International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Concepts, Techniques, Challenges and Future Trends of EEG Seizure Detection: A Survey

Suresh Nalla [*1], Dr. Seetharam Khetavath[2]

Submitted: 17/01/2024 **Revised**: 25/02/2024 **Accepted**: 03/03/2024

Abstract: Epilepsy is a term that is commonly used to refer to a condition of the central nervous system. Epilepsy is characterized by an aberrant pattern of brain activity, which can result in episodes of bizarre behavior, seizures, and even a temporary loss of awareness. Patients with epilepsy experience difficulties in their day-to-day lives as a direct result of the measures they are need to take in order to adapt to their disease. This is especially true for situations in which they are required to utilize heavy equipment, such as when driving a vehicle. Studies on epilepsy rely heavily on electroencephalography (EEG) signals as their primary method for analyzing the activity of the brain during seizures. To manually determine the location of seizures in EEG signals is a laborious and time-consuming process that can be frustrating at times. One of the most important instruments that can assist medical professionals and people in taking the necessary safety measures is the automatic detection framework. This article explores the mental disorder of epilepsy, along with the various forms of seizures. It also discusses the preprocessing operations carried out on EEG data, which is a commonly retrieved feature from the signal. Additionally, it provides a full overview of the classification processes employed in addressing this issue. Furthermore, this essay provides valuable perspectives on the difficulties and prospective areas for future investigation in this innovative topic. This paper offers a comprehensive review of recent approaches to studying epileptic seizures. It also presents researchers with ideas and concepts for developing an automated system that uses EEG data, Internet of Things technology, and machine learning classifiers to remotely monitor patients with epilepsy in smart healthcare systems. Furthermore, this paper provides an overview of new approaches employed in studying the epileptic seizure phenomenon. The identification of seizures using EEG poses several challenges and unresolved research questions, which are the focus of this last examination.

Keywords: *Epilepsy, Electroencephalography (EEG), Features extraction, Classification, Artificial intelligence.*

1. Introduction

In addition to being one of the most common neurological conditions that affect people, epilepsy is a condition that cannot be passed on to other individuals. Typically, it is characterized by episodes that occur very quickly [1]. A quick and early abnormality in the electrical activity of the brain is the root cause of seizures, which can disturb either a region of the body or the entire body [2]. Seizures can come on unexpectedly and are caused by this initial irregularity. It is estimated that over sixty million individuals throughout the world are affected by epileptic seizures, which can take many different forms [3]. There are instances in which these attacks lead to cognitive problems, which, if they are not treated, can result in major physical injuries for the one who is affected. In addition, individuals who suffer from epileptic seizures usually feel mental suffering due to the fact that they are humiliated by their disease and do not have a social position that is appropriate for them. Because of this, recognizing epileptic seizures in their early stages can be useful to patients and can improve the quality of life that they lead. Functional and structural neuroimaging modalities are examples of screening procedures that can be utilized for the diagnosis of epileptic seizures [4–9]. There are two important categories of neuroimaging modalities, which are as follows. Functional neuroimaging is a technique that gives medical professionals and neurologists the ability to get vital information about the functioning of the brain during the occurrence of epileptic seizures [4–9]. When it comes to the anatomical composition of the brains of patients who are having epileptic seizures, the structural neuroimaging modalities provide medical practitioners with a significant quantity of information [4–9]. The most important techniques for functional neuroimaging are electroencephalography (EEG) [5, magnetoencephalography (MEG) [6, positron emission tomography (PET) [7, single-photon emission computed tomography (SPECT) [7,10], functional magnetic resonance imaging (fMRI) [4,11], electrocorticography (ECoG) [12], and functional near-infrared spectroscopy (fNIRS) [13]. On the other hand, structural magnetic resonance imaging (sMRI) and diffusion tensor imaging (DTI) are thought to be two of the most significant methods for structural neuroimaging [4,14]. The use of functional neuroimaging modalities is significantly more common than the use of structural neuroimaging modalities when it comes to the diagnosis of epileptic seizures [4–9]. Electroencephalogram (EEG) techniques are the ones that

[1]*Research Scholar, Department of ECE, Chaitanya Deemed to be University, Hanamkonda , Warangal ,Telangana ,India.*
[2]*Professor, Department of ECE, Chaitanya Deemed to be University, Hanamkonda , Warangal ,Telangana ,India.*
seetharamkhetavath@gmail.com
** Corresponding Author Email: sureshnalla44@gmail.com*

are utilized by medical professionals the most frequently, as indicated by the outcomes of research that were conducted on the identification of epileptic seizures. Because of their cheap cost, mobility, and capacity to clearly depict rhythms in the frequency domain, electroencephalogram (EEG) signals are the most favored choice among researchers [8,9]. The changes in voltage that are produced by the ionic current of neurons in the brain and that are reported by the electroencephalogram (EEG) are an indicator of the bioelectric activity that is taking place in the brain [15]. It is vital to keep a record of epileptic seizures for a considerable amount of time in order to identify them before they occur. The fact that these data are captured on a large number of channels adds another layer of complexity to the analysis process. The data from the electroencephalogram are also subject to artifacts that are brought about by the main power supply, the movement of the electrodes, and muscle tremor [16]. As a consequence of this, the physicians may experience challenges while attempting to diagnose epileptic seizures by making use of noisy EEG results. Currently, a substantial amount of research is being undertaken in an effort to overcome these issues in order to diagnose and forecast epileptic seizures [17,18]. The focus of this research is on EEG modalities and other techniques such as magnetic resonance imaging (MRI) in conjunction with artificial intelligence approaches. Conventional machine learning and deep learning approaches have been utilized in the application of artificial intelligence techniques to the field of epileptic seizure detection [19–22].

Recent years have seen the development of a large variety of machine learning techniques that are capable of identifying epileptic episodes [23,24]. Utilizing statistical, temporal, frequency, time-frequency domain, and nonlinear aspects are some of the components that these algorithms incorporate. When it comes to identifying both the features to be utilized and the classifiers to be utilized, the conventional approaches to machine learning rely on a process that is referred to as "trial and error" [25,26]. It is necessary to have a comprehensive grasp of the procedures involved in signal processing and data mining in order to be able to design a model that can give accurate results. Despite having a little quantity of data, some models are able to function well. There is a possibility that the effectiveness of machine learning techniques has decreased with time due to the fact that there is currently more data available than there has ever been before. As a consequence of this, the DL approaches, which are the most recent and cutting-edge methodologies, have been utilized [27,28]. When it comes to machine learning, the training process for deep learning models involves a large amount of data [29]. This is in contrast to more standard techniques to machine learning. It is because these models contain a considerable number of feature spaces that they are prone to the problem of overfitting [29]. This is because in the case that there is inadequate data, these models are susceptible to the problem of overfitting.

The bulk of the simulations that were performed using traditional machine learning methods were carried out in the Matlab software environment. On the other hand, deep learning models are commonly developed using the Python programming language and a range of open-source toolboxes. With the support of the Python programming language, which provides a greater number of DL toolboxes that are open to the general public, the researchers have been able to develop one-of-a-kind automated systems. Furthermore, as a result of cloud computing, computational resources are now more easily accessible to all individuals. As can be shown in Figure 1, TensorFlow and Keras, which is one of its high-level application programming interfaces, are often utilized for the purpose of epileptic seizure detection through the utilization of deep learning in the works that were reviewed. This is most likely attributable to the adaptability and versatility of both of these technological advancements.

Epilepsy, a neurological ailment, has been identified as an issue on a worldwide scale and is considered to be one of the most severe risks to the continued existence of human beings. According to the statistics that were published by the World Health Organisation (WHO), epilepsy affects around fifty million individuals all over the world. This makes epilepsy quite possibly the most well-known kind of neurological disease on a global scale [30-35]. Not only does epilepsy impact women and men, but it also affects children and in some cases even younger people. In terms of the symptoms that are associated with the seizure, there is a broad range of diversity [36, 37].

Some people who have epilepsy can merely gaze into space for a few seconds during a seizure, while other people will shake their limbs or legs repeatedly. Both of these characteristics are associated with epilepsy. Having a single seizure does not always indicate that you have epilepsy, even if you have had one. It is normally essential to monitor the occurrence of at least two seizures that are unprovoked in order to arrive at a diagnosis of epilepsy. When it comes to the diagnosis of epileptic seizures, electroencephalography (EEG) is one of the most widely utilized technologies that is used to examine electrical abnormalities in the human brain [38-044]. For the purpose of identifying any anomalies that could be present in the brain, this approach is taken.

The usual shape of electroencephalogram (EEG) data goes through a noticeable change whenever an epileptic seizure occurs. Due to the different characteristics of the EEG signal, the states of epileptic patients can be categorized into one of three categories: normal, preictal, or ictal. Normal indicates that the patient is not experiencing any seizures. A phase that happens prior to the actual commencement of a seizure is referred to as the preictal stage. This stage is distinguished by a number of electrical irregularities that start to take place in the cerebrum of epileptic patients. For the purpose of identifying seizures while a patient is in the ictal stage, it is required to record any electrical disturbances that occur in the brain of a patient during the transition from the normal stage to the ictal stage [45-49]. This approach of early identification of epileptic seizures in the preictal stage has the ability to save the lives of patients by providing them with the chance to take preventative measures against occurrences that may be both detrimental and potentially deadly. As a consequence, this method has the potential to save the lives of patients. A cap or a material that resembles paste will be used to connect electrodes to your head in order to capture the electrical activity that occurs during an electroencephalogram (EEG) examination. Once the electrodes have been positioned in your head, they will begin to record the electrical activity that occurs in your brain [50-52].

As was noted previously, there is an essential need for an automatic and efficient approach for the early diagnosis of epileptic seizures. This is necessary in order to have the ability to save the lives of thousands of epileptic patients each year. It is necessary for this system to have the capability of notifying patients, their relatives, and hospitals in the surrounding area prior to the actual occurrence of epileptic seizures. Therefore, epileptic patients might profit from this system in the case of an emergency, both for the goal of preserving their lives and for the purpose of increasing the quality of life they have [53, 54].

Recent efforts have been undertaken to investigate the identification of epileptic seizures in order to facilitate the creation of an automatic diagnosis system that will liberate medical professionals from the laborious task that they are now responsible for. In this regard, a large number of research articles that are relevant to the diagnosis of epileptic seizures are made available for consumption by the general public. The application of automatic seizure detection might prove to be beneficial due to the fact that it enhances both the dependability and the speed of the operation. Academics who are interested in exploring a number of techniques and domains, including as the frequency domain, the time domain, the time-frequency domain, empirical mode decomposition, and nonlinear approaches, are drawn to this specific domain because of the fact that it piques their curiosity. In spite of this, the findings of the experiments suggested that the performance might be greatly enhanced by combining two or more of the methodologies that are usually used. A number of entropies that are utilized for the purpose of an automated diagnosis of epilepsy through the utilization of EEG data are presented by U. Rajendra [55]. Additionally, the purposes of entropies, as well as the advantages and disadvantages of utilizing them, are discussed. Strategies for the automated identification of epileptic seizures based on various domain techniques were analyzed and addressed in [56]. [56] was the reference for this article. On the basis of EEG data, the authors of [57] explain a variety of pattern recognition algorithms that may be utilized to detect those who are experiencing seizures. DWT features are also evaluated for their usefulness when paired with other classifiers, which is another aspect of their research. A difference is established between focal and non-focal characterization in order to determine the regions that are affected by seizures [58]. Md Shafiqul Islam suggested a dynamic technique that makes use of a deep learning model called Epileptic-Net in order to detect epileptic seizures from a dynamic perspective. It was necessary to make use of dense convolutional blocks, feature attention modules, residual blocks, and the hypercolumn approach in order to implement this method [59]. By analyzing the performance of a seizure detection system, Gaetano Zazzaro and Luigi Pavone are able to determine whether or not the system is capable of reliably recognizing seizures, minimizing the amount of false alarms that it creates, and deciding whether or not it can be applied to a broader group of patients [60]. The purpose of the study [61] is to evaluate the feasibility of using wearable multi-modal monitoring for epileptic patients and to look for effective techniques of seizure detection. Within the realm of contemporary medical care, the Internet of Things (IoT) is now playing a role that is both dynamic and essential. In order to accomplish this, it provides significant solutions for a wide range of applications in the medical and healthcare fields. Wearable technology makes it feasible to monitor patients' health in a continuous and real-time manner. This monitoring is made possible by technologies that are connected to the Internet of Things. One such use of these technologies is the collection and transmission of electroencephalogram (EEG) data from patients who suffer from epilepsy. When applied to these sorts of technologies, the application of machine learning algorithms gives the prospect of efficient solutions for the identification of seizure phases based on received EEG data. This is in addition to the technologies that you have mentioned. As an additional point of interest, the Internet of Things, when combined with the processes of artificial intelligence and the services of cloud computing, has emerged as a powerful technology that has the potential to resolve a variety of problems that are encountered in the field of medical care. The requirement to provide a framework for the automatic recognition of epileptic seizures in order to facilitate the early detection of epileptic seizures through the utilization of pre-existing communication technologies in conjunction with machine learning, the internet of things, and cloud computing [62, 63]. For the purpose of providing an accurate diagnosis of epileptic seizures, this is required.

Because of this project, researchers will be brought up to speed on significant feature extraction methodologies, statistical and machine learning classifiers, and latest deep learning algorithms. This will be accomplished by providing updated information. The researchers will be able to locate databases that are accessible to the general public and contain recorded epileptic seizure signals with the assistance of this study, which is another advantage of performing this evaluation. As a conclusion, many suggestions for the directions that future research should go are offered, all of which are based on the most recent review. In conclusion, the following is a list of the most significant contributions that can be derived from this body of work:

• Discuss the process of seizure identification and provide an overview of EEG signals, in addition to supplying information on the various EEG datasets that are currently accessible.

• Conducting a literature review of works that have been completed utilising a variety of deep learning models for the automated detection of epileptic seizures using a variety of modalities.

• Investigate the difficulties associated with the identification of epileptic seizures and conduct an analysis of the model that performs the best for the various modalities of data.

• Investigate and provide automated seizure detection based on both artificial intelligence and the internet of things.

• Describe potential avenues for further study as well as the current state of the art in this particular field of cutting-edge research.

2. Dl Techniques for Epileptic Seizures Detection

The operation of a computer-aided diagnosis system (CADS) for epileptic seizures that makes use of DL structures is depicted in Figure 1. The EEG, MEG, ECoG, fNIRS, PET, SPECT, and MRI are all examples of possible inputs for the DL model. Following that, the signal is put through the preprocessing step in order to get rid of the noise. The DL models are developed with the help of these signals that have been deleted. Accuracy, sensitivity, and specificity are the metrics that are utilized in order to assess the performance of the model [64].

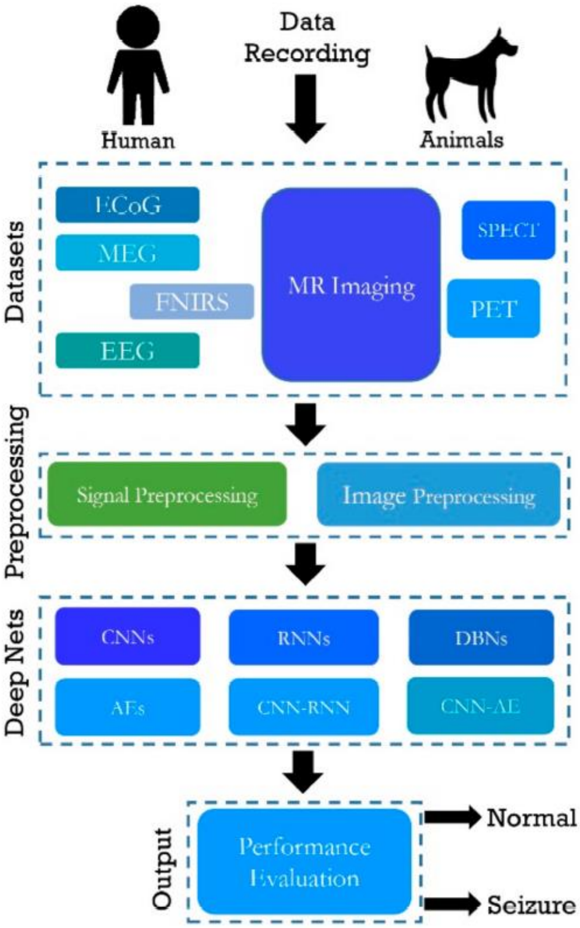

Fig.1: Block diagram of a DL-based CAD system for epileptic seizures[65]

2.1. Dataset

The utilization of datasets is a significant factor that contributes to the development of CADS that are accurate and trustworthy. When it comes to the process of building automated epileptic seizure detection systems, there are a variety of EEG datasets that may be utilized. There are datasets from Freiburg [66], CHB-MIT [67], Kaggle [68], Bonn [69], Flint-Hills [70], Bern-Barcelona [71], Hauz Khas [72], and Zenodo [73] that are included in this collection. All of the signals that are included in these datasets were either captured from the scalp of animals or people, or they were recorded from within the skull of the animals.

2.1.1. Fribourg

During the pre-surgical epilepsy monitoring that took conducted at the epilepsy center of the University Hospital Fribourg, invasive EEG signals from 21 patients who were suffering from refractory focal epilepsy were acquired and included in the EEG dataset. These patients were all individuals who had undergone epilepsy surgery. Within the epilepsy center, these individuals were undergoing treatment for their condition. Utilizing the intracortical grid, strip, and depth electrodes allowed for direct recording to be gained from the focal region, the eradication of artefacts to be accomplished, and a better signal-to-noise ratio (SNR) to be achieved. All of these benefits were achieved through the utilization of the electrodes. Electroencephalogram (EEG) data were recorded utilizing a Neurofile NT system that had 128 channels and six contact electrodes, three of which were focal and three of which were extra focal. A 16-bit analog-to-digital converter (A/D) with a sampling rate of 256 hertz was then used to digitize the signals. Ictal data and interictal data are also available for each individual subject. The ictal data includes seizures that have occurred in the pre-ictal area for a minimum of fifty minutes, and the interictal data includes about twenty-four hours of EEG data that has not been connected with a seizure [74-78].

2.1.2 The CHB-MIT

A total of 163 seizures were recorded from 23 children during 844 hours of continuous monitoring of scalp EEG signals that are contained in the database. There were 256 samples taken at a rate of 256 times per second, and the recordings were carried out in accordance with the planned placement of 10–20 standard electrode positions. The term "inter-ictal area" refers to the time period that begins at least four hours before the commencement of a seizure and continues until four hours after the seizure has stopped. Both mixed seizures and primary seizures, which are the two types of seizures that can occur during an epileptic episode, are covered in this database together with their respective information.

When we talk about cluster seizures, we are referring to seizures that occur in close proximity to one another. On the other hand, when we talk about massive seizures, we are talking about seizures that may be expected. In average, patients who experience less than ten seizures each day are the ones who will perceive the prediction to be important enough to warrant attention. This database contains adequate data from thirteen individuals who have epilepsy [79]. These patients have experienced at least three major seizures and have recorded their inter-ictal intervals over a period of three hours.

2.1.3. Kaggle

In response to a challenge posed by the American Epilepsy Society to foresee epileptic episodes, the database was developed. It contains recordings of intracranial electroencephalograms taken from five dogs and two individuals who had a total of 48 seizures that lasted for a combined time of 627 hours. 16 electrodes that were implanted in the dogs were used to gather the electroencephalogram (EEG) data, and the sampling rate for these recordings was 400 kilohertz. On the other hand, the electroencephalogram (EEG) signals of patients 1 and 2 were recorded using twenty-four subdural electrodes and fifteen deep electrodes, respectively, and the sampling rate for these recordings was five kilohertz. The pre-ictal and inter-ictal data in this database are organized into 10-minute segments. Additionally, for each seizure, there are six pre-ictal segments that are available, with each segment being separated by ten seconds, up to five minutes before the commencement of the seizure. In order to identify which interictal segments will be utilized, a random selection is conducted at the very least one week prior to each seizure [80-85].

2.1.4. Bonn

The Bonn database is made up of five different datasets that are denoted by the letters A, B, C, D, and E. There are one hundred single-channel EEG signals included in each dataset, and each dataset has a duration of 23.6 seconds. At a sample rate of 173.61 hertz, the electroencephalogram (EEG) signals were digitized with the help of an A/D converter that had a resolution of 12 bits. In Dataset A and Dataset B, respectively, the normal signals of five people with their eyes open and closed are depicted. These participants did not have their eyes closed. Both datasets C and D comprise electroencephalogram (EEG) signals that were acquired from certain regions of the hippocampus, namely the epileptogenic and left regions, respectively. These impulses are connected to the pre-ictal area of the brain in the neurological system. A connection has been made between the EEG waves that are included in the E dataset and the ictal area. The signals that were acquired for datasets A and B were collected by employing a scalp EEG standard that ranged from 10 to 20. In order to capture intracranial EEG, depth electrodes were utilized, which resulted in the acquisition of the signals that were used in datasets C and D. After everything was said and done, the signals of dataset E were collected by employing strip electrodes in addition to depth electrodes. Strip electrodes are located in the lateral and base parts of the neocortex [86-91], whereas depth electrodes are distributed symmetrically on the surface of the hippocampus. This is because strip electrodes are more superficial than depth electrodes.

2.1.5. Flint-Hills

According to the database, the electrocardiography signals have a total lifespan of 1419 hours, and the sampling rate at which they are provided is 249 hertz. For your convenience, this section also includes meta-data relating to 59 seizures as well as information on the positioning of the electrodes. The signals that were gathered for this database were obtained by employing anything from 48 to 64 electrodes for each individual patient [92-94].

2.1.6 Bern Barcelona

Focused epilepsy is present in each and every one of the people whose cerebral electroencephalograms are included in the Barcelona database. The brain department of Bern Hospital in Barcelona was the source of the information that was used to create this database. Over the course of many days, the participants were monitored without the administration of any antiepileptic medication in order to determine whether or not there was a risk of experiencing seizures or surgery. The signals were collected by employing AD-Tech intracortical electrodes, and in addition to those, an extra reference electrode that was based on a 10–20 standard was utilized between the PZ and FZ locations. This was done in order to maintain a consistent calibration. The EEG signals that were included in the database were both focal and extra focal. The focused EEG signals were the most prevalent type of EEG signals. Every single dataset had 3,750 distinct pairs of signals that were captured concurrently. Each of these signals lasted for twenty seconds and had a sampling rate of 512 hertz every single time. There are a total of 83 hours' worth of EEG data contained inside this database [95]. These data were obtained from five individuals of varied ages.

2.1.7. Hauz Khas

The scalp electroencephalogram (EEG) signals of ten patients were acquired using an AS40 device and sampled at a rate of 200 Hz in Hauz Khas neurons for the database. The database was assembled in a brain center in Delhi, India, in India. After the signals were filtered using a band-pass filter that had a pass frequency ranging from 0.5 to 70 Hz, neurology specialists classified them into three distinct classes: pre-ictal, inter-ictal, and ictal according to their characteristics [96].

2.1.8. Zenodo

This dataset contains multichannel electroencephalogram recordings of 79 human babies that were obtained from the Helsinki University Hospital after they were born. Seventy-four minutes was the median amount of time that these recordings were recorded for. The electroencephalogram (EEG) data were examined by three specialists, and each specialist annotated about 460 seizures. After reaching an agreement, it was determined that 39 newborns had seizures, whereas 22 neonates did not have seizures [97]. When it comes to the automated identification of seizures through the application of DL approaches, it has been shown that the Bonn dataset is the one that is utilized the most frequently.

2.2. The Preparatory Steps

During the preprocessing stage of the construction of CADS with DL models that make use of EEG signals, there are three phases that are required: the removal of noise, the normalization of the signals, and the preparation of the signals for use in machine learning network applications [98,99]. During the process of noise removal, filters that have either a finite impulse response (FIR) or an infinite impulse response (IIR) are commonly utilized in order to eliminate any further signal noise that may be present. Following that, the normalization process is carried out using a number of different approaches, one of which is the implementation of the z-score methodology. As a conclusion, in order to get the signals suitable for the deployment of deep networks, a number of strategies are utilized. These techniques are utilized in the time domain, the frequency domain, and the time–frequency domain.

2.3. A Review of Techniques Used in Deep Learning

On the other hand, deep neural networks are structures that have more than two hidden layers. This is in contrast to shallow neural networks, which are the conventional form of neural networks. Deep neural networks are compared to shallow neural networks. In response to the substantial increase in the size of the networks, there has been a precipitous increase in the total number of characteristics that are used to define the networks. In order to prevent the learned networks from being unduly adapted to their data, it is necessary to implement appropriate learning strategies. Convolutional networks involve the utilization of filters that are convolved with input patterns, as opposed to the multiplication of a weight vector (matrix), which is the traditional method. This results in a significant reduction in the number of parameters that may be controlled through training. In addition to this, further methods are suggested as a means of assisting the network in the process of information acquisition [100]. Through the use of pooling layers, the size of the input pattern that is then transmitted to the succeeding convolutional layer is reduced. Batch normalization, dropout, early pausing, unsupervised or semi-supervised learning, and regularization are some of the techniques that are utilized in order to prevent the learned network from being overfit and to enhance both the learning capacity and the learning pace. After the AE and DBN are used as a kind of unsupervised learning, the parameters are fine-tuned to prevent overfitting for the data that is available with labels. This is done in order to preserve the integrity of the data. In the realm of recurrent neural networks (RNNs), those with long short-term memory (LSTM), which are also referred to as gated recurrent units (GRU), are capable of revealing the long-term time dependencies of data samples.

Convolutional Neural Networks (also known as CNNs)

Convolutional neural networks (CNNs), which are among the most well-known classes of deep learning networks, have been the focus of the vast bulk of research conducted in the field of machine learning [101]. This category of network includes CNNs, which are a notable example. They were initially designed for use in applications that included image processing; but, in recent years, they have been adapted for use in one- and two-dimensional designs for the aim of detecting and forecasting diseases by making use of biological information [102]. This allows them to be used in applications that involve image processing. The analysis of electroencephalogram (EEG) signals using this particular category of deep learning networks is currently the standard method for diagnosing epileptic seizures. This is a technique that has been utilized for a considerable amount of time.

To convert the one-dimensional (1D) electroencephalogram (EEG) signals into two-dimensional plots, visualization techniques such as spectrogram [103], higher-order bispectrum [104,105], and wavelet transformations are applied. These approaches are utilized in order to convert the signals. After that, these plots are utilized in the process of applying them to the input of the convolutional network in two-dimensional convolutional neural networks, which are referred to as 2D-CNN. In the designs that are referred to as 1D, the signals of the electrical activity of the brain, which are also known as EEG, are introduced into the input of convolutional networks in the form of a vector that is just one dimension in size. The fundamental architecture of the 2D-CNN in these networks is modified, which enables it to process the 1D-EEG signals. These modifications are described in more detail below. These alterations happen as a consequence of the adjustments that were made. Consequently, in the field of epileptic seizure detection, both one-dimensional convolutional neural networks (1D-CNNs) and two-dimensional convolutional neural networks (2D-CNNs) are applied. Despite this, all of the many kinds of convolutional neural networks are being researched independently.

A. Convolutional Neural Networks in Two Dimensions (also known as 2D-CNNs)

Deep two-dimensional networks are currently being utilized in a wide variety of medical applications, which are a result of their widespread availability. A few examples of these applications are the identification of autism spectrum diseases by the utilization of MRI modalities [108] and the diagnosis of COVID-19 in CT and X-ray [106,107]. The employment of this network was recommended by Krizovsky et al. [109] as a means of overcoming challenges that were associated with the categorization of pictures in the year 2012. After that, they quickly implemented comparable networks for a variety of tasks, such as the classification of medical images, in an effort to circumvent the flaws that were demonstrated by earlier networks and to address more complex problems with a higher degree of precision. This was done in an effort to get around the difficulties that were caused by networks that came before it. In Figure 6, a broad picture of the epileptic seizure detection process is shown. This process is carried out using a convolutional neural network in two dimensions. The development of two-dimensional convolutional neural networks (CNNs) is widely considered to be the most significant architectural approach utilized in deep neural networks. This is due to the fact that these architectures are extremely important. SeizNet is the name of a convolutional network that has sixteen layers, and it is shown in one of the studies (50). Additionally, there are dropout layers and batch normalization (BN) layers that are located behind each convolutional layer. These layers have a topology that is comparable to that of the VGG-Net classification system. Every single one of these levels possesses its own set of distinctive qualities. A unique convolutional neural network (CNN) model with two dimensions was proposed by the authors of the paper [110]. Using the spectral and temporal characteristics of the EEG data, this model is able to learn about the overall structure of seizures by first extracting those characteristics and then using those characteristics. Through the utilization of this model, the authors were able to make significant progress in their comprehension of the overall structure of seizures. In the study conducted by Zuo and colleagues [111], it was established that higher-frequency oscillations (HFO) epilepsy may be diagnosed by utilizing a 16-layer 2D-CNN in conjunction with electroencephalogram (EEG) recordings throughout the diagnostic process.

An approach to deep learning that is referred to as SeizureNet is proposed in reference number 112 of the document. This framework is distinguished by the substantial number of connections it contains as well as the employment of convolution layers. A novel deep learning model, which the authors of paper [113] referred to as the temporal graph convolutional network (TGCN), was proposed by the authors. This model is composed of five different architectures, each of which has 14, 18, 22, 23, and 26 layers accordingly. Each of these architectures is included in this model. In the beginning, Bouaziz et al. [114] divided the EEG recordings that were obtained from CHB-MIT into time intervals of two seconds. These recordings contained a total of twenty-three channels. Following that, the EEG signals were converted into density pictures, which are a type of spatial representation, and then they were utilized as inputs for a CNN network.

B. AlexNet

ImageNet was a project that was founded by Professor FeiFei Li of Stanford University. Her dataset consisted of labelled photographs of real-world items, and she referred to her work as ImageNet [115]. ImageNet holds an annual event called ILSVRC, which is a computer vision competition, with the goal of finding solutions to the picture categorization issues. Alex Krizhevsky's algorithm, AlexNet, was the one that won the 2012 ImageNet challenge and kicked off the entire DL era [116]. This victory was the beginning of a revolution in the world of picture categorization. AlexNet came out on top of the competition by attaining an accuracy score of 84.6% across all five tests. The AlexNet network was utilised by [117] in order to diagnose focal epileptic episodes. The proposed network made use of the approach known as feature extraction, and in the end it utilised the Softmax layer for classification purposes. This network was successful in achieving accuracy of one hundred percent. In a different type of research, the AlexNet computer network was used [118]. By feeding the 1D signal via the Signal2Image (S2I) module, they were able to turn it into a 2D image. Signal as image, spectrogram, one-layer 1D-CNN, and two-layer 1D-CNN are some of the various ways that are utilised in this process.

C. VGG

In 2014, a group of researchers from Oxford came up with the idea for the visual geometry group (VGG) model [119]. They configured a number of different models, including the VGG-16, which was one of the models that was entered into the ILSVRC 2014 competition. The VCG-16 consists of 16 layers and achieved good results when used to image classification issues. In their study [120], Ahmedt-Aristizabal and colleagues used the VGG-16 architecture to detect epilepsy based on facial pictures data. The methodology that they developed sought to automatically extract and categorise semiological patterns of different facial states. After the images have been recorded, the suggested VGG architecture is trained primarily through the use of well-known datasets, and then in the final few layers, it is trained through the use of a variety of networks such as 1D-CNN and LSTM. One-dimensional and two-dimensional signals were employed in the VGG network that was described in [121].

Adam's optimizer and a cross-entropy error function were utilised in the process of training the models. They determined that 20 was an appropriate batch size, and 100 was the appropriate number of epochs. Emami et al. [122] investigated the possibility of identifying epileptic episodes based on the plots of the sEEG signals. During the preprocessing stage, the data were divided up into several time windows, and then the VGG-16 algorithm was utilised for classification. This algorithm made use of modest (3 _ 3) convolution filters in order to effectively detect minute alterations in the EEG signal. This architecture was pre-trained by applying an ImageNet dataset to differentiate 1000 classes, and the final two layers each have 4096 and 1000 dimensional vectors respectively.

In order to distinguish between seizure classes and non-seizure classes, they adjusted the last two layers so that they had 32 and 2 dimensions, respectively.

D. GoogleNet

The 2014 ImageNet competition was won by Google's GoogLeNet thanks to its 93.3% top-5 test accuracy [123]. In recognition of Yann Lecun, the architect of LeNet, this 22-layer network was given the name GoogLeNet. Before GoogleNet was developed, it was commonly believed that one might improve their accuracy and the results they obtained by conducting more in-depth research. In spite of this, the Google team came up with a new architecture that they named "inception." This architecture improved efficiency without increasing depth by focusing instead on better design. By applying filters of varying widths to the same image, it demonstrated a solution that was both reliable and adaptable. This architecture has lately garnered the interest of researchers in the field of electroencephalogram (EEG) data processing, which is used to diagnose epileptic seizures. Epileptic seizures were successfully diagnosed by [124] using this network in their preliminary tests. Their model was put to use in the Bern-Barcelona dataset, where it was able to successfully extract features, resulting in good results.

E. ResNet

ResNet, developed by Microsoft, was able to achieve 96.4% accuracy and win the ImageNet competition by implementing a 152-layer network that made use of a ResNet module [125]. Through the utilisation of skip connections that transferred the inputs of each layer into the subsequent layer, residual blocks in this network that were capable of teaching deep architecture were brought into existence. The purpose of advancing to the next tier was to acquire fresh and distinct knowledge. There has only been a modest amount of study carried out so far on the application of ResNet networks to the diagnosis of epilepsy; nevertheless, it is possible that this number may greatly increase in the days to come. Bizopoulos et al. [126] presented two different designs, ResNet and DenseNet, with the goal of diagnosing epileptic episodes. They were successful in doing so.

3. Challenges and Open Research Points

Working on the seizure detection based on EEG presents a number of obstacles, including the following:

• The automated seizure registration approaches for enhancing the quality of seizure data. • an accurate professional database, because seizure monitoring is vital for the treatment decisions that are made for patients or caretakers. The management of the patient is negatively impacted when the seizure documentation is inaccurate.

• There is still a need for a seizure detection system that operates in real time and subsequent evaluation by specialists.

• For reasons having to do with technology, getting longer recordings has proven difficult.

• Because the majority of epilepsy patients are unable to actively punch an alert button, traditional emergency call systems are not ideal for them; therefore, alternate methods are required.

• The diagnostic accuracy is still lacking, so multimodal techniques that incorporate the measurement of independently operating parameters (for example, heart rate or muscular activity) will be necessary to detect these seizures in the future.

• The compromise that must be made between the accuracy of a seizure detection algorithm (SDA) and its detection speed means that such advancements may come at the expense of an increased level of invasive surveillance.

• Managing non-stationarity as well as background noise. The EEG is susceptible to a wide variety of artefacts, any one of which might obscure the true nature of the underlying brain activity.

• Minimizing computational cost.

• Evaluation of the SDA's Performance. In order to conduct an accurate performance evaluation of any SDA, extensive prospective validation of the SDA is required.

With regard to this fascinating subject, there are a number of unanswered study questions that can direct the researcher towards working on future projects, such as the following:

Investigate how the Corona Virus influences EEG brain signals in epilepsy patients and how it has an effect on the symptoms of epilepsy patients.

• Construct an effective model for the identification of seizures by making use of spectrograms to represent the EEG signals.

• The utilisation of the Internet of Things for the purpose of performing remote monitoring of epileptic patients.

• In order to identify epilepsy in real time, deep learning structures need to be carefully selected based on the particulars of the problem, and relevant datasets need to be included. In a similar vein, hybrid deep learning approaches need to have much research done on them.

• Careful consideration needs to be given to the selection of AI-based classifiers to ensure that none of the important EEG channels or electrodes are overlooked or skipped over.

• Create mobile applications that allow for the remote observation of epilepsy patients by medical professionals and family members.

• Because epileptic seizure datasets tend to be rather large and have a high dimension, it is essential to make use of dimensional reduction techniques in order to cut down on the size of the datasets while maintaining the vital information contained within them. These techniques need to be investigated further. Therefore, acceptable qualities that lessen the computational complexity and amount of time required by the classifier ought to be believed.

4. Conclusion

In recent years, employing manual monitoring and researching EEG to diagnose epilepsy has become an extremely demanding and challenging task. This task requires examining extensive records and making decisions based on previous experience. Accurate identification is becoming more and more important as the number of people suffering with epilepsy continues to rise. In a similar vein, effectively detecting seizures from an overwhelming amount of information becomes a tough task. In addition, machine learning and deep learning algorithms classifiers are a helpful and appropriate tool for reliable seizure diagnosis due to the complexity of EEG signals in such datasets. This complexity makes such datasets difficult to analyse using traditional methods. For the foreseeable future, the provision of an automated seizure detection system that is a promising tool for neurologists in the process of epilepsy diagnosis is subject to a precondition. To get a more favourable outcome, additional research into the various methods of seizure detection needs to be carried out in depth. As a result, the purpose of this work was to evaluate and review a number of different automated EEG epileptic seizure detection and categorization systems. Additionally. It brought attention to both conventional methods of feature extraction as well as statistical and machine learning classifiers. In addition, the focus of this work was on the emerging trends in the IoT framework for the diagnosis of epilepsy. In conclusion, the difficulties and unsolved research questions surrounding EEG seizure detection are discussed.

Reference

[1] Ghassemi, N.; Shoeibi, A.; Rouhani, M.; Hosseini-Nejad, H. Epileptic seizures detection in EEG signals using TQWT and ensemble learning. In Proceedings of the 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, Iran, 24–25 October 2019; pp. 403–408.

[2] Shoeibi, A.; Ghassemi, N.; Alizadehsani, R.; Rouhani, M.; Hosseini-Nejad, H.; Khosravi, A.; Panahiazar, M.; Nahavandi, S. A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals. Expert Syst. Appl. **2021**, 163, 113788.

[3] Bhattacharyya, A.; Pachori, R.B.; Upadhyay, A.; Acharya, U.R. Tunable-Q wavelet transform based multiscale entropy measure for automated classification of epileptic EEG signals. Appl. Sci. **2017**, 7, 385.

[4] Kulaseharan, S.; Aminpour, A.; Ebrahimi, M.; Widjaja, E. Identifying lesions in paediatric epilepsy using morphometric and textural analysis of

magnetic resonance images. Clin. NeuroImage **2019**, 21, 101663.

[5] Zazzaro, G.; Cuomo, S.; Martone, A.; Montaquila, R.V.; Toraldo, G.; Pavone, L. Eeg signal analysis for epileptic seizures detection by applying data mining techniques. Internet Things **2019**, 100048.

[6] van Klink, N.; Mooij, A.; Huiskamp, G.; Ferrier, C.; Braun, K.; Hillebrand, A.; Zijlmans, M. Simultaneous MEG and EEG to detect ripples in people with focal epilepsy. Clin. Neurophysiol. **2019**, 130, 1175–1183.

[7] Pianou, N.; Chatziioannou, S. Imaging with PET/CT in Patients with Epilepsy. In Epilepsy Surgery and Intrinsic Brain Tumor Surgery; Springer: Cham, Switzerland, 2019; pp. 45–50.

[8] Subasi, A.; Kevric, J.; Canbaz, M.A. Epileptic seizure detection using hybrid machine learning methods. Neural Comput. Appl. **2019**, 31, 317–325.

[9] Acharya, U.R.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adeli, H.; Subha, D.P. Automated EEG-based screening of depression using deep convolutional neural network. Comput. Methods Programs Biomed. **2018**, 161, 103–113.

[10] Lauretani, F.; Longobucco, Y.; Ravazzoni, G.; Gallini, E.; Salvi, M.; Maggio, M. Imaging the Functional Neuroanatomy of

[11] Parkinson’s Disease: Clinical Applications and Future Directions. Int. J. Environ. Res. Public Health **2021**, 18, 2356.

[12] Carbó-Carreté, M.; Cañete-Massé, C.; Figueroa-Jiménez, M.D.; Peró-Cebollero, M.; Guàrdia-Olmos, J. Relationship between Quality of Life and the Complexity of Default Mode Network in Resting State Functional Magnetic Resonance Image in Down Syndrome. Int. J. Environ. Res. Public Health **2020**, 17, 7127.

[13] Morales Chacón, L.M.; González González, J.; Ríos Castillo, M.; Berrillo Batista, S.; Batista García-Ramo, K.; Santos Santos, A.; Cordero Quintanal, N.; Zaldívar Bermúdez, M.; Garbey Fernández, R.; Estupiñan Díaz, B.; et al. Surgical Outcome in Extratemporal Epilepsies Based on Multimodal Pre-Surgical Evaluation and Sequential Intraoperative Electrocorticography. Behav. Sci. **2021**, 11, 30.

[14] Takagi, S.; Sakuma, S.; Morita, I.; Sugimoto, E.; Yamaguchi, Y.; Higuchi, N.; Inamoto, K.; Ariji, Y.; Ariji, E.; Murakami, H. Application of Deep Learning in the Identification of Cerebral Hemodynamics Data Obtained from Functional Near-Infrared Spectroscopy: A Preliminary Study of Pre-and Post-Tooth Clenching Assessment. J. Clin. Med. **2020**, 9, 3475.

[15] Ronan, L.; Alhusaini, S.; Scanlon, C.; Doherty, C.P.; Delanty, N.; Fitzsimons, M. Widespread cortical morphologic changes in juvenile myoclonic epilepsy: Evidence from structural MRI. Epilepsia **2012**, 53, 651–658.

[16] Sharma, R.; Pachori, R.B. Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions. Expert Syst. Appl. **2015**, 42, 1106–1117.

[17] Sheoran, M.; Kumar, S.; Chawla, S. Methods of denoising of electroencephalogram signal: A review. Int. J. Biomed. Eng. Technol. **2015**, 18, 385.

[18] Romaine, J.; Martín, M.P.; Ortiz, J.S.; Crespo, J.M. EEG—Single-Channel Envelope Synchronisation and Classification for Seizure Detection and Prediction. Brain Sci. **2021**, 11, 516.

[19] Perez-Sanchez, A.V.; Perez-Ramirez, C.A.; Valtierra-Rodriguez, M.; Dominguez-Gonzalez, A.; Amezquita-Sanchez, J.P.Wavelet Transform-Statistical Time Features-Based Methodology for Epileptic Seizure Prediction Using Electrocardiogram Signals. Mathematics **2020**, 8, 2125.

[20] Raschka, S.; Mirjalili, V. Python Machine Learning: Machine Learning and Deep Learning with Python. In Scikit-Learn and TensorFlow, 2nd ed.; Packt Publishing Ltd.: Birmingham, UK, 2017.

[21] Bonaccorso, G. Machine Learning Algorithms; Packt Publishing Ltd.: Birmingham, UK, 2017.

[22] Gulli, A.; Pal, S. Deep Learning with KERAS; Packt Publishing Ltd.: Birmingham, UK, 2017.

[23] Tang, X.; Zhang, X. Conditional adversarial domain adaptation neural network for motor imagery EEG decoding. Entropy **2020**,

[24] Alickovic, E.; Kevric, J.; Subasi, A. Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. Biomed. Signal Process. Control **2018**, 39, 94–102.

[25] Sharma, M.; Bhurane, A.A.; Acharya, U.R. MMSFL-OWFB: A novel class of orthogonal wavelet filters for epileptic seizure detection. Knowl. Based Syst. **2018**, 160, 265–277.

[26] Mohammadpoor, M.; Shoeibi, A.; Shojaee, H. A hierarchical classification method for breast tumor detection. Iran. J. Med. Phys. **2016**, 13, 261–268.

[27] Assi, E.B.; Nguyen, D.K.; Rihana, S.; Sawan, M. Towards accurate prediction of epileptic seizures: A review. Biomed. Signal Process. Control. **2017**, 34, 144–157.

[28] Khodatars, M.; Shoeibi, A.; Ghassemi, N.; Jafari, M.; Khadem, A.; Sadeghi, D.; Moridian, P.; Hussain, S.; Alizadehsani, R.; ZARE, A.; et al. Deep Learning for Neuroimaging-based Diagnosis and Rehabilitation of Autism Spectrum Disorder: A Review. arXiv **2020**, arXiv:2007.01285.

[29] Sadeghi, D.; Shoeibi, A.; Ghassemi, N.; Moridian, P.; Khadem, A.; Alizadehsani, R.; Teshnehlab, M.; Gorriz, J.M.; Nahavandi, S. An Overview on Artificial Intelligence Techniques for Diagnosis of Schizophrenia Based on Magnetic Resonance Imaging Modalities: Methods, Challenges, and FutureWorks. arXiv **2021**, arXiv:2103.03081.

[30] Craik, A.; He, Y.; Contreras-Vidal, J.L. Deep learning for electroencephalogram (EEG) classification tasks: A review. J. Neural Eng. **2019**, 16, 031001.

[31] Ghassemi, N.; Shoeibi, A.; Khodatars, M.; Heras, J.; Rahimi, A.; Zare, A.; Pachori, R.B.; Gorriz, J.M. Automatic Diagnosis of COVID-19 from CT Images using CycleGAN and Transfer Learning. arXiv **2021**, arXiv:2104.11949.

[32] Sharifrazi, D.; Alizadehsani, R.; Hassannataj Joloudari, J.; Shamshirband, S.; Hussain, S.; Alizadeh Sani, Z.; Hasanzadeh, F.; Shoaibi, A.; Dehzangi, A.; Alinejad-Rokny, H. CNN-KCL: Automatic Myocarditis Diagnosis using Convolutional Neural Network Combined with K-means Clustering. Preprints **2020**, 2020070650.

[33] Srivastava, N.; Salakhutdinov, R. Multimodal Learning with Deep Boltzmann Machines. NIPS **2012**, 1, 2.

[34] Yu, D.; Deng, L. Deep Learning and Its Applications to Signal and Information Processing Exploratory DSP. IEEE Signal Process. Mag. **2011**, 28, 145–154. [CrossRef]

[35] Ihle, M.; Feldwisch-Drentrup, H.; Teixeira, C.A.;Witon, A.; Schelter, B.; Timmer, J.; Schulze-Bonhage, A. EPILEPSIAE–A European epilepsy database. Comput. Methods Programs Biomed. **2012**, 106, 127–138.

[36] Shoeb, A.H. Application of Machine Learning to Epileptic Seizure onset Detection and Treatment; Massachusetts Institute of Technology: Cambridge, MA, USA, 2009.

[37] Seizure Prediction Challenge. Available online: https://www.kaggle.com/c/seizure-prediction (accessed on 15 May 2021).

[38] Andrzejak, R.G.; Lehnertz, K.; Mormann, F.; Rieke, C.; David, P.; Elger, C.E. Indications of nonlinear deterministic and finitedimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Phys. Rev. E **2001**, 64, 061907.

[39] Andrzejak, R.G.; Schindler, K.; Rummel, C. Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. Phys. Rev. E **2012**, 86, 046206.

[40] Stevenson, N.J.; Tapani, K.; Lauronen, L.; Vanhatalo, S. A dataset of neonatal EEG recordings with seizure annotations. Sci. Data **2019**, 6, 1–8.

[41] Sharma, R.; Sircar, P.; Pachori, R.B. Computer-aided diagnosis of epilepsy using bispectrum of EEG signals. In Application of Biomedical Engineering in Neuroscience; Springer: Singapore, 2019; pp. 197–220.

[42] Goodfellow, I.; Bengio, Y.; Courville, A.; Bengio, Y. Deep Learning; MIT Press: Cambridge, UK, 2016; Volume 1, p. 2.

[43] Faust, O.; Hagiwara, Y.; Hong, T.J.; Lih, O.S.; Acharya, U.R. Deep learning for healthcare applications based on physiological signals: A review. Comput. Methods Programs Biomed. **2018**, 161, 1–13.

[44] Yildirim, O.; Talo, M.; Ay, B.; Baloglu, U.B.; Aydin, G.; Acharya, U.R. Automated detection of diabetic subject using pre-trained 2D-CNN models with frequency spectrum images extracted from heart rate signals. Comput. Biol. Med. **2019**, 113, 103387.

[45] Martis, R.J.; Acharya, U.R.; Lim, C.M.; Mandana, K.M.; Ray, A.K.; Chakraborty, C. Application of higher order cumulant features for cardiac health diagnosis using ECG signals. Int. J. Neural Syst. **2013**, 23, 1350014.

[46] Pham, T.-H.; Vicnesh, J.; Wei, J.K.E.; Oh, S.L.; Arunkumar, N.; Abdulhay, E.W.; Ciaccio, E.J.; Acharya, U.R. Autism Spectrum Disorder Diagnostic System Using HOS Bispectrum with EEG Signals. Int. J. Environ. Res. Public Health **2020**, 17, 971.

[47] Alizadehsani, R.; Roshanzamir, M.; Hussain, S.; Khosravi, A.; Koohestani, A.; Zangooei, M.H.; Abdar, M.; Beykikhoshk, A.; Shoeibi, A.; Zare, A.; et al. Handling of uncertainty in medical data using

machine learning and probability theory techniques: A review of 30 years (1991–2020). Ann. Oper. Res. **2021**, 1–42.

[48] 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. Uncertainty-Aware Semi-supervised Method using Large Unlabelled and Limited Labeled COVID-19 Data. arXiv **2021**, arXiv:2102.06388.

[49] Shoeibi, A.; Khodatars, M.; Alizadehsani, R.; Ghassemi, N.; Jafari, M.; Moridian, P.; Khadem, A.; Sadehi, D.; Hussain, S.; Zare, A.; et al. Automated detection and forecasting of covid-19 using deep learning techniques: A review. arXiv **2020**, arXiv:2007.10785.

[50] Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. Commun. ACM **2012**, 60, 1097–1105.

[51] Avcu, M.T.; Zhang, Z.; Chan, D.W.S. Seizure detection using least eeg channels by deep convolutional neural network. In Proceedings of the ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing, Brighton, UK, 12–17 May 2019; pp. 1120–1124.

[52] Hossain, M.S.; Amin, S.U.; Alsulaiman, M.; Muhammad, G. Applying Deep Learning for Epilepsy Seizure Detection and Brain Mapping Visualization. ACM Trans. Multim. Comput. Commun. Appl. **2019**, 15, 1–17.

[53] Zuo, R.; Wei, J.; Li, X.; Li, C.; Zhao, C.; Ren, Z.; Liang, Y.; Geng, X.; Jiang, C.; Yang, X.; et al. Automated Detection of High-Frequency Oscillations in Epilepsy Based on a Convolutional Neural Network. Front. Comput. Neurosci. **2019**, 13, 6.

[54] Aayesha M, Qureshi B, Afzaal M, Qureshi MS, Fayaz M (2021) Machine learning-based EEG signals classification model for epileptic seizure detection. Multimed Tools Appl 80(12):17849–17877. https://doi.org/10.1007/s11042-021-10597-6

[55] Abdelhameed A, Bayoumi M (2021) A deep learning approach for automatic seizure detection in children with epilepsy. Front Comput Neurosci 15:29. https://doi.org/10.3389/fncom.2021.650050

[56] Abualsaud K, Mohamed A, Khattab T, Yaacoub E, Hasna M, Guizani M (2018) Classification for imperfect EEG epileptic seizure in IoT applications: a comparative study. 2018 14th Int. Wirel. Commun. Mob. Comput. Conf. IWCMC 2018, pp 364–369. https://doi.org/10.1109/IWCMC.2018.8450279

[57] Acharya UR, Fujita H, Sudarshan VK, Bhat S, Koh JEW (2015) Application of entropies for automated diagnosis of epilepsy using EEG signals: a review. Knowl-Based Syst 88:85–96. https://doi.org/10.1016/j.knosys.2015.08.004

[58] Acharya UR et al (2019) Characterization of focal EEG signals: a review. Futur Gener Comput Syst 91: 290–299. https://doi.org/10.1016/j.future.2018.08.044

[59] Achilles F, Tombari F, Belagiannis V, Loesch-Biffar A, Noachtar S, Navab N (2016) Convolutional neural networks for real-time epileptic seizure detection. Comput Methods Biomech Biomed Eng Imaging Vis 6: 1–6. https://doi.org/10.1080/21681163.2016.1141062

[60] Ahammad N, Fathima T, Joseph P (2014) Detection of epileptic seizure event and onset using EEG. Biomed Res Int 2014:450573. https://doi.org/10.1155/2014/450573

[61] Ahmad I et al (2022) EEG-based epileptic seizure detection via machine/deep learning approaches: a systematic review. Comput Intell Neurosci 2022:6486570. https://doi.org/10.1155/2022/6486570

[62] Aileni RM, Pasca S, Florescu A (2020) EEG-brain activity monitoring and predictive analysis of signals using artificial neural networks. Sensors (Basel) 20(12):3346. https://doi.org/10.3390/s20123346

[63] Akareddy S, Kulkarni P (2013) EEG signal classification for epilepsy seizure detection using improved approximate entropy. Int J Public Health Sci 2:23–32. https://doi.org/10.11591/ijphs.v2i1.1836

[64] Akut R (2019) Wavelet based deep learning approach for epilepsy detection. Heal Inf Sci Syst 7:1–9. https://doi.org/10.1007/s13755-019-0069-1

[65] Shoeibi A, Khodatars M, Ghassemi N, Jafari M, Moridian P, Alizadehsani R, Panahiazar M, Khozeimeh F, Zare A, Hosseini-Nejad H, Khosravi A, Atiya AF, Aminshahidi D, Hussain S, Rouhani M, Nahavandi S, Acharya UR. Epileptic Seizures Detection Using Deep Learning Techniques: A Review. Int J Environ Res Public Health. 2021 May 27;18(11):5780. doi: 10.3390/ijerph18115780. PMID: 34072232; PMCID: PMC8199071.

[66] Al Ghayab HR, Li Y, Abdulla S, Diykh M, Wan X (2016) Classification of epileptic EEG signals based on simple random sampling and sequential feature selection. Brain Inform 3(2):85–91. https://doi.org/10.1007/s40708-016-0039-1

[67] Alam SM, Bhuiyan M (2013) Detection of seizure and epilepsy using higher order statistics in the EMD domain. IEEE J Biomed Health Inform 17:312–318. https://doi.org/10.1109/JBHI.2012.2237409

[68] Alhussein M, Muhammad G, Hossain MS (2019) EEG pathology detection based on deep learning. IEEE Access 7:27781–27788. https://doi.org/10.1109/ACCESS.2019.2901672

[69] Almustafa KM (2020) Classification of epileptic seizure dataset using different machine learning algorithms. Inform Med Unlocked 21:100444. https://doi.org/10.1016/j.imu.2020.100444

[70] Alotaibi SM, Atta-ur-Rahman, Basheer MI, Khan MA (2021) Ensemble machine learning based identification of pediatric epilepsy. Comput Mater Contin 68(1):149–165. https://doi.org/10.32604/cmc.2021.015976

[71] Alotaiby TN, Alshebeili SA, Alshawi T, Ahmad I, Abd El-Samie FE (2014) EEG seizure detection and prediction algorithms: a survey. EURASIP J Adv Signal Process 2014(1):183. https://doi.org/10.1186/1687-6180-2014-183

[72] Antoniades A, Spyrou L, Took CC, Sanei S (2016) Deep learning for epileptic intracranial EEG data. In: 2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP), pp 1–6. https://doi.org/10.1109/MLSP.2016.7738824