A Literature Review on Automated Detection of Epileptic Seizures using Machine learning & Deep Learning Techniques

Vandana Govindan T. K[1], S Thomas George[1], M.S.P.Subathra[2], Hemanth Jaison[3]
[1]*Dept. of Biomedical Engineering, Karunya Institute of Technology and Sciences*
[2]*Dept. of Robotics Engineering, Karunya Institute of Technology and Sciences*
[3]*Dept. of Electrical & Electronics Engineering, College of Engineering Vadakara*

Abstract— **The application of Artificial Intelligence (AI) techniques for the automated detection and classification of epileptic seizures is a rapidly evolving and highly promising field within neurology and biomedical engineering. This area aims to influence the power of AI, particularly machine learning (ML) and deep learning (DL), to analyze vast amounts of physiological data, primarily Electroencephalogram (EEG) signals, to identify and categorize seizure events with greater accuracy and efficiency than traditional manual methods. This paper presents a comprehensive review of the advances made in detection and classification of normal to epileptic seizures using ML and DL techniques. This review summarizes various conventional and deep machine learning algorithms used for automated seizure detection, discussed in the existing literatures. Also, the paper highlights about the epilepsy data bases available in public used by most of the papers for developing ML and DL algorithms. A general comparison on various deep learning techniques used for seizure detection is also presented.**

Keywords— Epileptic seizure, Machine Learning, Deep Learning.

I. INTRODUCTION

Epilepsy is one of the most persistent neurological disorders that affects 65 million people globally [1]. It is a condition characterised by frequent seizures that are caused by sudden abnormal bursts of electrical activity in the brain. These fits may be random and all over the spectrum ranging between temporary loss of consciousness to full-on convulsions. It complicates the treatment of epilepsy. The consequences to human life tend to be severe including physical harm, social stigmatization, diminished self-reliance and the sudden and unexpected death in epilepsy in certain cases. Seizures should be detected in time by an accurate diagnosis so that they can be treated and intervention made quickly. Seizures are traditionally identified in the process of reviewing EEG or electroencephalogram records, which is still commonly used in medicine. Manual EEG analysis, however, is very time-consuming and domain-specific and may be subject to errors, including those due to human error in the case of extended monitoring. This has focused attention on the necessity to create automated seizure detection systems to aid clinicians and promote real-time and user-friendly solutions [2]. Previous automatic methods employed classical machine learning models which relied on manually developed features such as certain signal patterns as determined by domain knowledge. These techniques had limited accuracy and generalisability although they seemed promising. In the past 10 years, it has been found that deep learning is a stronger option, particularly in biomedical signal processing. Deep learning algorithms as a convolutional neural network or CNN, recurrent neural network or RNN and attention models like transformer have also demonstrated spectacular performance in the analysis of EEG data [3]. These models can learn spatial, temporal and spectral aspects using raw input signals. It is usually more effective than conventional methods in regard to precision and flexibility. CNNs with RNNs or attention mechanisms have been particularly successful in modelling complex seizure activity and hybrid architectures have shown that CNNs in combination with RNNs or attention mechanisms perform better at capturing the dynamics of their seizure. This literature review will focus on explaining the current advancements in deep learning-based epileptic seizure detection that are specific to the analysis of EEG data. It is regarded in the literature that has appeared between 2020 and 2025 and disregards classical machine learning techniques to keep its scope narrow. Major architectures, datasets and performance will be discussed in the review. This review seeks to discuss the nature of the present deep-learning methods of detecting epileptic seizures. It pays attention to the deep learning models without the conventional machine learning approaches. Their review studies major architectures, datasets, evaluation procedures and results found in the recent literature.

II. A GENERAL EPILEPTIC SEIZURE DETECTION METHODOLOGY

A Deep Learning (DL) based system for epileptic seizure detection and classification typically follows a structured pipeline. The general seizure detection methodology using machine learning techniques consists of the following steps:

• *Raw EEG Data Acquisition*: Raw EEG data acquisition is the initial process of capturing the brain's electrical activity using electrodes, typically placed on the scalp (scalp EEG) or directly on/in the brain (intracranial EEG). These minuscule electrical signals, measured in microvolts, are amplified and then converted from analog to digital format at a specific sampling rate and resolution.

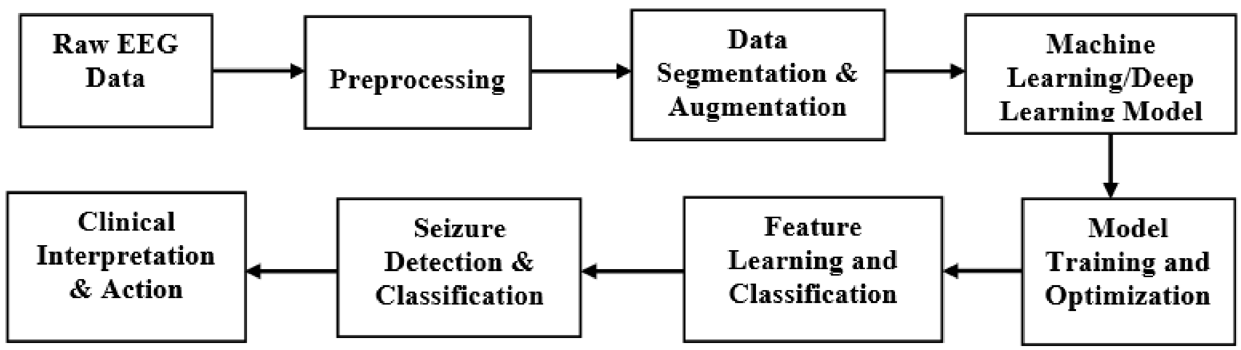

Fig 1. Different steps of Machine learning/Deep Learning techniques for seizure detection

• *Preprocessing*: Preprocessing raw EEG signals is an essential step to enhance the signal-to-noise ratio and prepare the data for analysis, involving several sequential stages: initially, filtering removes unwanted frequency components; subsequently, re-referencing re-calculates electrode potentials against a common reference to improve signal clarity; finally, artifact removal techniques are applied to eliminate non-brain physiological signals and other non-biological noise, sometimes followed by optional down sampling and segmentation, to yield clean, usable EEG data.

• *Data Segmentation & Augmentation*: Data segmentation involves dividing the continuous, pre-processed EEG stream into shorter, fixed-duration time windows which are the fundamental units for subsequent analysis, feature extraction, or input to machine learning models, often with overlapping windows to ensure continuous monitoring and avoid missing events at boundaries.

• Machine Learning/*Deep Learning Model*: The hand-crafted features are fed into a machine learning algorithm for learning patterns and making predictions. The selected ML model is trained on the labeled dataset. It learns a mapping from the input features to the corresponding seizure classes. Once trained, the model takes new, unseen sets of extracted features and predicts whether the corresponding EEG segment contains a seizure or classifies its type.

• *Model Training & Optimization*: The deep learning model's numerous internal parameters (weights and biases) are iteratively adjusted to minimize the difference between its predictions and the true labels. This involves setting up a loss function and using an optimizer to update the model's parameters during training over multiple epochs and batches of data. This phase is computationally intensive and often requires powerful GPUs.

• *Feature Learning & Classification*: Once trained, the deep learning model is deployed to analyse new EEG data and make predictions. The trained DL model's internal layers automatically extract complex, hierarchical features directly from the input EEG segments. The final layers then use these learned features to classify the segments, outputting probability scores for each possible class.

• *Seizure Detection & Classification*: The final result provided by the automated system, regardless of the underlying ML/DL approach typically includes a binary decision (Seizure Detected / No Seizure).

• *Clinical Interpretation & Action*: The ultimate goal is to integrate the AI system's output into clinical practice to aid neurologists and improve patient care. The AI system serves as a decision support tool, flagging suspicious EEG segments for review by an expert neurologist, thereby significantly reducing the laborious manual review time.

III. CONVENTIONAL AND DEEP LEARNING APPROACHES USED FOR SEIZURE DETECTION IN VARIOUS LITERATURES

Deep learning has been used in the detection of epileptic seizures especially in the feature analysis of epileptic EEG signals and this has led to improved detections notably due to the speed at which deep learning advances. Compared to the traditional machine learning models which demand hand-crafted features and deep learning models are enabled to independently learn meaningful representations which result in improved accuracy and generalisation. There is a large number of recent studies showing how they can apply different deep learning systems including CNNs, RNNs and hybrid models in detecting seizures. In a review paper, [4] reviewed various deep learning models that have been used to detect seizures in EEG data and have found those based on CNN to be especially useful finding that CNN models exhibit strong performance with features related to space.

According to [5], multi-layer perception (MLP) is used for classification after using discrete wavelet transform (DWT) and K-means algorithm for feature extraction. Artificial neural networks (ANNs) were examined for classification after using a one-dimensional local gradient pattern (1D-LGP) and local neighbor descriptive pattern (LNDP) for feature extraction. Convolutional neural networks (CNNs) are combined with both classification and automatic feature learning. For automatic seizure detection deep CNN uses thirteen layers and for the same reason, a system has been designed that integrates bidirectional long short-term memory (Bi-LSTM) with 1D CNN. On the other hand, support vector machines (SVM) and CNN are incorporated together for the classification of EEG signals and feature extraction.

According to [6], in order to resolve the problem of the "traditional brain signals classification model" a new technique has been developed which is Automated Deep Learning-Enabled Brain Signal Classification for Epileptic Seizure Detection (ADLBSC-ESD). The primary aim of this technique is to divide the brain signal to examine the existence of a seizure or not. In the ADLBSC-ESD technique, the results are different measures and a simulation takes place. This technique follows three different stage processes which are pre-processing, ITLBO-based feature selection, and SSA-DBN-based classification.

According to [7], EEG signal data first need to be preprocessed and a bandpass filter is applied to delete noise outside the defined frequency range. Discrete Wavelet Transform (DWT) is integrated to reconstruct and decompose the signal. The newly constructed EEG signal is decomposed once again into 5 different sub bands such as D1, D2, D3, D4, and D5. From each of these sub bands, four types of features are extracted which are Approximate Entropy (ApEn), standard deviation (STD), Sample Entropy (SampEn), and Fuzzy Entropy (FuzzyEn). In order to decrease dimensionality and enhance classification performance, feature selection was conducted. Lastly, CNN is utilized to classify the EEG signals based on a few selected features.

According to [8], Random Forest is a learning method that is similar to XGBoost and it operates by constructing a multitude of decision trees during the training period. It results in the final classification based on the mode of the predictive class and this is popularly known for high predictive accuracy. In the study, estimators are set to 1000 which allows the model to build a diverse and large ensemble of trees. The criterion used to examine the quality of a split in each tree is "gini" and a lower Gini indicates better node purity.

IV. DEEP LEARNING AND MACHINE LEARNING CLASSIFICATION MODELS FOR EPILEPTIC SEIZURE DETECTION

Machine Learning (ML) classification models are a cornerstone of automated epileptic seizure detection, primarily when used in conjunction with expertly engineered features extracted from Electroencephalography (EEG) signals. This section gives a detailed look at the most commonly used ML classification models for epileptic seizure detection.

1. Support Vector Machines (SVMs):

SVMs are powerful discriminative classifiers that aim to find the optimal hyperplane that best separates data points of different classes in a high-dimensional feature space. Once a set of discriminative features is extracted from EEG segments, these features form the input vectors for the SVM. For linear SVMs, a straight line (or hyperplane in higher dimensions) separates the seizure and non-seizure feature sets.
For non-linear SVMs, which are far more common in EEG analysis, kernel functions are used. These kernels implicitly map the input features into a higher-dimensional space where they might become linearly separable. This allows SVMs to capture complex, non-linear relationships within the EEG features that differentiate seizures.

2. Random Forests (RFs):

Random Forests are an ensemble learning method that builds many decision trees during training. Each individual tree is constructed using a random subset of the training data and a random subset of the features at each split point. For classification, the final decision is made by aggregating the predictions of all individual trees.
RFs are highly versatile and can directly handle a large number of the various EEG features (time-domain, frequency-domain, non-linear, etc.) without extensive pre-processing or scaling, unlike some other algorithms. They are adept at capturing complex, non-linear interactions between features that might characterize seizure activity.

3. K-Nearest Neighbors (KNN):

KNN is a simple, non-parametric, instance-based learning algorithm. It classifies a new data point based on the majority class among its 'k' nearest neighbors in the feature space. There is no explicit training phase; the model simply memorizes the training data.
Given a set of extracted EEG features for a new, unseen segment, KNN calculates its distance (e.g., Euclidean distance, Manhattan distance) to all other labeled segments in the training dataset. It then identifies the 'k' closest neighbors and assigns the class label (seizure or non-seizure) that is most frequent among these neighbors.

4. Gradient Boosting Machines

Gradient Boosting is an ensemble learning technique that builds an additive model in a sequential fashion. It constructs a series of weak learners where each new tree attempts to correct the errors of the previous ones. Like Random Forests, these models can effectively handle diverse sets of hand-crafted EEG features.
Their iterative error-correction mechanism makes them very powerful at learning complex patterns and fine-tuning decision boundaries for precise seizure detection.

5. Convolutional Neural Networks (CNNs)

CNNs are particularly well-suited for processing grid-like data, like images or time series. They use convolutional layers with learnable filters that slide over the input data, automatically detecting local patterns. These filters capture spatially invariant or temporally invariant features. Pooling layers follow convolutional layers to reduce dimensionality, making the model more robust to minor shifts in the input and reducing computational load.
1D CNNs are most commonly applied to raw multi-channel EEG time series. The 1D filters can slide along the temporal dimension of each channel, identifying specific temporal patterns like sharp waves, spikes, rhythmic activity, or sudden amplitude changes that are characteristic of seizures. If multiple channels are considered, the filters can also learn relationships across adjacent channels.

6. Long Short-Term Memory (LSTM) Networks

A specific type of RNN that addresses the "vanishing gradient problem" of standard RNNs. LSTMs use sophisticated "gates" (input, forget, output) that control the flow of information into and out of a cell state (memory unit). This enables them to learn and retain long-term dependencies, which is critical for understanding seizure progression, which can unfold over seconds or minutes.

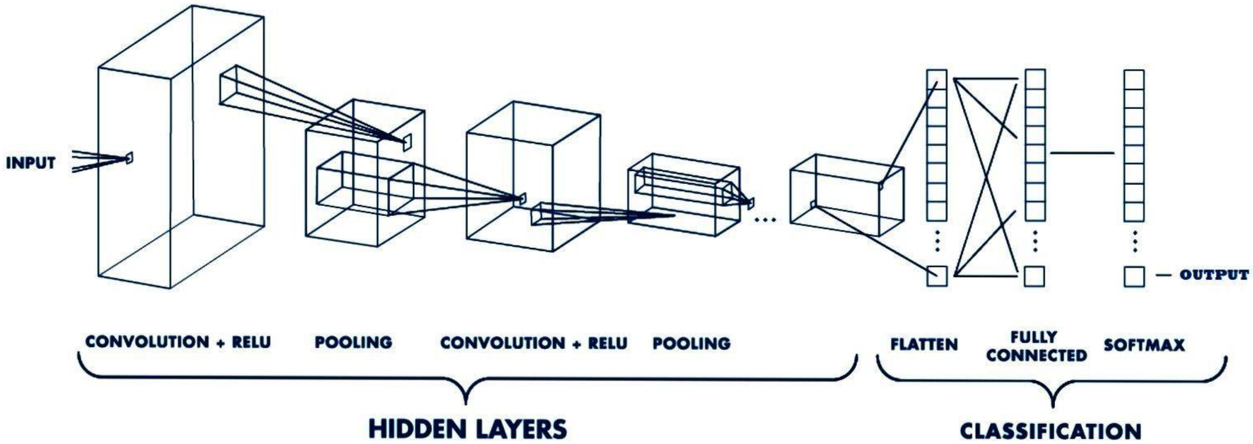

Fig. 2 A Convolutional Neural Network based classification

TABLE I. LITERATURE REVIEW

Literature	Year	Method Used	Classifier	Performance(%)
[14] Muayed S et al	2023	SDFT	Decision tree	Accuracy=97.23
[15] Yao Gua et al	2022	EMD	SVM,Gradient boosting	Accuracy =98.57
[16] Jiaxiu et al.	2022	TQWT	Logistic Model Tree	Accuracy =97.60
[17]Mustafa sameer et al.	2022	1D CNN	Hybrid classical quantum classifier	Accuracy =100
[18]Muhammed Baykara et al.	2021	Adaptive feature extraction	Extreme learning machine	Accuracy =90.00
[19] Dattaprasad et al.	2021	TQWT	Random Forest	Accuracy =97.30
[20] Ozlem et al.	2020	Ensemble EMD	KNN	Accuracy =97.00
[21] Raluca et al.	2020	DWT	ANN	Accuracy =91.10
[22] Mahjoub et al.	2020	TQWT,IMFs,MEMD	SVM	Accuracy =98.78
[23] Saminu et al.	2019	DWT,entropies,energy	SVM,FFANN	Accuracy =99.00
[24] Fasil O.K.; Rajesh R	2019	Time domain	Exponenetial Energy	Accuracy =99.50
[25] Osman and Alzahrani	2019	SOM	RBFNN	Accuracy =97.47
[26] Dalal et al.	2019	FAWT and FD	RELS-TSVM	Accuracy =90.20
[27] Bose et al.	2019	Multifractal detrended fluctuation analysis	SVM	Accuracy =100
[28] Wang et al.	2019	Symletwavelet processingand grid search optimizer	Gradient Boosting Machine	Accuracy =96.10
[29] Wani et al.	2018	DWT	ANN	Accuracy =95
[30] Tanveer et al.	2018	FAWT and entropies	RELS-TSVM	Accuracy =100
[31] Li et al.	2018	WPT and KDE	LS-SVM	Accuracy =99.60
[32] Cooman et al.	2018	HRI features	SVM+Adaptive Heuristic classifier	EPsensitivity=83.3
[33] Kocadagli and Langari 2017	2017	DWT and fuzzy relations	ANN	Accuracy =99.90
[34] Diykh et al.	2017	Weighted complex network combined with time domain features	LS-SVM	Accuracy =98.00
[35] Patidar et al.	2017	TQWT and Kraskov entropy	LS-SVM	Accuracy =97.75
[36] Sharma and Pachori 2017	2017	TQWT	LS-SVM+FD	Accuracy =100
[37] Pippa et al.	2016	Time domain and frequency domain features	Bayesian Net	Accuracy =95.00
[38] Kabir et al.	2016	Optimum allocation technique	LMT	Accuracy =95.33
[39] Ghayab et al.	2016	SRS and SFS	LS-SVM	Accuracy =99.90
[40] Li et al.	2016	DD-DWT	LS-SVM	Accuracy =99.36
[41] Waseem et al.	2023	DWT	Bi-LSTM	Accuracy =99.8
[42]Xiang Liu et al	2022	VMD	Deep Forest	Accuracy =99.32
[43] Yongxin et al.	2022	Entropy feature fusion	CNN	Accuracy =94.36

[44]Athar A et al	2022	Tegaear Kaiser energy operator	CNN	Accuracy =86.11
[45]Loukas Illias et al.	2022	STFT	CNN	Accuracy =93.00
[46]Bahareh Salafian	2021	SDFT	1D CNN	Accuracy =89.00
[47] Sreelegha	2021	Emperical WT	Deep Ensemble N	Accuracy =98.93
[48] Wei Zhao et al.	2020	Not available	1D DNN	Accuracy =99.52
[49] Fabio et al.	2020	Not available	CNN	Accuracy =98.82
[50] Gao et al.	2020	Not available	Deep CNN	Accuracy =92.60
[51] Rahib et al.	2020	Not available	Deep CNN	Accuracy =98.67
[52] Akyol	2020	WT	SEA	Accuracy =97.17
[53] Turk et al.	2019	WT	CNN	Accuracy =93.6
[54] Thara et al.	2019	WT	DNN	Accuracy =97.21
[55] Rohan Akut	2019	WT	CNN	Accuracy =99.40
[56] Haotian Liu	2019	LSTM,GRU	CNN	Accuracy =96.00
[57] Jang and Cho	2019	LSTM	Dual Deep Neural Network	Epsen=100
[58] Hussein et al.	2019	LSTM+FC		Epsen=100
[59] Maria Hugle et al.	2018	DWT	CNN	Epsen=96.00
[60] Tjepkema-Cloostermans et al.	2018	LSTM	1D and 2D CNN	Epsen=99.90
[61] Acharya et al.	2018	Not available	CNN	Accuracy =88.67
[62] Ullah et al.	2018	Not available	P- 1D CNN	Accuracy =99.90
[63] Gogna et al.	2017	Not available	Semi supervised stacked autoencoder	Accuracy =96.90
[64] Yuan et al.	2017	Not available	STFT-Mssda	Accuracy =93.82
[65] Wei et al.	2017	Not available	Multichannel CNN	Accuracy =92.40

V. EPILEPSY RELATED DATASETS FOR SEIZURE DETECTION

For research and development in automated seizure detection, access to high-quality, well-annotated epilepsy datasets is absolutely crucial. These datasets provide the "training ground" for AI algorithms to learn the complex patterns associated with epileptic seizures in EEG signals. This section includes some of the publicly available epilepsy-related datasets commonly used in AI research for seizure detection and classification.

A. CHB-MIT Scalp EEG Database (Children's Hospital Boston - Massachusetts Institute of Technology)

One of the most frequently used benchmark datasets. It contains long-term continuous scalp EEG recordings from 23 pediatric subjects (5 males aged 3-22 years, 17 females aged 1.5-19 years) with intractable seizures. Recordings, grouped into 24 cases (one patient has two recordings 1.5 years apart), total approximately 969 hours and include 198 seizures of various types (e.g., clonic, atonic, tonic). Signals are sampled at 256 Hz with 16-bit resolution, and most files contain 23 EEG channels following the International 10-20 system. Seizure start and end times are meticulously annotated.

B. Temple University Hospital (TUH) EEG Seizure Corpus (TUSZ)

This is currently the largest publicly available EEG dataset for epilepsy research, specifically designed for seizure detection. It's a vast collection of real-world clinical EEG recordings (thousands of recordings) from a diverse patient population at Temple University Hospital. It includes detailed manual annotations for various seizure types, as well as common EEG artifacts and other events. The data is organized into several sub-corpora, including TUSZ (seizure events), TUAB (abnormal EEG), TUAR (artifacts), and TUEP (epilepsy vs. non-epilepsy).

C. University of Bonn EEG Dataset

One of the earliest and most frequently cited datasets. It's relatively small and highly segmented, comprising 5 sets (A-E) of 100 single-channel EEG segments each (23.6 seconds duration), sampled at 173.61 Hz.

- Sets A and B: Healthy volunteers (eyes open/closed).
- Sets C and D: Interictal EEG from epileptic patients (from non-epileptogenic and epileptogenic zones, respectively).
- Set E: Ictal EEG from epileptic patients during seizures.

D. SIENA SCALP EEG DATABASE

This database contains continuous scalp EEG recordings from adult and pediatric patients with epilepsy. It Includes long-term EEG data with expert-annotated seizure events, sometimes with information on seizure types and presumed seizure onset zones.

E. Kaggle Epilepsy Seizure Prediction Challenge Datasets - Intracranial EEG (iEEG) Datasets

Datasets from past Kaggle. These often feature long-term iEEG recordings from human patients and sometimes canine models. Typically includes iEEG, meticulously segmented into ictal, interictal, and often pre-ictal (before seizure) periods. They present complex challenges, especially for predicting seizures.

CONCLUSION

This paper investigated about different machine learning deep learning methods used for automated detection and classification of epileptic seizures. It also gives a general comparison of different seizure detection methods detailed in various literatures. The effectiveness of each method for different applications are also discussed. To collect the epilepsy datasets is more complex and a time-consuming process. Hence researchers mainly depend on the public datasets available in open source. This paper also details about some of the available popular public datasets. Therefore this review gives an idea about the deep-learning-based detection and classification of epileptic seizures and deliver valuable procedures for research.

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