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REVIEW

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Applications of Artificial Intelligence in Automatic Detection of Epileptic Seizures Using EEG Signals: A Review

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Abstract: Correctly interpreting an electroencephalogram signal with high accuracy is a tedious and time-consuming task that may take several years of manual training due to its complexity, noisy, non-stationarity, and nonlinear nature. To deal with the vast amount of data and recent challenges of meeting the requirements to develop low cost, high speed, low complexity smart internet of medical things computer-aided devices (CAD), artificial intelligence (AI) techniques which consist of machine learning and deep learning (DL) play a vital role in achieving the stated goals. Over the years, machine learning techniques have been developed to detect and classify epileptic seizures. But until recently, DL techniques have been applied in various applications such as image processing and computer visions. However, several research studies have turned their attention to exploring the efficacy of DL to overcome some challenges associated with conventional automatic seizure detection techniques. This article endeavors to review and investigate the fundamentals, applications, and progress of AI-based techniques applied in CAD system for epileptic seizure detection and characterization. It would help in actualizing and realizing smart wireless wearable medical devices so that patients can monitor seizures before their occurrence and help doctors diagnose and treat them. The work reveals that the recent application of DL algorithms improves the realization and implementation of mobile health in a clinical environment.

Keywords: EEG, CAD system, machine learning, deep learning, artificial intelligence, epileptic seizures

1. Introduction

With the rapid development of smart internet of things devices and the successful deployment of the 5G network, the integration of health care services for monitoring, diagnosis, and analysis of various diseases can never be overemphasized. One chronic brain disorder that happens due to abnormal excitation of brain cells which leads to unprovoked seizures is called epilepsy. Some leading causes of seizures are low blood sugar levels, malformations, and oxygen shortage during childbirth (Sazgar & Young, 2019; Sirven, 2015). Epileptic seizures can happen anytime and cause a loss of consciousness, leading to injuries and even death. Generally, there are two main types of seizures, generalized and partial, depending on whether the seizures affect some part or all of the brain region. In generalized seizures, all brain sections are affected; for partial seizures, only an area of the brain is affected (Fisher, 2017; Patel & Moshé, 2020). Figure 1 shows a block diagram of different types of seizures. It is vital to predict the occurrence of these seizures since it is challenging for

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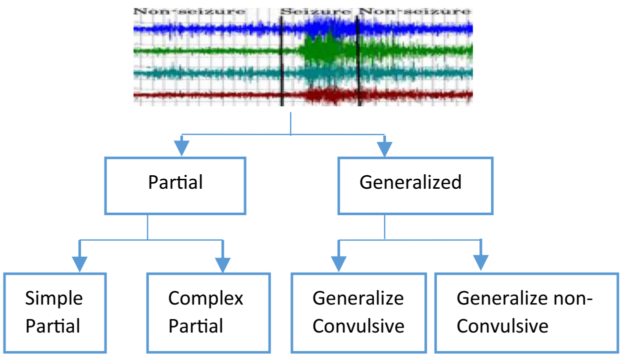
Figure 1
General block diagram of different types of epileptic seizures



a patient to predict when they will happen so that preventive measures can be taken to avoid loss of consciousness and even can sometimes lead to death (Falco et al., 2018; Saminu et al., 2020).

Manual visual inspection and analysis of epileptic electroencephalogram (EEG) signals are traditional methods of detection and classification by experts, which tends to be time-consuming, tedious, and prone to errors. Therefore, investigation of automatic modes that employ artificial intelligence (AI) is paramount to overcome the problem associated with visual inspection and traditional machine learning techniques. Various traditional and machine learning methods have been developed, such as using time, frequency, time–frequency, and nonlinear methods (Gavvala et al., 2015; Siuly et al., 2017). However, with the advent of generating a huge amount of data in the form of signals, texts, images, and sounds, among others in health care management and the need for automated, smart, portable, wearable, and low-cost devices to improve patient diagnosis, DL algorithms find its applications in epileptic seizure prediction and classification. Much success has been recorded due to its ability to deal with a large amount of data and learn from the raw data, eliminating the need for hand feature extraction as in conventional techniques (Hu et al., 2019; Malekzadeh et al., 2021).

An EEG signal is a one-dimensional (1D) signal in a time domain that measures the changes in the brain's electrical activity. It is measured either from the scalp (EEG) or intracranial (ECoG) recorded using electrodes to indicate the normal from abnormal conditions such as seizure and non-seizure conditions in epilepsy patients (Minasyan et al., 2010). Early detection and identification of these seizures are vital and prevent patients from losing consciousness that may lead to injury and even death, and help doctors in diagnosis and treatment. EEG measured during seizure occurrence is called ictal EEG and, due to the unpredictability of seizure, makes it difficult to rely on only ictal EEG in differentiating between seizure and non-seizure epileptic signals (Acharya et al., 2018). Interictal EEG is also used to distinguish between an epileptic seizure and other conditions as it reveals the possible epileptic seizure occurrence to assist in diagnosis, monitoring, and treatment (Freestone et al., 2017; Kuhlmann et al., 2018). The general block diagram of epileptic seizure detection stages consists of data acquisition, preprocessing, feature extraction, classification, and performance evaluation, as depicted in Figure 2.

This article tends to review the recent trends and progress in epileptic seizure detection using AI such as the deep learning (DL) technique, which is the extension of machine learning. The article reviews the recent works from 2016 to 2021 using the Google Scholar, PubMed, and ScienceDirect databases that cover the science and engineering fields. Keyword combinations such as "Epileptic seizures detection using machine learning," "machine learning in EEG signals," "deep learning in EEG signals," "epileptic seizure detection using deep learning," "automatic seizure detection and characterisation using deep neural network," "CAD systems for epileptic seizure detection and classification," among others were used. This work includes related studies from engineering, science and medical conferences, journal articles, review articles, books, thesis, and other electronics repositories. The selection criteria for the state-of-the-art techniques include the initial selection of 376 published research articles from the mentioned search engines. Two hundred and 43 research articles were selected after the keyword and title search from the initial obtained research articles. Thereafter, manual search of the full-text articles was conducted to finally select 187 best articles considered in this review. Some of the exclusion criterion includes articles that used other neuroimaging techniques apart from EEG such as magnetoencephalography, functional MRI among others in their study, non-availability of the performance metrics in the results presented such as accuracy, sensitivity, and specificity, and those articles that used other languages rather than English among others.

Yannick et al. (2019) listed the data items to be extracted and considered in each reviewed study, such as type of study, data used in the study, EEG processing methods, DL techniques, and results presented in the study and reproducibility of the study. Table 1 depicts the details of data items extracted in the study with their description.

Several works in literature endeavor to review the works carried out in epilepsy detection and classification using various techniques. In our previous work (Saminu et al., 2021), an investigation on the recent advances in epileptic seizure detection and classification was conducted. The work presents detail highlight on the conventional techniques used in the stages during the detection and classification of epileptic seizures such as data acquisition, preprocessing, feature ranking, and selection and classification. The work covered the period of 2010–2020. DL was briefly discussed to explore some recent trends in the area. Another recent review work presents a narrative summary in epileptic seizure diagnosis and management (Nair et al., 2021). The authors discussed the role of AI in the areas such as seizure detection, understanding epileptogenesis, medical management, surgical management, neurostimulation, and wearable devices. A quick review on machine learning applications in EEG epileptic seizures detection and application was presented by Si (2020). The author briefly discussed the conventional classification techniques commonly employed in detection and classification of epileptic seizures such as support vector machine (SVM), k-nearest neighbor (k-NN), random forest, and artificial neural network (ANN). This article covers the most recent investigation of works

Figure 2
General block diagram of epileptic seizures detection system

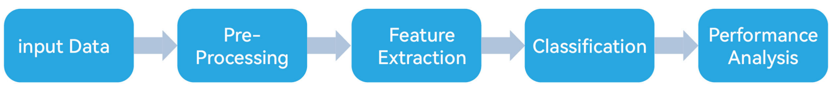


Table 1
Components to be considered in a review study

Category	Data item	Description
Origin of article	*Type of Publication*	Journal article, conference paper, book, thesis
	Venue	Name of journal and publisher
	Affiliations	Affiliation of lead author
Data	Quantity of data	Number of samples and duration of recording
	Hardware	Model of recording device
	Number of channels	EEG channels used during recording
	Sampling rate	Sampling rate (Hz)
	Subject	Number of subjects used in the analysis
	Data split and cross-validation	Dividing data into training, testing, and validation
	Data augmentation	Data augmentation technique used
EEG processing	Preprocessing	Raw data preparation
	Denoising	Artifact denoising applied or not
	Feature extracted (where applicable)	Significant and relevant features extracted for
Deep learning techniques	Architecture	Structure of the neural network
	Number of layers	A measure of architecture depth
	EEG-specific design choices	Specific architecture selection for processing EEG data
	Training procedure	Selected technique to train the network
		Constraint on the hypothesis class intended to improve a learning algorithm generalization performance
	Regularization	Parameter update rule
	Optimization	Whether a specific method was employed in order to tune
	Hyperparameter search	the hyperparameter set
		Intra- versus inter-subject analysis
	Subject handling	The method used to inspect a trained DL model
	Inspection of trained Models	
Results	Type of baseline	Baseline models included in the study or not
	Performance metrics	Performance measures used to evaluate the model
	Validation procedure	The method used to validate the trained model
	Statistical testing	The statistical method used to evaluate the model
	Comparison of results	Results of the study
Reproducibility	*Dataset*	Dataset used in the study (public or private)
	Code	Availability of the code used in the study

performed in detection and classification of epileptic seizures. The work covers the detail list of works carried out using DL architectures unlike the previous works that focussed on conventional machine learning techniques as highlighted. This work also differs from the previous reviews discussed and that of (Minasyan et al., 2010; Paul Fergus & Hussain, 2015) as the work reported in this article provides an extensive discussion on the stand-alone and hybrid techniques in terms of complexity, accuracy, ease of implementation, and requirement of larger datasets. The most unique feature of this review is the investigation and discussion of hybrid approaches that consist of conventional machine learning techniques and DL algorithms which provides a new phase and direction in the detection, classification, and localization of epileptogenic zone research.

1.1. Objectives and contribution of the study

This study covers the systematic and comprehensive analysis of the state of the art of recent publications related to the application of AI in automated epileptic seizure detection and prediction. Many recent publications have analyzed both machine learning and DL techniques to provide an insight to those researchers familiar with traditional approaches and interested in exploring the efficacy of AI techniques. Also, the study aims to review the recent machine learning and DL techniques in the same place to help the existing researchers in the field to compare and expand their techniques with their benchmarking dataset easily. Several components of machine learning and DL methodological pipeline have been provided. Various publicly EEG epileptic seizure databases have been highlighted and summarized.

1.2. Organization of the article

The remaining part of the article is organized as follows. Section 2 provides a background study of AI that consists of machine learning and DL networks. Section 3 describes the feature extraction and classification techniques in artificial intelligence, discussion of the reviewed study of the article was described in Section 4, and Section 5 concludes the review presented in the article.

2. Background

2.1. Machine learning

The concept of AI is that in which vast knowledge and intelligence acquired by human experts are translated and built into machines and computers so that they can learn and perform the function of human experts. Several types of machine learning models which are part of AI have been proposed in the literature to detect and classify epileptic seizures, such as ANN, SVM, k-means clustering, naive Bayes, logistic regression, among others (Ahmed et al., 2018; Saminu et al., 2021). These ML algorithms overcome human limitations such as variations in interpretations, time consumption, and fatigue. Machine learning can be classified as either supervised or unsupervised learning. In supervised learning, the input data are labeled and then used in training the algorithm to estimate the outputs for unlabeled data. An algorithm uncovers the outliers, trends, and subgroups of unlabeled input data in unsupervised learning. An example of supervised and unsupervised learning is shown in Figure 3. In epileptic seizure detection, supervised learning is called supervised learning when the algorithm is trained with annotated EEG data to detect seizure or non-seizure automatically. While in unsupervised learning, the algorithm detects the seizure or non-seizures with raw EEG data recording without annotation (Saminu et al., 2019; Series, 2021). This section highlights and briefly explains some of the commonly employed ML structures as follows:

In ANN, the structure consists of the interconnection of nodes called neurons, input, hidden, and output layers, as shown in Figure 4(a); the advancement of ANN ranges from its simple

Figure 3
Types of machine learning. (a) Supervised learning and (b) unsupervised learning

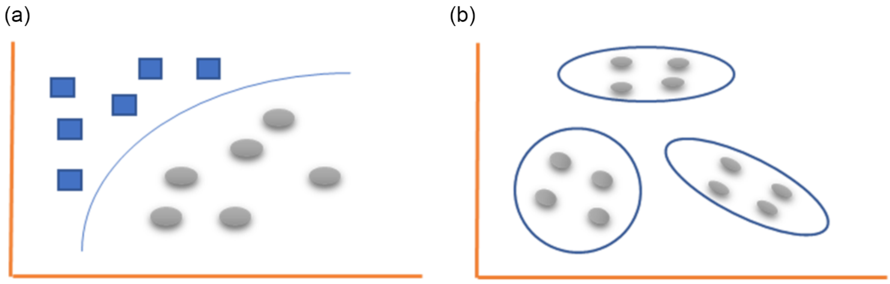
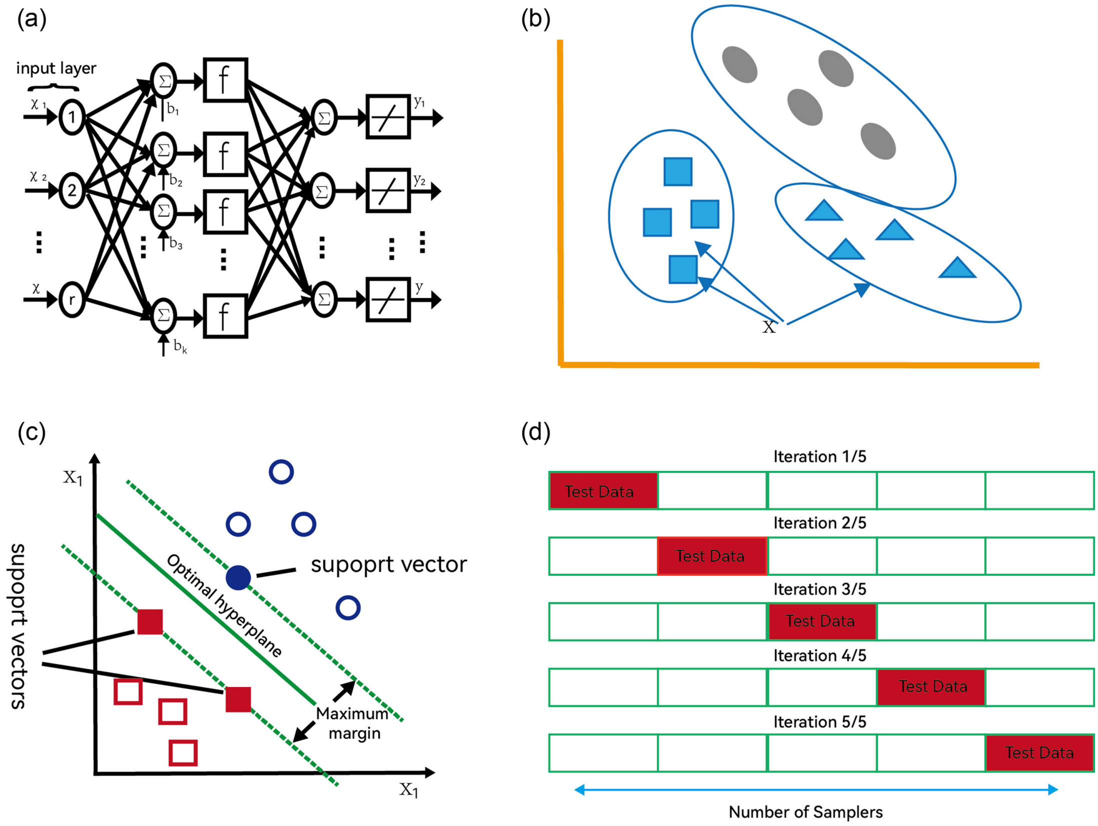


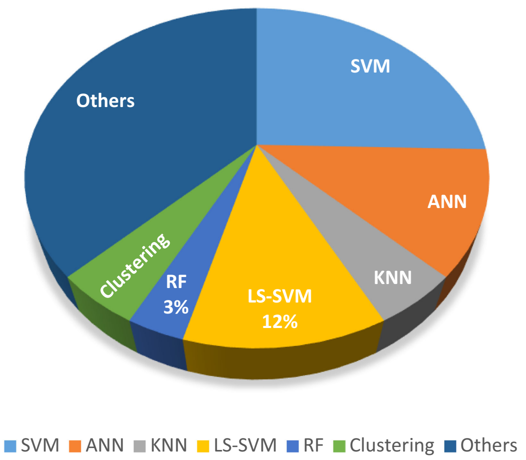
Figure 4
Machine learning techniques. (a) ANN, (b) k-NN, (c) SVM, and (d) k-cross validation



perceptron structure into a deeper neural network with several cascaded interconnected hidden layers that can handle huge amount and complex different types of data (Mello & Ponti, 2018). In k-NN classification, as shown in Figure 4(b), input data and labeled data are represented and plotted as a vector within a feature space, and the distance between the vectors is calculated in the training set. The class of k-nearest input data is then assigned, a class of majority. In the SVM classifier, Figure 4(c), a higher dimensional feature space is used to generate a hyperplane to provide a decision boundary and assign a class to new input data by maximally separating clusters of labeled input data. In the machine learning approach, relevant and informative features are calculated and selected either manually or by the algorithm. The output prediction of these features is generated using a mapping function. Several factors determined the selection of mapping function in a particular application, such as sample size, relative interpretability, and simplicity. However, the choice of mapping function may sometimes be iterative, empirical, or by the experimenter's experience. To overcome the problem of overfitting the training data due to the model's complexity and small amount of data, the training data are divided into a training set, validation set, and testing set. The process of k-fold cross-validation is applied in which the partitioning is repeated a pre-specified number of times or across the entire dataset, and holding out a single data point for validation in each iteration (leave-one-out cross-validation), the final model can be generally estimated to evaluate its performance using a withheld testing data. The process of k-fold validation is shown in Figure 4(d) with $k = 5$ (Jaiswal & Banka, 2018).

Recently, much of the researchers' attention have been focused on hybrid techniques when adopting conventional techniques in detection and prediction of epileptic seizures as shown in Figure 5. From the figure, the hybrid techniques cover 39% of the works reviewed in this study. The advantages of the SVM classifier is that of simplicity, capability to deal with many predictors, it is suitability for binary classification, and high accuracy make it the most employed stand-alone classifier with 23%. ANN classifier covered 13% of the conventional methods reviewed in this article. RF and clustering technique shared the 3% of the investigated approaches. ANN which uses number of neurons and layers unlike in SVM which uses kernel function covered 12% of the articles reviewed in this work as shown in Figure 5.

Figure 5
The percentage of conventional techniques involved in epilepsy studies



2.2. DL techniques

DL algorithms were employed in the automated epilepsy detection system to solve the limitations of machine learning techniques. DL does not require hand-crafted features to be extracted manually; due to its multilayer architecture, it can deal with large datasets, execute imbalanced datasets, and provide a result without biasing toward a majority class (Boonyakitanont et al., 2020; Mu & Zeng, 2019). Some of the DL architectures include convolutional neural network (CNN), long short-term network (LSTM), and gated recurrent unit (GRU). This article discusses the basic idea and underlying principles of the most common types of DL models. The basic concept of DL models is to produce output for a given input after approximating a function; different challenges can be handled by different models with different input data and the type of function to be performed, such as for speech, images, and texts, among others. The structure of the model consists of hidden layers which consist of interconnected neurons that connect an input to output. The sequence of activation was produced through the weighted functions (Sharmila & Geethanjali, 2019; Tzimourta et al., 2019).

2.2.1. Convolutional neural network

A CNN is a common DL model that mimics the biological human brain processing in which the connection between neurons resembles the human neurons. Various convolutional models have been proposed and applied by different researchers to investigate their capability in automated epilepsy detection systems (Ouichka et al., 2022). The most common approach is a CNN with a variety of architectures such as temporal CNN (TCNN), temporal graph convolutional networks (TGCNs), and CNN-recurrent neural network (CNN-RNN). The basic structure of CNN consists of

Figure 6
Basic structure of CNN architecture

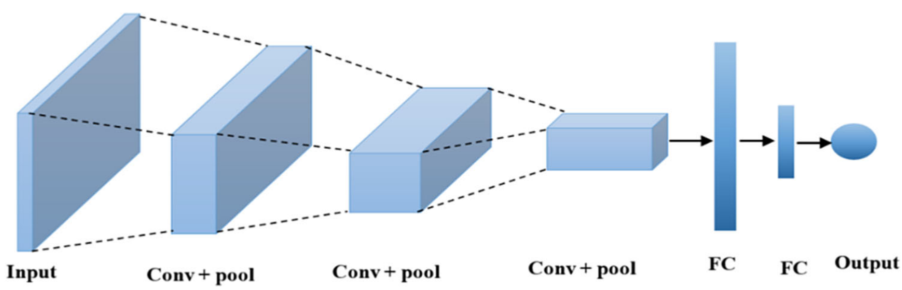
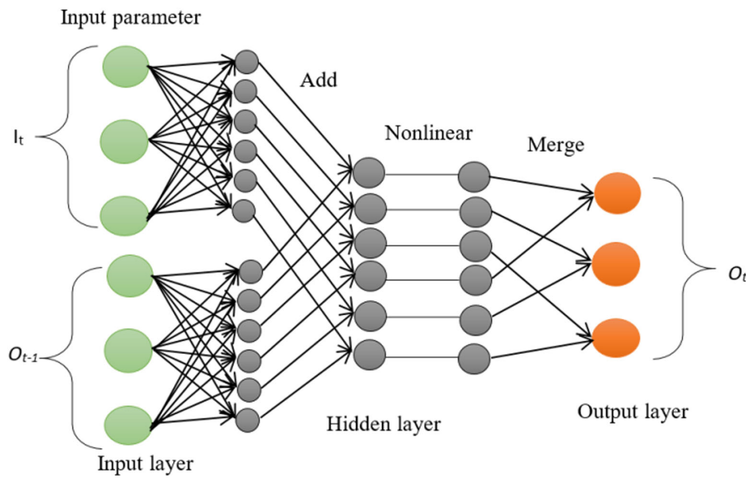


Figure 7
Basic structure of RNN architecture



convolutional layers, max-pooling layers, fully connected layers, and softmax layers (Josh & Adam, 2017; Mu & Zeng, 2019), as shown in Figure 6. Although DL algorithms outperform their conventional counterpart, the requirement of large datasets for their operation is its major limitation.

2.2.2. Recurrent neural network

RNN forms a directed graph sequence when its hidden layer has a connection between neurons. This temporal dynamic state feature makes it useful in applications where the previous state influences the output. Therefore, the interdependent data are used in training the network so that previous computations information can be maintained. RNN uses memory in its operation at a given time depending on the inputs' recent, past, and current source. Unlike other DL models, RNN adopted the same weight for all layers, reducing the number of parameters the network needs to learn. The major drawback of this model is exploding gradient and long sequence that cause a vanishing gradient (Beanbonyka et al., 2020). In Hochreiter and Schmidhuber (1997), a solution to this problem by inventing a LSTM network is proposed. A GRU is another variant of RNN. The basic structure of RNN architecture is shown in Figure 7.

3. Feature Extraction and Classification in AI Techniques

A good and relevant dataset is needed to train and classify EEG epileptic signals by DL models. This raw input data can extract meaningful features and then be used as input or supplied directly into the network without the feature extraction stage. Some researchers have employed DL models as feature extractors with conventional machine learning techniques used as classifiers, Figure 8(a), while others use conventional techniques as feature extractors and DL networks as classifiers, as shown in Figure 8(b). For the direct method or end-to-end learning, the raw input data are directly fed to the DL networks as classifiers, as shown in Figure 8(c).

3.1. Performance measures

Some statistical metrics evaluate the performance of machine learning and DL techniques. Accuracy is the most common metric used by researchers in assessing the classifier's efficiency. Accuracy can be defined as in equation

$$Accuracy = \frac{TN + TP}{TN + TP + FP + FN}$$

where TN is the "true negative," TP is the "true positive," FP is the "false positive," and FN is the "false negative."

Other metrics that are also used are precision, sensitivity, and specificity, among others

$$Precision = \frac{TP}{TP + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{\text{TP} + \text{FP}}$$

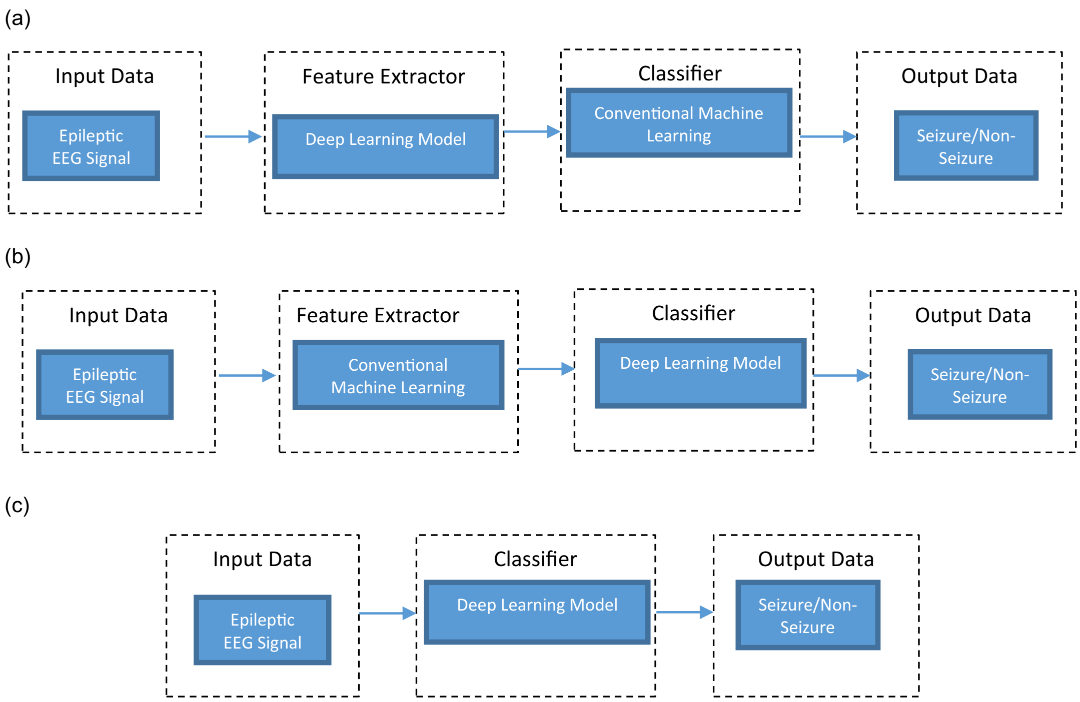
$$\text{F1\_Score} = 2\frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

The area under the curve (AUC) and the receiver operating characteristics are performance measures for evaluating the DL networks. Other performance measures calculated based on the seizure events of epileptic EEG signals are good detection rate and False Positive Rate (FPR) per hour.

The list of works in automated epilepsy detection and analysis that uses DL methods is summarized in Table 1. The most common DL networks employed in computer-aided device system for epileptic seizure detection are highlighted below.

One of the limitations of machine learning approaches is the ineffectiveness of the models in dealing with multichannel EEG signals and a huge amount of data. DL networks are designed to handle those limitations. From our survey, as shown in Table 1, researchers commonly employ CNN networks to effectively detect and classify epileptic seizures. CNN extracts learnable features automatically instead of machine learning classifiers that require the features to be extracted manually. Several works used CNN to propose an automatic seizure detection model. Hossain et al. (2019) proposed a model based on CNN architecture using a

Figure 8
Feature extraction and classification architecture. (a) Deep learning (DL) model as feature extractor and machine learning model as a classifier. (b) Machine learning model as feature extractor and DL model as a classifier. (c) End- to-end learning



multichannel CHB-MIT dataset to perform binary classification of seizure and non-seizure classes. The model extracts spatial, spectral, and temporal features from cross-patient and patient-specific EEG data. The model's overall performance in terms of accuracy is 98.1% and 99.7% for cross-patient and patient specific, respectively. Authors in (Boonyakitanont et al., 2019) used both CNN and ANN to propose a seizure detection method in which time domain, frequency domain, and time–frequency domain features were extracted and used in ANN for the classification of seizures while raw EEG data were used in CNN architecture. CNN architecture provides better accuracy than the ANN network, with an accuracy of 99.1%. Acharya et al. (2018) proposed a multi-classification approach for detecting ictal, preictal, and normal epileptic seizures using a CNN architecture with a Bonn University dataset. Detail of work that employed various types of DL architectures is provided in Table 2.

Table 2
List of works that used deep learning in detecting and classifying EEG epileptic seizures

Author	Year	Features	Performance (%)
Johansen et al. (2016)	2016	CNN	Accuracy = 94.7
Antoniades et al. (2016)	2016	CNN	Accuracy = 87.51
Lin et al. (2016)	2016	SSAE	Accuracy = 96.0
Achilles et al. (2016)	2016	CNN	Accuracy = 78.3
Thodoroff et al. (2016)	2016	CNN + RNN	Sensitivity = 85.0
Page et al. (2016)	2016	MPCNN	NA
Vidyaratne et al. (2016)	2016	DRNN	NA
Yan et al. (2016)	2016	SAE	Accuracy = 100.0
Lin et al. (2016)	2016	SSAE	Accuracy = 100.0
Hosseini et al. (2016)	2016	SSAE	Accuracy = 94.0
Wei et al. (2018)	2016	Multichannel CNN	Accuracy = 92.4
Golmohammadi et al. (2017)	2016	CNN-RNN	NA
Taqi et al. (2017)	2017	AlexNet, GoogleNet, LeNet	Accuracy= 100.0
O'Shea et al. (2017)	2017	1D-FCNN	NA
Talathi (2017)	2017	GRU	Accuracy = 98.0
Yuan et al. (2017)	2017	SSDA	Accuracy = 93.8
Le et al. (2017)	2017	DBN	Accuracy = 96.9

(Continued)

Table 2
(*Continued***)**

Author	Year	Features	Performance (%)
Hosseini et al. (2017)	2017	2D-CNN	NA
Gogna et al. (2017)	2017	Semi-supervised SAE	Accuracy = 96.9
Achilles et al. (2018)	2017	2D-CNN	NA
Park et al. (2018)	2018	1D-CNN, 2D-CNN	Accuracy = 90.5
Roy et al. (2018)	2018	1D-CNN, GRU	Accuracy = 99.2
Ahmedt-Aristizabal et al. (2018)	2018	FRCNN	Accuracy = 95.2
Thomas et al. (2018)	2018	1D-CNN	Accuracy = 83.8
Daoud et al. (2018)	2018	1D-CNN	Accuracy = 98.6
Zhang et al. (2018)	2018	1D-TCNN	Accuracy = 100.0
Ullah et al. (2018)	2018	P-1D-CNN	Accuracy = 99.1
Acharya et al. (2018)	2018	1D-CNN	Accuracy = 86.7
Yıldırım et al. (2018)	2018	1D-CNN	Accuracy = 79.3
Chen et al. (2018)	2018	1D-CNN	Accuracy = 97.3
Yuvaraj et al. (2018)	2018	1D-CNN	NA
Hussein et al. (2018)	2018	LSTM	Accuracy = 100.0
Ahmedt-Aristizabal et al. (2018)	2018	LSTM	Accuracy = 91.3
Hussein et al. (2018)	2018	LSTM	Accuracy = 100.0
Rajaguru and Prabhakar (2018)	2018	AE, EM-PCA	Accuracy = 93.9
Sharathappriyaa et al. (2018)	2018	AE	Accuracy = 98.7
Qiu et al. (2018)	2018	DSAE	Accuracy = 100.0
Yuan et al. (2018)	2018	mSSDA	Accuracy = 96.6
Gasparini et al. (2018)	2018	SAE	Accuracy = 86.5
Karim et al. (2018)	2018	SAE	Accuracy = 96.0
Singh and Malhotra (2018)	2018	SAE	Accuracy = 88.8
Fang et al. (2018)	2018	ST-GRU ConvNets	Accuracy = 77.3
Yuan et al. (2018)	2018	CNN-AE	Accuracy = 94.4
Wen and Zhang (2018)	2018	CNN-AE	Accuracy = 92.0
Abdelhameed et al. (2018)	2018	1D-CNN, LSTM	Accuracy = 99.3
Antoniades et al. (2018)	2018	ASAE-CNN	Accuracy = 66.0
Gill et al. (2018)	2018	2D-CNN	NA
Hao et al. (2018)	2018	ResNet	NA
Yan et al. (2018)	2018	3D-CNN	Accuracy = 89.8
Gleichgerrcht et al. (2018)	2018	2D-CNN	NA
Ullah et al. (2018)	2018	P-1D-CNN	Accuracy = 99.9
Acharya et al. (2018)	2018	CNN	Accuracy = 88.7
Tjepkema-Cloostermans et al. (2018)	2018	CNN (1D and 2D) and/or LSTMs	Specificity = 99.9
Hügle et al. (2018)	2018	CNN	Sensitivity = 96.0
Thomas et al. (2018)	2018	CNN	Accuracy = 83.9
Hussein et al. (2019)	2019	LSTM + FC	Specificity = 100.0
Emami et al. (2019)	2019	CNN	Accuracy = 100.0
Jang and Cho (2019)	2019	Dual deep neural network	Sensitivity = 100.0
Nejedly et al. (2019)	2019	CNN	NA
Iesmantas and Alzbutas (2019)	2019	CNN	Accuracy = 74.0
Avcu et al. (2019)	2019	SeizNet	NA
Hossain et al. (2019)	2019	CNN	Accuracy = 98.1
Zuo et al. (2019)	2019	CNN	NA
Asif et al. (2019)	2019	SeizureNet	NA
Covert et al. (2019)	2019	TGCN	NA
Bouaziz et al. (2019)	2019	CNN	Accuracy = 99.5
Emami et al. (2019)	2019	CNN	NA
San-Segundo et al. (2019)	2019	CNN	Accuracy = 99.5
Sui et al. (2019)	2019	CNN	Accuracy = 91.8
Akut (2019)	2019	CNN	Accuracy = 100.0
Turk and Ozerdem (2019)	2019	CNN	Accuracy = 100.0
Liu and Woodson (2019)	2019	CNN	Accuracy = 99.6
Tian et al. (2019)	2019	CNN	Accuracy = 99.5
Ansari et al. (2019)	2019	CNN	NA
Cao et al. (2019)	2019	CNN	Accuracy = 99.3
Boonyakitanont et al. (2019)	2019	CNN	Accuracy = 99.1
Craley et al. (2019)	2019	PCM-CNN	NA

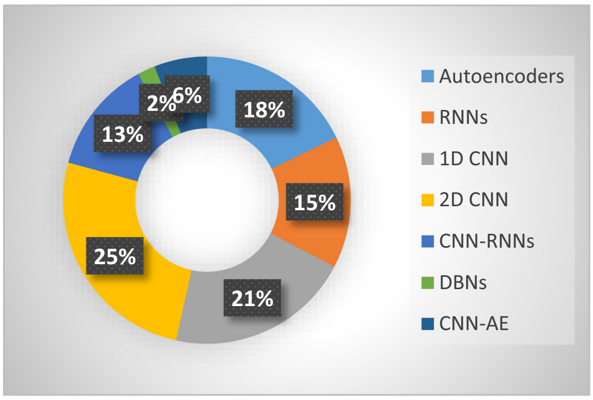
(*Continued*)

Table 2
(*Continued*)

Author	Year	Features	Performance (%)
Yao et al. (2019)	2109	IndRNN	Accuracy = 87.0
Lu and Triesch (2019)	2019	CNN	Accuracy = 99.0
Wei et al. (2019)	2019	CNN	Accuracy = 84.0
Meisel et al. (2019)	2019	CNN	Accuracy = 86.3
Fukumori et al. (2019)	2019	CNN-LSTM-GRU	NA
Yao et al. (2019)	2019	ADIndRNN	Accuracy = 88.7
Roy et al. (2019)	2019	ChronoNet	Accuracy = 90.6
Jaafar and Mohammadi (2019)	2019	LSTM	Accuracy = 97.7
Emami et al. (2019)	2019	AE	NA
Karim et al. (2019)	2019	DeSAE	Accuracy = 100.0
Choi et al. (2019)	2019	CNN-GRU	Accuracy = 99.4
Liang et al. (2019)	2019	CNN-LSTM	Accuracy = 99.0
RaviPrakash et al. (2019)	2019	CNN-LSTM	Accuracy = 89.7
Dev et al. (2019)	2019	CNN	NA
Jiang et al. (2019)	2019	ResNet,VGG	Accuracy = 98.2
Shiri et al. (2019)	2019	DAC	NA
Haotian et al. (2019)	2019	CNN, LSTM, GRU	Accuracy = 96.0
Rohan (2019)	2019	WT-CNN	Accuracy = 99.4
Wei et al. (2020)	2020	DNN	Accuracy = 99.5
Kyung et al. (2020)	2020	CNN	AUC = 0.99
Fabio et al. (2020)	2020	CNN	Accuracy = 98.3
Gao et al. (2020)	2020	Deep CNN	Accuracy = 90.0
Dongmei and Xuemei (2020)	2020	Improved RBF	NA
Jaoude et al. (2020)	2020	CNN-BP	NA
Sue et al. (2021)	2021	CNN	Accuracy= 94.3
Malekzadeh et al. (2021)	2021	CNN-RNN	Accuracy =99.7
Peng et al. (2021)	2021	CNN	Sensitivity=91.2
Mrutyunjaya et al. (2021)	2021	RDCNN	Accuracy =100.0
Rashed et al. (2021)	2021	CNN	Accuracy =99.2
Islam et al. (2022)	2021	DCB,FAM,RB,HT	Accuracy =99.9

The number of reviewed articles employing different DL techniques in this article is summarized and presented in Figure 9.

Figure 9
Number of deep learning techniques reviewed in this article



3.2. Dataset source

EEG epileptic seizure detection and classification studies using DL models have been studied using the scalp and intracranial EEG recording. Many studies conducted used publically available online databases such as Bonn University Germany database, University Hospital of Freiburg, Germany, Boston Children's Hospital, Bern-Barcelona Database from the University of Bern, Barcelona, Spain, CHB-MIT Scalp EEG database, and many more private datasets that are recorded in laboratories of hospitals and institutions that are not publically available, in some cases researchers can obtain the data based on permission from the owners.

4. Discussion

Despite the contribution and effort by researchers to develop and improve seizure prediction and characterization algorithms, the realization of clinical devices by converting these existing algorithms into clinical use has been a significant bottleneck. Based on the studies of algorithms, it is evident that specific buildup to a seizure state is responsible for the occurrence of seizure and not a random process.

DL models have applications in epileptic seizure prediction and characterization in either feature extraction or classification tasks. Regarding the model most researchers employed, CNN is the most widely used neural network, followed by RNN with LSTM structure. Some works combine CNN and RNN networks to enhance the performance. Different training architectures have been investigated, and from our review, we found that traditional machine learning methods are still used together with DL models by extracting features using the machine learning method while the DL network is used for classification. This structure improves the system's accuracy because the raw EEG epileptic data are converted into feature data with higher dimensionality and discriminative features than the raw data. However, labeling hand-crafted features by the machine learning method increases the burden on the feature extractor; therefore, DL model can be used as feature extractor while machine learning models are classifiers. To reduce the structural complexity and optimize the DL models without relying on the raw data, DL models train the raw EEG epileptic signals and produce the output directly.

Standardization of epileptic seizure techniques is also an issue of concern because homogenous comparison performance measures must be grouped to provide a homogeneous and standard comparison. Another problem is recording the EEG signal duration in either scalp EEG or intracranial EEG.

Each of the recent state of the art techniques reviewed in this work has its own advantages and disadvantages, based on the investigations performed in this work, we summarized the performance of these techniques in terms of complexity, accuracy, ease of implementation and requirement of larger datasets, etc. as follows: conventional machine learning methods such as SVM, ANN, and k-NN performed very well in the detection and classification of epileptic seizures. However, as SVM performed better in binary classification and better accuracy than k-NN and ANN, it has higher computational complexity. In contrast, low performance was observed in k-NN classifier, but it has low complexity and can handle high dimensional dataset. Hybrid techniques provide high performance accuracy such as SVM-ANN and SVM-ANN as compared to single machine learning model. However, their computational complexity limits their suitability for practical implementation.

On the part of DL algorithms that are mostly used in detection and classification of epileptic seizures, these models help in extraction and development of high dimensional features without the need for extraction of hand-crafted features with high accuracy. The most common models are CNN, RNN, and LSTM. Based on our survey in this article, LSTM has some computational complexity issues as compared to CNN and RNN in some publicly available dataset such as Bonn and CHB-MIT. In contrast, RNN shows a lower performance accuracy but exhibits a faster in computation compared to other two DL models. A combination of two different DL structures or DL and conventional machine learning models shows a higher performance accuracy in selection and classification of epileptic seizures. However, these models normally have high computation time complexity.

4.1. Challenges/Limitations

Despite the progress achieved in detection and classification of epileptic seizures recently, there are still some challenges and limitations holding the researchers back that includes among others: (1) artifacts, noise, and non-brain activities such as EMG, ECG, power line interference removal without distorting loss of the required signal/information. (2) Though there are many available datasets used by researches in their work, however combining these datasets is quite difficult as each has different sampling frequency, number of electrodes, and other parameters, which hinders the researchers to combine different datasets in order to obtain large dataset for training the model. (3) To realize real-world applications in clinical setup, real-time signals need to be used for detection and classification but most of the datasets available contain a chosen segments of EEG signals that are not suitable for real-world clinical implementation. (4) Channel selection is another limitation of reviewed technique as using a single channel leads to little information, while using multi-channel approach leads to lack of coordination among the channels. (5) Lack of standardization among the developed algorithms is another challenge which makes homogenous performance comparison difficult. (6) In case of recent DL models, requirement of higher computational resources that are not available by some researches hinders the realization of reliable, practical, and precise non-invasive models that meet the demand of mobile health and internet of medical things.

4.2. Future research direction

This article provides a comprehensive investigation on epileptic seizure identification and detection techniques. Over the years, tremendous progress has been witnessed ranging from traditional techniques to the recent application of DL. However, some of the challenges and limitations have been identified and raised that brings some interested research questions which still need to be addressed for the successful implementation and improvement of these developed models.

The following are some of the suggestions for uplifting future research and addressed the mentioned limitations in Section 4.1.

1. Advanced artifacts removal techniques need to be thoroughly investigated and developed to identify and eliminate the artifacts and non-brain activities.
2. With large volume and high dimension of epileptic seizures dataset, dimensional reduction techniques that reduce the dataset dimension and still retain the significant signal information need to be further investigated.
3. Suitable features that reduce the classifiers computational complexity and time should be considered in selecting statistical and machine learning classifiers.
4. For models that use invasive recordings, the developed methods must be able to identify seizure onset and to also measure the seizure strength.
5. Channel selection strategies should be adopted in epileptic detection algorithms for choosing optimal channels that represent the EEG seizure activities.
6. Researchers should choose a classifier that will not miss or skip all the relevant EEG channels and electrodes.

5. Conclusion

This article presents a survey on epileptic seizure detection and classification techniques based on EEG signals using AI, specifically studies that employed DL architectures in their work. The study also highlighted a brief overview of some machine learning techniques most commonly used by researchers in detecting and classifying epileptic seizures. The work reveals that DL methods record a huge success, with most of the works in literature utilizing the efficacy of CNN architecture. Recently, some researchers have investigated other types of DL architectures. At the same time, some combine hybrid architectures such as CNN-RNN methods, while some have been studying the combination of machine learning techniques and DL techniques to detect, classify, and predict epileptic seizures using EEG signals. Future work should investigate the hybrid techniques, hardware implementation of the developed methods, and the realization of these techniques in the clinical setup.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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