Applications of Epileptic Seizures Detection in Neuroimaging Modalities Using Deep Learning Techniques: Methods, Challenges, and Future Works

Afshin Shoeibi\textsuperscript{a,b,*}, Navid Ghassemi\textsuperscript{a,b}, Marjane Khodatars\textsuperscript{e}, Mahboobeh Jafari\textsuperscript{d}, Parisa Moridian\textsuperscript{d}, Roohallah Alizadehsani\textsuperscript{f}, Ali Khadem\textsuperscript{g}, Yinan Kong\textsuperscript{h}, Assef Zare\textsuperscript{i}, Juan Manuel Gorriz\textsuperscript{j}, Javier Ramírez\textsuperscript{j}, Maryam Panahiazar\textsuperscript{k}, Abbas Khosravi\textsuperscript{f}, Saeid Nahavandi\textsuperscript{f}

\textsuperscript{a}Faculty of Electrical Engineering, Clinical Studies Lab, K. N. Toosi University of Technology, Tehran, Iran.
\textsuperscript{b}Computer Engineering department, Ferdowsi University of Mashhad, Mashhad, Iran.
\textsuperscript{c}Department of Medical Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran.
\textsuperscript{d}Electrical and Computer Engineering Faculty, Semnan University, Semnan, Iran.
\textsuperscript{e}Faculty of Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.
\textsuperscript{f}Intelligent for Systems Research and Innovation (IISRI), Deakin University, Victoria 3217, Australia.
\textsuperscript{g}Faculty of Electrical Engineering, K. N. Toosi University of Technology, Tehran, Iran.
\textsuperscript{h}School of Engineering, Macquarie University, Sydney 2109, Australia.
\textsuperscript{i}Faculty of Electrical Engineering, Gonabad Branch, Islamic Azad University, Gonabad, Iran.
\textsuperscript{j}Department of Signal Theory, Networking and Communications, Universidad de Granada, Spain.
\textsuperscript{k}University of California San Francisco, San Francisco, CA, USA.

Abstract

Epileptic seizures are a type of neurological disorder that affect many people worldwide. Specialist physicians and neurologists take advantage of structural and functional neuroimaging modalities to diagnose various types of epileptic seizures. Neuroimaging modalities assist specialist physicians considerably in analyzing brain tissue and the changes made in it. One method to accelerate the accurate and fast diagnosis of epileptic seizures is to employ computer aided diagnosis systems (CADS) based on artificial intelligence (AI) and functional

\textsuperscript{*}Corresponding author

Email addresses: afshin.shoeibi@gmail.com (Afshin Shoeibi), navidghassemi@mail.um.ac.ir (Navid Ghassemi), khodatars1marjane@gmail.com (Marjane Khodatars), mahbube.jafari@yahoo.com (Mahboobeh Jafari), parisamoridian@yahoo.com (Parisa Moridian), ralizadehsani@deakin.edu.au (Roohallah Alizadehsani), alikhadem@kntu.ac.ir (Ali Khadem), yinan.kong@mq.edu.au (Yinan Kong), assefzare@gmail.com (Assef Zare), gorriz@ugr.es (Juan Manuel Gorriz), javierrp@ugr.es (Javier Ramírez), Maryam.Panahiazar@usf.edu (Maryam Panahiazar), abbas.khosravi@deakin.edu.au (Abbas Khosravi), saeid.nahavandi@deakin.edu.au (Saeid Nahavandi)
and structural neuroimaging modalities. AI encompasses a variety of areas, and one of its branches is deep learning (DL). Not long ago, and before the rise of DL algorithms, feature extraction was an essential part of every conventional machine learning method, yet handcrafting features limit these models’ performances to the knowledge of system designers. DL methods resolved this issue entirely by automating the feature extraction and classification process; applications of these methods in many fields of medicine, such as the diagnosis of epileptic seizures, have made notable improvements. In this paper, a comprehensive overview of the types of DL methods exploited to diagnose epileptic seizures from various neuroimaging modalities has been studied. Additionally, rehabilitation systems and cloud computing in epileptic seizures diagnosis applications have been exactly investigated using various modalities.

Keywords: Epileptic Seizures, Diagnosis, Neuroimaging, Deep Learning, 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, 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 (Misiunas 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 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
Figure 2: Showing different types of general and focal epileptic seizures (Ngoh and Parker, 2017).

(fMRI) (Vaughan and Jackson, 2020) Garner et al., 2019, magnetoencephalography (MEG) (Colon et al., 2018) Ramp 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.

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 (Birjand-talab 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 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.

![Deep Learning Techniques Diagram](image)

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.
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 \cite{Ihle2012}, CHB-MIT \cite{Shoeb2009}, Kaggle \cite{George2020}, Bonn \cite{Andrzejak2001}, Flint-Hills \cite{Assi2017}, Bern-Barcelona \cite{Andrzejak2012}, Hauz Khas \cite{Assi2017}, and Zenodo \cite{Stevenson2019} 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                 | Continuous intracranial long term ECoG | 1419                  | 249                     |
| Hauz Khas (Assi et al., 2017) | 10                | NA                 | Scalp EEG (sEEG)            | NA                   | 200                     |
| Freiburg (Hilde et al., 2012) | 21                | 87                 | Intracranial Electroencephalography (IEEG) | 708                  | 256                     |
| CHB-MIT                  | 22                | 163                | sEEG                        | 844                  | 256                     |
| Kaggle (George et al., 2020) | 5 Dogs            | 48                 | IEEG                        | 622                  | 600                     |
| Bonn (Andrzejak et al., 2001) | 10                | NA                 | Surface and IEEG            | 39m                  | 171.61                  |
| Bonn 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 segmenta-
tion. 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 pre-processing. 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) (Abibul-laev 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 (Good-
fellow 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.

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 $N \times N$ 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 straightforward 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.

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.](image)

**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
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.

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.
This has led to more research papers being 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.
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
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-
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
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.
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
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
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 hard-
ware 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., 2020)            | CHB-MIT     | sEEG     | Segmentation                                | STFT                  | 2D Spectrograms | PyTorch  | 2D-CNN | RLS        | 95.65 | 95.85 |      |      |
| (Park et al., 2018)           | SNUH        | sEEG     | Segmentation, Filtering                     | DA                    | Preprocessed Data | NA      | 1D with 2D-CNN | Sigmoid     | 90.58 | 90.20 | 91.00 |      |
| (Tjepkema-Cloostermans et al., 2018) | Clinical | IEEG     | Filtering, Down-Sampling                    | the preprocessed 2 s epochs | Keras | 2D-CNN | Softmax |              | –   | 47.40 | 98.00 |      |
| (Avcu et al., 2019)           | CHB-MIT     | sEEG     | Segmentation, Filtering, Preprocessed Data  | DA                    | Preprocessed Data | Keras | SeNet  |              | –   | 95.86 |      |      |
| (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 |      |      |
| (Welody et al., 2019)         | Clinical    | IEEG     | Z-Normalization                             | STFT                  | Raw IEEG Signals | PyTorch | CNN | Softmax | 79.09 |       |      |      |
| (Hossain et al., 2020)        | CHB-MIT     | sEEG     | –                                            | Visualization         | Raw EEG as 2D Array | PyTorch | 2D-CNN | Softmax | 98.05 | 90   | 91.65 |      |
| (Kim 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 | 87.55 | 83.23 | 79.36 |      |
| (Asif et al., 2019)           | TUH         | sEEG     | –                                            | DivSpec               | 3D Visual Representation | PyTorch | SeNet | Softmax | 90.83 | 77.04 | 72.27 |      |
| (Imansitas and Alzbutas, 2020)| TUH         | sEEG     | Feature Extraction                          | Pattern Matrices      | TensorFlow       | 2D-CNN | 10 Softmax | 74 | 68 | 67 |      |
| (Zeng et al., 2020)           | 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 | IEEG | –                                            | Raw IEEG Signals      | IMF             | Keras | 2D-CNN | 5 Softmax | 99.80 |       |      |      |
| (Gui et al., 2019)            | Bern Barcelona | IEEG | Z-Normalization                             | RMD, FWT, FT          | Wavelet Coefficients | Module Values |         |      |        |      |      |      |      |
| (Chatzichristos et al., 2019) | TUH         | sEEG     | Multi-Channel Subspace Filters               | IC Label              | Multiple Attention-Gated U-Net | 10 Bi-LSTM + FC Layer | – | – | – | – |
| (Covert et al., 2019)         | Clinical    | sEEG     | –                                            | STFT                  | 2D Spectrograms | NA | TGNCN | Sigmoid | 92.80 |       |      |      |
| (Akrim, 2019)                 | Bonn        | sEEG and IEEG | –                                            | DWT                   | Wavelet Coefficients | NA | 2D-CNN | Sigmoid | 100 | 100 | 100 |      |
| Year          | Location     | Dataset Type | Methodology                                                                 | Tools/Techniques          | Accuracy | Precision | Recall | –     |
|--------------|--------------|--------------|-----------------------------------------------------------------------------|----------------------------|----------|-----------|--------|--------|
| 2019         | Bonn         | sEEG and IEEG| –                                                                           | CWT                        | 10       | Softmax   | 100    | 100    |
| 2019         | Bonn         | sEEG and IEEG| Filtering                                                                   | –                          | Black and White Plots of The Amplitude Scaled Wave Files | 2D-CNN   | –       | –      | –      |
| 2019         | Bonn         | sEEG and IEEG| Over Sampling Method                                                        | FFT, WPD                   | Time Domain | 2D-CNN   | 99.60  | –      | –      |
| 2019         | Bonn         | sEEG and IEEG| Segmentation                                                                | Spatial Representation by Producing A Set of Intensity Images | 2D Data | NA        | 2D-CNN | 99.49  | –      | 99.49  |
| 2019         | 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     |
| 2019         | Clinical     | sEEG         | –                                                                           | Different Methods          | 2D Data | MATLAB    | 2D-CNN | 99.49  | –      | –      |
| 2018         | CHB-MIT      | sEEG         | –                                                                           | Sub-band Mean Amplitude of Spectrum (MAS) Map of Multi-channel EEGs     | MAS Map Image | SCNN (4 CNNs) | 5     | 99.33  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | Caffe     | –      | 89.00  | –      | –      |
| 2017         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | GoogleNet | –      | 98.86  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | LeNet     | –      | 99.33  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | 2D-CNN    | –      | 92.00  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | DenseNet  | –      | 80.00  | –      | –      |
| 2020         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | TensorFlow | –      | 85.30  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | TensorFlow | –      | 99.33  | –      | –      |
| 2019         | Clinical     | sEEG         | –                                                                           | –                          | 2D Data | TensorFlow | –      | 99.49  | –      | –      |
| 2017         | Bern Barcelona | IEEG         | –                                                                           | –                          | 2D Data | Caffe     | –      | 100.00 | –      | –      |
| 2019         | Bern Barcelona | IEEG         | –                                                                           | –                          | 2D Data | GoogleNet | –      | 80.00  | –      | –      |
| 2019         | Bern Barcelona | IEEG         | –                                                                           | –                          | 2D Data | LeNet     | –      | 80.00  | –      | –      |
| 2019         | UCI          | sEEG         | –                                                                           | –                          | 2D Data | PyTorch   | –      | 85.30  | –      | –      |
| 2019         | UCI          | sEEG         | –                                                                           | –                          | 2D Data | TensorFlow | –      | 92.00  | –      | –      |

Notes:
- sEEG: subdural electroencephalography
- IEEG: intracranial electroencephalography
- CWT: Continuous Wavelet Transform
- 2D-CNN: Two-Dimensional Convolutional Neural Network
- Softmax
- 1D-CNN: One-Dimensional Convolutional Neural Network
- 2D-CNN: Two-Dimensional Convolutional Neural Network
- SCNN: Spatial Convolutional Neural Network
- RF: Random Forest
- AlexNet
- GoogLeNet
- LeNet
- TensorFlow
- Keras
- Deep ANN
- MATLAB
- Python
- Caffe
- Chainer
- PyTorch
- Different Pre-Train Networks
- Feature Selection
- Textural Features

References:
- Türk and Özerdem, 2019
- Liu and Woodson, 2019
- Tian et al., 2019
- Bouaziz et al., 2019
- Prasanth et al., 2020
- Prasanth et al., 2019
- Ansari et al., 2019
- Cao et al., 2019
- Taqi et al., 2017
- Rizkanti et al., 2019
- Thanaraj et al., 2020
- Bizopoulos et al., 2019
- Thanaraj et al., 2020
| Authors                  | Dataset       | Type     | Methods                                      | STFT          | Feature            | Model            | Accuracy 1 | Accuracy 2 | Accuracy 3 | Accuracy 4 |
|-------------------------|---------------|----------|----------------------------------------------|---------------|--------------------|-------------------|------------|------------|------------|------------|
| Zhang et al., 2020      | CHB-MIT       | sEEG     | Segmentation, Resizing                       | STFT          | 2D Spectrograms    | VGG-16            | 98.26      |            |            |            |
| Cho and Jang, 2020      | CHB-MIT       | IEEG     | Segmentation, Down-Sampling, Raw EEG time series | STFT          | 2D Spectrograms    | VGG-19            | 99.90      | 98.76      | 99.90      |            |
| Liu et al., 2020        | Freiburg      | IEEG     | Segmentation, Normalization                  | STFT          | 2D Spectrograms    | MATLAB            | 10         | 98.12      | 97.01      | 98.12      |
| Bouallegue et al., 2020 | Bonn          | sEEG     | Segmentation                                 | STFT          | 2D Spectrograms    | MATLAB            | Inception-V3 | 88.3       |            |            |
| Raghu et al., 2020      | TUH           | sEEG     | Filtering                                    | STFT          | 2D Spectrograms    | Keras             | 2D-CNN     | 100        |            |            |
| Li et al., 2020         | TUSZ          | sEEG     | Segmentation, Recalculating, Transformation into 20 Common Channels, Baseline Removal and Detrending, Filtering | STFT          | Spectral-Temporal Features | PyTorch            | Inception-V3 | 99.80      |            |            |
| Usman et al., 2020      | CHB-MIT       | sEEG     | Filtering, Segmentation                      | STFT          | 2D Spectrograms    | Keras             | 2D-CNN     |            | 92.7       | 90.8       |
| Baskeyvelavan et al., 2020 | Bonn         | sEEG and IEEG | Filtering, Segmentation, Converting 1D EGG Data into 2D EGG Images | STFT          | RPS Images         | Caffe             | 10         | 98.5       | 100        | 97.83      |
| Bhagat et al., 2020     | CHB-MIT       | sEEG     | Filtering, Segmentation                       | STFT          | RPS Images         | AlexNet           | 10         | 94.98      |            |            |
| George et al., 2020     | CHB-MIT       | sEEG     | Filtering                                    | STFT          | Spectral-Temporal Features | ResNet-152       | 10         | 94.4       | 99         | 96.8       |
| Authors         | Dataset                  | Task                          | Preprocessing Methods                                                                 | 2D Data | Model             | Parameters  | Accuracy    |
|-----------------|--------------------------|-------------------------------|---------------------------------------------------------------------------------------|---------|-------------------|-------------|-------------|
| Gao et al., 2020| CHB-MIT                  | Segmentation                  | DWT Threshold Denoising Method, PSD Analysis, PSDED                                   | NA      | Inception-ResNet-v2| –           | 92.60       |
|                 |                          |                               |                                                                                       |         | Inception-v3      | 92.60       | 97.10       |
| Singh et al., 2020| Bonn                     | Filtering, Segmentation       | DWT Features from 2D Data                                                             | NA      | 2D-CNN            | –           | 97.74       |
|                 |                          |                               |                                                                                       |         |                   | –           | –           |
| Bhattacherjee, 2020| Bonn                     |                               | Bi-Linear Interpolation, Concatenation of DWT and Power Spectrum Band                  | 2D Data| Multi Column CNN  | Softmax     | 99.99       |
|                 |                          |                               |                                                                                       |         |                   | –           | –           |
| Lian et al., 2020| Bonn                     | Filtering                     | Raw EEG Signals                                                                       | NA      | Combination of 1D-CNN and 2D-CNN | 10          | 99.3        |
|                 |                          |                               |                                                                                       |         | Softmax           | 99.5        | 99.6        |
| Madhavan et al., 2019| Bonn, Barcelona           | Filtering, Segmentation      | FSTST, WEST Time-Frequency Matrix                                                      | PyTorch | 2D-CNN            | 5           | 99.94       |
|                 |                          |                               |                                                                                       |         |                   | 99.94       | 99.94       |
| Ghak et al., 2020| Clinical                 |                               | EGG Signals Segmentation                                                              | Keras   | ScalpNet          | –           | 94.4        |
|                 |                          |                               |                                                                                       |         |                   | –           | –           |
| Hussein et al., 2020| Clinical               | Segmentation                  | CWT 2D Scalograms                                                                     | NA      | SDCN              | Sigmoid     | 88.30       |
|                 |                          |                               |                                                                                       |         |                   | 89.52       | –           |
| Kaya, 2020      | Bonn                     | Normalization                 | CWT, mRMR Algorithm                                                                  | 2D Scalograms | Combination of AlexNet and VGG16 | 10          | 98.78       |
|                 |                          |                               |                                                                                       |         |                   | 99.15       | 98.46       |
| Shankar et al., 2020| Bonn                     | Noise Removal, Instantaneous Power Calculation, Segmentation | Gramian Angular Summation Field (GASF) and Gramian Angular Difference Field (GADF) | 2D Data | 2D-CNN            | Sigmoid     | 98          |
|                 |                          |                               |                                                                                       |         |                   | 99          | 98.9        |
| Bashsh-A-Mahfuz et al., 2021| Bonn | Segmentation                  | STFT and CWT, RGB Representation, DA                                                  | 2D Data (Spectrogram, Scalogram) | Keras | FT-VGG16       | Softmax     | 99.21       |
|                 |                          |                               |                                                                                       |         |                   | 99.04       | 99.38       |
| Study                                    | Dataset             | Modality | Feature Extraction/Filtering | Feature Representation | Deep Learning Models | Accuracy | Sensitivity | Specificity |
|-----------------------------------------|---------------------|----------|------------------------------|------------------------|----------------------|----------|-------------|-------------|
| Hu et al., 2020                         | CHB-MIT and iNeuro  | eEEG     | Filtering, Segmentation      | Mean Amplitude Spectrum (MAS), Mean Power Spectral Density (MPSD), and Wavelet Packet Features (WPFs) | AlexNet, VGG-19, Inception-v3, ResNet152, Inception-ResNet-v2 | –        | 98.97       | –           |
| (Mary et al., 2020)                     | Bonn                | eEEG and IEEG | –                          | DWT, Nonlinear, and Entropy-based features | Hybridized Adaptive Haar Wavelet-based Binary Grasshopper Optimization Algorithm and Deep Neural Network (AHW-BGOA-DNN) | 10       | –           | –           |
| MohanBabu et al., 2020                  | CHB-MIT             | eEEG     | Filtering, Differentiating   | Hilbert Transform, Segmentation, Phase-Synchronization Measures, Graph Model | Keras, TensorFlow Optimized Deep Learning Network Model (ODLN) | –        | 100         | –           |
| You et al., 2019                        | Clinical            | eEEG     | Reviewed Separately by 2 Epileptologists, Filtering | Segmentation, STFT, Normalization, Rescaling, Stack 3 Images to form a Data Structure | TensorFlow AnoGAN | –        | 96.6        | –           |
| Truong et al., 2019                     | CHB-MIT, EPILEPSIAE | eEEG     | Segmentation                  | STFT                   | TensorFlow DCGAN | –        | 77.68       | –           |
| Authors                  | Database | Type | Signal Type | Pre-Processing | Feature Extraction | Classification | Results          |
|-------------------------|----------|------|-------------|----------------|--------------------|----------------|-----------------|
| Pascual et al. 2019     | EPILEPSIAE | aEEG | Segmentation | DWT, Power and Non-Linearity per Electrode Features Extraction | Non-Seizure (inter-ictal) EEG Sample | NA | Conditional GAN – RF – – – – |
| Torfi and Fox 2020      | UCI      | aEEG | NA          | Different Methods Matrix | NA | CorGAN | Softmax – – – 21 |
| Sharan and Berovsky 2020 | CHB-MIT  | aEEG | Segmentation, Filtering | FFT and WT | 135 x 154 with FFT and 122 x 154 with WT | NA | 1D-CNN | 97.25 97.25 97.25 – |
| Hu et al. 2020          | CHB-MIT  | aEEG | Filtering, Decomposition | Feature Extraction (MAs, MPFD, WPPs) | Multiple Paced EEG Features | NA | Different Pre-Train Net | Hierarchical Neural Network (HNN) 98.97 – – – |
| Ullah et al. 2018       | Bonn     | aEEG and IEEG | – | DA | EEG Signals Segment | TensorFlow | P-1D-CNN | 10 Majority Voting 99.1 – – – |
| Acharya et al. 2018     | Bonn     | aEEG and IEEG | Z- Normalization | – | Normalized EEG Signals | MATLAB | 1D-CNN | 10 Softmax 88.67 95 90 – |
| Wang et al. 2020        | Berne-Barcelona | EEG | NA | – | Raw EEG Signals | NA | Time-ReNeXt | – Softmax 91.5 – – – |
| Page et al. 2016        | CHB-MIT  | aEEG | Filtering | – | EEG Signals Segment | NA | MPCNN | Softmax 96 100 – – – |
| Zhang et al. 2020       | Bonn     | aEEG and IEEG | Normalization | – | Raw EEG Signals | Keras | Multi-Scale Non-Local (MNL) Network | 10 Softmax |
| O’Shea et al. 2017b     | Clinical | aEEG | Down-Sampling, Filtering | – | EEG Signals Segment | Keras | 1D-FCNN | 5 Softmax 97.1 – – – |
| Thomas et al. 2020b     | Clinical | aEEG | 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 | aEEG | Filtering | – | Raw EEG Signals | Theano | 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     | aEEG and IEEG | Normalization | – | Raw EEG Signals | Keras, TensorFlow | SeizureNet | 10 Softmax 98.5 97 100 – |
| Authors          | Dataset        | Type                          | Methodology                          | Formulation                  | Classifier                  | Stacked                          | Meta Learner | SVM  | ACC  | F1  | MCC | MRE  | RMSE  |
|------------------|----------------|-------------------------------|--------------------------------------|------------------------------|-----------------------------|--------------------------------|---------------|------|------|------|-----|------|-------|
| Akyol et al., 2020 | Bonn           | sEEG and iEEG                 | Normalization                         | Raw EEG Signals              | Keras, TensorFlow           | Stacked Ensemble based DNN Modeling | 10            | NA   | 97.17 | 93.11 | 98.18 | NA   |       |
| Thomas et al., 2018 | MGH Epileptic Dataset | sEEG                          | Filtering, Down Sampling             | Raw EEG Signals              | TensorFlow, 1D-CNN          | SVM                            | 4             | NA   | 83.86 | NA   |      |      |       |
| Gyttenhove et al., 2020 | TUH            | sEEG                          | Filtering, Segmentation              | EGG Signals Segment          | Keras, TensorFlow           | Tiny-Visual Geometry Group (T-VGG) | 5             | NA   | 79.38 | 82.98 |      |      |       |
| Boonyakitanont et al., 2019 | CHB-MIT       | sEEG                          | Segmentation, Normalization          | Raw Multi-Channel EEG Signals | Keras, TensorFlow           | 1D-CNN                         | 10            | NA   | 99.07 | 99.63 | 93.69 |      |       |
| Chen et al., 2018 | Bonn           | sEEG and iEEG                 | DWT, Segmentation, Normalization     | Preprocessed EEG Signals     | Keras, TensorFlow           | 1D-CNN                         | 5             | Sigmoid | 97.27 | NA   |      |      |       |
| Zhang et al., 2020 | TUSZ           | sEEG                          | Montage Selection, Segmentation      | 4 Wavelet Coefficient Packages | PyTorch, DWT-Net             | Softmax                         | 25.24         |      |      |      |      |      |       |
| Zhang et al., 2018 | Bonn           | sEEG and iEEG                 | Normalization                         | Raw EEG Signals              | Keras, TensorFlow           | 1D-TCNN                        | 100           | 100  | 100  | 100  |      |      |       |
| Zhao et al., 2020 | CHB-MIT and Another Dataset | sEEG                          | NA                                    | Raw EEG Signals              | Keras, TensorFlow           | Binary Single-Dimensional Convolutional Neural Network (BSDCNN) | Sigmoid | 94.69 | NA   |      |      |      |       |
| Daoud et al., 2018 | Bonn           | sEEG and iEEG                 | EMD Feature Extraction                | IMFs of EMD                  | Keras, TensorFlow           | 1D-CNN                         | 10            | Softmax | 100  | 100  | 100  | 100  |       |
| Daoud et al., 2020 | CHB-MIT        | sEEG                          | EEG Channel Selection                 | Raw EEG signals              | DCNN                         | NA                             | 96.1          | 97.41 | 94.8 |      |      |      |       |
| Lu and Friends, 2019 | Bonn           | sEEG and iEEG                 | Filtering, Z-Normalization           | Raw EEG signals              | TensorFlow, 1D-CNN          | Softmax                         | 99.6          |      |      |      |      |      |       |
| Corley et al., 2019 | CHB-MIT        | sEEG                          | Filtering                             | Raw EEG signals              | PyTorch, 1D-PGM-CNN          | Softmax                         | 88.00         |      |      |      |      |      |       |
| Hst et al., 2019  | CHB-MIT        | sEEG                          | –                                     | MIDS, WGANs                  | 1D-CNN                       | Softmax                         | 74.98         | 92.46 |      |      |      |      |       |
| Qin et al., 2020a | Bonn           | sEEG and iEEG                 | NA                                    | Raw EEG signals              | TensorFlow, 1D-CNN          | Softmax                         | 98.67         | 99   | 98  |      |      |      |       |
| Moesel et al., 2019 | Clinical       | Multi Modal Wristband Sensor Data | Segmentation, Down Sampling          | Raw EEG signals              | Keras, TensorFlow           | 1D-CNN                         | 4             | Sigmoid | 71.4 | NA   |      |      |       |
| Authors            | Data Source          | Methodology                                                                 | EEG Signals Segment | Platform          | Architecture         | Accuracy (%)   | Sensitivity (%) | Specificity (%) | Duration |
|--------------------|----------------------|------------------------------------------------------------------------------|---------------------|------------------|----------------------|----------------|----------------|----------------|----------|
| Zhang et al. 2020c | TUH                  | EEG Decomposition to Seizure and Patient Components                           | –                   | NA               | CNN                  | 14             | Sigmoid        | 88.5           | 97.4     | 88.1     | –               |
| Yuvaraj et al. 2018| CHB-MIT              | Filtering, Segmentation                                                       | EEG Signals Segment | TensorFlow      | 1D-CNN               | 4              | Softmax        | –              | 96.29    | –        | –               |
| Abou Jaoude et al.2020 | Clinical         | Down Sampling, Filtering                                                     | DA                  | Keras            | CNN-BP               | 5              | Sigmoid        | 99.60          | 84.00    | –        | –               |
| Fukumori et al. 2017| Clinical            | Filtering                                                                     | DWT                 | NA               | LSTM                 | –              | Softmax        | 96.10          | –        | –        | –               |
| Zden et al. 2020   | UC Irvine Machine Learning Repository | aEEG Normalization, Feature Extraction, Data Cleaning                           | –                   | TensorFlow       | DNN                  | –              | NA             | 88.00          | –        | 71.60    | –               |
| Kaziha and Bonni 2020| CHB-MIT             | aEEG Segmentation                                                            | EEG Signals Segment | Keras            | 1D-CNN               | 5              | Sigmoid        | 96.74          | 93.35    | 100      | –               |
| Truong et al. 2020 | EPILEPSIAR          | aEEG                                                                         | –                   | Bayesian         | Convolutional Neural Network (BCNN) | 5 | Softmax | – | – | – | – |
| Zhao et al. 2020   | Bonn-Barcelona       | Filtering                                                                    | Augmented EEG Signals | NA               | DNN                  | 10             | NA             | 89.28          | –        | –        | –               |
| Soonyakitanon et al.2020 | CHB-MIT           | aEEG Segmentation                                                            | EEG Signals Segment | TensorFlow      | 1D-CNN               | –              | On-set-offset Detection Method | 99.72 | 72.78 | 99.82 | 64.4 |
| Khalilpour et al. 2020 | CHB-MIT            | aEEG Segmentation, Normalization                                             | EEG Signals Segment | Keras            | 1D-CNN               | 10             | Softmax        | 97             | 98.5     | 98.47    | –               |
| Zhao et al. 2020   | Bonn                | aEEG and IEEG                   Segmentation, Normalization                          | EEG Signals Segment | Keras            | 1D-CNN               | 10             | Softmax        | 99.52          | –        | –        | –               |
| Alyeyev et al. 2020 | Bonn                 | aEEG and IEEG                   Normalization                                  | Raw EEG signals    | Keras            | 1D-CNN               | 10             | Softmax        | 98.67          | 97.67    | 98.83    | –               |
| Piana et al. 2020  | Clinical            | Segmentation, Thresholding, Filtering                                         | Augmented EEG Signals | MATLAB          | 1D-CNN               | –              | Softmax        | 96.39          | 93.2     | 96.81    | –               |
| Lu et al. 2020     | Clinical (Mice)      | Filtering, Segmentation                                                       | EEG Signals Segment | MATLAB          | DNN                  | 7              | Softmax        | 73.00          | –        | 78.00    | –               |
| Authors          | Year       | Data Set | Methodology                                                                 |
|------------------|------------|----------|-----------------------------------------------------------------------------|
| Xu et al.        | 2020c      | CHB-MIT  | Segmentation – EEG Signals Segment – Keras – TensorFlow – CNN – Softmax     |
| Lin et al.       | 2020c      | Clinical | EEG Signals Segment – NA – Deep ConvNet – 10 – Softmax – 80 – 70 – 90 – 77.7 |
| Jana et al.      | 2020c      | CHB-MIT  | Filtering, Normalization, Segmentation, Re-sampling Strategies – EEG Signals Segment – Keras – 1D-CNN – Softmax – 77.57 – 75.59 – 79.54 – |
| Gao et al.       | 2020a      | Bonn     | Segmentation – ApEn and RQA Features – Feature Vectors – MATLAB – 1D-CNN – Softmax – 99.26 – 98.84 – 99.35 – |
| Thomas et al.    | 2020a     | CHB-MIT  | EEG Signals Segment – Resample, Rescales – Raw EEG signals – Keras – 1D-CNN – NA – 84.1 – – – |
| Vance et al.     | 2020c      | Clinical | EEG Signals Segment – Online Augmentations – Sequence Length of 10 Seconds – Keras – 1D-CNN – Sigmoid – 77 – 60.6 – 82.8 – |
| Jia and Richardson | 2020c     | CHB-MIT  | EEG Signals Segment – Raw EEG signals – Tensorflow – LSTM – 1D-CNN – 10 – Weighted Majority Voting (WMV) – 89.21 – 89.50 – 94.86 – |
| Vidyaratne et al.| 2016       | CHB-MIT  | Filtering – Montage Mapping – 2D Grid – MATLAB – DRNN – MLP – 100 – – – |
| Hussein et al.   | 2018a      | Bonn     | EEG Signals Segment – Keras – LSTM – 10 – Softmax – 100 – 100 – 100 – |
| Ahmadzist-Aristizabal et al. | 2018b | Bonn | EEG Signals Segment – Keras – LSTM – 10 – Sigmoid – 95.54 – – – |
| Yao et al.       | 2019b      | CHB-MIT  | EEG Signals Segment – IndHNN – 10 – NA – 87 – 87.3 – 86.7 – 87.07 – |
| Verma and Jangbi | 2021       | Bonn     | EEG Signals Segment – Keras – RNN – NA – LR – 98.5 – – – |
| Hussein et al.   | 2019a      | Bonn     | EEG Signals Segment – Keras – LSTM – 10 – Softmax – 100 – 100 – 100 – |
| Jaafar and Mohammadi | 2019b  | Freiburg | EEG Signals Segment – LSTM – 5 – Softmax – 97.75 – – – |
| Hu et al.        | 2020c      | CHB-MIT  | EEG Signals Segment – Keras – LSTM – 5 – Softmax – 97.75 – – – |
| Yue et al.       | 2019a      | CHB-MIT  | EEG Signals Segment – LSTM – 5 – Softmax – 97.75 – – – |
| Authors                        | Dataset          | Preprocessing                      | Feature Extraction | Segmentation Method | Classifiers          | Keras | GRU/LSTM | LR | SAD | SVM | 100 | 98 | 97.2| 100 |
|-------------------------------|------------------|------------------------------------|--------------------|---------------------|----------------------|-------|----------|----|-----|-----|-----|----|-----|------|
| Talathi et al., 2017          | Bonn             | sEEG and IEEG                       | –                  | Auto-Correlation    | EEG Signals Segment  | Keras | GRU      | LR | SAD | SVM | 100 | 98 | 97.2| 100  |
| Roy et al., 2019              | TUH              | EEEG                               | –                  | TCP                 | Raw EEG signals      | NA    | ChronicNet |   |     |     |     |    |     |      |
| Hussein et al., 2018          | Bonn             | sEEG and IEEG                       | Filtering          | –                   | EEG Signals Segment  | NA    | LSTM     | 100| 100| 100 |     |    |     |      |
| Geng et al., 2020             | Freiburg         | IEEG                               | Segmentation       | DA, Stockwell       | 2D Spectrograms      | TensorFlow | Bi-LSTM | 98.91| 98.08| 98.91| 86   |    |     |      |
| Praveen and Alkhodari, 2020   | Bonn-Barcelona   | IEEG                               | Filtering          | Linear Feature Extraction | Linear Features | MATLAB | Bi-LSTM | 98.6 | 99.55| 99.65| 86   |    |     |      |
| Hu and Yokoi, 2019            | Bonn             | sEEG and IEEG                       | Filtering          | Linear Feature Extraction | Linear Features | MATLAB | Bi-LSTM | 98.56| 100 | 97.14| 86   |    |     |      |
| Abbasi et al., 2019           | Bonn             | sEEG and IEEG                       | Segmentation, Normalization, Standardization | DCT, Hurst Exponent and ARMA Features Extraction | Feature Vectors | NA | LSTM     | 99.17| 98.88| 99.45| 86   |    |     |      |
| Yao et al., 2021              | CHB-MIT          | sEEG                               | Segmentation       | –                   | EEG Signals Segment  | –     | Attention | 10 | 87.8| 87.3| 88.3| 87.74|      |      |
| Patna and Ushikawa, 2021      | Clinical         | sEEG                               | Segmentation       | –                   | EEG Signals Segment  | MATLAB | LSTM     | 97.9 |     |     |     |    |     |      |
| Rajaguru and Prabakaran, 2018 | Clinical         | EEEG                               | Segmentation       | –                   | EEG Signals Segment  | NA    | AE with EM-PCA | 93.92| 96.11| 91.73| 86   |    |     |      |
| Sharathapriyaa et al., 2018   | Bonn             | sEEG and IEEG                       | Filtering          | HWPT, FD            | Feature Vectors      | MATLAB | AE       | 98.67| 98.18| 100  | 86   |    |     |      |
| Emami et al., 2019            | Clinical         | sEEG                               | Down Sampling, Filtering, Normalization | – | EEG Signals Segment | TensorFlow | AE | Sigmoid | 100 |     |     |     |    |     |      |
| Yuan et al., 2017             | CHB-MIT          | sEEG                               | –                  | STFT                | 2D Spectrograms      | NA    | SDA      | 93.82|     |     |     |    |     |      |
| Qiu et al., 2018              | Bonn             | sEEG and IEEG                       | Segmentation, Z-Normalization, Standardization | – | EEG Signals Segment | MATLAB | DSAE | LR | 100 | 100 | 100 | 86   |    |     |      |
| Golmohammadi et al., 2019     | TUE              | sEEG                               | –                  | Different Methods   | A Vector of 6 Posterior Probabilities | Theano | SDA | LR | 90 |     |     |    |     |      |
| Van et al., 2018              | Bonn             | sEEG and IEEG                       | Filtering          | –                   | Raw EEG signals      | NA    | SAE      | 100 | 100 | 100 |     |    |     |      |
| Lin et al., 2018              | Bonn             | sEEG and IEEG                       | Segmentation, Normalization | – | EEG Signals Segment | NA    | SSAE     | 100 | 100 | 100 |     |    |     |      |
| Yuan et al., 2018             | CHB-MIT          | sEEG                               | Segmentation       | Scalogram           | 2D Scalograms       | Theano | Wave2Vec | 93.92|     |     |     |    |     | 96.05 |
| Gasparini et al., 2018        | Clinical         | EEEG                               | Filtering          | CWT, Feature Extraction | Feature Vectors | NA | SAE      | Softmax | 86.5 | 88.8 | 90.7 |     |      |
| Authors                  | Dataset/Location | Preprocessing/Feature Extraction | Model Features | Model Architecture | Model Parameters | Results |
|-------------------------|------------------|----------------------------------|----------------|--------------------|------------------|---------|
| Karim et al. 2018a      | Bonn             | sEEG and IEEG                    | Raw EEG signals | SSAE               | Softmax          | 99.8    |
|                         |                  |                                  |                |                    |                  |         |
| Karim et al. 2019       | Clinical         | EEG                               | Dimension Reduction, RSD | Feature Vectors | SSAE             | 100     |
|                         |                  |                                  |                |                    |                  |         |
| Karim et al. 2018b      | Bonn             | sEEG and IEEG                    | Raw EEG signals | SSAE               | Softmax          | 96      |
|                         |                  |                                  |                |                    |                  |         |
| Yuan et al. 2018c       | CHB-MIT          | sEEG                             | Different Methods | 2D Spectrograms | SSAE             | 96.81   |
|                         |                  |                                  |                |                    |                  | 87.85   |
| Shamma et al. 2020      | Bonn             | sEEG and IEEG                    | Raw EEG signals in to 2D Space using the Third-Order Cumulant | SSAE | Softmax | 100     |
|                         |                  |                                  |                |                    |                  | 100     |
| Siddharth et al. 2020   | Bonn             | sEEG                             | Waveform Features | MATLAB | DBN | NA      |
|                         |                  |                                  |                |                    |                  | 87.35   |
|                         |                  |                                  |                |                    |                  | 97.89   |
| Le et al. 2018          | Clinical         | EEG                               | Normalization, Standardization, Feature Extraction | Feature Vectors | Theano | DBN | LR | 85 |
|                         |                  |                                  |                |                    |                  |         |
| Tang et al. 2017        | Clinical         | EEG                               | Decomposition, Multi-View Feature Extraction | 3 Feature Set (Local Fractal Spectrum, Relative Band Energy, Synchronization Modularity) | Multi-View CNN-GRU | Softmax | 94.5 |
|                         |                  |                                  |                |                    |                  |         |
| Thodoroff et al. 2019   | CHB-MIT          | sEEG                             | Image Based Representation | 2D Data | 2D CNN-LSTM | NA      |
|                         |                  |                                  |                |                    |                  |         |
| Saqib et al. 2020       | TUSZ             | Resampling, Filtering, Segmentation | STFT, 2D-mapping | 2D Spectrograms | 3D-CNN, Bi GRU | NA      |
|                         |                  |                                  |                |                    |                  | 99.40   |
|                         |                  |                                  |                |                    |                  | 99.50   |
| Choi et al. 2015        | CHB-MIT          | sEEG                             | Converted Into a Series of Two Seconds Waveform Images | EGG Signals Segment | LRCN | Softmax | 99 |
|                         |                  |                                  |                |                    |                  | 84      |
|                         |                  |                                  |                |                    |                  | 99      |
| Liang et al. 2020       | CHB-MIT          | sEEG                             | EGG Signals Segment | 1D-CNN-RNN | Softmax | 78.39 |
|                         |                  |                                  |                |                    |                  |         |
| Roy et al. 2018         | TUH              | sEEG                             | Various Preprocessing Technique | EGG Signals Segment | CNN-LSTM | Different Activation Functions | 39.09 |
|                         |                  |                                  |                |                    |                  | 76.84   |
| Tecme-Kanmaddi et al. 2017 | TUH           | sEEG                             | Feature Extraction, left to right channel independent GMM-HMM, PCA, IPCA | EGG Signals Segment (210 frames of EEGs) | CNN-LSTM | Softmax | NA |
|                         |                  |                                  |                |                    |                  |         |
| Study                        | Dataset | EEG Type | Methods                                                                 | Evaluation | Framework | Parameters |
|------------------------------|---------|----------|-------------------------------------------------------------------------|------------|-----------|------------|
| Li et al. (2020)             | Bonn    | sEEG and IEEG | Segmentation, Filtering, Normalization                                |            | TensorFlow |            |
| Liu et al. (2020)            | CHB-MIT | sEEG     | Segmentation                                                            |            | NA        | C-LSTM     |
| Yang et al. (2021)           | Clinical| sEEG     | Long-Term Video-EEG Monitoring                                          |            | Keras,     | CNN-LSTM   |
| Xu et al. (2020a)            | UCI     | sEEG     | Normalization                                                           |            | C-LSTM    |            |
| Yuan et al. (2021)           | CHB-MIT | sEEG     | –                                                                         |            | 1D CNN-LSTM|            |
| Wen and Zhong (2018)         | Bonn    | sEEG and IEEG | Channel Selection                                                       |            | NA        | CNN-AE     |
| Abdelhameed et al. (2018)    | Bonn    | sEEG and IEEG | Segmentation                                                            |            | 1D-CNN-AE | MLP/LSTM/ Bi-LSTM |
| Antonides et al. (2018)      | Clinical| sEEG     | –                                                                         |            | Theano    |            |
| Yuan and Lu (2015)           | CHB-MIT | sEEG     | –                                                                         |            | CNN-AE    |            |
| Dacund and Hayouni (2019)    | Bonn    | sEEG and IEEG | Segmentation, Filtering, Normalization                                |            | DCAE      |            |
| Bern Barcelona               |         | IEEG     |                                                                            |            | DCAE      |            |
| Shoebi et al. (2021)         | Bonn    | sEEG and IEEG | Filtering, Segmentation                                                |            | TensorFlow| CNN-AE     |
| Takahashi et al. (2020)      | Clinical| sEEG     | Filtering, Segmentation                                                |            | Softmax   |            |
Table 3: Summary of related works done using medical imaging methods and DL.

| Work                  | Dataset          | Modalities | Preprocessing                                      | Preprocessing Toolbox | Input Network | DNN toolbox | DNN | Classifier | K-fold | Performance criteria (%) |
|-----------------------|------------------|------------|---------------------------------------------------|------------------------|---------------|-------------|-----|------------|--------|--------------------------|
| (Dev et al., 2019)    | SCTIMST          | MRI        | Noise Reduction with BM3D Algorithm, Skull-Stripping, FCD Lesion Segmentation | FSL                    | 256 x 256 Image Size | FCN          | Keras | 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-sMRI   | Filtering, ICA, BCG, GLM, MCS                     | Brain Vision Analyzer Software | IEDs          | ResNet      | NA  | Triplet    | -      | - 84.40 -                 |
| (Hosseini et al., 2018)| Clinical        | EEG/CoG    | Different Methods                                | Preprocessed EEG and sMRI Data | 2D-CNN        | NA          | SVM | -          | -      | - - - - -                  |
| (Yan et al., 2019)    | Clinical         | MRI        | Preprocessing the Connectivity Matrix, Construction of The SZ and SZF Binary Masks, Applying Masks to Reduce Dimensionality of Input Connectivity Matrix | 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                     | 2D ROI        | 2D-CNN      | NA  | Softmax    | -      | - - - - -                  |
| (Huang et al., 2019)  | Clinical         | PET        | ROI, Normalization, AAL, CNNI, Down-sampling, NNI (3D images) | NA                     | 2D ROI        | 2D-CNN      | NA  | Softmax    | -      | 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., 2020)   | Clinical         | MRI        | Bias Field Correction, Skull-Stripping, Intensity Normalization, Patch Extraction, DA | NA                     | Patches       | CNN         | MATLAB | Softmax    | -      | 88 90 85 -                |
| (Shakeri et al., 2019)| a Rolandic        | MRI        | Rezing, DA                                       | NA                     | Single 2D Slice | FCN          | MATLAB | Softmax    | -      | - - - - -                  |
| (Pignon et al., 2020) | HCP Dataset      | MRI        | Simulated LF Images                               | NA                     | Paired HF and Simulated LF Images | Aniso-U-Net | NA     | -          | -      | - - - - -                  |
| (Pomini et al., 2019) | Clinical         | sMRI, re- sMRI | Reizing, Denoising                               | SPM, FSL              | 3D Scans      | VonCNN-B    | NA   | Softmax    | 5      | - - - - -                  |
### Clinical DWI, fMRI Different Methods

| Work                          | Clinical | DWI, fMRI | Different Methods | SPM, FSL | DWI Streamline Coordinate | DCNN-CL-ATT | PyTorch | Softmax | – | – | – | – | – |
|-------------------------------|----------|-----------|------------------|----------|---------------------------|-------------|---------|---------|----|----|----|----|----|
| Xu et al., 2019               | Clinical | DWI, fMRI | Minimal Pre-Processing Pipeline For The Human Connectome Project (HCP) Version 5.4.0 | FSL      | sMRI Features, rs-fMRI and task-fMRI Based ROI Correlation Matrices, and PDC | SPM, FSL    | PyTorch | Softmax | – | – | – | – | – |
| Torres-Velázquez et al., 2020 | ECP Project | sMRI, re- fMRI and task-fMRI, PDC data | Ground Truth Generation using FreeSurfer, Skull-Stripping, Re-Sampled and Cropped, Re-Scaled, DA | FreeSurfer | Preprocessed MRI | FSL | PyTorch | Softmax | – | – | – | – | – |
| Rebsamen et al., 2020         | Inselspital MRI | Standard Preprocessing, Generate The Connectivity Matrix using HARDI and (NODDI) Methods | Connectivity-Strength Based Weight ICVF | Inception ResNet_v2 | NA | Softmax | – | – | – | – | – | – | – |
| Si et al., 2020               | Clinical | Diffusion 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 | – | – |
| Huang et al., 2020            | Clinical | MRI | 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.
| Authors            | Year   | Method                  | Description                                                                 | Optimizer | Loss Function         |
|--------------------|--------|-------------------------|-----------------------------------------------------------------------------|-----------|-----------------------|
| Avcu et al.        | 2019   | SeizNet                 | 4 Conv Layers + 4 Max Pooling Layers + 5 Dropout Layers + 4 BN Layers + 1 FC Layer | Adam      | BCE                   |
| Zhan and Hu.       | 2019   | D-CNN                   | 4 Conv Layers + 4 PC Layers                                                 | NA        | NA                    |
| Negadly et al.     | 2019   | CNN                     | 6 Conv Layers + 6 BN Layers + 3 Dropout Layers + 3 FC Layers                | Softmax   | Adam, CE              |
| Hussaini et al.    | 2019   | 2D-CNN                  | 4 Conv layers + 2 Max Pooling Layers + 4 BN layers + 1 Dropout Layer        | Softmax   | Minibatch SGD, NA     |
| Khan et al.        | 2019   | 2D-CNN                  | 3 Conv layers + 3 pooling layers + ReLU activation function                 | Softmax   | 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     |
| Akif et al.        | 2019   | SeizureNet              | 52 Conv Layers + 5 Pooling Layers + 51 BN Layers + 24 Dropout Layers        | Softmax   | Adam, Proposed Loss Function |
| Kolmogorov and Akhtasov | 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 |
| Bai 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 | Bit-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               |
| 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 Özdemir  | 2015   | 2D-CNN                  | 2 Conv Layers + 2 Max Pooling Layers                                        | Softmax   | Adadelta, NA          |
| Liu and Woodhead   | 2019   | 2D-CNN                  | 3 Conv layers + 3 BN layers + 2 Max Pooling Layers + 1 FC Layer             | Softmax   | NA                    |
| Tian et al.        | 2019   | 2D-CNN                  | 4 Conv Layers + 3 PC Layers                                                 | MV-TSK-FS | NA, CE                |
| Bouazza 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                |
| Lazzari et al.     | 2019   | 2D-CNN                  | 7 Conv Layers + 8 Pooling Layers + 2 FC Layers                             | Sigmoid   | NA, NA                |
| Cao et al.         | 2019   | 2D-CNN                  | 2 Conv Layers + 2 Max Pooling Layers + 1 Dropout Layer + 2 FC Layers        | KELM      | SGD, NA                |
| Study                  | Model/Architectural Details                                                                 | Optimizer | Loss Function | Miscellaneous |
|-----------------------|---------------------------------------------------------------------------------------------|-----------|---------------|---------------|
| Taqi et al. (2017)    | GoogleNet                                                                                  | Softmax   | CE            |               |
|                       | AlexNet                                                                                     | NA        |               |               |
|                       | ResNet                                                                                      | NA        |               |               |
| Esmail et al. (2018)  | 2D-CNN                                                                                     | Softmax   | Adam          | NA            |
|                       | VGG-16                                                                                      | NA        |               |               |
| Bazopoulos et al. (2019) | 3D-CNN                                                                                 | Softmax   | NA            | NA            |
|                       | Standard Networks                                                                         | NA        |               |               |
| (Emami et al., 2019b) | 2D-CNN                                                                                     | Softmax   | NA            | NA            |
|                       | AlexNet, VGG-16, VGG-19                                                                    | Softmax   | NA            | NA            |
| Thamiraj et al. (2020) | Custom CNN                                                                                | Softmax   | NA            | NA            |
|                       | 3 Conv Layers, 1 BN Layer + 1 Max-Pooling Layer + 2 FC Layers                              | Softmax   | NA            | NA            |
| Zhang et al. (2020a)  | VGG-16                                                                                     | Softmax   | SGD           | Softmax Cross Entropy (SCE) |
|                       | ResNet-50                                                                                  | NA        |               |               |
| Cho and Jang (2020a)  | 2D-CNN                                                                                     | Softmax   | Adam          | NA            |
|                       | 2 Conv Layers + 2 Max Pooling Layers + 2 FC Layers + 2 Dropout Layers                      | Output Layer | Adam          | NA            |
|                       | 1D-CNN                                                                                     | Softmax   | Adam          | CE            |
|                       | 2 Conv Layers + 2 Max Pooling Layers + 2 Dropout Layers                                     | Softmax   | Adam          | MSE           |
| Liu et al. (2020a)    | 2D-CNN                                                                                     | Softmax   | Adam          | NA            |
|                       | 2 Conv Layers + 4 BN Layers + 3 Max Pooling Layers + 1 Dropout Layer                       | Softmax   | Adam          | CE            |
|                       | 2 Conv Layers + Max Pooling Layers + FC Layers + Dropout Layer + ReLU                      | Softmax   | Adam          | NA            |
| Bonnalleque et al. (2020) | RNN-GRU                                                                               | Softmax   | Adam          | NA            |
|                       | 2 GRU Layers + 1 FC Layer + ReLU Activation Function                                       | NA        |               |               |
| Bhagat et al. (2020)  | Inception-V3                                                                                | SVM       | SGD, RMSProp, Adam | NA           |
| Li et al. (2020a)     | Res3DNet                                                                                  | MLP       | Adam          | CE            |
| Usman et al. (2020)   | 2D-CNN                                                                                     | SVM       | NA            | NA            |
| Hakkani et al. (2020) | AlexNet                                                                                     | Softmax   | SGD           | CE            |
| Bhagat et al. (2020)  | ResNet-50                                                                                  | Softmax   | Adam          | Categorical CE|
| George et al. (2020)  | ResNet                                                                                     | Softmax   | Adam          | NA            |
| Cao et al. (2020)     | Inception-RosNet-v2                                                                        | Softmax   | NA            | OHEM          |
|                       | Inception-V3                                                                               | NA        |               |               |
| Garg et al. (2020)    | 2D-CNN                                                                                     | Softmax   | SGD           | NA            |
|                       | 2 Conv Layers + 2 BN Layers + 1 Max-Pooling Layer + 1 FC Layer                             | Softmax   | SGD           | NA            |
| Bhattacharjee et al. (2020) | Multi Column CNN                        | Softmax   | NA            | NA            |
| Lian et al. (2020)    | Combination of 1D-CNN and 2D-CNN                                                          | Softmax   | NA            | SLF           |
|                       | 2 1D-Conv Layers + 3 2D-Conv Layers + 1 FC Layer                                          | Softmax   | NA            | SLF           |
| Authors/Year                        | Type       | Architecture                                                                 | Activation | Optimizer | Loss          |
|------------------------------------|------------|------------------------------------------------------------------------------|------------|-----------|---------------|
| Madhavan et al., 2019              | 2D-CNN     | 5 Conv Layers + 5 Pooling Layers + 5 FC Layers                               | Softmax    | SGD       | CE            |
| Pasha et al., 2020                 | ScalpNet   | 11 Conv Layers + 10 Dropout Layers + 1 FC Layer                              | Sigmoid    | NA        | Focal Loss    |
| Hanxin et al., 2020                | SDCN       | 6 SDC Blocks + 2 FC Layers                                                   | Sigmoid    | Adam      | BCE           |
| Kaya et al., 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           |
| Hashed-Al-Mahbub 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            |
| Glory et al., 2020                 | HNN        | 3 Cascaded Learning Blocks                                                   | Softmax    | Adaptive Optimization, SGD with CLRA | CCE           |
| Mohan Babu 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) |
| Truong et al., 2018                | DCGAN      | Generator: FC Layer + Reshape Layer + 3 de-Conv Layers, Discriminator: 3 Conv Layers + Flatten Layers + 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 BNN | Mini-Batch Gradient Descent (MBGD) |               |
| Jullik et al., 2019                | P-1D-CNN   | 3 Conv Layers + 3 BN Layers + 1 Dropout Layer + 2 FC Layers                 | majority voting | Adam      | CE            |
| Ankarya et al., 2018               | 1D-CNN     | 5 Conv Layers + 5 Max Pooling Layers + 2 FC Layers                          | Softmax    | NA        | NA            |
| Wang et al., 2020                  | Time-ResNets | 1-3 pairs of Conv and Max Pooling Layers + 1-3 FC Layers + Dropout         | Softmax    | Adam      | CE            |
| Ng et al., 2019                    | MFCNN      | 3 Conv Layers + 3 BN Layers + 2 Max Pooling Layers + 1 Multi-Scale Non-Local Layer + 2 FC Layers + RELU Activation Function | Softmax    | Adam      | CE            |
| Zhang et al., 2020b                 | MNLN       | 6 Conv Layers + 1 BN Layer + 3 Pooling Layers                              | Softmax    | SGD       | CCE           |
| O’Shea et al., 2017a               | 1D-FCNN    |                                                                       |            |           |               |
| Study                        | Model | Layers/Details                                                                 | Activation | Optimizer | Loss   |
|-----------------------------|-------|--------------------------------------------------------------------------------|------------|-----------|--------|
| Thomas et al. 2020b         | 1D-CNN| 2 Conv Layers + Max Pooling Layer + 2 FC Layers + Dropout Layer + ReLU          | Softmax    | Adam      | CE     |
| O’Shaughnessy 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          | 1D-CNN| 10 Conv Layers + 10 BN Layers + 6 Max Pooling Layers + 1 FC Layer + 1 Dropout Layer + ReLU | Softmax    | Adam      | BCE    |
| Akyol 2020                  |       | Stacked Ensemble based DNN modeling                                           | 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 + 5 Max Pooling Layers + 2 FC Layer + ReLU Activation | Output Layer | Adam     | BCE    |
| Boonyakhrinount et al. 2018 | 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. 2020c          | 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 | Softmax    | Adam      | BCE    |
| 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| 5 Conv Layers + 3 Max Pooling Layers + 3 BN Layers + 4 Dropout Layers + 1 FC Layer | Softmax    | Adam      | NA     |
| Palyo 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     |
| Qiu et al. 2020c            | 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     |
| Motaed et al. 2019          | 1D-CNN| 4 Conv Layers + 2 Pooling Layers + 3 Dropout Layers                          | Sigmoid    | NA        | NA     |
| Authors et al. | Model | Layers/Units | Activation | Optimizer | Loss Function |
|---------------|-------|--------------|------------|-----------|---------------|
| Zhang et al., 2020c | CNN | 1 Conv Layer + 1 Max Pooling Layer + ReLU Activation Function + de-Conv Layer | Sigmoid | Adam | MSE |
| 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 Pooling Layers + 3 Dropout Layers + 1 GC Layer | Sigmoid | Adam | Log (CE) |
| Payam et al., 2019 | LSTM | Reshape Layer + 4 LSTM/GRU + 1 FC Layer | Sigmoid | NA | NA |
| Ghu et al., 2020 | DNN | 5 Hidden Layers | NA | NA | NA |
| Khalilpour and Hsu, 2020 | 1D-CNN | 5 Conv Layers + 5 BN Layers + 5 Avg Pooling Layers + 2 FC Layers | Sigmoid | RMSprop | NA |
| Tung et al., 2020 | BCNN | 3 Conv Blocks + 2 FC Layers | Softmax | ELBO | Negative of ELBO |
| Zhao et al., 2020b | 1D-CNN | 4 Conv Layers + 3 Max Pooling Layers + 1 FC Layer | NA | NA | NA |
| Boonyaikitnarat et al., 2020 | 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 | 3 Conv Layers + 3 BN Layers + 5 Dropout Layers + 3 Max Pooling Layers + 2 FC Layers | Softmax | NA | NA |
| Zhao et al., 2020b | 1D-CNN | 4 Conv Layers + 4 Pooling Layers + 1 Dropout Layer + 2 FC Layers | Softmax | RMSprop | Proposed Loss Function |
| Abay et al., 2020 | 1D-CNN | 8 Conv Layers + 4 Pooling Layers + 1 Dropout Layer + 2 FC Layers | Softmax | SGD | NA |
| Lu et al., 2020 | DNN | 16 Blocks with Residual Connections | Softmax | NA | NA |
| Xu et al., 2020 | 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 |
| Authors                          | Model          | Layers Description                                                                 | Output Layer   | Optimizer | Loss Function |
|---------------------------------|----------------|-------------------------------------------------------------------------------------|----------------|----------|---------------|
| Vidyaratne et al. 2016          | DRNN           | DRNN Layers                                                                          | MLP with 2 Layers | Adam     | NA            |
| Hussein et al. 2018             | LSTM           | 1 LSTM Layer + 1 Time Distributed Dense Layer + 1 Average Pooling Layer              | Softmax        | Adam     | CCE           |
| Ahmadzadeh et al. 2018          | LSTM           | 1 LSTM Layer + 1 Dropout Layer + 1 FC Layer                                         | Sigmoid        | Adam     | BCE           |
| Vao et al. 2019                 | 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. 2018             | LSTM           | 1 LSTM Layer + 1 Time Distributed FC Layer + 1 Average Pooling Layer                | Softmax        | Adam     | CCE           |
| Jadie and Mohammadi 2019        | LSTM           | 1 LSTM Layer + 1 Time Distributed FC Layer                                          | Softmax        | NA       | NA            |
| Hu et al. 2020                  | Bi-LSTM        | Bi-LSTM Layer + dropout Layer                                                       | Softmax        | Adam     | Cross Entropy |
| Vao et al. 2019                 | ADIndRNN       | Attention Layer + 9 IndRNN Layers + 9 BN Layers + 3 Max Pooling Layers + 1 Avg Pooling Layer + 2 FC Layers | NA             | Adam     | NA            |
| Talathi 2017                    | GRU            | 2 GRU Layers + 1 Time Distributed FC Layer                                          | LR             | Adam     | NA            |
| Roy et al. 2019                 | LSTM           | 1 LSTM Layer + 1 Time Distributed FC Layer + 1 Max Pooling Layer                    | Softmax        | Adam     | NA            |
| Hameed et al. 2018              | LSTM           | 3 Conv Layers + 4 GRU Layers                                                         | SGD            | CE       | NA            |
| Gong et al. 2020                | Bi-LSTM        | 1 Bi-LSTM Layer                                                                     | Softmax        | Adam     | NA            |
| Prasad and Akhloobari 2020      | Bi-LSTM        | 1 LSTM Layer + 2 FC Layers                                                          | Softmax        | Adam     | NA            |
| Hu and Yuan 2019                | Bi-LSTM        | 2 Bi-LSTM Layer                                                                     | Softmax        | Adam     | NA            |
| Ahnani et al. 2019              | LSTM           | 2 LSTM Layers + 2 Dropout Layers + FC Layer                                         | Softmax        | Adam     | NA            |
| Vao et al. 2021                 | 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            |
| Basaguru and Prabhakar 2018     | MAR            | NA                                                                                   | GA             | NA       | NA            |
| Sharathappriyaa et al. 2018     | AE             | 2 Hidden Layers                                                                     | Softmax        | NA       | MSE           |
| Authors | Model | Architecture | Loss Function | Optimizer | Other Parameters |
|---------|-------|--------------|---------------|-----------|------------------|
| 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 | DSAR | 1 Hidden Layer | LR | SGD | NA |
| Golmohammadi et al. 2017 | SSPW-SDA | 6W-SDA | LR | Mini Batch SGD | Cross Entropy |
| Xu et al. 2016 | EYRS-SDA | Single Layer | SVM | Batch Gradient Descent | NA |
| Van et al. 2019 | SARE | 3 Hidden Layers | Softmax | L-BFGS | Proposed Loss Function |
| Gharapirani et al. 2018 | SAR | 2 Hidden Layers | Adadelta | Softmax | CE |
| Karim et al. 2019a | SAR | 2 Autoencoders | Softmax | NA | Taguchi Method |
| Karim et al. 2019b | SAR | 2 Autoencoders | Softmax | NA | MSE |
| Van et al. 2018 | SAR | 2 Layers | Softmax | Adam | CE |
| Siddharth et al. 2020 | SAR | 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) |
| Sagh 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-GRU | – | NA | Adam | NA |
| Kang et al. 2020 | LRCN | 4 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 | Softmax | Adam | NA |
| 1D-CNN-RNN | 3 Conv Layers + 3 GRU Layers | Softmax | Adam | NA |
| TCNN-RNN | 3 Conv Layers + 3 Max Pooling + 2 GRU + FC Layers | Softmax | Adam | NA |
| Authors and Year | Methodology | Details | Proposed Loss Function |
|------------------|-------------|---------|------------------------|
| 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 Layers | Sigmoid, Adam, MSE |
| Li et al., 2020 | PC-NLSTM | 3 Conv Layers + 2 Pooling Layers + 1 NLSTM Layer + 1 FC Layer | Softmax, Adam, CCE |
| Liu et al., 2020a | 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: 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 |
| Wang and Zhang, 2018 | CNN-AE | 8 Conv Layers + 3 Max Pooling Layers + 12 BN Layers + 3 Up sampling Layers | LSTM, Adam, BCE |
| Antoniadis et al., 2018 | CNN-ASAE | 4 Conv Layers + 2 FC layers + 2 ASAE Hidden layers | MLP, Adadelta, MSE |
| Yuan and Jia, 2019 | CNN-AE | 16 Conv Layers + 15 Pooling Layers | Softmax, Adadelta, CE |
| David and Bayoumi, 2017 | DCAE | Encoder: 2 Conv Layers + 2 Pooling Layers + 2BN Layers, Decoder: 2-de-Conv Layers + 2 UpSampling Layers + 2 BN Layers | MLP, RMSprop, MSE |
| Schaefer et al., 2017 | DCVAE | Encoder: 4 Conv Layers + 4 Pooling Layers + 4 BN Layers + 2 FC Layers, Probabilistic Model Parameter Layer | K-means clustering, RMSprop, BCE |
| Takashio et al., 2018 | CNN-AE | 5 Conv Layers + 4 Pooling Layers + 3 BN Layers + 1 Dropout Layer | Softmax, Adadelta, SGD, NA |
| Seer et al., 2019 | CNN-AE | 5 Conv Layers + 4 Pooling Layers + 3 BN Layers + 1 Dropout Layer + VGG16 | Softmax, Adadelta, NA, NA |
| Gill et al., 2018 | PCN | 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 |
| Hao et al., 2018 | Two-Stage CNN Cascade | 3 Conv Layers + 2 BN Layers + 3 Max Pooling Layers + 1 Dropout Layer | Softmax, Adadelta, BCE |
| Huang et al., 2017 | ResNet | 29 Conv Layers + 1 Dropout Layer + 1 FC Layer | Triplet, NA, NA |
| Van et al., 2018 | 2D-CNN | 5 Conv Layers + 3 Max Pooling Layers + 1 BN Layer + 1 FC Layer | Softmax, NA, NA |
| Van et al., 2018a | 3D-CNN | 5 Conv Layers + 3 Max Pooling Layers + 1 BN Layer + 1 FC Layer | Softmax, Adam, NA |
| Authors            | Model Type | Proposed Architecture                                                                 | Layers | Optimizer   | Loss   |
|--------------------|------------|----------------------------------------------------------------------------------------|--------|-------------|--------|
| Gleichgerricht et al., 2018 | 2D-CNN     | Combination of ResNet50, VGG16, Inception-V3, SVGG-C3D                                 | NA     | NA          | NA     |
| Jiang et al., 2019  | 2D-CNN     | VGG16 + Global Average Pooling 2D Layer                                                |        | 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 | 2D-CNN     | Combination of ResNet50, VGG16, Inception-V3, SVGG-C3D                                 |        | Adam        | MSE    |
|                    |            | VGG16 + Global Average Pooling 2D Layer                                                |        | Adam        | MSE    |
|                    |            | ResNet50 + Global Average Pooling 2D Layer                                             |        | Adam        | MSE    |
|                    |            | Inception-V3 + Global Average Pooling 2D Layer                                          |        | Adam        | MSE    |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | MSE    |
| Wang et al., 2020a | CNN        | Deep-DAC                                                                                | Tank   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
| Shakeri et al., 2016 | CNN        | Deep-DAC                                                                                | Tanh   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | CE     |
| Rigoni et al., 2020 | CNN        | Deep-DAC                                                                                | Tanh   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | CE     |
| Wang et al., 2019   | 3D-CNN     | Deep-DAC                                                                                | Tanh   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | CE     |
| Si et al., 2020     | 3D-CNN     | Deep-DAC                                                                                | Tanh   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | CE     |
| Lee et al., 2020    | CNN        | Deep-DAC                                                                                | Tanh   | Adam        | MSE    |
|                    |            | 9 Conv Layers + 51 BN Layers + 3 Max Pooling Layers + 3 De-Conv Layers + 3 Dropout Layers |        | Adam        | MSE    |
|                    |            | CNN                                                                                    | Softmax| Adam        | CE     |
|                    |            | 5 Convolutional Layers + 5 BN Layers + 1 Max Pooling Layer + 1 Dropout Layer + 2 FC Layers |        | Adam        | CE     |
|                    |            | SVGG-C3D + Global Average Pooling 2D Layer                                             |        | Adam        | CE     |

**Loss Functions:**
- CE: Cross Entropy
- MSE: Mean Squared Error
- Adam: Adam Optimizer
- Tanh: Tanh Activation Function
- Softmax: Softmax Loss
- SGD: Stochastic Gradient Descent
- Adam: Adam Optimizer
- BCE: Binary Cross Entropy
- Proposed Loss: Proposed Loss Function.
References

Aarabi, A., Fazel-Rezai, R., and Aghakhani, Y. (2009). A fuzzy rule-based system for epileptic seizure detection in intracranial eeg. *Clinical Neurophysiology*, 120(9):1648–1657.

Abbasi, B. and Goldenholz, D. M. (2019). Machine learning applications in epilepsy. *Epilepsia*, 60(10):2037–2047.

Abbasi, M. U., Rashad, A., Basalamah, A., and Tariq, M. (2019). Detection of epilepsy seizures in neo-natal eeg using lstm architecture. *IEEE Access*, 7:179074–179085.

Abdelfattah, S. M., Abdelrahman, G. M., and Wang, M. (2018). Augmenting the size of eeg datasets using generative adversarial networks. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–6. IEEE.

Abdelhameed, A. M., Daoud, H. G., and Bayoumi, M. (2018). Epileptic seizure detection using deep convolutional autoencoder. In *2018 IEEE International Workshop on Signal Processing Systems (SiPS)*, pages 223–228. IEEE.

Abibullaev, B., Seo, H. D., and Kim, M. S. (2010). Epileptic spike detection using continuous wavelet transforms and artificial neural networks. *International journal of wavelets, multiresolution and information processing*, 8(01):33–48.

Abiyev, R., Arslan, M., Idoko, J. B., Sekeroglu, B., and Ilhan, A. (2020). Identification of epileptic eeg signals using convolutional neural networks. *Applied Sciences*, 10(12):4089.

Abou Jaoude, M., Jing, J., Sun, H., Jacobs, C. S., Pellerin, K. R., Westover, M. B., Cash, S. S., and Lam, A. D. (2020). Detection of mesial temporal lobe epileptiform discharges in intracranial electrodes using deep learning. *Clinical Neurophysiology*, 131(1):133–141.

Abramovici, S. and Bagić, A. (2016). Epidemiology of epilepsy. *Handbook of clinical neurology*, 138:159–171.
Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., and Adeli, H. (2018). Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals. *Computers in biology and medicine*, 100:270–278.

Acharya, U. R., Sree, S. V., Swapna, G., Martis, R. J., and Suri, J. S. (2013). Automated eeg analysis of epilepsy: a review. *Knowledge-Based Systems*, 45:147–165.

Achilles, F., Tombari, F., Belagiannis, V., Loesch, A. M., Noachtar, S., and Navab, N. (2018). Convolutional neural networks for real-time epileptic seizure detection. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, 6(3):264–269.

Ahmedt-Aristizabal, D., Fookes, C., Nguyen, K., Denman, S., Sridharan, S., and Dionisio, S. (2018a). Deep facial analysis: A new phase i epilepsy evaluation using computer vision. *Epilepsy & Behavior*, 82:17–24.

Ahmedt-Aristizabal, D., Fookes, C., Nguyen, K., and Sridharan, S. (2018b). Deep classification of epileptic signals. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 332–335. IEEE.

Akut, R. (2019). Wavelet based deep learning approach for epilepsy detection. *Health information science and systems*, 7(1):1–9.

Akyol, K. (2020). Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection. *Expert Systems with Applications*, 148:113239.

Alam, S. S. and Bhuiyan, M. I. H. (2013). Detection of seizure and epilepsy using higher order statistics in the emd domain. *IEEE journal of biomedical and health informatics*, 17(2):312–318.

Allhussein, M., Muhammad, G., Hossain, M. S., and Amin, S. U. (2018). Cognitive iot-cloud integration for smart healthcare: case study for epileptic seizure detection and monitoring. *Mobile Networks and Applications*, 23(6):1624–1635.
Ali, Z. S., Subramanian, N., and Erbad, A. (2020). Smart health monitoring for seizure detection using mobile edge computing. In 2020 International Wireless Communications and Mobile Computing (IWCMC), pages 1903–1908. IEEE.

Alizadehsani, R., Sharifrazi, D., Izadi, N. H., Joloudari, J. H., Shoeibi, A., Gorriz, J. M., Hussain, S., Arco, J. E., Sani, Z. A., Khozeimeh, F., et al. (2021). Uncertainty-aware semi-supervised method using large unlabelled and limited labeled covid-19 data. arXiv preprint arXiv:2102.06388.

Amin, S. U., Hossain, M. S., Muhammad, G., Alhussein, M., and Rahman, M. A. (2019). Cognitive smart healthcare for pathology detection and monitoring. IEEE Access, 7:10745–10753.

Andrzejak, R. G., Lehnertz, K., Mormann, F., Ricke, C., David, P., and Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Physical Review E, 64(6):061907.

Andrzejak, R. G., Schindler, K., and Rummel, C. (2012). Nonrandomness, non-linear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. Physical Review E, 86(4):046206.

Ansari, A. H., Cherian, P. J., Caicedo, A., Naulaers, G., De Vos, M., and Van Huffel, S. (2019). Neonatal seizure detection using deep convolutional neural networks. International journal of neural systems, 29(04):1850011.

Antoniades, A., Spyrou, L., Martin-Lopez, D., Valentin, A., Alarcon, G., Sanei, S., and Took, C. C. (2018). Deep neural architectures for mapping scalp to intracranial eeg. International journal of neural systems, 28(08):1850009.

Antoniades, A., Spyrou, L., Took, C. C., and Sanei, S. (2016). Deep learning for epileptic intracranial eeg data. In 2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP), pages 1–6. IEEE.

Asif, U., Roy, S., Tang, J., and Harrer, S. (2019). Seizurenet: a deep convolutional neural network for accurate seizure type classification and seizure detection. arXiv preprint arXiv:1903.03232.
Assi, E. B., Nguyen, D. K., Rihana, S., and Sawan, M. (2017). Towards accurate prediction of epileptic seizures: A review. *Biomedical Signal Processing and Control*, 34:144–157.

Avcu, M. T., Zhang, Z., and Chan, D. W. S. (2019). Seizure detection using least eeg channels by deep convolutional neural network. In *ICASSP 2019-2019 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 1120–1124. IEEE.

Ballester, P. and Araujo, R. (2016). On the performance of googlenet and alexnet applied to sketches. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 30.

Bank, D., Koenigstein, N., and Giryes, R. (2020). Autoencoders. *arXiv preprint arXiv:2003.05991*.

Bao, Y., He, R., Zeng, Q., Zhu, P., Zheng, R., and Xu, H. (2018). Investigation of microstructural abnormalities in white and gray matter around hippocampus with diffusion tensor imaging (dti) in temporal lobe epilepsy (tle). *Epilepsy & Behavior*, 83:44–49.

Behroozi, M., Daliri, M. R., and Boyaci, H. (2011). Statistical analysis methods for the fmri data. *Basic and Clinical Neuroscience*, 2(4):67–74.

Bell, M. L., Rao, S., So, E. L., Trenerry, M., Kazemi, N., Matt Stead, S., Cascino, G., Marsh, R., Meyer, F. B., Watson, R. E., et al. (2009). Epilepsy surgery outcomes in temporal lobe epilepsy with a normal mri. *Epilepsia*, 50(9):2053–2060.

Bhagat, P. N., Ramesh, K., Matcha, V. G. R., and Patil, S. (2020). Robust prior stage epileptic seizure diagnosis system using resnet and backpropagation techniques. *International Journal*, 8(5).

Bharath, R. D., Panda, R., Raj, J., Bhardwaj, S., Sinha, S., Chaitanya, G., Raghavendra, K., Mundlamuri, R. C., Arimappamagan, A., Rao, M. B., et al. (2019). Machine learning identifies “rsfmri epilepsy networks” in temporal lobe epilepsy. *European radiology*, 29(7):3496–3505.
Bhattacherjee, I. (2020). Epileptic seizure detection using multicolour convolutional neural network. In 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom), pages 58–63. IEEE.

Bird, J. J., Faria, D. R., Manso, L. J., Ayrosa, P. P., and Ekart, A. (2021). A study on cnn image classification of eeg signals represented in 2d and 3d. Journal of Neural Engineering, 18(2):026005.

Birjandtalab, J., Pouyan, M. B., Cogan, D., Nourani, M., and Harvey, J. (2017). Automated seizure detection using limited-channel eeg and non-linear dimension reduction. Computers in biology and medicine, 82:49–58.

Bizopoulous, P., Lambrou, G. I., and Koutsouris, D. (2019). Signal2image modules in deep neural networks for eeg classification. In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 702–705. IEEE.

Boonyakitanont, P., Lek-uthai, A., Chomtho, K., and Songsiri, J. (2019). A comparison of deep neural networks for seizure detection in eeg signals. bioRxiv, page 702654.

Boonyakitanont, P., Lek-Uthai, A., Chomtho, K., and Songsiri, J. (2020a). A review of feature extraction and performance evaluation in epileptic seizure detection using eeg. Biomedical Signal Processing and Control, 57:101702.

Boonyakitanont, P., Lek-Uthai, A., and Songsiri, J. (2020b). Automatic epileptic seizure onset-offset detection based on cnn in scalp eeg. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 1225–1229. IEEE.

Boran, E., Sarunthein, J., Krayenbühl, N., Ramantani, G., and Fedele, T. (2019). High-frequency oscillations in scalp eeg mirror seizure frequency in pediatric focal epilepsy. Scientific reports, 9(1):1–10.

Bouallegue, G., Djemal, R., Alshebili, S. A., and Aldhalaan, H. (2020). A dynamic filtering df-rnn deep-learning-based approach for eeg-based neurological disorders diagnosis. IEEE Access, 8:206992–207007.
Bouaziz, B., Chaari, L., Batatia, H., and Quintero-Rincón, A. (2019). Epileptic seizure detection using a convolutional neural network. In Digital Health Approach for Predictive, Preventive, Personalised and Participatory Medicine, pages 79–86. Springer.

Burda, Y., Grosse, R., and Salakhutdinov, R. (2015). Importance weighted autoencoders. arXiv preprint arXiv:1509.00519.

Cao, J., Zhu, J., Hu, W., and Kummert, A. (2019). Epileptic signal classification with deep eeg features by stacked cnns. IEEE Transactions on Cognitive and Developmental Systems, 12(4):709–722.

Centeno, M. and Carmichael, D. W. (2014). Network connectivity in epilepsy: resting state fmri and eeg–fmri contributions. Frontiers in neurology, 5:93.

Cerulli Irelli, E., Morano, A., Cocchi, E., Casciato, S., Fanella, M., Albini, M., Avorio, F., Basili, L. M., Fisco, G., Barone, F. A., et al. (2020). Doing without valproate in women of childbearing potential with idiopathic generalized epilepsy: Implications on seizure outcome. Epilepsia, 61(1):107–114.

Chapman, K., Wyllie, E., Najm, I., Ruggieri, P., Bingaman, W., Lüders, J., Kotagal, P., Lachhwani, D., Dinner, D., and Lüders, H. (2005). Seizure outcome after epilepsy surgery in patients with normal preoperative mri. Journal of Neurology, Neurosurgery & Psychiatry, 76(5):710–713.

Chatzichristos, C., Dan, J., Narayanan, A. M., Sceuws, N., Vandecasteele, K., De Vos, M., Bertrand, A., and Van Huffel, S. (2020). Epileptic seizure detection in eeg via fusion of multi-view attention-gated u-net deep neural networks. In Proceedings of the IEEE Signal Processing in Medicine and Biology Symposium (SPMB), page 7.

Chen, M., Shi, X., Zhang, Y., Wu, D., and Guizani, M. (2017a). Deep features learning for medical image analysis with convolutional autoencoder neural network. IEEE Transactions on Big Data.

Chen, X., Ji, J., Ji, T., and Li, P. (2018). Cost-sensitive deep active learning for epileptic seizure detection. In Proceedings of the 2018 ACM International
Chen, Z., Huang, L., Shen, Y., Wang, J., Zhao, R., and Dai, J. (2017b). A new algorithm for classification of ictal and pre-ictal epilepsy ecog using mi and svm. In 2017 International Conference on Signals and Systems (ICSigSys), pages 212–216. IEEE.

Cho, K.-O. and Jang, H.-J. (2020). Comparison of different input modalities and network structures for deep learning-based seizure detection. Scientific reports, 10(1):1–11.

Choi, G., Park, C., Kim, J., Cho, K., Kim, T.-J., Bae, H., Min, K., Jung, K.-Y., and Chong, J. (2019). A novel multi-scale 3d cnn with deep neural network for epileptic seizure detection. In 2019 IEEE International Conference on Consumer Electronics (ICCE), pages 1–2. IEEE.

Clarke, S., Karoly, P. J., Nurse, E., Seneviratne, U., Taylor, J., Knight-Sadler, R., Kerr, R., Moore, B., Hennessy, P., Mendis, D., et al. (2019). Computer-assisted eeg diagnostic review for idiopathic generalized epilepsy. Epilepsy & Behavior, page 106556.

Colon, A., van Osch, M., Buijs, M., Grond, J., Hillebrand, A., Schijns, O., Wagner, G., Ossenblok, P., Hofman, P., Buchem, M., et al. (2018). Meg-guided analysis of 7t-mri in patients with epilepsy. Seizure, 60:29–38.

Covert, I. C., Krishnan, B., Najm, I., Zhan, J., Shore, M., Hixson, J., and Po, M. J. (2019). Temporal graph convolutional networks for automatic seizure detection. In Machine Learning for Healthcare Conference, pages 160–180. PMLR.

Craley, J., Johnson, E., and Venkataraman, A. (2019). Integrating convolutional neural networks and probabilistic graphical modeling for epileptic seizure detection in multichannel eeg. In International Conference on Information Processing in Medical Imaging, pages 291–303. Springer.

Daoud, H. and Bayoumi, M. (2019). Deep learning approach for epileptic focus localization. IEEE transactions on biomedical circuits and systems, 14(2):209–220.
Daoud, H., Williams, P., and Bayoumi, M. (2020). Iot based efficient epileptic seizure prediction system using deep learning. In 2020 IEEE 6th World Forum on Internet of Things (WF-IoT), pages 1–6. IEEE.

Daoud, H. G., Abdelhameed, A. M., and Bayoumi, M. (2018). Automatic epileptic seizure detection based on empirical mode decomposition and deep neural network. In 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), pages 182–186. IEEE.

Dash, S., Acharya, B. R., Mittal, M., Abraham, A., and Kelemen, A. G. (2020). Deep learning techniques for biomedical and health informatics. Springer.

Del Gaizo, J., Mofrad, N., Jensen, J. H., Clark, D., Glenn, R., Helpern, J., and Bonilha, L. (2017). Using machine learning to classify temporal lobe epilepsy based on diffusion mri. Brain and behavior, 7(10):e00801.

Dev, K. B., Jogi, P. S., Niyas, S., Vinayagamani, S., Kesavadas, C., and Rajan, J. (2019). Automatic detection and localization of focal cortical dysplasia lesions in mri using fully convolutional neural network. Biomedical Signal Processing and Control, 52:218–225.

Dey, N. (2016). Classification and clustering in biomedical signal processing. IGI global.

Dhull, S. K., Singh, K. K., et al. (2021). A review on automatic epilepsy detection from eeg signals. In Advances in Communication and Computational Technology, pages 1441–1454. Springer.

Duncan, J. S., Sander, J. W., Sisodiya, S. M., and Walker, M. C. (2006). Adult epilepsy. The Lancet, 367(9516):1087–1100.

Ebrahimzadeh, E., Shams, M., Fayaz, F., Rajabion, L., Mirbagheri, M., Araabi, B. N., and Soltanian-Zadeh, H. (2019). Quantitative determination of concordance in localizing epileptic focus by component-based eeg-fmri. Computer methods and programs in biomedicine, 177:231–241.

El Tahry, R., Wang, Z. I., Thandar, A., Podkorytova, I., Krishnan, B., Tousseyn, S., Guiyun, W., Burgess, R. C., and Alexopoulos, A. V. (2018). Magnetoe-
cephalography and ictal spect in patients with failed epilepsy surgery. *Clinical Neurophysiology*, 129(8):1651–1657.

Emami, A., Kunii, N., Matsuo, T., Shinozaki, T., Kawai, K., and Takahashi, H. (2019a). Autoencoding of long-term scalp electroencephalogram to detect epileptic seizure for diagnosis support system. *Computers in biology and medicine*, 110:227–233.

Emami, A., Kunii, N., Matsuo, T., Shinozaki, T., Kawai, K., and Takahashi, H. (2019b). Seizure detection by convolutional neural network-based analysis of scalp electroencephalography plot images. *NeuroImage: Clinical*, 22:101684.

Fan, M. and Chou, C.-A. (2018). Detecting abnormal pattern of epileptic seizures via temporal synchronization of eeg signals. *IEEE Transactions on Biomedical Engineering*, 66(3):601–608.

Fergus, P., Hignett, D., Hussain, A., Al-Jumeily, D., and Abdel-Aziz, K. (2015). Automatic epileptic seizure detection using scalp eeg and advanced artificial intelligence techniques. *BioMed research international*, 2015.

Figini, M., Lin, H., Ogbole, G., Arco, F. D., Blumberg, S. B., Carmichael, D. W., Tanno, R., Kaden, E., Brown, B. J., Lagunju, I., et al. (2020). Image quality transfer enhances contrast and resolution of low-field brain mri in african paediatric epilepsy patients. *arXiv preprint arXiv:2003.07216*.

Fisher, R. S. (2012). Therapeutic devices for epilepsy. *Annals of neurology*, 71(2):157–168.

Fraiwan, L. and Alkhodari, M. (2020). Classification of focal and non-focal epileptic patients using single channel eeg and long short-term memory learning system. *IEEE Access*, 8:77255–77262.

Frauscher, B. and Gotman, J. (2019). Sleep, oscillations, interictal discharges, and seizures in human focal epilepsy. *Neurobiology of disease*, 127:545–553.

Fukumori, K., Nguyen, H. T. T., Yoshida, N., and Tanaka, T. (2019). Fully data-driven convolutional filters with deep learning models for epileptic spike detection. In *ICASSP 2019-2019 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 2772–2776. IEEE.
Gaillard, W. D., Balsamo, L., Xu, B., Grandin, C., Braniecki, S., Papero, P., Weinstein, S., Conry, J., Pearl, P., Sachs, B., et al. (2002). Language dominance in partial epilepsy patients identified with an fmri reading task. Neurology, 59(2):256–265.

Gao, J., Sultan, H., Hu, J., and Tung, W.-W. (2009). Denoising nonlinear time series by adaptive filtering and wavelet shrinkage: a comparison. IEEE signal processing letters, 17(3):237–240.

Gao, X., Yan, X., Gao, P., Gao, X., and Zhang, S. (2020a). Automatic detection of epileptic seizure based on approximate entropy, recurrence quantification analysis and convolutional neural networks. Artificial intelligence in medicine, 102:101711.

Gao, Y., Gao, B., Chen, Q., Liu, J., and Zhang, Y. (2020b). Deep convolutional neural network-based epileptic electroencephalogram (eeg) signal classification. Frontiers in neurology, 11.

Garner, R., La Rocca, M., Barisano, G., Toga, A. W., Duncan, D., and Vespa, P. (2019). A machine learning model to predict seizure susceptibility from resting-state fmri connectivity. In 2019 Spring Simulation Conference (SpringSim), pages 1–11. IEEE.

Gasparini, S., Campolo, M., Ieracitano, C., Mammone, N., Ferlazzo, E., Sueri, C., Tripodi, G. G., Aguglia, U., and Morabito, F. C. (2018). Information theoretic-based interpretation of a deep neural network approach in diagnosing psychogenic non-epileptic seizures. Entropy, 20(2):43.

Geng, M., Zhou, W., Liu, G., Li, C., and Zhang, Y. (2020). Epileptic seizure detection based on stockwell transform and bidirectional long short-term memory. Ieee Transactions on Neural Systems and Rehabilitation Engineering, 28(3):573–580.

George, F., Joseph, A., Baby, B., John, A., John, T., Deepak, M., Nithin, G., and Sathidevi, P. (2020). Epileptic seizure prediction using eeg images. In 2020 International Conference on Communication and Signal Processing (ICCSP), pages 1595–1598. IEEE.
Ghassemi, N., Shoeibi, A., and Rouhani, M. (2020). Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images. *Biomedical Signal Processing and Control*, 57:101678.

Ghiasi, G., Cui, Y., Srinivas, A., Qian, R., Lin, T.-Y., Cubuk, E. D., Le, Q. V., and Zoph, B. (2020). Simple copy-paste is a strong data augmentation method for instance segmentation. *arXiv preprint arXiv:2012.07177*.

Gill, R. S., Hong, S.-J., Fadaie, F., Caldairou, B., Bernhardt, B. C., Barba, C., Brandt, A., Coelho, V. C., d’Incerti, L., Lenge, M., et al. (2018). Deep convolutional networks for automated detection of epileptogenic brain malformations. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 490–497. Springer.

Giudice, M. L., Varone, G., Ieracitano, C., Mammone, N., Bruna, A. R., Tomaselli, V., and Morabito, F. C. (2020). 1D convolutional neural network approach to classify voluntary eye blinks in EEG signals for BCI applications. In 2020 *International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE.

Gleichgerrcht, E., Munsell, B., Bhatia, S., Vandergrift III, W. A., Rorden, C., McDonald, C., Edwards, J., Kuzniecky, R., and Bonilha, L. (2018). Deep learning applied to whole-brain connectome to determine seizure control after epilepsy surgery. *Epilepsia*, 59(9):1643–1654.

Gloor, P. and Fariello, R. (1988). Generalized epilepsy: some of its cellular mechanisms differ from those of focal epilepsy. *Trends in neurosciences*, 11(2):63–68.

Glory, H. A., Vigneswaran, C., Jagtap, S. S., Shruthi, R., Hariharan, G., and Sriram, V. S. (2020). Ahw-bgoa-dnn: a novel deep learning model for epileptic seizure detection. *Neural Computing and Applications*, pages 1–29.

Golmohammadi, M., Harati Nejad Torbati, A. H., Lopez de Diego, S., Obeid, I., and Picone, J. (2019). Automatic analysis of EEGs using big data and hybrid deep learning architectures. *Frontiers in Human Neuroscience*, 13:76.
Golmohammadi, M., Ziyabari, S., Shah, V., de Diego, S. L., Obeid, I., and Picone, J. (2017). Deep architectures for automated seizure detection in scalp eegs. arXiv preprint arXiv:1712.09776.

Goodfellow, I., Bengio, Y., Courville, A., and Bengio, Y. (2016). Deep learning, volume 1. MIT press Cambridge.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative adversarial networks. arXiv preprint arXiv:1406.2661.

Gotman, J. (2008). Epileptic networks studied with eeg-fmri. Epilepsia, 49:42–51.

Guevara, E., Flores-Castro, J.-A., Peng, K., Nguyen, D. K., Lesage, F., Pouliot, P., and Rosas-Romero, R. (2020). Prediction of epileptic seizures using fnirs and machine learning. Journal of Intelligent & Fuzzy Systems, 38(2):2055–2068.

Guha, A., Ghosh, S., Roy, A., and Chatterjee, S. (2020). Epileptic seizure recognition using deep neural network. In Emerging Technology in Modelling and Graphics, pages 21–28. Springer.

Gupta, V., Bhattacharyya, A., and Pachori, R. B. (2020). Automated identification of epileptic seizures from eeg signals using fbse-ewt method. In Biomedical Signal Processing, pages 157–179. Springer.

Hao, Y., Khoo, H. M., von Ellenrieder, N., Zazubovits, N., and Gotman, J. (2018). Deepied: An epileptic discharge detector for eeg-fmri based on deep learning. NeuroImage: Clinical, 17:962–975.

Hartmann, K. G., Schirrmeister, R. T., and Ball, T. (2018). Eeg-gan: Generative adversarial networks for electroencephalographic (eeg) brain signals. arXiv preprint arXiv:1806.01875.

Hazra, D. and Byun, Y.-C. (2020). Synsiggan: Generative adversarial networks for synthetic biomedical signal generation. Biology, 9(12):441.

Hinton, G. E. (2009). Deep belief networks. Scholarpedia, 4(5):5947.
Holden, D., Saito, J., Komura, T., and Joyce, T. (2015). Learning motion manifolds with convolutional autoencoders. In SIGGRAPH Asia 2015 Technical Briefs, pages 1–4.

Hossain, M. S., Amin, S. U., Alsulaiman, M., and Muhammad, G. (2019). Applying deep learning for epilepsy seizure detection and brain mapping visualization. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 15(1s):1–17.

Hosseini, M.-P., Soltanian-Zadeh, H., Elisevich, K., and Pompili, D. (2016). Cloud-based deep learning of big eeg data for epileptic seizure prediction. In 2016 IEEE global conference on signal and information processing (GlobalSIP), pages 1151–1155. IEEE.

Hosseini, M.-P., Tran, T. X., Pompili, D., Elisevich, K., and Soltanian-Zadeh, H. (2017). Deep learning with edge computing for localization of epileptogenicity using multimodal rs-fmri and eeg big data. In 2017 IEEE international conference on autonomic computing (ICAC), pages 83–92. IEEE.

Hsu, K.-Y., Li, H.-Y., and Psaltis, D. (1990). Holographic implementation of a fully connected neural network. Proceedings of the IEEE, 78(10):1637–1645.

Hu, D., Cao, J., Lai, X., Wang, Y., Wang, S., and Ding, Y. (2020a). Epileptic state classification by fusing hand-crafted and deep learning eeg features. IEEE Transactions on Circuits and Systems II: Express Briefs.

Hu, D., Cao, J., Lai, X., Wang, Y., Wang, S., and Ding, Y. (2020b). Epileptic state classification by fusing hand-crafted and deep learning eeg features. IEEE Transactions on Circuits and Systems II: Express Briefs.

Hu, X. and Yuan, Q. (2019). Epileptic eeg identification based on deep bi-lstm network. In 2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT), pages 63–66. IEEE.

Hu, X., Yuan, S., Xu, F., Leng, Y., Yuan, K., and Yuan, Q. (2020c). Scalp eeg classification using deep bi-lstm network for seizure detection. Computers in Biology and Medicine, 124:103919.

68
Huang, J., Xu, J., Kang, L., and Zhang, T. (2020). Identifying epilepsy based on deep learning using dki images. *Frontiers in Human Neuroscience*, 14:465.

Hussein, A. F., Arunkumar, N., Gomes, C., Alzubaidi, A. K., Habash, Q. A., Santamaria-Granados, L., Mendoza-Moreno, J. F., and Ramirez-Gonzalez, G. (2018a). Focal and non-focal epilepsy localization: A review. *IEEE Access*, 6:49306–49324.

Hussein, R., Lee, S., Ward, R., and McKeown, M. J. (2020). Epileptic seizure prediction: A semi-dilated convolutional neural network architecture. *arXiv preprint arXiv:2007.11716*.

Hussein, R., Palangi, H., Wang, Z. J., and Ward, R. (2018b). Robust detection of epileptic seizures using deep neural networks. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 2546–2550. IEEE.

Hussein, R., Palangi, H., Ward, R., and Wang, Z. J. (2018c). Epileptic seizure detection: A deep learning approach. *arXiv preprint arXiv:1803.09848*.

Hussein, R., Palangi, H., Ward, R. K., and Wang, Z. J. (2019). Optimized deep neural network architecture for robust detection of epileptic seizures using eeg signals. *Clinical Neurophysiology*, 130(1):25–37.

Iandola, F. N., Han, S., Moskewicz, M. W., Ashraf, K., Dally, W. J., and Keutzer, K. (2016). SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and 0.5 mb model size. *arXiv preprint arXiv:1602.07360*.

Iasemidis, L. D. (2003). Epileptic seizure prediction and control. *IEEE Transactions on Biomedical Engineering*, 50(5):549–558.

Iešmantas, T. and Alzbutas, R. (2020). Convolutional neural network for detection and classification of seizures in clinical data. *Medical & Biological Engineering & Computing*, 58(9):1919–1932.

Ihle, M., Feldwisch-Drentrup, H., Teixeira, C. A., Witon, A., Schelter, B., Timmer, J., and Schulze-Bonhage, A. (2012). Epilepsiae–a european epilepsy database. *Computer methods and programs in biomedicine*, 106(3):127–138.
Ilakiyaselvan, N., Khan, A. N., and Shahina, A. (2020). Deep learning approach to detect seizure using reconstructed phase space images. *Journal of Biomedical Research, 34*(3):240.

Jaafar, S. T. and Mohammadi, M. (2019). Epileptic seizure detection using deep learning approach. *UHD Journal of Science and Technology, 3*(2):41–50.

Jaber, H. A., Aljobouri, H. K., Çankaya, İ., Koçak, O. M., and Algin, O. (2019). Preparing fmri data for postprocessing: Conversion modalities, preprocessing pipeline, and parametric and nonparametric approaches. *IEEE Access, 7*:122864–122877.

Jana, G. C., Sharma, R., and Agrawal, A. (2020). A 1d-cnn-spectrogram based approach for seizure detection from eeg signal. *Procedia Computer Science, 167*:403–412.

Jiang, H., Gao, F., Duan, X., Bai, Z., Wang, Z., Ma, X., and Chen, Y.-W. (2019a). Transfer learning and fusion model for classification of epileptic pet images. In *Innovation in Medicine and Healthcare Systems, and Multimedia*, pages 71–79. Springer.

Jiang, X., Bian, G.-B., and Tian, Z. (2019b). Removal of artifacts from eeg signals: a review. *Sensors, 19*(5):987.

Karim, A. M., Güzel, M. S., Tolun, M. R., Kaya, H., and Çelebi, F. V. (2018a). A new generalized deep learning framework combining sparse autoencoder and taguchi method for novel data classification and processing. *Mathematical Problems in Engineering, 2018.*

Karim, A. M., Güzel, M. S., Tolun, M. R., Kaya, H., and Çelebi, F. V. (2019). A new framework using deep auto-encoder and energy spectral density for medical waveform data classification and processing. *Biocybernetics and Biomedical Engineering, 39*(1):148–159.

Karim, A. M., Karal, Ö., and Çelebi, F. (2018b). A new automatic epilepsy serious detection method by using deep learning based on discrete wavelet transform. *no, 4*:15–18.
Kaya, D. (2020). The mrmr-cnn based influential support decision system approach to classify eeg signals. *Measurement, 156*:107602.

Kaziha, O. and Bonny, T. (2020). A convolutional neural network for seizure detection. In *2020 Advances in Science and Engineering Technology International Conferences (ASET)*, pages 1–5. IEEE.

Keren, G. and Schuller, B. (2016). Convolutional rnn: an enhanced model for extracting features from sequential data. In *2016 International Joint Conference on Neural Networks (IJCNN)*, pages 3412–3419. IEEE.

Khalifa, Y., Mandic, D., and Sejdić, E. (2020). A review of hidden markov models and recurrent neural networks for event detection and localization in biomedical signals. *Information Fusion*.

Khalilpour, S., Ranjbar, A., Menhaj, M. B., and Sandooghdar, A. (2020). Application of 1-d cnn to predict epileptic seizures using eeg records. In *2020 6th International Conference on Web Research (ICWR)*, pages 314–318. IEEE.

Khodatars, M., Shoeibi, A., Ghassemi, N., Jafari, M., Khadem, A., Sadeghi, D., Moridian, P., Hussain, S., Alizadehsani, R., Zare, A., et al. (2020a). Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: A review. *arXiv preprint arXiv:2007.01285*.

Khodatars, M., Shoeibi, A., Ghassemi, N., Jafari, M., Khadem, A., Sadeghi, D., Moridian, P., Hussain, S., Alizadehsani, R., Zare, A., et al. (2020b). Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: A review. *arXiv preprint arXiv:2007.01285*.

Kim, S.-P. (2018). Preprocessing of eeg. In *Computational EEG Analysis*, pages 15–33. Springer.

Kiral-Kornek, I., Roy, S., Nurse, E., Mashford, B., Karoly, P., Carroll, T., Payne, D., Saha, S., Baldassano, S., O’Brien, T., et al. (2018). Epileptic seizure prediction using big data and deep learning: toward a mobile system. *EBioMedicine, 27*:103–111.

Kowalczyk, M. A., Omidvarnia, A., Abbott, D. F., Tailby, C., Vaughan, D. N., and Jackson, G. D. (2020). Clinical benefit of presurgical eeg-fmri in difficult-
to-localize focal epilepsy: A single-institution retrospective review. Epilepsia, 61(1):49–60.

Krizhevsky, A. and Hinton, G. (2010). Convolutional deep belief networks on cifar-10. Unpublished manuscript, 40(7):1–9.

Kwak, Y., Kong, K., Song, W.-J., Min, B.-K., and Kim, S.-E. (2020). Multilevel feature fusion with 3d convolutional neural network for eeg-based workload estimation. IEEE Access, 8:16009–16021.

Lai, C. Q., Ibrahim, H., Abdullah, M. Z., Abdullah, J. M., Suandi, S. A., and Azman, A. (2018). Artifacts and noise removal for electroencephalogram (eeg): A literature review. In 2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), pages 326–332. IEEE.

Lashgari, E., Liang, D., and Maoz, U. (2020). Data augmentation for deep-learning-based electroencephalography. Journal of Neuroscience Methods, page 108885.

Le, T. X., Le, T. T., Dinh, V. V., Tran, Q. L., Nguyen, L. T., and Nguyen, D. T. (2018). Deep learning for epileptic spike detection. VNU Journal of Science: Computer Science and Communication Engineering, 33(2):1–13.

Lee, M.-H., O’Hara, N., Sonoda, M., Kuroda, N., Juhasz, C., Asano, E., Dong, M., and Jeong, J.-W. (2020). Novel deep learning network analysis of electrical stimulation mapping-driven diffusion mri tractography to improve pre-operative evaluation of pediatric epilepsy. IEEE Transactions on Biomedical Engineering, 67(11):3151–3162.

LeVan, P., Urrestarazu, E., and Gotman, J. (2006). A system for automatic artifact removal in ictal scalp eeg based on independent component analysis and bayesian classification. Clinical neurophysiology, 117(4):912–927.

Li, J., Li, B., Xu, J., Xiong, R., and Gao, W. (2018). Fully connected network-based intra prediction for image coding. IEEE Transactions on Image Processing, 27(7):3236–3247.
Li, S., Kawale, J., and Fu, Y. (2015). Deep collaborative filtering via marginalized denoising auto-encoder. In Proceedings of the 24th ACM international on conference on information and knowledge management, pages 811–820.

Li, Y., Liu, Y., Cui, W.-G., Guo, Y.-Z., Huang, H., and Hu, Z.-Y. (2020a). Epileptic seizure detection in eeg signals using a unified temporal-spectral squeeze-and-excitation network. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(4):782–794.

Li, Y., Yu, Z., Chen, Y., Yang, C., Li, Y., Allen Li, X., and Li, B. (2020b). Automatic seizure detection using fully convolutional nested lstm. International journal of neural systems, 30(04):2050019.

Lian, J., Zhang, Y., Luo, R., Han, G., Jia, W., and Li, C. (2020). Pair-wise matching of eeg signals for epileptic identification via convolutional neural network. IEEE Access, 8:40008–40017.

Liang, W., Pei, H., Cai, Q., and Wang, Y. (2020). Scalp eeg epileptogenic zone recognition and localization based on long-term recurrent convolutional network. Neurocomputing, 396:569–576.

Lin, L.-C., Ouyang, C.-S., Wu, R.-C., Yang, R.-C., and Chiang, C.-T. (2020). Alternative diagnosis of epilepsy in children without epileptiform discharges using deep convolutional neural networks. International journal of neural systems, 30(05):1850060.

Lin, Q., Ye, S.-q., Huang, X.-m., Li, S.-y., Zhang, M.-z., Xue, Y., and Chen, W.-S. (2016). Classification of epileptic eeg signals with stacked sparse autoencoder based on deep learning. In International Conference on Intelligent Computing, pages 802–810. Springer.

Liu, F., Wang, Y., Li, M., Wang, W., Li, R., Zhang, Z., Lu, G., and Chen, H. (2017). Dynamic functional network connectivity in idiopathic generalized epilepsy with generalized tonic–clonic seizure. Human brain mapping, 38(2):957–973.

Liu, G., Zhou, W., and Geng, M. (2020a). Automatic seizure detection based on s-transform and deep convolutional neural network. International journal of neural systems, 30(04):1950024.
Liu, J. and Woodson, B. (2019). Deep learning classification for epilepsy detection using a single channel electroencephalography (eeg). In Proceedings of the 2019 3rd International Conference on Deep Learning Technologies, pages 23–26.

Liu, X. and Richardson, A. G. (2020). Embedded deep learning for neural implants. arXiv preprint arXiv:2012.00307.

Liu, Y., Huang, Y.-X., Zhang, X., Qi, W., Guo, J., Hu, Y., Zhang, L., and Su, H. (2020b). Deep c-lstm neural network for epileptic seizure and tumor detection using high-dimension eeg signals. IEEE Access, 8:37495–37504.

Liu, Y., Zhou, W., Yuan, Q., and Chen, S. (2012). Automatic seizure detection using wavelet transform and svm in long-term intracranial eeg. IEEE transactions on neural systems and rehabilitation engineering, 20(6):749–755.

Lu, D., Bauer, S., Neubert, V., Costard, L. S., Rosenow, F., and Triesch, J. (2020). Staging epileptogenesis with deep neural networks. In Proceedings of the 11th ACM International Conference on Bioinformatics, Computational Biology and Health Informatics, pages 1–10.

Lu, D. and Triesch, J. (2019). Residual deep convolutional neural network for eeg signal classification in epilepsy. arXiv preprint arXiv:1903.08100.

Luo, C., Li, Q., Lai, Y., Xia, Y., Qin, Y., Liao, W., Li, S., Zhou, D., Yao, D., and Gong, Q. (2011). Altered functional connectivity in default mode network in absence epilepsy: a resting-state fmri study. Human brain mapping, 32(3):438–449.

Ma, K., Zhang, X., Zhang, H., Yan, X., Gao, A., Song, C., Wang, S., Lian, Y., and Cheng, J. (2020). Mean apparent propagator-mri: a new diffusion model which improves temporal lobe epilepsy lateralization. European journal of radiology, 126:108914.

Madhavan, S., Tripathy, R. K., and Pachori, R. B. (2019). Time-frequency domain deep convolutional neural network for the classification of focal and non-focal eeg signals. IEEE Sensors Journal, 20(6):3078–3086.
Makhzani, A., Shlens, J., Jaitly, N., Goodfellow, I., and Frey, B. (2015). Adversarial autoencoders. arXiv preprint arXiv:1511.05644.

Makropoulos, A., Counsell, S. J., and Rueckert, D. (2018). A review on automatic fetal and neonatal brain mri segmentation. NeuroImage, 170:231–248.

Manjón, J. V. (2017). Mri preprocessing. In Imaging Biomarkers, pages 53–63. Springer.

Mao, W., Fathurrahman, H., Lee, Y., and Chang, T. (2020). Eeg dataset classification using cnn method. In Journal of Physics: Conference Series, volume 1456, page 012017. IOP Publishing.

Mei, Z., Zhao, X., Chen, H., and Chen, W. (2018). Bio-signal complexity analysis in epileptic seizure monitoring: A topic review. Sensors, 18(6):1720.

Meisel, C., Atrache, R. E., Jackson, M., Schubach, S., Ufongene, C., and Loddenkemper, T. (2019). Deep learning from wristband sensor data: towards wearable, non-invasive seizure forecasting. arXiv preprint arXiv:1906.00511.

Misiunas, A. V. M., Meskauskas, T., and Samaitiené, R. (2019). Algorithm for automatic eeg classification according to the epilepsy type: Benign focal childhood epilepsy and structural focal epilepsy. Biomedical signal processing and control, 48:118–127.

Modir, A., Khalilzadeh, M. A., and Gorji, A. (2017). Detection of focal epileptic seizure using nirs signal based on discrete wavelet transform. International Clinical Neuroscience Journal, 4(4):134.

Mohammadpoor, M., Shoeibi, A., Shojaei, H., et al. (2016). A hierarchical classification method for breast tumor detection. Iranian Journal of Medical Physics, 13(4):261–268.

Mohammadpoory, Z., Nasrolahzadeh, M., Mahmoodian, N., Sayyah, M., and Haddadnia, J. (2019). Complex network based models of ecog signals for detection of induced epileptic seizures in rats. Cognitive neurodynamics, 13(4):325–339.
MohanBabu, G., Anupallavi, S., and Ashokkumar, S. (2020). An optimized deep learning network model for eeg based seizure classification using synchronization and functional connectivity measures. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–13.

Muhammad, G., Masud, M., Amin, S. U., Alrobaea, R., and Alhamid, M. F. (2018). Automatic seizure detection in a mobile multimedia framework. *IEEE Access*, 6:45372–45383.

Naik, G., Chai, R., Su, S., Rong, S., and Nguyen, H. T. (2020). Comparison of independence of triceps brachii and biceps brachii between paretic and non-paretic side during different mvcs—a case study. In *Biomedical Signal Processing*, pages 71–79. Springer.

Nair, D. R., Laxer, K. D., Weber, P. B., Murro, A. M., Park, Y. D., Barkley, G. L., Smith, B. J., Gwinn, R. P., Doherty, M. J., Noe, K. H., et al. (2020). Nine-year prospective efficacy and safety of brain-responsive neurostimulation for focal epilepsy. *Neurology*, 95(9):e1244–e1256.

Nejedly, P., Kremen, V., Sladky, V., Nasseri, M., Guragain, H., Klimes, P., Cimbalknik, J., Varatharajah, Y., Brinkmann, B. H., and Worrell, G. A. (2019). Deep-learning for seizure forecasting in canines with epilepsy. *Journal of neural engineering*, 16(3):036031.

Ngoh, A. and Parker, A. P. (2017). New developments in epilepsy management. *Paediatrics and Child Health*, 27(6):281–286.

Nguyen, D. K., Tremblay, J., Pouliot, P., Vannasing, P., Florea, O., Carmant, L., Lepore, F., Sawan, M., Lesage, F., and Lassonde, M. (2012). Non-invasive continuous eeg-fnirs recording of temporal lobe seizures. *Epilepsy research*, 99(1-2):112–126.

Noachtar, S. and Peters, A. S. (2009). Semiology of epileptic seizures: a critical review. *Epilepsy & Behavior*, 15(1):2–9.

Noble, W. S. (2006). What is a support vector machine? *Nature biotechnology*, 24(12):1565–1567.
Ocak, H. (2009). Automatic detection of epileptic seizures in eeg using discrete wavelet transform and approximate entropy. *Expert Systems with Applications*, 36(2):2027–2036.

Oldan, J. D., Shin, H. W., Khandani, A. H., Zamora, C., Benefield, T., and Jewells, V. (2018). Subsequent experience in hybrid pet-mri for evaluation of refractory focal onset epilepsy. *Seizure*, 61:128–134.

O’Shea, A., Lightbody, G., Boylan, G., and Tenko, A. (2017a). Neonatal seizure detection using convolutional neural networks. In *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*, pages 1–6. IEEE.

O’Shea, A., Lightbody, G., Boylan, G., and Tenko, A. (2017b). Neonatal seizure detection using convolutional neural networks. In *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*, pages 1–6. IEEE.

Pachori, R. B. and Bajaj, V. (2011). Analysis of normal and epileptic seizure eeg signals using empirical mode decomposition. *Computer methods and programs in biomedicine*, 104(3):373–381.

Page, A., Shea, C., and Mohsenin, T. (2016). Wearable seizure detection using convolutional neural networks with transfer learning. In *2016 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1086–1089. IEEE.

Park, B.-y., Byeon, K., and Park, H. (2019). Funp (fusion of neuroimaging preprocessing) pipelines: a fully automated preprocessing software for functional magnetic resonance imaging. *Frontiers in neuroinformatics*, 13:5.

Park, C., Choi, G., Kim, J., Kim, S., Kim, T.-J., Min, K., Jung, K.-Y., and Chong, J. (2018). Epileptic seizure detection for multi-channel eeg with deep convolutional neural network. In *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, pages 1–5. IEEE.

Pascual, D., Aminifar, A., Atienza, D., Ryvlin, P., and Wattenhofer, R. (2019). Synthetic epileptic brain activities using gans. In *Machine Learning for Health (ML4H) at the 33rd Conf. on Neural Information Processing Systems*. 77
Patan, K. and Rutkowski, G. (2021). Application of deep learning to seizure classification. In *Advances in Diagnostics of Processes and Systems*, pages 157–172. Springer.

Patro, S. and Sahu, K. K. (2015). Normalization: A preprocessing stage. *arXiv preprint arXiv:1503.06462*.

Paul, Y. (2018). Various epileptic seizure detection techniques using biomedical signals: a review. *Brain informatics*, 5(2):1–19.

Pellegrino, G., Mecarelli, O., Pulitano, P., Tombini, M., Ricci, L., Lanzone, J., Brienza, M., Davassi, C., Di Lazzaro, V., and Assenza, G. (2018). Eslicarbazepine acetate modulates eeg activity and connectivity in focal epilepsy. *Frontiers in neurology*, 9:1054.

Peng, K., Nguyen, D. K., Tayah, T., Vannasing, P., Tremblay, J., Sawan, M., Lassonde, M., Lesage, F., and Pouliot, P. (2014). fnirs-eeg study of focal interictal epileptiform discharges. *Epilepsy research*, 108(3):491–505.

Peng, K., Nguyen, D. K., Vannasing, P., Tremblay, J., Lesage, F., and Pouliot, P. (2016). Using patient-specific hemodynamic response function in epileptic spike analysis of human epilepsy: a study based on eeg–fnirs. *NeuroImage*, 126:239–255.

Peng, W. (2019). Eeg preprocessing and denoising. In *EEG Signal Processing and Feature Extraction*, pages 71–87. Springer.

Pisano, F., Sias, G., Fanni, A., Cannas, B., Dourado, A., Pisano, B., and Teixeira, C. A. (2020). Convolutional neural network for seizure detection of nocturnal frontal lobe epilepsy. *Complexity*, 2020.

Polat, K. and Güneş, S. (2007). Classification of epileptiform eeg using a hybrid system based on decision tree classifier and fast fourier transform. *Applied Mathematics and Computation*, 187(2):1017–1026.

Pominova, M., Artemov, A., Sharaev, M., Kondrateva, E., Bernstein, A., and Burnaev, E. (2018). Voxelwise 3d convolutional and recurrent neural networks for epilepsy and depression diagnostics from structural and functional mri
data. In 2018 IEEE International Conference on Data Mining Workshops (ICDMW), pages 299–307. IEEE.

Pouliot, P., Tremblay, J., Robert, M., Vannasing, P., Lepore, F., Lassonde, M., Sawan, M., Nguyen, D. K., and Lesage, F. (2012). Nonlinear hemodynamic responses in human epilepsy: a multimodal analysis with fNIRS-EEG and fMRI-EEG. Journal of neuroscience methods, 204(2):326–340.

Prasanth, T., Thomas, J., Yuvaraj, R., Jing, J., Cash, S. S., Chaudhari, R., Leng, T. Y., Rathakrishnan, R., Rohit, S., Saini, V., et al. (2020). Deep learning for interictal epileptiform spike detection from scalp EEG frequency sub-bands. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pages 3703–3706. IEEE.

Qin, H., Deng, B., Wang, J., Yi, G., Wang, R., and Zhang, Z. (2020a). Deep multi-scale feature fusion convolutional neural network for automatic epilepsy detection using EEG signals. In 2020 39th Chinese Control Conference (CCC), pages 7061–7066. IEEE.

Qin, Y., Zheng, H., Chen, W., Qin, Q., Han, C., and Che, Y. (2020b). Patient-specific seizure prediction with scalp EEG using convolutional neural network and extreme learning machine. In 2020 39th Chinese Control Conference (CCC), pages 7622–7625. IEEE.

Qiu, Y., Zhou, W., Yu, N., and Du, P. (2018). Denoising sparse autoencoder-based ictal EEG classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(9):1717–1726.

Raghu, S., Sriraam, N., Temel, Y., Rao, S. V., and Kubben, P. L. (2020). EEG based multi-class seizure type classification using convolutional neural network and transfer learning. Neural Networks, 124:202–212.

Rajaguru, H. and Prabhakar, S. K. (2018). Multilayer autoencoders and emPCA with genetic algorithm for epilepsy classification from EEG. In 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), pages 353–358. IEEE.
Rampp, S., Stefan, H., Wu, X., Kaltenhäuser, M., Maess, B., Schmitt, F. C., Wolters, C. H., Hamer, H., Kasper, B. S., Schwab, S., et al. (2019). Magnetoencephalography for epileptic focus localization in a series of 1000 cases. *Brain*, 142(10):3059–3071.

Rashed-Al-Mahfuz, M., Moni, M. A., Uddin, S., Alyami, S. A., Summers, M. A., and Eapen, V. (2021). A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (eeg) data. *IEEE Journal of Translational Engineering in Health and Medicine*, 9:1–12.

Rasheed, K., Qayyum, A., Qadir, J., Sivathamboo, S., Kwan, P., Kuhlmann, L., O’Brien, T., and Razi, A. (2020). Machine learning for predicting epileptic seizures using eeg signals: A review. *IEEE Reviews in Biomedical Engineering*.

RaviPrakash, H., Korostenskaja, M., Castillo, E. M., Lee, K. H., Salinas, C. M., Baumgartner, J., Anwar, S. M., Spampinato, C., and Bagci, U. (2020). Deep learning provides exceptional accuracy to ecog-based functional language mapping for epilepsy surgery. *Frontiers in Neuroscience*, 14:409.

Rebsamen, M., Suter, Y., Wiest, R., Reyes, M., and Rummel, C. (2020). Brain morphometry estimation: From hours to seconds using deep learning. *Frontiers in neurology*, 11:244.

Rosas-Romero, R., Guevara, E., Peng, K., Nguyen, D. K., Lesage, F., Pouliot, P., and Lima-Saad, W.-E. (2019). Prediction of epileptic seizures with convolutional neural networks and functional near-infrared spectroscopy signals. *Computers in biology and medicine*, 111:103355.

Roy, S., Kiral-Kornek, I., and Harrer, S. (2018). Deep learning enabled automatic abnormal eeg identification. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 2756–2759. IEEE.

Roy, S., Kiral-Kornek, I., and Harrer, S. (2019). Chrononet: a deep recurrent neural network for abnormal eeg identification. In *Conference on Artificial Intelligence in Medicine in Europe*, pages 47–56. Springer.
Rüber, T., David, B., and Elger, C. E. (2018). Mri in epilepsy: clinical standard and evolution. *Current opinion in neurology*, 31(2):223–231.

Saab, M. and Gotman, J. (2005). A system to detect the onset of epileptic seizures in scalp eeg. *Clinical Neurophysiology*, 116(2):427–442.

Sadeghi, D., Shoeibi, A., Ghassemi, N., Moridian, P., Khadem, A., Alizadehsani, R., Teshnehlab, M., Gorriz, J. M., and Nahavandi, S. (2021). An overview on artificial intelligence techniques for diagnosis of schizophrenia based on magnetic resonance imaging modalities: Methods, challenges, and future works. *arXiv preprint arXiv:2103.03081*.

Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., and Baik, S. W. (2019). Multi-grade brain tumor classification using deep cnn with extensive data augmentation. *Journal of computational science*, 30:174–182.

Sakai, T., Shoji, T., Yoshida, N., Fukumori, K., Tanaka, Y., and Tanaka, T. (2020). Scalpnet: Detection of spatiotemporal abnormal intervals in epileptic eeg using convolutional neural networks. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1244–1248. IEEE.

Samiee, K., Kovacs, P., and Gabbouj, M. (2014). Epileptic seizure classification of eeg time-series using rational discrete short-time fourier transform. *IEEE transactions on Biomedical Engineering*, 62(2):541–552.

San-Segundo, R., Gil-Martín, M., D’Haro-Enriquez, L. F., and Pardo, J. M. (2019). Classification of epileptic eeg recordings using signal transforms and convolutional neural networks. *Computers in biology and medicine*, 109:148–158.

Saqib, M., Zhu, Y., Wang, M., and Beaulieu-Jones, B. (2020). Regularization of deep neural networks for eeg seizure detection to mitigate overfitting. In *2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC)*, pages 664–673. IEEE.

Sayem, M. A., Sarker, M. S. R., Ahad, M. A. R., and Ahmed, M. U. (2021). Automatic epileptic seizures detection and eeg signals classification based on
multi-domain feature extraction and multiscale entropy analysis. In *Signal Processing Techniques for Computational Health Informatics*, pages 315–334. Springer.

Schlegl, T., Seeböck, P., Waldstein, S. M., Langs, G., and Schmidt-Erfurth, U. (2019). f-anogan: Fast unsupervised anomaly detection with generative adversarial networks. *Medical image analysis*, 54:30–44.

Schroff, F., Kalenichenko, D., and Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 815–823.

Shakeri, M., Tsogkas, S., Ferrante, E., Lippe, S., Kadoury, S., Paragios, N., and Kokkinos, I. (2016). Sub-cortical brain structure segmentation using f-cnn’s. In *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, pages 269–272. IEEE.

Shankar, A., Khaing, H. K., Dandapat, S., and Barma, S. (2020). Epileptic seizure classification based on gramian angular field transformation and deep learning. In *2020 IEEE Applied Signal Processing Conference (ASPCON)*, pages 147–151. IEEE.

Sharan, R. V. and Berkovsky, S. (2020). Epileptic seizure detection using multichannel eeg wavelet power spectra and 1-d convolutional neural networks. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 545–548. IEEE.

Sharathappriyaa, V., Gautham, S., and Lavanya, R. (2018). Auto-encoder based automated epilepsy diagnosis. In *2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pages 976–982. IEEE.

Sharifrazi, D., Alizadehsani, R., Roshanzamir, M., Joloudari, J. H., Shoeibi, A., Jafari, M., Hussain, S., Sani, Z. A., Hasanzadeh, F., Khozeimeh, F., et al. (2021). Fusion of convolution neural network, support vector machine and sobel filter for accurate detection of covid-19 patients using x-ray images. *Biomedical Signal Processing and Control*, page 102622.
Sharma, R., and Pachori, R. B. (2015). Classification of epileptic seizures in eeg signals based on phase space representation of intrinsic mode functions. *Expert Systems with Applications*, 42(3):1106–1117.

Sharma, R., Pachori, R. B., and Sircar, P. (2020). Seizures classification based on higher order statistics and deep neural network. *Biomedical Signal Processing and Control*, 59:101921.

Sharmila, A. (2018). Epilepsy detection from eeg signals: a review. *Journal of medical engineering & technology*, 42(5):368–380.

Shiri, I., Ghafarian, P., Geramifar, P., Leung, K. H.-Y., Ghelichoghli, M., Oveis, M., Rahmim, A., and Ay, M. R. (2019). Direct attenuation correction of brain pet images using only emission data via a deep convolutional encoder-decoder (deep-dac). *European radiology*, 29(12):6867–6879.

Shoeb, A. H. (2009a). *Application of machine learning to epileptic seizure onset detection and treatment*. PhD thesis, Massachusetts Institute of Technology.

Shoeb, A. H. (2009b). *Application of machine learning to epileptic seizure onset detection and treatment*. PhD thesis, Massachusetts Institute of Technology.

Shoeb, A. H. and Guttag, J. V. (2010). Application of machine learning to epileptic seizure detection. In *Proceedings of the 27th International Conference on Machine Learning (ICML-10)*, pages 975–982.

Shoeibi, A., Ghassemi, N., Alizadehsani, R., Rouhani, M., Hosseini-Nejad, H., Khosravi, A., Panahiazar, M., and Nahavandi, S. (2021). A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in eeg signals. *Expert Systems with Applications*, 163:113788.

Shoeibi, A., Khodatars, M., Alizadehsani, R., Ghassemi, N., Jafari, M., Moridian, P., Khadem, A., Sadeghi, D., Hussain, S., Zare, A., et al. (2020). Automated detection and forecasting of covid-19 using deep learning techniques: A review. *arXiv preprint arXiv:2007.10785*.
Shoka, A., Dessouky, M., El-Sherbeny, A., and El-Sayed, A. (2019). Literature review on eeg preprocessing, feature extraction, and classifications techniques. *Menoufia J. Electron. Eng. Res.*, 28(1):292–299.

Si, X., Zhang, X., Zhou, Y., Sun, Y., Jin, W., Yin, S., Zhao, X., Li, Q., and Ming, D. (2020). Automated detection of juvenile myoclonic epilepsy using cnn based transfer learning in diffusion mri. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 1679–1682. IEEE.

Siddharth, T., Gajbhiye, P., Tripathy, R. K., and Pachori, R. B. (2020). Eeg-based detection of focal seizure area using fbse-ewt rhythm and sae-svm network. *IEEE Sensors Journal*, 20(19):11421–11428.

Siddiqui, M. K., Islam, M. Z., and Kabir, M. A. (2019). A novel quick seizure detection and localization through brain data mining on ecog dataset. *Neural Computing and Applications*, 31(9):5595–5608.

Siddiqui, M. K., Morales-Menendez, R., Huang, X., and Hussain, N. (2020). A review of epileptic seizure detection using machine learning classifiers. *Brain informatics*, 7:1–18.

Singh, A., Pusarla, N., Sharma, S., and Kumar, T. (2020). Cnn-based epilepsy detection using image like features of eeg signals. In *2020 International Conference on Electrical and Electronics Engineering (ICE3)*, pages 280–284. IEEE.

Singh, K. and Malhotra, J. (2018). Stacked autoencoders based deep learning approach for automatic epileptic seizure detection. In *2018 First International Conference on Secure Cyber Computing and Communication (IC-SCCC)*, pages 249–254. IEEE.

Sirpal, P., Kassab, A., Pouliot, P., Nguyen, D. K., and Lesage, F. (2019). fnirs improves seizure detection in multimodal eeg-fnirs recordings. *Journal of biomedical optics*, 24(5):051408.

Skarpaas, T. L., Jarosiewicz, B., and Morrell, M. J. (2019). Brain-responsive neurostimulation for epilepsy (rms® system). *Epilepsy research*, 153:68–70.
Sønderby, C. K., Raiko, T., Maaløe, L., Sønderby, S. K., and Winther, O. (2016). Ladder variational autoencoders. *arXiv preprint arXiv:1602.02282*.

Stevenson, N., Tapani, K., Lauronen, L., and Vanhatalo, S. (2019). A dataset of neonatal eeg recordings with seizure annotations. *Scientific data*, 6(1):1–8.

Subasi, A. (2005). Epileptic seizure detection using dynamic wavelet network. *Expert Systems with Applications*, 29(2):343–355.

Sui, L., Zhao, X., Zhao, Q., Tanaka, T., and Cao, J. (2019). Localization of epileptic foci by using convolutional neural network based on ieeg. In *IFIP International Conference on Artificial Intelligence Applications and Innovations*, pages 331–339. Springer.

Sun, Y., Liang, D., Wang, X., and Tang, X. (2015). Deepid3: Face recognition with very deep neural networks. *arXiv preprint arXiv:1502.00873*.

Sung, F., Yang, Y., Zhang, L., Xiang, T., Torr, P. H., and Hospedales, T. M. (2018). Learning to compare: Relation network for few-shot learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1199–1208.

Tak, S. and Ye, J. C. (2014). Statistical analysis of fnirs data: a comprehensive review. *Neuroimage*, 85:72–91.

Takahashi, H., Emami, A., Shinozaki, T., Kunii, N., Matsuo, T., and Kawai, K. (2020). Convolutional neural network with autoencoder-assisted multiclass labelling for seizure detection based on scalp electroencephalography. *Computers in Biology and Medicine*, 125:104016.

Talathi, S. S. (2017). Deep recurrent neural networks for seizure detection and early seizure detection systems. *arXiv preprint arXiv:1706.03283*.

Tan, M. and Le, Q. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. In *International Conference on Machine Learning*, pages 6105–6114. PMLR.

Tang, L., Xie, N., Zhao, M., and Wu, X. (2020). Seizure prediction using multi-view features and improved convolutional gated recurrent network. *IEEE Access*, 8:172352–172361.
Taqi, A. M., Al-Azzo, F., Mariofanna, M., and Al-Saadi, J. M. (2017). Classification and discrimination of focal and non-focal eeg signals based on deep neural network. In 2017 international conference on current research in computer science and information technology (ICCIT), pages 86–92. IEEE.

Targ, S., Almeida, D., and Lyman, K. (2016). Resnet in resnet: Generalizing residual architectures. arXiv preprint arXiv:1603.08029.

Thanaraj, K. P., Parvathavarthini, B., Tanik, U. J., Rajinikanth, V., Kadry, S., and Kamalanand, K. (2020). Implementation of deep neural networks to classify eeg signals using gramian angular summation field for epilepsy diagnosis. arXiv preprint arXiv:2003.04534.

Thodoroff, P., Pineau, J., and Lim, A. (2016). Learning robust features using deep learning for automatic seizure detection. In Machine learning for healthcare conference, pages 178–190. PMLR.

Thomas, A. H., Aminifar, A., and Atienza, D. (2020a). Noise-resilient and interpretable epileptic seizure detection. In 2020 IEEE International Symposium on Circuits and Systems (ISCAS), pages 1–5. IEEE.

Thomas, J., Comoretto, L., Jin, J., Dauwels, J., Cash, S. S., and Westover, M. B. (2018). Eeg classification via convolutional neural network-based interictal epileptiform event detection. In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 3148–3151. IEEE.

Thomas, J., Jin, J., Thangavel, P., Bagheri, E., Yuvaraj, R., Dauwels, J., Rathakrishnan, R., Halford, J. J., Cash, S. S., and Westover, B. (2020b). Automated detection of interictal epileptiform discharges from scalp electroencephalograms by convolutional neural networks. International journal of neural systems, 30(11):2050030.

Tian, X., Deng, Z., Ying, W., Choi, K.-S., Wu, D., Qin, B., Wang, J., Shen, H., and Wang, S. (2019). Deep multi-view feature learning for eeg-based epileptic seizure detection. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 27(10):1962–1972.
Tjepkema-Cloostermans, M. C., de Carvalho, R. C., and van Putten, M. J. (2018). Deep learning for detection of focal epileptiform discharges from scalp eeg recordings. *Clinical neurophysiology*, 129(10):2191–2196.

Torfi, A. and Fox, E. A. (2020). Corgan: Correlation-capturing convolutional generative adversarial networks for generating synthetic healthcare records. *arXiv e-prints*, pages arXiv–2001.

Torres-Velázquez, M., Hwang, G., Cook, C. J., Hermann, B., Prabhakaran, V., Meyerand, M. E., and McMillan, A. B. (2020). Multi-channel deep neural network for temporal lobe epilepsy classification using multimodal mri data. In *2020 IEEE 17th International Symposium on Biomedical Imaging Workshops (ISBI Workshops)*, pages 1–4. IEEE.

Truong, N. D., Kuhlmann, L., Bonyadi, M. R., Querlioz, D., Zhou, L., and Kavehei, O. (2019). Epileptic seizure forecasting with generative adversarial networks. *IEEE Access*, 7:143999–144009.

Truong, N. D., Yang, Y., Maher, C., Nikpour, A., and Kavehei, O. (2020). Epileptic seizure forecasting: Probabilistic seizure-risk assessment and data-fusion. *arXiv preprint arXiv:2005.07196*.

Tuncer, T., Dogan, S., Ertam, F., and Subasi, A. (2020). A novel ensemble local graph structure based feature extraction network for eeg signal analysis. *Biomedical Signal Processing and Control*, 61:102006.

Türk, Ö. and Özerdem, M. S. (2019). Epilepsy detection by using scalogram based convolutional neural network from eeg signals. *Brain sciences*, 9(5):115.

Turner, J., Page, A., Mohsenin, T., and Oates, T. (2017). Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection. *arXiv preprint arXiv:1708.08430*.

Tzallas, A. T., Tsipouras, M. G., Tsalikakis, D. G., Karvounis, E. C., Astrakas, L., Konitsiotis, S., and Tzaphlidou, M. (2012). Automated epileptic seizure detection methods: a review study. *Epilepsy-histological, electroencephalographic and psychological aspects*, pages 75–98.
Ullah, I., Hussain, M., Aboalsamh, H., et al. (2018). An automated system for epilepsy detection using eeg brain signals based on deep learning approach. *Expert Systems with Applications*, 107:61–71.

Usman, S. M., Khalid, S., and Aslam, M. H. (2020). Epileptic seizures prediction using deep learning techniques. *Ieee Access*, 8:39998–40007.

Uyttenhove, T., Maes, A., Van Steenkiste, T., Deschrijver, D., and Dhaene, T. (2020). Interpretable epilepsy detection in routine, interictal eeg data using deep learning. In *Machine Learning for Health*, pages 355–366. PMLR.

van Lanen, R., Colon, A., Wiggins, C., Hoeberigs, M., Hoogland, G., Roebroeck, A., Ivanov, D., Poser, B., Rouhl, R., Hofman, P., et al. (2021). Ultra-high field magnetic resonance imaging in human epilepsy: A systematic review. *NeuroImage: Clinical*, page 102602.

Vance, C., Kim, Y., Zhang, G., Lhatoo, S., Tao, S., Cui, L., Li, X., and Jiang, X. (2020). Learning to detect the onset of slow activity after a generalized tonic–clonic seizure. *BMC Medical Informatics and Decision Making*, 20(12):1–8.

Vaughan, D. N. and Jackson, G. D. (2020). Imaging epileptic seizures using fmri. In *fMRI*, pages 193–216. Springer.

Verma, A. and Janghel, R. R. (2021). Epileptic seizure detection using deep recurrent neural networks in eeg signals. In *Advances in Biomedical Engineering and Technology*, pages 189–198. Springer.

Vidyaratne, L., Glandon, A., Alam, M., and Iftekharuddin, K. M. (2016). Deep recurrent neural network for seizure detection. In *2016 International Joint Conference on Neural Networks (IJCNN)*, pages 1202–1207. IEEE.

Wainberg, M., Merico, D., Delong, A., and Frey, B. J. (2018). Deep learning in biomedicine. *Nature biotechnology*, 36(9):829–838.

Wang, H., Ahmed, S. N., and Mandal, M. (2020a). Automated detection of focal cortical dysplasia using a deep convolutional neural network. *Computerized Medical Imaging and Graphics*, 79:101662.

Wang, L., Guo, S., Huang, W., and Qiao, Y. (2015). Places205-vgnet models for scene recognition. *arXiv preprint arXiv:1508.01667*. 88
Wang, S., Wang, S., Zhang, S., and Wang, Y. (2020b). Time-resnext for epilepsy recognition based on eeg signals in wireless networks. *EURASIP Journal on Wireless Communications and Networking*, 2020(1):1–12.

Wang, X., Hu, W., McGonigal, A., Zhang, C., Sang, L., Zhao, B., Sun, T., Wang, F., Zhang, J.-g., Shao, X., et al. (2019). Electroclinical features of insulo-opercular epilepsy: an seeg and pet study. *Annals of clinical and translational neurology*, 6(7):1165–1177.

Wei, Z., Zou, J., Zhang, J., and Xu, J. (2019). Automatic epileptic eeg detection using convolutional neural network with improvements in time-domain. *Biomedical Signal Processing and Control*, 53:101551.

Wen, T. and Zhang, Z. (2018). Deep convolution neural network and autoencoders-based unsupervised feature learning of eeg signals. *IEEE Access*, 6:25399–25410.

Weng, W. and Khorasani, K. (1996). An adaptive structure neural networks with application to eeg automatic seizure detection. *Neural Networks*, 9(7):1223–1240.

Woermann, F. G. and Vollmar, C. (2009). Clinical mri in children and adults with focal epilepsy: a critical review. *Epilepsy & Behavior*, 15(1):40–49.

Wong, S. and Kuhlmann, L. (2020). Computationally efficient epileptic seizure prediction based on extremely randomised trees. In *Proceedings of the Australasian Computer Science Week Multiconference*, pages 1–3.

Xu, G., Ren, T., Chen, Y., and Che, W. (2020a). A one-dimensional cnn-lstm model for epileptic seizure recognition using eeg signal analysis. *Frontiers in Neuroscience*, 14:1253.

Xu, H., Dong, M., Lee, M.-H., O’Hara, N., Asano, E., and Jeong, J.-W. (2019). Objective detection of eloquent axonal pathways to minimize postoperative deficits in pediatric epilepsy surgery using diffusion tractography and convolutional neural networks. *IEEE transactions on medical imaging*, 38(8):1910–1922.
Xu, H., Zhu, H., Luo, L., and Zhang, R. (2020b). Altered gray matter volume in mri-negative focal to bilateral tonic–clonic seizures. *Acta Neurologica Belgica*, pages 1–9.

Xu, Y., Yang, J., Zhao, S., Wu, H., and Sawan, M. (2020c). An end-to-end deep learning approach for epileptic seizure prediction. In *2020 2nd IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)*, pages 266–270. IEEE.

Yan, B., Wang, Y., Li, Y., Gong, Y., Guan, L., and Yu, S. (2016). An eeg signal classification method based on sparse auto-encoders and support vector machine. In *2016 IEEE/CIC International Conference on Communications in China (ICCC)*, pages 1–6. IEEE.

Yan, M., Liu, L., Chen, S., and Pan, Y. (2018). A deep learning method for prediction of benign epilepsy with centrotemporal spikes. In *International Symposium on Bioinformatics Research and Applications*, pages 253–258. Springer.

Yang, G., Yu, S., Dong, H., Slabaugh, G., Dragotti, P. L., Ye, X., Liu, F., Arridge, S., Keegan, J., Guo, Y., et al. (2017). Dagan: Deep de-aliasing generative adversarial networks for fast compressed sensing mri reconstruction. *IEEE transactions on medical imaging*, 37(6):1310–1321.

Yang, Y., Sarkis, R., El Atrache, R., Loddenkemper, T., and Meisel, C. (2021). Video-based detection of generalized tonic-clonic seizures using deep learning. *IEEE Journal of Biomedical and Health Informatics*.

Yao, X., Cheng, Q., and Zhang, G.-Q. (2019a). Automated classification of seizures against nonseizures: A deep learning approach. *arXiv preprint arXiv:1906.02745*.

Yao, X., Cheng, Q., and Zhang, G.-Q. (2019b). A novel independent rnn approach to classification of seizures against non-seizures. *arXiv preprint arXiv:1903.09326*.

Yao, X., Li, X., Ye, Q., Huang, Y., Cheng, Q., and Zhang, G.-Q. (2021). A robust deep learning approach for automatic classification of seizures against non-seizures. *Biomedical Signal Processing and Control*, 64:102215.
Yi, X., Walia, E., and Babyn, P. (2019). Generative adversarial network in medical imaging: A review. *Medical image analysis*, 58:101552.

Yıldırım, Ö., Baloglu, U. B., and Acharya, U. R. (2018). A deep convolutional neural network model for automated identification of abnormal eeg signals. *Neural Computing and Applications*, pages 1–12.

You, S., Cho, B. H., Yook, S., Kim, J. Y., Shon, Y.-M., Seo, D.-W., and Kim, I. Y. (2020). Unsupervised automatic seizure detection for focal-onset seizures recorded with behind-the-ear eeg using an anomaly-detecting generative adversarial network. *Computer methods and programs in biomedicine*, 193:105472.

Yuan, Y. and Jia, K. (2019). Fusionatt: deep fusional attention networks for multi-channel biomedical signals. *Sensors*, 19(11):2429.

Yuan, Y., Xun, G., Jia, K., and Zhang, A. (2017). A multi-view deep learning method for epileptic seizure detection using short-time fourier transform. In *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, pages 213–222.

Yuan, Y., Xun, G., Jia, K., and Zhang, A. (2018a). A multi-context learning approach for eeg epileptic seizure detection. *BMC systems biology*, 12(6):47–57.

Yuan, Y., Xun, G., Jia, K., and Zhang, A. (2018b). A multi-view deep learning framework for eeg seizure detection. *IEEE journal of biomedical and health informatics*, 23(1):83–94.

Yuan, Y., Xun, G., Ma, F., Suo, Q., Xue, H., Jia, K., and Zhang, A. (2018c). A novel channel-aware attention framework for multi-channel eeg seizure detection via multi-view deep learning. In *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, pages 206–209. IEEE.

Yuan, Y., Xun, G., Suo, Q., Jia, K., and Zhang, A. (2019). Wave2vec: Deep representation learning for clinical temporal data. *Neurocomputing*, 324:31–42.
Yuvaraj, R., Thomas, J., Kluge, T., and Dauwels, J. (2018). A deep learning scheme for automatic seizure detection from long-term scalp eeg. In 2018 52nd Asilomar Conference on Signals, Systems, and Computers, pages 368–372. IEEE.

Zeng, M., Zhang, X., Zhao, C., Lu, X., and Meng, Q. (2021). Grp-dnet: A gray recurrence plot-based densely connected convolutional network for classification of epileptiform eeg. Journal of Neuroscience Methods, 347:108953.

Zeng, R., Wu, J., Shao, Z., Senhadji, L., and Shu, H. (2014). Quaternion softmax classifier. Electronics letters, 50(25):1929–1931.

Zhan, Q. and Hu, W. (2020). An epilepsy detection method using multiview clustering algorithm and deep features. Computational and Mathematical Methods in Medicine, 2020.

Zhang, B., Wang, W., Xiao, Y., Xiao, S., Chen, S., Chen, S., Xu, G., and Che, W. (2020a). Cross-subject seizure detection in eegs using deep transfer learning. Computational and Mathematical Methods in Medicine, 2020.

Zhang, G., Le Yang, B. L., Lu, Y., Liu, Q., Zhao, W., Ren, T., Zhou, J., Wang, S.-H., and Che, W. (2020b). Mnl-network: A multi-scale non-local network for epilepsy detection from eeg signals. Frontiers in Neuroscience, 14.

Zhang, J., Wu, H., Su, W., Wang, X., Yang, M., and Wu, J. (2018). A new approach for classification of epilepsy eeg signals based on temporal convolutional neural networks. In 2018 11th International Symposium on Computational Intelligence and Design (ISCID), volume 2, pages 80–84. IEEE.

Zhang, X., Yao, L., Dong, M., Liu, Z., Zhang, Y., and Li, Y. (2020c). Adversarial representation learning for robust patient-independent epileptic seizure detection. IEEE journal of biomedical and health informatics, 24(10):2852–2859.

Zhang, Y., Jiang, L., Zhang, D., Wang, L., Fei, X., Liu, X., Fu, X., Niu, C., Wang, Y., and Qian, R. (2020d). Thalamocortical structural connectivity abnormalities in drug-resistant generalized epilepsy: A diffusion tensor imaging study. Brain research, 1727:146558.
Zhang, Z., Ren, Y., Sabor, N., Pan, J., Luo, X., Li, Y., Chen, Y., and Wang, G. (2020e). Dwt-net: Seizure detection system with structured eeg montage and multiple feature extractor in convolution neural network. *Journal of Sensors*, 2020.

Zhao, S., Yang, J., Xu, Y., and Sawan, M. (2020a). Binary single-dimensional convolutional neural network for seizure prediction. In *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1–5. IEEE.

Zhao, W. and Wang, W. (2020). Seizurenet: a model for robust detection of epileptic seizures based on convolutional neural network. *Cognitive Computation and Systems*, 2(3):119–124.

Zhao, W., Zhao, W., Wang, W., Jiang, X., Zhang, X., Peng, Y., Zhang, B., and Zhang, G. (2020b). A novel deep neural network for robust detection of seizures using eeg signals. *Computational and mathematical methods in medicine*, 2020.

Zhao, X., Solé-Casals, J., Li, B., Huang, Z., Wang, A., Cao, J., Tanaka, T., and Zhao, Q. (2020c). Classification of epileptic ieeeg signals by cnn and data augmentation. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 926–930. IEEE.

Zhao, X., Zhang, H., Zhu, G., You, F., Kuan, S., and Sun, L. (2019). A multi-branch 3d convolutional neural network for eeg-based motor imagery classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 27(10):2164–2177.

Zheng, L., Liao, P., Luo, S., Sheng, J., Teng, P., Luan, G., and Gao, J.-H. (2019). Ems-net: A deep learning method for autodetecting epileptic magnetoencephalography spikes. *IEEE transactions on medical imaging*, 39(6):1833–1844.

Zihlmann, M., Perekrestenko, D., and Tschannen, M. (2017). Convolutional recurrent neural networks for electrocardiogram classification. In *2017 Computing in Cardiology (CinC)*, pages 1–4. IEEE.
Zijlmans, M., Huiskamp, G., Hersevoort, M., Seppenwoolde, J.-H., van Huffelen, A. C., and Leijten, F. S. (2007). Eeg-fmri in the preoperative work-up for epilepsy surgery. *Brain*, 130(9):2343–2353.

Zuo, R., Wei, J., Li, X., Li, C., Zhao, C., Ren, Z., Liang, Y., Geng, X., Jiang, C., Yang, X., et al. (2019). Automated detection of high-frequency oscillations in epilepsy based on a convolutional neural network. *Frontiers in computational neuroscience*, 13:6.