2019a)	AE	1-layer AE consisting of an Encoder and a Decoder	Sigmoid	Adam	L2 Loss function
(Yuan et al., 2017)	SSDA	2 hidden layers (intra channel) & 3 hidden layer (cross channel) + 2 FC layers	Softmax	NA	CE
(Qiu et al., 2018)	DSAE	1 Hidden Layer	LR	SGD	NA
(Golmohammadi et al., 2019)	SPSW-SDA	Each Model has 3 Hidden Layers	LR	Mini Batch SGD	Cross Entropy
	6W-SDA				
	EYEM-SDA				
(Yan et al., 2016)	SAE	Single Layer	SVM	Batch Gradient Descent	NA
(Lin et al., 2016)	SSAE	3 Hidden Layers	Softmax	L-BFGS	Proposed Loss Function
(Yuan et al., 2019)	Wave2Vec	SAE Layer	Softmax	Adadelta	CE
	SSDAE	2 Hidden Layers	Softmax		
(Gasparini et al., 2018)	SAE	2 Hidden Layers	Softmax	NA	NA
(Karim et al., 2018a)	SSAE	2 Autoencoders	Softmax	Taguchi Method	
(Karim et al., 2019)	DSAEs	2 Autoencoders	Softmax	NA	MSE
(Karim et al., 2018b)	SAE	2 Autoencoders	Softmax	NA	NA
(Yuan et al., 2018c)	SAEs	2 Layers	Softmax	Adam	CE
(Sharma et al., 2020)	SAE	2 Hidden Layers	Softmax	NA	Proposed Loss Function
(Siddharth et al., 2020)	SAE	2 Hidden Layers	SVM	Proposed Optimization	NA
(Le et al., 2018)	DBN	1 Input Layer + 3 Hidden Layers + 1 Output Layer	NA	NA	NA
(Turner et al., 2017)	DBN	1 Input Layer + 2 Hidden Layers + 1 Output Layer	LR	NA	NA
(Tang et al., 2020)	MV CNN-GRU	9 Conv Layers + 9 BN Layers + 6 Max Pooling Layers + ReLU Activation Function + Attention Layer + GRU Layer + 1 FC Layer	Softmax	NA	CE
(Thodoroff et al., 2016)	2D-CNN-LSTM	4 Conv Layers + 2 Pooling Layers + 1 LSTM Layer + 1FC Layer	NA	RMSProp	Gradient Descent (GD)
(Saqib et al., 2020)	2D CNN-LSTM	6 Conv Layer + 6 Max Pooling Layers + 6 BN Layers + ReLU activation function + LSTM Layer + FC Layer + Dropout Layer	Softmax	Adam	NA
(Choi et al., 2019)	3D-CNN-BiGRU	–	NA	Adam	NA
(Liang et al., 2020)	LRCN	10 Conv layers + 5 Max-pooling layers + 1 LSTM Layer	Softmax	Adam	NA
(Roy et al., 2018)	2D-CNN	3 Conv Layers + 3 Max Pooling Layers + 1 FC Layer	Softmax	Adam	NA
	1D-CNN	5 Conv Layers			
	1D-CNN-RNN	3 Conv Layers + 3 GRU Layers			
	TCNN-RNN	3 Conv Layers + 3 Max Pooling + 2 GRU + FC Layers			

(Golmohammadi et al., 2017)	2D-CNN-BiLSTM	3 2D-Conv Layers + 3 2D-Max Pooling layers + 1D-Conv Layer + 1D-Max Pooling Layer +2 Bi-LSTM	Sigmoid	Adam	MSE
	LSTM	1 LSTM Layer	LR	MSGD	CE
	SdA	3 Hidden Layers	Sigmoid	NA	NA
(Li et al., 2020b)	FC-NLSTM	3 Conv Layers + 2 Pooling Layers + 1 NLSTM Layer + 1 FC Layer	Softmax	Adam	CCE
(Liu et al., 2020b)	C-LSTM	2 Conv Layers + 2 BN Layers + 2 Dropout Layers + 1 LSTM Layer + 2 FC Layers	Softmax	Adam	NA
(Yang et al., 2021)	CNN-LSTM	3 Conv Layers + 3 BN Layers + 2 Max Pooling Layers + 4 Dropout Layers + 3 FC Layers + 1 LSTM Layer	Sigmoid	Adam	BCE
(Xu et al., 2020a)	1D CNN-LSTM	4 Conv Layers + 1 Pooling Layer + 1 Dropout Layer + 2 LSTM Layers + 3 FC Layers	Softmax	NA	NA
(Yuan et al., 2018b)	CNN-AE	Encoder: 2 Conv Layers + 2 Pooling Layers, Decoder: 2 de-Conv Layers + 2 Unpooling Layers	Softmax	Adadelta	CE
(Wen and Zhang, 2018)	CNN-AE	Encoder: 3 Conv Layers + 3 Pooling Layers + 1 FC Layer, Decoder: 1 FC Layer + 4 de-Conv Layers + 3 de-Pooling Layers	Different Classifiers	Adam	Proposed Loss Function
(Abdelhameed et al., 2018)	1D-CNN-AE	8 Conv Layers + 3 Max Pooling Layers + 12 BN Layers + 3 Up sampling Layers	LSTM	Adam	BCE
			Bi-LSTM		
			MLP	Adadelta	MSE
(Antoniades et al., 2018)	CNN-ASAE	4 Conv Layers + 2 FC layers + 2 ASAE Hidden layers	LR	SGD	CE
	CNN-AAE	4 Conv Layers + 2 FC layers + 1 AAE Hidden layer			
(Yuan and Jia, 2019)	CNN-AE	16 Conv Layers + 15 Pooling Layers	Softmax	Adadelta	CE
(Daoud and Bayoumi, 2019)	DCAE	Encoder: 2 Conv Layers + 2 Pooling Layers + 2BN Layers, Decoder: 2 de-Conv Layers + 2 Upsamplign Layers + 2 BN Layers	MLP	RMSprop	MSE
	DCVAE	Encoder: 4 Conv Layers + 4 Pooling Layers + 4 BN Layers 2 FC Layers, Probabilistic Model Parameter Layer Decoder: 2 FC Layers + 4 de-Conv Layers + 4 Upsampling Layers + 4 BN Layers	K-means clustering	RMSprop	BCE
(Shoeibi et al., 2021)	CNN-AE	5 Conv Layers + 4 Pooling Layers + 3 BN Layers + 1 Dropout Layer	Softmax	Adadelta, SGD	NA
(Takahashi et al., 2020)	CNN-AE	1 AE Layer + VGG16	Softmax	NA	NA
(Dev et al., 2019)	FCN	15 Conv Layers + 7 BN Layers + 3 Max Pooling Layers + 3 de-Conv Layers+ 1 Dropout Layer	Sigmoid	Adam	Combination of BCE and the Dice Loss
(Gill et al., 2018)	Two-Stage CNNx Cascade	3 Conv Layers + 2 BN Layers + 3 Max Pooling Layers + 1 Dropout Layer	Softmax	Adadelta	BCE
(Hao et al., 2018)	ResNet	29 Conv Layers + 1 Dropout Layer + 1 FC Layer	Softmax	NA	NA
			Triplet		
(Hosseini et al., 2017)	2D-CNN	NA	SVM	NA	NA
(Yan et al., 2018)	2D-CNN	5 Conv Layers + 3 Max Pooling Layers + 1 BN Layer + 1 FC Layer	Softmax	Adam	NA
	3D-CNN	5 Conv Layers + 3 Max Pooling Layers + 1 BN Layer + 1 FC Layer			

(Gleichgerrcht et al., 2018)	2D-CNN	Proposed Architecture	NA	NA	NA
(Jiang et al., 2019a)	Combination of ResNet50, VGG16, Inception-V3, SVGG-C3D	VGG16 + Global Average Pooling 2D Layer	Different DL Layers	RMSprop	CE
		ResNet50 + Global Average Pooling 2D Layer			
		Inception-V3 + Global Average Pooling 2D Layer			
		SVGG-C3D + Global Average Pooling 2D Layer			
(Shiri et al., 2019)	Deep-DAC	9 Conv Layers + 11 BN Layers + 3 Max Pooling Layers +3 De-Conv Layers + 3 Dropout Layers	Tanh	Adam	MSE
(Wang et al., 2020a)	CNN	5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers	Softmax	SGDM	CE
(Shakeri et al., 2016)	FCN	7 Conv Layers + 7 holes + 5 Pooling Layers + 4 Dropout (0.5)	Softmax	SGD	Softmax loss
(Figini et al., 2020)	Aniso-U-Net	Proposed U-Net Architecture	–	–	mean voxel-wise square error (MVWSE)
(Pominova et al., 2018)	VoxCNN-B	4 Volumetric Convolutional Blocks + 4 Max Pooling Layers + 2 FC Layers + 1 Dropout Layer	Softmax	Adam	CE
(Xu et al., 2019)	DCNN-CL-ATT	1 Conv Layer + 1 BN Layer + 1 Max Pooling Layer + 4 ResBlocks + 1 Avg Pooling + 1 FC Layer + Dropout Layers + 4 Attention Units	Softmax	Adam	Focal loss, Center loss
(Torres-Velázquez et al., 2020)	mDNN	5 Parallel Neural Network Blocks + 1 Additional Neural Network Block + 2 Concatenation Blocks	Output Layer	Adam	BCE
(Rebsamen et al., 2020)	3D-CNN	3 Conv Layers + 3 Max Pooling Layers + 2 Dropout (0.4) + 3 FC Layers + ReLU Activation Function	–	Adam	MSE
(Si et al., 2020)	Inception _ResNet_v2	Modified Version	Softmax	Adam	CE
(Huang et al., 2020)	CNN	VGG16	SVM	NA	NA
(Lee et al., 2020)	DCNN	ResNet 18	Softmax	Adam	Proposed Loss

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