Diagnosis and Prognosis: Literature Review on Prediction of Epilepsy using Machine Learning Techniques

Alina Ahsan
Student of Computer Science and Engineering
Integral University, Lucknow

Sifatullah Siddiqi
Faculty of Computer Science and Engineering
Integral University Lucknow

ABSTRACT
Researchers are working to integrate machine learn- ing (ML) and artificial intelligence (AI) tools to im- prove and develop clinical practice. Machine learn- ing is becoming more important in medical image analysis. One of the fundamental goals of health- care is to provide timely preventative measures by early disease diagnosis and prognosis. This is cer- tainly relevant for epilepsy, which is characterized by recurring and unpredictable episodes. If epilep- tic seizures can be detected in advance, patients can avoid the unfavourable repercussions. Seizure prog- nosis remains an unsolved problem despite decades of research. This is likely to continue partly due to a lack of information to resolve this issue .Promis- ing new advancements in the ML-based techniques have the ability to alter the situation in the detec- tion and prediction of ES. We present a complete re- view of cutting-edge ML techniques for early seizure prediction with the help of EEG signals. We will highlight research gaps and problems and give rec- ommendations for future initiatives.

Keywords
EEG, Machine Learning, Seizure

1. INTRODUCTION
Over the past 20 years, machine learning (ML), a cornerstone of artificial intelligence has undergone significant development. To reveal the hidden characteristics and underlying relationships of data, machine learning (ML) employs statistics and computer science (Awad & Khanna, 2015) to create algorithms whose performance improves when exposed to relevant data rather than when given explicit instructions (Libbrecht & Noble, 2015).

ML tasks can be divided into two categories: supervised and unsupervised (Mello & Ponti, 2018). The former uses prelabelled input data and try towards finding the classifier model using an approach that has been trained for unlabeled data classification. (A. Singh, Thakur, & Sharma, 2016). Unsupervised methods (e.g., dimensionality reduction and clustering algorithms), in contrast to the supervised technique, relate to the process of creating mathematical models after assessing the similarities between unlabeled inputs to find trends, subgroups, or outliers. (Celebi & Aydin, 2016). Semi supervised machine learning a bridges the gap among unsupervised and supervised learning by integrating a few labeled dataset with a significant number of unlabeled datasets to produce a classification system (or model function). It considerably enhances learn- ing accuracy to some extent. cite6. Reinforcement learning is a turning approach in dynamical systems (for example, evolving, time-varying systems, and power systems) that automatically learns optimal control techniques. (Sutton & Barto, 2018).

Machine learning is being utilized widely in a wide range of industries, including voice recognition, image pattern classification, web browsing, spam mail filtering, autopilot, image classification, and textual translation. It is also being used more and more in a number of medical applications. In medicine, ML improves prognosis evaluation, disease identification, and prediction accuracy. Principled, automatic, and objective algorithms for complex, high-dimensional biological data are provided by ML (Rojas, Joya, & Catala, 2015). For example, ML outperforms the use of traditional feature selection methods in gene selection. Similar advances have been made in epilepsy, owing to continuous regard to data gathering, storage, and processing.

Epilepsy is a widely recognized chronic, noncom- municable condition that affects 3% to 15% of organ transplant patients and 60-70 million people globally. (Stelzle et al., 2021).An epileptic seizure is a sud- den disruption in the electrical processes of the brain, characterised by excessive bursts of neuronal activity within the cerebral cortex and impacting the entire body. (Sazgar & Young, 2019). As per World Health Organization (WHO), 70 million people worldwide suffer from epilepsy, and epilepsy ranks fourth in the most common brain diseases, trailing only stroke, Alzheimer's disease and migraine (England, Liver- man, Schultz, & Strawbridge, 2012). The pathophys- iology of epileptic seizures involves aberrant neuronal discharge, which shows as high electrical pulses on an EEG. To clarify, we consider seizure to be a tran- sient brain disorder caused by increased synchronous neural activity, and the sites of epileptic attacks are called epileptic foci. Recognizing and quantifying epileptogenic foci is essential for epilepsy diagno- sis. However, anti-epileptic drugs can effectively con- trol seizures in approximately 70% of patients with epilepsy (Eadie, 2012) the remaining 30% of patient populations have failed in controlling seizures, result- ing in drug-resistant epileptic seizures or intractable epilepsy. Intractable epilepsy is associated with a high mortality risk as well as poor prognosis, necessi- tating surgical intervention (Fisher et al., 2014). Fol- lowing a brief overview of common machine learning algorithms, this work highlights recent applications in automated detection and diagnosis, evaluation of imaging as well as clinical information, epilepsy local- ization, and medical and surgical outcome prediction to demonstrate the broad utility of machine learning techniques in epilepsy.

2. EPILEPSY DIAGNOSIS
Machine learning models are used by researchers to describe possible epileptic subjects to highlight the features which can help doctors and enhance the di- agnostic workflow. However , such activities were designed to save labor for highly qualified

physicians. Algorithms with high sensitivity, on the other hand, increase the likelihood of detecting potential 'invisi- ble' regions that human experts may overlook.

To classify patients and health controls, old- fashioned machine learning methods were widely used (Cantor-Rivera, Khan, Goubran, Mirsattari, & Pe- ters, 2015; J. Wang, Li, Wang, & Huang, 2018; JIANG, LIU, GAO, & MIAO, 2017; Del Gaizo et al.,

2017; Liedlgruber et al., 2019; Höller et al., 2020). It may also discover the most contributing factors as- sociated with a given disease during the procedure. Several manual features were relied on in some studies due to prior knowledge. SVM, for example, was used to identify patients with tonic-clonic epilepsy from the normal group using 2 hand-crafted MRI variables (fALFF from fMRI and Gray Matter Volume from T1). On PET images, similar conventional methods have been used. Multi-linear PCA was used to ex- tract features from the hemisphere symmetry tensor, and SVM was used to classify abnormal and normal images (JIANG et al., 2017).

3. EPILEPSY PROGNOSIS

Computer-aided prognosis tasks are critical for di- recting clinicians to the most appropriate treatment. Clinical indicators that include the epidemiology- based mortality rating in the Engel classification and the status epilepticus are commonly used to assess epilepsy prognosis. On the basis of patient's brain scans, ML models can be built to anticipate treat- ment results, providing those information before time that is useful for treatment. The classification task of classifying the postoperative state is commonly re- ferred to as prognosis prediction (i.e, no seizures or persistent seizures).

However, End-to-end DNNs have been used to determine the most probable treatment out- come in addition to classic machine learning methods(Gleichgerrcht et al., 2018; Samson, 2018; B. C. Munsell et al., 2015).

4. ML APPROACHES

Scientists have been attempting to overcome the problems in diagnosing and forecasting epilepsy. The investigation of EEG recordings was the primary priority of the ES prediction study since EEG are a significant source for analysing activity in the brain before, during, and after an epileptic seizure. EEG data are contaminated by eye movements, blinks, cardiac signals, and muscular noise. Several filtering and noise cancellation techniques are used to reduce the effects of these multiple noise sources and distortion (Mannan, Kamran, & Jeong, 2018).

An algorithm that can automatically recognize epileptiform discharges, for instance, may be trained using annotated EEG data. This can be done by using Supervised Machine Learning technique. Whereas an unsupervised algorithm may find poten- tial epileptiform discharges by spotting anomalies in background EEG recording. Either way, the algo- rithm itself, with no need for domain knowledge, or a human expert, identify informative input features through a process known as feature selection, which is then processed by using a mapping function to provide output predictions from such features (Deo, 2015).

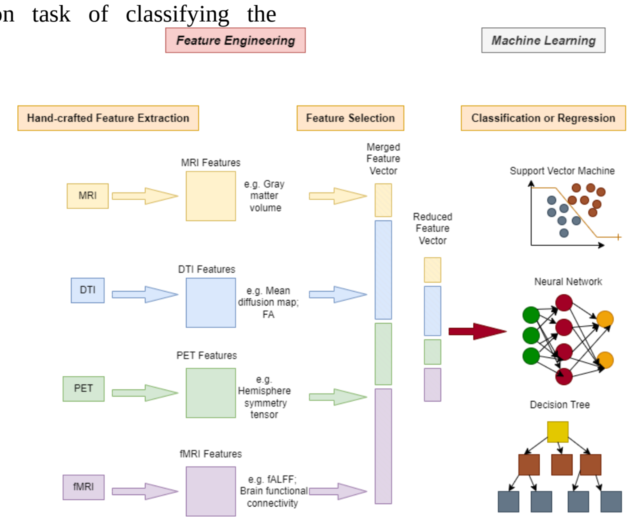

Figure 1: The conventional machine learning method. It is divided into two stages: machine learning and feature engineering.

4.1 Conventional machine learning approach

Two steps make up the traditional machine learning approach: manually feature engineering and machine learning (Fig. 1.). The hand-crafted features are ex- tracted from brain pictures during the feature engi- neering stage. The machine learning step then feeds these data into a machine learning model for a spe- cific goal, like regression (B. Munsell et al., 2019) or classification (Alaverdyan, Jung, Bouet, & Lartizien, 2020) (to determine whether the brain is normal or impaired).The machine learning algorithm employed in this methodology is often a simple classifier rather than a deep neural network.

In traditional machine learning models, feature en- gineering is an essential step. Using distinguishing characteristics extracted from medical pictures can successfully minimise data dimension and avoid model overfitting. Because we want to save as much information as possible in the original medical images, the extracted features are frequently very re- dundant.

Following the feature engineering, the features of sig- nificance will be incorporated into ML models for use in real-world applications. It should be noted that standard machine learning methods, such as support vector machine and linear discrimination analysis are highly reliant on the collected features.

Linear discrimination analysis (LDA) is a popular su- pervised method for feature extraction, data dimen- sionality reduction, and pattern discovery.

The initial SVM seeks a hyperplane in the di- mensional space to split samples into two classes (Cortes & Vapnik, 1995). It was designed for two- class classification at first, but was later enlarged to multi-class classification. Also, SVR (support vector regression)(Smola & Schölkopf, 2004) has been employed to resolve regression problems.

5. LITERATURE REVIEW

In this work, several writers have previously evaluated the seizure detection techniques and strategies. A brief analysis of various strategies for seizure detection based on signal characteristics is provided below.

Two strategies are offered by Jaiswal et al. (Jaiswal & Banka, 2018) : "cross sub pattern" and "sub pattern Principal Component Analysis ("SubXPCA" and "SpPCA") utilising SVM method.The proposed techniques' conclusions were 100% accurate, and their average was greater than other methods such as "Naive Bayes", Support Vector Machine" and " k- nearest neighbour".The authors of (Jaiswal & Banka, 2018) developed a method for predicting epilep- tic seizures by categorising EEG data into seizure and non-seizure signals.Using an Local Binary Pat- tern that utilizes key point computations, EEG data may be categorized into seizure and non-seizure cat- egories (Tiwari et al., 2016).

The first stage of EEG data processing is key point localization, followed by key point-based LBP calcu- lation and finally by histogram feature.

In Abualsaud et al. (Abualsaud et al., 2015), the ensemble classifier was used to test its efficacy on in- complete EEG data. The ensemble classifier outper- formed other trials, achieving 90% accuracy in com- parison to 85%, 85.9%, and 89.5% in the other stud- ies.

Three learning strategies were employed by the au- thors in (Satapathy et al., 2017b) SVM, "multino- mial logistic regression," and "logistic model trees" (LMTs). In terms of accuracy, the findings demon- strated that LMT classifier outscored the others. Us- ing the epilepsy data, several approaches such as SVM, RVM, fractal dimension and neural networks were also applied (Lima et al., 2016).

Further techniques included k-means, random for- est, and Gaussian mixture models (Senders et al., 2018) and the SVM method was efficient in solving binary classification problems.

A brand-new device known as "Computerized Au- tomated Detection of Focal Epileptic Seizure" (CAD- FES) was presented by Raghu et al. in their study (Raghu & Sriraam, 2018) and the major aim was preprocessing of EEG data for identification of fo- cal and non-focal epileptic episodes. The authors first extracted 28 characteristics from the data set, using "Neighborhood Component Analysis" (NCA) to maximize the number of features, and then uti- lized SVM, KNN, Random Forest and the AdaBoost classifier for evaluating algorithm performance. The outcome showed that SVM had the highest accuracy of 95.9%.

Tharayil et al. (Tharayil et al., 2017) created a sys- tem to predict epilepsy in both adult and paediatric patients simultaneously.

This technique, the linear mixed model, was ap- plied to approximately 1.2 million reported seizures. The primary conclusion was that all developed mod- els worked better on adult than on children. The au- thors offered numerous hypotheses, including differ- ences in seizure patterns between children and adult and a lack of data on underreported seizures in chil- dren. Early detection of epileptic seizure can help the patient avoid detrimental effects on the human brain. Usman et al. (Usman et al., 2017a) em- ployed the technique of preprocessing data to reduce 23 EEG signal channels to one in order to increase the SNR (signal to noise ratio), and then EMD (em-

Table 1: Recently applied ML techniques for seizure detection with their corresponding performances

S.NO	YEAR	AUTHOR	ML ALGO-RITHM	DATASET SOURCE	FEATURE ANALY-SIS	NUMBER OF SAM-PLES/SUBSETS	ACCURACY (%)	LIMITATIONS
1	2015	Abualsaud and Mah-muddin (Abualsaud et al., 2015)	Ensemble classifer	_	(NSC) Noise-aware Signal Combina-tion	4096	90	_
2	2015	Bandarabadi et al.(Bandarabadi et al., 2015a)	Supportet Vector Machines	EPILEPSIAE	Spectral power, Ampli-tude distribu-tion his-togram	24	73.98	_
3	2015	Lecun et al. (LeCun et al., 2015)	Res-CNN	BONN	Conventional - feature extrac-tion method	_	95.70	_

4	2015	Logesparan et al. (Logesparanet al., 2015)	ANN, SVM	CHB-MIT	Line length feature analysis	_	52	Accuracy(Low)
5	2015	Talathi and Vartak (Talathi & Vartak, 2015)	GRU, RNN	_	RNNs	_	94	High (time complex-ity)
6	2015	Bandarabadi et al. (Bandarabadi et al., 2015b)	SVM	_	Relative Spectral Power Features	24	73.98	_
7	2015	Amin et al. (Amin et al., 2015)	KNN, SVM, Naıve bayes, MLP	EPILEPSY 5	_	_	98.75	_
8	2015	Donos et al. (Donos et al., 2015)	Random forest	EPILEPSY	Frequency, Time	_	93.8	Spec not men-tioned
9	2015	Zhang et	SVM,	BCI Lab	SE and	_	95.58	High

18	2016	Sabrina et al. (Belhadj et al., 2016)	PHA–unsupervised	CHB-MIT	Intrinsic mode functions, Euclidean distance, Bhat-tacharya distance	22	98.84	_
19	2016	Orellana et al. (Orellana & Cerqueira, 2016)	Random forest	CHB-MIT	PCA, STF, moving maximum	_	97	_

20	2016	Kabir and Siuly (Kabir et al., 2016)	Support Vector Machine (SVM), Logistic model trees (LMT), Multinomial Logistic Regression (MLR)	_	Optimum Allocation Technique (OAT)	4097	95.33(LMT)	least square SVM (LS-SVM) classifier
21	2017	Chen et al. (D. Chen et al., 2017)	SVM	BONN	DWT	5120, 4097	86.83	Low sen, pres
22	2017	Satapathy et al. (Satapathy et al., 2017a)	Neural network, SVM	BONN	CWT, DWT	_	99.1	High detection time
23	2017	Kumar et al. (Kumar et al., 2017)	approximate entropy ANN, SVM	CHB-MIT	DWT based approximate entropy	500	100	High time complexity
24	2017	JianJia, Balaji Goparaju, JiangLing Song, et al. (Jia et al., 2017)	Random Forest	BONN 6	Complete ensemble empirical mode decomposition along with adaptive	5	98	_
28	2017	Wanzhong Chen, MingyangLi and TaoZhang. (Li et al., 2017b)	Neural network	BONN	Envelope analysis	5	98.78	_
29	2017	Abeg Kumar Jaiswal, Haider Banka. (Jaiswal & Banka, 2017)	ANN (Artificial Neural Network)	BONN	"LNDP (Local neighbor descriptive Pattern)"	5	99.82	LBP is sensitive to local variation

30	2017	Bhattacharyya Pachori R. (Bhattacharyya & Pachori, 2017)	RF A, classifier and SMOTE technique	CHB MIT	EWT	23	99.41	_
31	2017	Birjandtalab et al. (Birjandtalab et al., 2017)	Random forest-KNN	CHB-MIT	Spectral power	_	80.87	Low sens, spec
32	2017	Sarif et al. (Sharif & Jafari, 2017)	SVM	Freiburg	Distribution (6 fuzzy rules)	19	96.60	limitation in number of training and test data.
33	2017	Datta Prasad et al. (Torse et al., 2017)	ANN	BONN	Incorporated Hilbert trans.	_	96	_
34	2017	Shivnarayan Patidar. and Trilochan Panigrahi (Patidar & Pani-grahi, 2017)	LS-SVM	University of Bonn Germany 7	"Kraskov entropy and Multi-stage TQWT"	5	97.75	_
35	2017	Hashem Kalbkhani and Mahrokh	KNN	BONN	KPCA (Kernel principal compo-	5	99.73	_
41	2017	Tharayil et al. (Tharayil et al., 2017)	Linear Mixed Model	SeizureTracker	Bayesian informa-tion criterion	3896	82	Noise
42	2017	Usman and Usman (Usman et al., 2017b)	SVM	CHB-MIT	Time-frequency	22	92.23	_
43	2017	Kumar (Satapathy	SVM	USC-SIPI	_	44	100(MPNN and EL)	_

		et al., 2017b)						
44	2018	Usman et al. (Usman & Hassan, 2018)	Naive Bayes, SVM, KNN	MIT	Skewness, Variance, SD, HP, Kurtosis, Entropy	24	97.07, 97.44, 90.66	_
45	2018	Kitano et al. (Kitano et al., 2018)	SOM	MIT	Zero-crossing (DWT co-efficients)	9	98	limitations in providing exact fre-quencies
46	2018	Yang et al. (Yang et al., 2018)	SVM	Freiburg	Permutation (Entropy)	21	94	Limitations in extracting features
47	2018	Park et al. (Park et al., 2018)	SoftMax, 2D CNN	CHB-MIT, SNUH-HYU data	_	54	90.58	Low sens, spec
48	2018	Jacobs D., Hilton T., Del Campo M. et al. (Jacobs et al., 2018)	MSC (Multi stage state classifier)	Toronto Western Hospital Epilepsy Monitor-ing Unit	CFC (cross frequency coupling)	12	82.4	_
49	2018	Ali Yener Mutlu (Mutlu, 2018)	LS-SVM	BONN 8	HVD (Hilbert vibration decompo-sition)	5	97.33-97.66	_
50	2018	Sutrisno Ibrahim, Ridha Djemal and	Linear SVM, KNN, LDA, DWT	BONN, CHB-MIT	Band power, standard deviation and DWT	5	100	_
54	2018	K, Ren D, Li,Wang D, et al. (D. Wang et al., 2018)	RBFSVM	XJU Decompo-sition	10	99.4	Existence of muscle artifact in long-term scalp EEG recordings	
55	2018	Faust et al. (Faust et al., 2018)	SoftMax, 2D CNN	Bern-Barcelona data	Wavelet transfor-mations (DWT)	_	94.5	Low accuracy

56	2018	Chen et al. (X. Chen et al., 2018)	SoftMax, LSTM	Zenodo	Wavelet transfor-mations (DWT)	5	90	Low prec
57	2018	Hussein (Hussein et al., 2018)	SoftMax, LSTM	Zenodo	Fully connected (FC) RNN	15	96	High training time
58	2018	Gasparini et al. (Gasparini et al., 2018)	SoftMax, SAE	Reggio Calabria data	Time-frequency, CWT	_	86.5	Low Sen, Spec, Acc
59	2018	Karim et al. (Karim, Karal, & Çelebi, 2018)	SoftMax, SAE	BONN	DWT	_	91	Confusion matrix Low prec
60	2018	Yuan et al. (Yuan et al., 2018)	SoftMax, SAE	CHB-MIT	AE and SE	23	92.61	_
61	2018	Karim et al. (Karim, Güzel, et al., 2018)	SoftMax, DSAE	Kaggle	ESD function	2000	94	_
62	2018	Birjandtalab et al. (Birjandtalab et al., 2018)	ANN	CHB-MIT	Spectral power	_	86	High detection high
63	2018	Sharma et al. (Sharma	LS SVM	BONN	_	122	98.6	_
68	2018	Raghu and Sriraam (Raghu & Sriraam, 2018)	Computerized Auto-mated Detection of Focal Epileptic Seizure(CADFES)	Bern-Barcelona database	time, frequency, and statistical domain	28	95.90	_
69	2019	Al Gahyab et al. (Al Ghayab et al., 2019)	LS-SVM	BONN	Uses simple FFT-DWT for feature extraction	_	99	_

9

70	2019	Tzimoutra et al. (Tzimourta et al., 2019)	Random forest	Bonn and Freiburg	Use of DWT for feature extraction	21	99.74	_
71	2019	Bizopoulos et al. (Bizopoulos et al., 2019)	SoftMax, standard networks	BONN	2D and 3D phase space presents the intrinsic mode and functions	4097	85.3	Low detection accuracy
72	2019	Ozerdem and Turk (Türk & Özerdem, 2019)	Softmax, 2D CNN	Freiburg	Frequency-time domain, CWT	23	93.6	Low spec for multi-class
73	2019	Sui et al. (Sui et al., 2019)	SoftMax, 2DCNN	Kaggle	FT	_	91.18	High time complex-ity
74	2019	Tian et al. (Tian et al., 2019)	MV-TSK-FS, 2D CNN	CHB MIT	FFT, WPD	_	95.33	_
75	2019	LeCun and Triesch (Lu & Triesch, 2019)	Softmax, 2D CNN	Bern Barcelona	Feature extracts from CNN	3800	95.90	High detection time
76	2019	San-Segundo et al. (San-Segundo	Softmax, 2D CNN	10 CHB-MIT	DWT	500	96.10	High training time

85	2019	Chen et al. (S. Chen et al., 2019)	SVM,Naive Bayes	CHB-MIT	RMS, variance, energy, entropy	4096	96.55	Low pre
86	2019	Mursalin et al. (Mursalin et al., 2019)	KNN, SVM, RF	BONN	15-features	4097	98	_
87	2019	Fasil and Rajesh. (Fasil & Rajesh, 2019)	SVM	BONN, Barcelona	Energy	_	99.5	_
88	2019	Selvakumari et al. (Selvakumari et al., 2019)	LS-SVM	Class Acc	DWT, FFT	23	100	High time complex-ity
89	2019	Siddiqui et al. (Siddiqui et al., 2019)	Random forest, boosting, decision forest	Bern Barcelona	Nine statistical features	_	96.67	Time complex-ity is high
90	2019	Wang et al. (X. Wang et al., 2019)	RF classifier	BONN	Mean, std dev, STFT, energy	500	96.7	Low sens, spec for multi-class
91	2019	Lahmiri and Shumel (Lahmiri & Shmuel, 2018)	KNN and GHE	BONN	_	5	100	_
				al. (Raghu etal., 2020)				
			KNN, adaboost Barcelona frequency men-tioned					
92	2020	Ahmed-Aristizabal (Ahmedt-Aristizabal et al., 2020)	SoftMax, LSTM	Mater advanced epilepsy Unit	Computer-based analytical ap-proaches	500	95	_
93	2020	Raghu et	RF,	Bern 11	Time-	_	97.60	NFR not
94	2020	Ilakiyaselvan et al. (Ilakiyaselvan et al.,	DL	University of Bonn (UoB)	spatial and temporal features	4097	Binary (98.5) Tertiary (95)	UoB dataset is clean dataset.

pirical mode decomposition) was used to optimize SNR. The authors utilised SVM technique for clas- sification, and the results showed that the frame- work predicted seizures by an average of 23.6 min- utes, with highest prediction time of approximately 33 minutes. The suggested method, however, accord- ing to the author of (Kabir et al., 2016), "optimum-allocated techniques" (OTA) were used to draw sam- ples for each of the classes before integrating all the samples. The features were then extracted from the OTA set which included splitting of EEG signals into subsets in accordance with time frame.

Patrick et al., (Luckett, 2018), used machine Learning techniques to integrate three techniques to predict and detect an epileptic episode.The first tech- nique, known as the p-s adjacency spectrum, used a plot of the p-s adjacency spectrum as a diagnos- tic markers for seizure detection and had 97% accu- racy rate. The second method, L spectrum, which achieved a 93% accuracy rate, used spectrum mea- surements as a diagnostic marker for seizure predic- tion. The last technique was p-s graph analysis, which utilized a subset of the edges of the phase- space graph as a diagnostic biomarker for diagnos- ing seizure and learning accuracy. The approach received 93% and 80% accuracy assessment. The author combined the p-s analysis approach and DL (deep learning) with the CNN algorithm to detect the commencement of seizures with 100% accuracy. In a number of studies, an ensemble classifier was employed to characterize epileptic episodes.

In (Subasi et al., 2019), the authors developed a new approach for detecting epileptic seizures. They employed hybrid SVM to calculate SVM parame- ters by combining a "genetic algorithm" (GA) with "particle swarm optimization" (PSO); this model ob- tained 99.38% accuracy.

Similar to this, Nair et al. (Nair et al., 2021) came to the conclusion that AI-based approaches have greatly aided in the diagnosis, prediction, and management of epilepsy for a society with better ac- cess to healthcare.

ML approaches for predicting epileptic seizures were compared, along with their effectiveness, by Lekshmy et al. (Lekshmy et al., 2022). According to the data, the RF (Random Forest) and LSTM (Long

Short Term Memory) algorithm achieved the highest accuracy rates of 97% and 98% respectively.

Similar to this, a complete examination of AI and ML seizure detection strategies was published by Natu et al. (Natu et al., 2022). Techniques for preparing data, methods for the classifiers or pre- diction model's channel selection, and other subjects were covered. Also, the limitations and shortcomings of this field of study were highlighted. They recom- mended feature selection method, dataset labelling and research into deep learning algorithms as a cure. Using correlation dimension (CD), authors in (Brari & Belghith, 2021) introduced a unique ML technique to epilepsy prediction and attained 100% accuracy. Due to a limited number of features and a unique mix of subsets, the proposed model demon- strates a significantly faster convergence than com- parable approaches in the literature across the same

dataset.

In (Ilakiyaselvan et al., 2020), scientists suggested using RPS (reconstructed phase space) rather than direct EEG data, which have chaotic and non-linear behavior and are therefore unsuitable for analysis, as a Deep Learning (DL) approach for seizure de- tection. With binary and tertiary classification, the method had accuracy rates of 98.5% and 95%, respec- tively. Bhattacharyya and Pachori (Bhattacharyya & Pachori, 2017) employed an information entropy based strategy to decrease the amount of EEG signals which was to be processed based on intensity fluctua- tions in the EEG signal, before breaking it down into smaller bands employing empirical wavelet transfor- mation. Each of the sub-band was divided into dis- tinct MODES, which showed the frequency and am- plitude constituents. A statistical approach was used to extract the feature from the individual instanta- neous amplitudes.

Jacobs et al. (Jacobs et al., 2018) used a multi- stage state classifier (MSC) with three RF classifiers to classify a pre-clinical seizure state. A 5-fold ROC (Receiver Operating Characteristic) evaluation was used to evaluate their system, which contrasted per- formance under two situations. The system having MSC training had a 95% accuracy, while the system before training had a 79% accuracy, suggesting that RF classifier enhances accuracy.

Patidar and Panigrahi (Patidar & Panigrahi, 2017) used a wavelet with two vanishing moments based on the Daubechies filter. Its adjustable QWT (Q wavelet transform) is filter that has the poten- tial to deliver significantly improved time-frequency resolutions. Filters with lower disappearing moments may be employed as well if their capacity to appropri- ately deconstruct signal information without spend- ing a large amount of resources is intentionally lim- ited. The Kraskov entropy, which utilizes a distance function, is employed in the system's feature extrac- tion stage.

Mahalanobis distance function is the distance func- tion that can be used in combination with a two class discriminating test, namely the Wilcoxon rank test, to increase performance.

Wang et al. (D. Wang et al., 2018) used a 5th level wavelet decomposition, which may assure efficient signal decomposition with effective resource trade- offs if 5 sub-bands are required.

Its dimensions were also kept to a minimum of five. When compared to different sub-bands of EEG signals, WDTF also enhanced selectivity. The feature extraction method produced an enormous vector with dimensions of 19*19. This dimension was reduced to 19*1 by using the directed transfer function.Because this dimension computation was re- lated to energy and entropies like Shannon's entropy assisted in reduction. Further, the employment of an elliptic band - pass filter before signal decomposition could increase frequency separation.

The Stockwell transform is based on an N-point discrete Fourier transform derivative developed by Kalbkhani and Shayesteh (Kalbkhani & Shayesteh, 2017). It had good time and frequency resolution. Other distance functions, such as the Hausdorff or Mahalanobis, can be used to improve their use of the nearest neighbour classifier.

In the study by Guergachi, Kaleem and Krish- nan citer710, the dominant wavelet was the level five Daubechies db6 wavelet with 6 vanishing mo- ments.

In this scenario, a greater proportion of disappear- ing moments was employed as they were more com- parable to the observed EEG signals.

The adoption of DT-CWT by Chen, Zhang and Li (Li et al., 2017a) in the decomposing phase was useful since it reduced the difficulties of unreal fre- quency, which gave way to the halfway band division. They could improve the system by using a proper LS SVM classifier.

The authors of (Jia et al., 2017) employed fea- ture extraction stage that used statistical approaches based on spectral moments. This approach was sim- pler to put into effect on hardware and provided greater mode mixing separation. In certain investiga- tions, the authors used a fairly well-founded decom- position technique. The key strength of the study by Chen, Zhang, and Li (T. Zhang et al., 2017) was the application of VMD based decomposition, which iso- lated the 2 harmonic signals of comparable frequency. HVD (Hilbert vibration decomposition) was used by Mutlu (Mutlu, 2018) which could decompose sig- nals in both narrow and wide bands. The LS SVM classifier too was effective due to its inequality type limitations. Butterworth low pass filter was included in the pre-processing stage which could be altered

with improved digital filters like elliptic filters.

The undulated local and global feature detection technique employed by Paul and Parvez (Parvez & Paul, 2016) was based on epochs, allowing it to han- dle the decomposition more accurately. Its applica- tion for example in phase correlation, worked by mov- ing information between two correlated signals using the Fourier transform. This approach made no use of any specific decomposition blocks. The window regu- larization procedure, on the other hand, was difficult and could be replaced by alternative approaches like the Hadamard transform.

The study by Ibrahim, Djemal, and Alsuwailem (Ibrahim et al., 2018) attained 100% accuracy by combining the discrete wavelet transformation with a Rosenstein algorithm, which was known to improve system robustness to noise. The next step for this system could be to test it with larger datasets in the future. The two-dimensional system and decompo- sition method utilized by Khan et al. (Khan et al., 2017) were focussed on Mexican hat mother wavelet function. By utilising weight sharing, their system had the benefit of reducing the trained parameter uti- lized in the neural network.

Shiao et al. (Shiao et al., 2016) had the design choices and performance metrics closely related to clinical objectives. However, their decision to use all channels for feature extraction was resource-intensive as they generated large dimensions for the feature extraction (nearly 96 to 120 dimensions) despite us- ing cross-channel correlation. For feature dimen- sions, techniques such as principal component analy- sis (PCA) methods can be used.

For dealing with high-frequency oscillation (HFO) signals, Jrad et al. (Jrad et al., 2016) employed a seizure detection method with exact non stationary signal decomposition. Its time-frequency localization has also been enhanced. It was also advantageous to use Gabor atoms because they were synchronised to degrade signals within the physiological band.

In their research, the authors of (Li et al., 2017b) employed an EA (wavelet-based envelope analysis) to identify envelope with the HT (Hilbert transform) and estimated the enclosure spectrum at each band. Its technology may detect slight but cru- cial changes in EEG waves. They also used a simple statistical model with low dimensions to extract fea- tures.

The procedure given in Jaiswal and Banka's work (Jaiswal & Banka, 2017) used a segmentation technique that was computationally straightforward, meaning that capabilities were effectively managed during the implementation stage. The ANN imple- mentation was efficient, however the CNN classifier outperformed it. Tsiouris et al. (Tsiouris et al., 2018) described a system that used machine learn- ing (unsupervised) classification method that did not require prior knowledge. It also incorporated an en- ergy based feature extraction stage that required lit- tle technology to implement.

Goksu's (Göksu, 2018) paper was a good illustra- tion of using an appropriate wavelet order for such a system. Despite the fact that three levels of wavelet transform were used, high accuracy was achieved, saving resources. The entropy used in the feature extraction phase was also simple, allowing useful in- formation to be extracted.

On a scalp EEG dataset, Usman et al. (Usman et al., 2017b) proposed a model that identified the begin- ning of the preictal state, a type of state that starts a few minutes just before onset of the convulsion, with a raised true positive rate, 92.23%, and maximum an- ticipation time frame of 33 minutes and mean average duration of 23.6 minutes.

Usman et al. (Usman & Hassan, 2018) proposed model demonstrated that pre-ictal time for predic- tion of epileptic seizure is 33.9 minutes, which was far better than observed using existing methods. Five univariate features were used to predict seizures. The prediction algorithm allowed enough time for affected patients to take medication in order to avoid seizures where Support vector machines (SVM) was found to perform better. K-nearest neighbour, Naive Bayes, and Support Vector Machines were three classifiers. SVM accuracy was 97.07%, with a true positive rate of 88.89%.

Kitano et al. (Kitano et al., 2018) advocated us- ing a modest quantity of data to predict seizures. From CHB MIT database's hours-long capture of 24 patients, researchers only used 20 mins of data from 9 patients. The data set lasted 20 minutes and was composed up of 10 minute of preictal data plus 10 mins of interictal data. They extracted zero cross- ing of DWT level 1 specific coefficients using Discrete wavelet transform on 4 sec non-overlapping window frames of 20-minutes of this data.

Where Sarif et al. (Sharif & Jafari, 2017) pre- sented a method for seizure prediction that encom- passes a novel technique for feature extraction from EEG. The algorithm begun by constructing an em- bedded space from EEG time - series data. Then, using an optimised and data-specific Poincare plane, it took samples with the majority of the informa- tion. The frequency analysis of these fuzzy system was used to determine the features in each minute. The qualities with the highest variance were then se- lected as ictal characteristics and decreased utilizing PCA once more.Finally, the shift from interictal to preictal condition was evaluated using SVM to see how these unique features could improve the seizure prediction algorithm's performance.

Yang et al. (Yang et al., 2018) employed PE as a characteristic retrieved from iEEG data from the Freiburg hospital. They studied 83 episodes from 19 subjects and used an SVM classifier with an RBF kernel using 5 second feature segments as input. As performance analysis measures, false prediction rate (FPR) and sensitivity were used. They averaged 94% diagnostic accuracy and 0.11 FPR with a mean du- ration of 61 minutes.

Bandarabadi et al. (Bandarabadi et al., 2015a) em- ployed relative combination of sub-band spectral strengths of EEG recordings among all feasible chan- nel pairings to track progressive changes preceding seizures. Using a newly created feature selection pro- cess, a series of strongest candidate values were fed to SVM in order to identify cerebrovascular condition as preictal or non-preictal. Long-term multi-channel invasive and scalp recordings were used to validate the proposed algorithm (seizures as 183, time as 3565 h). The best results demonstrated a responsiveness of 75.8 percent (66 of 87 episodes) and 0.1 hour of FPR. The performance was analyzed statistically and proved to outperform an analytical randomized pre- dictor.

Direito et al. (Direito et al., 2017) calculated 22 univariate features per channel using NW sam- ples and an EEG epoch (the observational window). Each feature vector was created by concatenating the features calculated from various EEG electrodes in order to capture spatial information at the same time. To avoid overfitting, SVM was used to dis- cover a decision function depending on training and validation sets. Bandarabadi et al. (Bandarabadi et al., 2015b) devised a method to predict epilep- tic episodes, which could assist epileptic subjects live longer lives. They retrieved spectral energy features and then used Support Vector Machines to classify them after picking the best ones. They observed 75.8 percent sensitivity , which meant that their classifier predicted 66 episodes from a total of 87. They con- cluded that utilizing these strategies after narrowing the suggested feature subset can improve seizure pre- diction performance. Goal of Abbasi et al (Abbasi & Esmaeilpour, 2017)'s research was to increase predic- tion accuracy and categorize various epilepsy stages from EEG signals. It classified the signal as being in a stable, epileptic, and convulsive state. The signal was divided into five levels by the authors using the Daubechies-4 wavelet to achieve this, although they only used the frequency components up to level 4 for analysis. A multilayer perceptron neural network was trained using statistical variables like mean, stan- dard deviation, maximum, and minimum that were taken from the data. The Bonn Database was used to test the classifier's performance, and it was discov- ered that it achieved an accuracy rate of 98.33%.

Sabrina et al. (Belhadj et al., 2016) established an innovative framework for automatic recognition of whole-brain epileptic episodes that employs a fast PHA (potential-based hierarchical agglomera- tive) Clustering Algorithm and Empirical Mode Decomposition (EMD). Different distances between the IMFs, such as Euclidian, Batacharay, and Kolo- mogorov, were calculated and utilized as input for the PHA cluster. The results of the evaluation were very encouraging, with an overall accuracy of 98.84%.

Similarly, Orellana et al. (Orellana & Cerqueira, 2016) investigated personalised seizure detection in epilepsy employing random forest classification on one-dimensional transformed EEG data.

The authors of (Torse et al., 2017) classified EEG data as non-seizure or seizure using an ANN and EMD. Al Gahyab et al. (Al Ghayab et al., 2019) sug- gested an improved algorithm for detecting seizures in EEG data by combining frequency response infor- mation with the InfoGain technique. There were four primary steps in the proposed technique. The FFT (fast Fourier transform) or DWT (discrete wavelet transform) were utilised first. Secondly, each band was separated into k windows, with each window con- taining a collection of statistical information. Lastly, the retrieved features were ranked using InfoGain. Lastly, to categorise the EEG, each characteristics were fed into LS-SVM classifier. This methodol- ogy was deployed and tested on a reference EEG database, as well as compared to other current meth- ods, based on several performance evaluation param- eters.

Tzimoutra et al. (Tzimourta et al., 2019) pre- sented a multicenter technique of analysis based on the DWT for automated seizure identification . A five level decomposition was employed in each EEG segment, and five features were derived from the wavelets. The feature vector obtained was employed to train a RF classifier, which was subsequently uti- lized to differentiate among preictal and interictal data.

However, Wu et al. (Wu et al., 2021) created a novel method for detecting HFOs in iEEG signals. There were three steps in this method: preliminary identification, extraction of features, and feature cat- egorization. The variable cutoff of Hilbert envelopes was employed In the initial detection phase to iden- tify EoIs from background activity, boosting the ef- fectiveness of HFO detection. To prevent the sub- jective bias induced by manually retrieved features, the SDAE network was utilised to extract the (time- frequency) domain features of EoIs. The (SWAF- ABSVM) ensemble classifier was created to differen- tiate between HFOs and observed EoIs. This en- semble classifier solved the issue of an imbalanced class between HFOs and fHFOs, resulting in better HFO detection performance. Dedeo et al. (Dedeo & Garg, 2021) developed a method for identifying crit- ical preictal locations and their associated frequen- cies in the high gamma band, which covers the range of 30 to 100 Hz, in order to diagnose convulsions in 10 (paediatric) cases at least 30 seconds before seizure onset.Further research into the potential fu- ture predictive performance of event-related future direction in this higher gamma band found that de- tection algorithms must accommodate varying inten- sities of a patient's usual extremes. Bizopoulos et al. citer356 described (S2Is) Signal2Image as non train- able or trainable prefix units that change signals, such as EEG to image like representation, mak- ing them appropriate for learning image based DNN. The time performance and accuracy of 4 S2Is (sig- nal as image, spectrogram, and both one- and two- layer CNNs) paired with a collection of 'base mod- els (LeNet, VGGnet, AlexNet, ResNet, DenseNet), in addition to depth-wise and 1D versions of the lat- ter were examined.

Antoniades et al. (Antoniades et al., 2016) inves- tigated convolutional neural networks (CNNs) in a subject-independent manner and discovered mean- ingful features that represented IEDs. The model achieved cutting-edge classification performance, of- fered insights into the various types of IEDs in the group, and was unaffected by IED temporal dis- parities. According to the findings of this work, deep learning based feature generation is applicable for EEG and IEDs in general.

Park et al. (Park et al., 2018) proposed a deep convolutional network-based epileptic seizure detec- tion method.The suggested network was constructed for multi channel EEG signals using 1D and 2D con- volution layer and took into account spatio temporal correlation feature in epileptic seizure identification. The temporal evolution of each channel's EEG signal was considered by the 1D convolutional layer, and the spatial relationships among EEG channels were considered by the 2D convolutional layer.

Sui et al. (Sui et al., 2019) established a new recognition approach for iEEG-based localization of epileptic focals based on STFT and CNN with ex- tra preprocessing in his paper, and developed a 15- layer CNN architecture for iEEG signal categoriza- tion. The findings with 91.8% accuracy revealed that this technique worked for localisation of focal seizure area with considerably efficient and rapid preprocess- ing step. Turk and Ozerdem (Türk & Özerdem, 2019), on the other hand, employed a CNN struc- ture to learn the properties of these scalogram data, and the classification performance of the structure was compared to earlier studies.

Faust et al. (Faust et al., 2018) illustrated the application of various deep learning algorithms cur- rently in use and Tian et al. (Tian et al., 2019) pro- posed a multiview deep feature extraction method in an attempt to identify effective features in EEG signals, which were critical for accurate seizure de- tection. The technique used wavelet packet decom- position (WPD) and Fast Fourier transform (FFT) to construct the first multi-view features and LeCun (LeCun et al., 2015) and Triesch (Lu & Triesch, 2019) contributed to the development of a deep CNN model with residual connections that achieved state-of-the- art classification of EEG signals in the context of epilepsy.

San-Segundo et al. (San-Segundo et al., 2019) in- vestigated a DNN for epileptic EEG signal catego- rization. Two convolution layer for feature extraction and 3 fully linked layers for classification comprised the deep learning architecture.

The EEG signal provided vital information about the brain's electrical activity. The analysis of these signals was critical for the detection of epilepsy. Be- cause of the human aspect, epilepsy identification can be subjective and potentially wrong. Machine Learn- ing (ML) techniques were created to address this issue by removing the human factor. This strategy, how- ever, was counter intuitive because it included the use of complicated features for epilepsy identification. Akut (Akut, 2019) at el. created a wavelet based deep learning approach that avoided the necessity of ex- tracting features and performed considerably better on fewer datasets than existing state-of-the-art ML algorithms, and Yao et al. (Yao et al., 2019b) devel- oped a new method for seizure/non-seizure classifica- tion based on an emerging deep learning framework, the independent recurrent neural network (IndRNN) (?, ?). The time scales were gradually enlarged by this new technology, enabling temporal and spatial information to be recovered from the regional time duration to the full record. Cross-validation exper- iments were used to evaluate the noisy data across subjects.

Chen et al. (X. Chen et al., 2018) suggested an expense sensitivedeep active learning strategy to de- tect epileptic episodes. To acquire the expense sen- sitive efficiency for the sample selection approach in the labelling process, a novel generic dual neu- ral network (dual-DNN) in particularly was applied. Three types of core neural networks were tested in the double DNN: 1D CNNs, recurring neural net- works with LSTM units, and recurring neural net- works with GRU(gated recurrent units). Hussein et al. (Hussein et al., 2019) established the practi- cal feasibility of epilepsy detection strategy based on a deep LSTM (Long Short-Term Memory) network that exceeded cutting-edge strategies in seizure de- tection efficacy and robustness. In this study, Talathi and Vartak (Talathi & Vartak, 2015) concentrated on a recently introduced weight initialization using iden- tity matrix for recurring weights in an RNN. This initialization was created using hidden nodes with non-linear Rectified Linear Units (ReLU). A simple dynamical systems perspective on the weight initial- ization process was also presented, allowing us to propose a modified weight initialization strategy and the author (Ahmedt-Aristizabal et al., 2020) demon- strated that recurrent deep convolutional neural net- works outperformed traditional methods of machine learning for sequence modelling using average cross-validation performance. The intuitive salient infor- mation of the model, including the placement of the most particular properties of a post-stimulus window, was explained in further detail. This baseline iden- tification approach in the field of mental illness sup- ported the findings of developmental and disease im- pacts in the pre-prodromal phase of psychosis.

Yao et al. (Yao et al., 2019a) coupled a develop- ing deep learning framework, the independently re- curring neural network (IndRNN), with an attention mechanism and a dense structure to leverage spatial and temporal discriminating characteristics and over- come seizure unpredictability. The thick structure was created to allow for optimal information trans- mission between levels.

Hussein (Hussein et al., 2018) presented an efficient seizure detection approach that dealt with both clean and noisy data. Long Short-Term Memory (LSTM) neural networks were used in the proposed method to extract representative EEG features relevant to seizures and Birjandtalab et al. (Birjandtalab et al., 2018) used a Gaussian mixture model (GMM) to de- tect epileptic seizures. They obtained satisfactory ac- curacy results and an F-measure of 85.1.

Hussein (Hussein et al., 2018) demonstrated an ef- fective seizure detection method that coped with both noisy and clean data. The proposed method used LSTM (Long Short-Term Memory) neural networks to retrieve representative EEG variables related to seizures, Birjandtalab et al. (Birjandtalab et al., 2018) utilised a GMM (Gaussian mixture model) to detect seizures. They got good overall accuracy as well as 85.1 F-measure . In order to reliably cat- egorise seizure detection, Raghu et al. (Raghu et al., 2020) proposed a hybrid SVM-KNN framework that was tested on raw EEG data, with test results exhibiting up to 90% accuracy. (Sharma et al., 2018) proposed ANN classifier on the EEG activity in the brain datasets with time and frequency do- main features in the literature. Amin et al. (Amin et al., 2015) introduced tritime domain techniques for selecting features in epileptic seizure detection em- ploying statistical parameters such as frequency, line length, and energy. In a study proposed by Satapa- thy et al. (Satapathy et al., 2017a), they applied two model types—SVM and neural networks (or "black-box" approaches)—on an EEG dataset in order to detect seizures. The findings of the tested models demonstrated that, when contrasted to other net- works, the SVM model was significantly more effec- tive in terms of precision and time complexity (sec). Hassan and Subasi (Hassan & Subasi, 2016) used GA (genetic algorithms), SVM, and PSO (particle swarm optimization) to detect seizures. This method reached the optimum accuracy of 92.38%, Lahmiri and Shmuel (Lahmiri & Shmuel, 2018) employed the HE (Hurst exponent) to correctly classify the acquired EEG dataset into non seizure and seizure with near 97% accuracy. Time-domain feature ex- traction approaches utilising 9 statistical characteris- tics (kurtosis, standard deviation, energy, skewness, mean, line length, mode, entropy and Hurst) were de- termined to be appropriate for epileptic seizure iden- tification in recent research that explored and anal- ysed a range of features (Kumar et al., 2017).

Similar to this, Donos et al. (Donos et al., 2015) created a classifier called decision forest us- ing statistical variables (time and frequency domains) extracted out of an EEG dataset and obtained accu- racy of up to 93.8% and Hosseini et al. (Hosseini et al., 2018) achieved 96.7% accuracy using the RF with grid search optimization (RF-GSO) approach.

A review of the studies looking at ML and AI in epilepsy is shown in Table I. It covers the dataset source that was used, the ML algorithm that was looked at, and metrics such as feature analysis, num- ber of samples, accuracy and limitations that were discovered. It demonstrates that ML remains promis- ing for identifying epilepsy with respect to accuracy and other metrics.

6. FINDINGS AND DISCUSSION

ML has solved various ES prediction issues, includ- ing manual, time-consuming and complex analysis methods. Interpretation of model is critical, because pattern recognition in data is just as important as data fitting. The accurate classification of disease and its subtypes is a key challenge in biomedicine. Massive amounts of biomedical data are now avail- able, which can lead to the identification of more extensive sub-types. There are numerous ways wherein ML has advanced EEG analysis. The hierarchical architecture of the neural networks has greatly expanded the possibilities for learning characteristics from raw or slightly processed input.

We investigated use of various machine learning algorithms for detection of epileptic seizure in this study.For instance, traditional ML (SVM, KNN and ANN) and RF-based ML were taken into consider- ation due to their exceptional efficacy in epileptic seizure identification in the prior studies.

This comprehensive investigation found that tra- ditional ML algorithms (KNN, SVM, and ANN) made a significant contribution to the analysis of brain information for seizure identification. Even so, each approach has benefits and drawbacks. SVM, for instance, has proven successful for binary clas- sification. It has a larger computation complexity (sec), particularly in comparison to KNN and ANN, but delivers a greater degree of detection preci- sion than ANN and KNN.While KNN can handle high-dimensional datasets, it has low detection com- plexity and low performance assessment measures (precision, recall, and F1-score). The precision, recall, detection accuracy and F1-score can all be increased by utilising a hybrid classification method (SVM-ANN or SVM-KNN) that integrates multiple ML models. Hybrid models are computationally more efficient than single design models, which restricts their utility in practical applications even if they can surpass single models in the accuracy of their predictions. However, a key issue with classical Ml techniques is that the reasoning process utilised to produce their predictions is challenging to comprehend and is frequently left unexplained for logical rules and patterns hidden within the model (the blackbox idea). They should not be used to extract relevant information from datasets.

For instance, the RNN model often executes more quickly than CNN and LSTM, but it has worse recall, accuracy and precision. LSTM, on the other hand, has time complexity challenges when used with CHB-MIT, BONN, and other datasets for seizure detection.While using traditional ML models for epileptic seizure detection, feature extraction is a key component of the overall scheme. Therefore, selecting the right feature extraction techniques is crucial for analyzing EEG signals.

Recent studies that investigated and analysed many characteristics discovered that time-domain based feature extraction techniques with 9 statistical datasets (entropy, kurtosis, standard deviation, mean, energy, skewness, line length, mode, and Hurst) might be useful for epileptic seizure identi- fication. It is because the aforementioned features, when used with ML models for categorising epileptic seizures based on EEG signals, have been demon- strated to generate average accuracies of 98–100%. Furthermore, it is crucial to reduce the model's sophistication by utilising a selection approach to pick a more manageable number of useful features. It leads to an examination of several feature selection approaches used mostly for dimensionality reduction.

The improvement of patients' quality of life is the main objective of ES prediction research. The bottleneck remains the expense-effective and efficient hardware implementation, not withstanding the current state of ML as it relates to ES prediction that we have provided in this study. The seizure detection system also employed decomposition, pre-processing, feature extraction, classification, and post-processing. Among the ML models, the feature engineering-based traditional ML models account for an amount of applications. Whereas excessive extraction of features will prolong the computa- tion time and cost. For an actual system for ES predictions to be practical, rapid predictions with low-power equipment and lower processing costs are required.

One of the key causes of a prediction algorithm's poor performance is missing observations. Because of failure in communication between implantable or wearable devices with limited storage space and storage device for a number of reasons, there are often zero or almost completely zero in the seen data. The ML field has paid little attention to learning from faulty or missing data. Yet, missingness signals in systems that can provide significant amounts of information for prediction are necessary.

The complexities and one-of-a-kind objectives of epilepsy applications might considerably inspire the advancement of machine learning algorithms. The heterogeneity of epileptic patients needs tailored medical management, which necessitates proper diag- nosis of every patient's stratification, such as the pri- mary cause of epilepsy, epilepsy location and epilepsy symptoms (Alaverdyan & Lartizien, 2018; Zhao, 2017). Because epilepsy prognosis is so important to a patient's well-being, every patient's longitudi- nal healthcare records should be kept and examined. These are compelling reasons for developing ML the- ory and methods.

7. FUTURE DIRECTIONS

The interaction of various machine learning tech- niques that can be used more effectively in the con- text of epilepsy diagnosis and prognosis will be high- lighted. Then we'll go over approaches for applying machine learning methods to our data, such as tra- ditional machine learning approaches and their vari- ations.Following that, the use of ML as well as tasks specifically related to prognosis and diagnosis will be further examined. Finally, we will examine current achievements, problems, and potential future initia- tives in this subject with the intention of paving the way towards computer-aided epilepsy diagnosis and prognosis.

8. RESEARCH GAP

Dataset availability is a serious difficulty in epilepsy. As a result, there is an immediate need to aggre- gate, normalize, and process diverse practice records across the world in order to build a comprehensive, uniform, and holistic dataset. The optimum prepro- cessing methodology for the normalised and unified dataset must be determined because preprocessing method influences predictive performance and model success. It is worth noting that much work remains to be done to enhance the precision of feature se- lection methods.For future investigation, the right system combinations should be chosen before modifying the parameters associated with the classifiers stated here for enhanced quality. Under certain con- ditions, channel selection can reduce computing loads for both pattern recognition and feature extraction , enabling online computation.

It is also feasible to use cloud computing linked via 5G technology to perform real-time EEG record- ing interchange.

Deep learning is a hot technique in image processing when it comes to ML methods. Sev- eral electrodes are used to record EEG signals, which increases the amount of the received signal. This makes analyzing multichannel EEG signals more dif- ficult. ES detection and prediction are often defined as tasks involving supervised learning requiring la- belled dataset, which is a costly, time-consuming, and tedious operation. Using extra training data is a nat- ural way to improve the efficacy of ML approaches.

9. CONCLUSION

In this study, we thoroughly evaluated the relevant literature and described why early ES prediction is critical, as well as how ML approaches are employed for ES prediction. In the scope of feature selection, EEG analysis, ES prediction and detection and the assessment of prediction or detection methods, ES prediction is a vast topic. This research sought to contrast and narrow down the vast number of ex- isting strategies for Electroencephalography seizure identification and categorization based on their im- proved performance. The objective of this overview was to examine seizure detection strategies currently published in a number of studies.It is simple to com- pare alternative methods when all of the typical per- formance metrics parameters (e.g., specificity, sen- sitivity and accuracy) are available. In contrast to the results of this article, most previous survey ar- ticles solely focused on the EEG analysis, only with a few covering the advancements of prediction meth- ods; whilst we tried to provide insights by taking into account aspects of prediction techniques, feature se- lection and evaluation methods, among others.

Furthermore, we identified research gaps and fu- ture work that require further investigation.

10. REFERENCES

[1] Abbasi, R., & Esmaeilpour, M. (2017). Selecting sta- tistical characteristics of brain signals to detect epileptic seizures using discrete wavelet trans- form and perceptron neural network. Interna- tional Journal of Interactive Multimedia & Ar- tificial Intelligence, 4 (5).

[2] Abualsaud, K., Mahmuddin, M., Saleh, M., & Mo- hamed, A. (2015). Ensemble classifier for epileptic seizure detection for imperfect eeg data. The Scientific World Journal , 2015 .

[3] Ahmedt-Aristizabal, D., Fernando, T., Denman, S., Robinson, J. E., Sridharan, S., Johnston, P. J., Fookes, C. (2020). Identification of children at risk of schizophrenia via deep learning and eeg responses. IEEE Journal of biomedical and health informatics, 25 (1), 69–76.

[4] Akut, R. (2019). Wavelet based deep learning ap- proach for epilepsy detection. Health informa- tion science and systems, 7 (1), 8.

[5] Alaverdyan, Z., Jung, J., Bouet, R., & Lartizien, C. (2020). Regularized siamese neural network for unsupervised outlier detection on brain multi- parametric magnetic resonance imaging: appli- cation to epilepsy lesion screening. Medical im- age analysis, 60 , 101618.

[6] Alaverdyan, Z., & Lartizien, C. (2018). Feature extraction with regularized siamese networks for outlier detection: application to lesion screening in medical imaging. arXiv preprint arXiv:1805.01717 .

[7] Al Ghayab, H. R., Li, Y., Siuly, S., & Abdulla, S. (2019). Epileptic seizures detection in eegs blending frequency domain with information gain technique. Soft Computing, 23 , 227–239.

[8] Alickovic, E., Kevric, J., & Subasi, A. (2018). Perfor- mance evaluation of empirical mode decompo- sition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. Biomedical signal processing and control , 39 , 94–102.

[9] Amin, H. U., Malik, A. S., Ahmad, R. F., Badruddin, N., Kamel, N., Hussain, M., & Chooi, W.-T. (2015). Feature extraction and classification for eeg signals using wavelet transform and machine learning techniques. Australasian physical & engineering sciences in medicine, 38 , 139–149.

[10] Antoniades, A., Spyrou, L., Took, C. C., & Sanei, S. (2016). Deep learning for epileptic intracranial eeg data. In 2016 ieee 26th international work- shop on machine learning for signal processing (mlsp) (pp. 1–6).

[11] Awad, M., & Khanna, R. (2015). Efficient learning machines: theories, concepts, and applications for engineers and system designers. Springer nature.

[12] Bandarabadi, M., Teixeira, C. A., Rasekhi, J., & Dourado, A. (2015a). Epileptic seizure pre- diction using relative spectral power features. Clinical Neurophysiology , 126 (2), 237–248.

[13] Bandarabadi, M., Teixeira, C. A., Rasekhi, J., & Dourado, A. (2015b). Epileptic seizure pre- diction using relative spectral power features. Clinical Neurophysiology , 126 (2), 237–248.

[14] Belhadj, S., Attia, A., Adnane, A. B., Ahmed-Foitih, Z., & Taleb, A. A. (2016). Whole brain epilep- tic seizure detection using unsupervised classi- fication. In 2016 8th international conference on modelling, identification and control (icmic) (pp. 977–982).

[15] Bhattacharyya, A., & Pachori, R. B. (2017). A multivariate approach for patient-specific eeg seizure detection using empirical wavelet trans- form. IEEE Transactions on Biomedical Engi- neering, 64 (9), 2003–2015.

[16] Birjandtalab, J., Jarmale, V. N., Nourani, M., & Har- vey, J. (2018). Imbalance learning using neu- ral networks for seizure detection. In 2018 ieee biomedical circuits and systems conference (bio- cas) (pp. 1–4).

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

[18] Bizopoulos, P., Lambrou, G. I., & Koutsouris, D. (2019). Signal2image modules in deep neural networks for eeg classification. In 2019 41st an- nual international conference of the ieee engi- neering in medicine and biology society (embc)(pp. 702–705).

[19] Brari, Z., & Belghith, S. (2021). A novel ma- chine learning approach for epilepsy diagnosis using eeg signals based on correlation dimen- sion. IFAC-PapersOnLine, 54 (17), 7–11.

[20] Cantor-Rivera, D., Khan, A. R., Goubran, M., Mir- sattari, S. M., & Peters, T. M. (2015). De- tection of temporal lobe epilepsy using support vector machines in multi-parametric quantita- tive mr imaging. Computerized

Medical Imag- ing and Graphics, 41 , 14–28.

[21] Celebi, M. E., & Aydin, K. (2016). Unsupervised learning algorithms (Vol. 9). Springer.

[22] Chen, D., Wan, S., Xiang, J., & Bao, F. S. (2017). A high-performance seizure detection algorithm based on discrete wavelet transform (dwt) and eeg. PloS one, 12 (3), e0173138.

[23] Chen, S., Zhang, X., Chen, L., & Yang, Z. (2019). Automatic diagnosis of epileptic seizure in elec- troencephalography signals using nonlinear dy- namics features. IEEE Access, 7 , 61046–61056. Chen, X., Ji, J., Ji, T., & Li, P. (2018). Cost-sensitive deep active learning for epileptic seizure detection. In Proceedings of the 2018 acm interna- tional conference on bioinformatics, computa- tional biology, and health informatics (pp. 226–235).

[24] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20 , 273–297.

[25] Dedeo, M., & Garg, M. (2021). Early detection of pe- diatric seizures in the high gamma band. IEEE Access, 9 , 85209–85216.

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

[27] Deo, R. C. (2015). Machine learning in medicine.

[28] Circulation, 132 (20), 1920–1930.

[29] Direito, B., Teixeira, C. A., Sales, F., Castelo- Branco, M., & Dourado, A. (2017). A realis- tic seizure prediction study based on multiclass svm. International journal of neural systems, 27 (03), 1750006.

[30] Donos, C., Dümpelmann, M., & Schulze-Bonhage, A. (2015). Early seizure detection algorithm based on intracranial eeg and random forest classifi- cation. International journal of neural systems, 25 (05), 1550023.

[31] Eadie, M. J. (2012). Shortcomings in the current treatment of epilepsy. Expert review of neu- rotherapeutics, 12 (12), 1419–1427.

[32] England, M. J., Liverman, C. T., Schultz, A. M., & Strawbridge, L. M. (2012). Epilepsy across the spectrum: Promoting health and understand- ing.: A summary of the institute of medicine report. Epilepsy & Behavior , 25 (2), 266–276.

[33] Fasil, O., & Rajesh, R. (2019). Time-domain expo- nential energy for epileptic eeg signal classifica- tion. Neuroscience letters, 694 , 1–8.

[34] Faust, O., Hagiwara, Y., Hong, T. J., Lih, O. S., & Acharya, U. R. (2018). Deep learning for healthcare applications based on physiological signals: A review. Computer methods and pro- grams in biomedicine, 161 , 1–13.

[35] Fisher, R. S., Acevedo, C., Arzimanoglou, A., Bo- gacz, A., Cross, J. H., Elger, C. E., . . . others (2014). Ilae official report: a practical clinical definition of epilepsy. Epilepsia, 55 (4), 475–482.

[36] Gasparini, S., Campolo, M., Ieracitano, C., Mam- mone, N., Ferlazzo, E., Sueri, C., . . . Morabito, F. C. (2018). Information theoretic-based inter- pretation of a deep neural network approach in diagnosing psychogenic non-epileptic seizures. Entropy, 20 (2), 43.

[37] Gleichgerrcht, E., Munsell, B., Bhatia, S., Vander- griftz, W. A., Rorden, C., McDonald, C., . . . Bonilha, L. (2018). Deep learning applied to whole-brain connectome to determine seizure control after epilepsy surgery. Epilepsia, 59 (9), 1643–1654.

[38] Göksu, H. (2018). Eeg based epileptiform pat- tern recognition inside and outside the seizure states. Biomedical Signal Processing and Con- trol , 43 , 204–215.

[39] Hassan, A. R., & Subasi, A. (2016). Automatic iden- tification of epileptic seizures from eeg signals using linear programming boosting. computer methods and programs in biomedicine, 136 , 65– 77.

[40] Höller, Y., Butz, K. H., Thomschewski, A. C.,Schmid, E. V., Hofer, C. D., Uhl, A., . . . oth- ers (2020). Prediction of cognitive decline in temporal lobe epilepsy and mild cognitive impairment by eeg, mri, and neuropsychology. Computational Intelligence and Neuroscience, 2020 .

[41] Hosseini, M.-P., Pompili, D., Elisevich, K., & Soltanian-Zadeh, H. (2018). Random ensemble learning for eeg classification. Artificial intelli- gence in medicine, 84 , 146–158.

[42] Hosseini, M.-P., Soltanian-Zadeh, H., Elisevich, K., & Pompili, D. (2016). Cloud-based deep learn- ing of big eeg data for epileptic seizure pre- diction. In 2016 ieee global conference on sig- nal and information processing (globalsip) (pp. 1151–1155).

[43] Hussein, R., Palangi, H., Wang, Z. J., & Ward, R. (2018). Robust detection of epileptic seizures using deep neural networks. In 2018 ieee in- ternational conference on acoustics, speech and signal processing (icassp) (pp. 2546–2550).

[44] Hussein, R., Palangi, H., Ward, R. K., & Wang, Z. J. (2019). Optimized deep neural network archi- tecture for robust detection of epileptic seizures using eeg signals. Clinical Neurophysiology, 130 (1), 25–37.

[45] Ibrahim, S., Djemal, R., & Alsuwailem, A. (2018). Electroencephalography (eeg) signal processing for epilepsy and autism spectrum disorder di- agnosis. Biocybernetics and Biomedical Engi- neering, 38 (1), 16–26.

[46] Ilakiyaselvan, N., Khan, A. N., & Shahina, A. (2020). Deep learning approach to detect seizure using reconstructed phase space images. Journal of Biomedical Research, 34 (3), 240.

[47] Jacobs, D., Hilton, T., Del Campo, M., Carlen, P. L., & Bardakjian, B. L. (2018). Classifica- tion of pre-clinical seizure states using scalp eeg cross-frequency coupling features. IEEE Trans- actions on Biomedical Engineering, 65 (11), 2440–2449.

[48] Jaiswal, A. K., & Banka, H. (2017). Local pattern transformation based feature extraction tech- niques for classification of epileptic eeg signals. Biomedical Signal Processing and Control , 34 , 81–92.

[49] Jaiswal, A. K., & Banka, H. (2018). Epileptic seizure detection in eeg signal using machine learning techniques.

Australasian physical & engineering sciences in medicine, 41 , 81–94.

[50] Jia, J., Goparaju, B., Song, J., Zhang, R., & West- over, M. B. (2017). Automated identification of epileptic seizures in eeg signals based on phase space representation and statistical features in the ceemd domain. Biomedical Signal Process- ing and Control , 38 , 148–157.

[51] JIANG, H.-y., LIU, R.-n., GAO, F.-f., & MIAO, Y.(2017). Hemisphere symmetry feature based on tensor space and recognition of epilepsy. Jour- nal of Northeastern University (Natural Sci- ence), 38 (7), 923.

[52] Jrad, N., Kachenoura, A., Merlet, I., Bartolomei, F., Nica, A., Biraben, A., & Wendling, F. (2016). Automatic detection and classification of high-frequency oscillations in depth-eeg sig- nals. IEEE Transactions on Biomedical Engi- neering, 64 (9), 2230–2240.

[53] Kabir, E., Zhang, Y., et al. (2016). Epileptic seizure detection from eeg signals using logistic model trees. Brain informatics, 3 (2), 93–100.

[54] Kalbkhani, H., & Shayesteh, M. G. (2017). Stockwell transform for epileptic seizure detection from eeg signals. Biomedical Signal Processing and Control , 38 , 108–118.

[55] Kaleem, M., Guergachi, A., & Krishnan, S. (2018). Patient-specific seizure detection in long-term eeg using wavelet decomposition. Biomedical Signal Processing and Control , 46 , 157–165.

[56] Karim, A. M., Güzel, M. S., Tolun, M. R., Kaya, H., & Çelebi, F. V. (2018). A new generalized deep learning framework combining sparse autoen- coder and taguchi method for novel data classi- fication and processing. Mathematical Problems in Engineering, 2018 .

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

[58] Karim, A. M., Karal, Ö., & Çelebi, F. (2018). A new automatic epilepsy serious detection method by using deep learning based on discrete wavelet transform. no, 4 , 15–18.

[59] Khan, H., Marcuse, L., Fields, M., Swann, K., & Yener, B. (2017). Focal onset seizure prediction using convolutional networks. IEEE Transac- tions on Biomedical Engineering, 65 (9), 2109–2118.

[60] Kitano, L. A. S., Sousa, M. A. A., Santos, S. D., Pires, R., Thome-Souza, S., & Campo, A. B. (2018). Epileptic seizure prediction from eeg signals using unsupervised learning and a polling-based decision process. In Artificial neural networks and machine learning–icann 2018: 27th international conference on artifi- cial neural networks, rhodes, greece, october 4- 7, 2018, proceedings, part ii 27 (pp. 117–126).

[61] Kumar, M., Pachori, R. B., & Acharya, U. R. (2017). Use of accumulated entropies for automated de- tection of congestive heart failure in flexible an- alytic wavelet transform framework based on short-term hrv signals. Entropy, 19 (3), 92.

[62] Lahmiri, S., & Shmuel, A. (2018). Accurate clas- sification of seizure and seizure-free intervals of intracranial eeg signals from epileptic pa- tients. IEEE Transactions on Instrumentation and Measurement, 68 (3), 791–796.

[63] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521 (7553), 436–444.

[64] Lee, H., & Kim, S. (2016). Black-box classifier inter- pretation using decision tree and fuzzy logic- based classifier implementation. International Journal of Fuzzy Logic and Intelligent Systems, 16 (1), 27–35.

[65] Lekshmy, H., Panickar, D., & Harikumar, S. (2022). Comparative analysis of multiple ma- chine learning algorithms for epileptic seizure prediction. In Journal of physics: Conference series (Vol. 2161, p. 012055).

[66] Li, M., Chen, W., & Zhang, T. (2017a). Automatic epileptic eeg detection using dt-cwt-based non- linear features. Biomedical Signal Processing and Control , 34 , 114–125.

[67] Li, M., Chen, W., & Zhang, T. (2017b). Classifi- cation of epilepsy eeg signals using dwt-based envelope analysis and neural network ensemble. Biomedical Signal Processing and Control , 31 ,357–365.

[68] Libbrecht, M. W., & Noble, W. S. (2015). Machine learning applications in genetics and genomics. Nature Reviews Genetics, 16 (6), 321–332.

[69] Liedlgruber, M., Butz, K., Höller, Y., Kuchukhidze, G., Taylor, A., Thomschevski, A., . . . Uhl, A. (2019). Can spharm-based features from auto- mated or manually segmented hippocampi dis- tinguish between mci and tle? In Image anal- ysis: 21st scandinavian conference, scia 2019, norrköping, sweden, june 11–13, 2019, proceedings 21 (pp. 465–476).

[70] Lima, C. A., Coelho, A. L., Madeo, R. C., & Peres,

[71] S. M. (2016). Classification of electromyog- raphy signals using relevance vector machines and fractal dimension. Neural Computing and Applications, 27 , 791–804.

[72] Logesparan, L., Rodriguez-Villegas, E., & Casson,A. J. (2015). The impact of signal normal- ization on seizure detection using line length features. Medical & biological engineering & computing, 53 , 929–942.

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

[74] Luckett, P. H. (2018). Nonlinear methods for detec- tion and prediction of epileptic seizures (Un- published doctoral dissertation). University of South Alabama.

[75] Mannan, M. M. N., Kamran, M. A., & Jeong, M. Y. (2018). Identification and removal of physio- logical artifacts from electroencephalogram sig- nals: A review. Ieee Access, 6 , 30630–30652.

[76] Mello, R. F., & Ponti, M. A. (2018). Machine learning: a practical approach on the statisti- cal learning theory. Springer.

[77] Munsell, B., Wu, G., Fridriksson, J., Thayer, K., Mofrad, N., Desisto, N., . . . Bonilha, L. (2019). Relationship between neuronal network archi- tecture and naming performance in temporal lobe epilepsy: A connectome based approach using machine learning. Brain and Language, 193 , 45–57.

[78] Munsell, B. C., Wee, C.-Y., Keller, S. S., Weber, B., Elger, C., da Silva, L. A. T., . . . Bonilha, L. (2015). Evaluation of machine learning algo- rithms for treatment outcome prediction in pa- tients with epilepsy based on structural connec- tome data. Neuroimage, 118 , 219–230.

[79] Mursalin, M., Islam, S. S., Noman, M. K., & Al- Jumaily, A. A. (2019). Epileptic seizure clas- sification using statistical sampling and a novel feature selection algorithm. arXiv preprint arXiv:1902.09962 .

[80] Mutlu, A. Y. (2018). Detection of epileptic dysfunc- tions in eeg signals using hilbert vibration de- composition. Biomedical Signal Processing and Control , 40 , 33–40.

[81] Nair, P. P., Aghoram, R., Khilari, M. L., et al. (2021). Applications of artificial intelligence in epilepsy. International Journal of Advanced Medical and Health Research, 8 (2), 41.

[82] Natu, M., Bachute, M., Gite, S., Kotecha, K., & Vid- yarthi, A. (2022). Review on epileptic seizure prediction: machine learning and deep learning approaches. Computational and Mathematical Methods in Medicine, 2022 .

[83] Orellana, M., & Cerqueira, F. (2016). Personalized epilepsy seizure detection using random forest classification over one-dimension transformed eeg data. bioRxiv (070300).

[84] Park, C., Choi, G., Kim, J., Kim, S., Kim, T.-J., Min, K., . . . Chong, J. (2018). Epileptic seizure detection for multi-channel eeg with deep con- volutional neural network. In 2018 interna- tional conference on electronics, information, and communication (iceic) (pp. 1–5).

[85] Parvez, M. Z., & Paul, M. (2016). Seizure predic- tion using undulated global and local features. IEEE Transactions on Biomedical Engineering, 64 (1), 208–217.

[86] Patidar, S., & Panigrahi, T. (2017). Detection of epileptic seizure using kraskov entropy applied on tunable-q wavelet transform of eeg signals. Biomedical Signal Processing and Control , 34 , 74–80.

[87] Raghu, S., & Sriraam, N. (2018). Classification of focal and non-focal eeg signals using neighbor- hood component analysis and machine learning algorithms. Expert Systems with Applications, 113 , 18–32.

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

[89] Rojas, I., Joya, G., & Catala, A. (2015). Advances in computational intelligence: 13th international work-conference on artificial neural networks, iwann 2015, palma de mallorca, spain, june 10-12, 2015. proceedings, part i (Vol. 9094). Springer.

[90] Samson, K. (2018). 'deep learning'model using ar- tificial intelligence predicts surgical success in intractable temporal lobe epilepsy. Neurology Today, 18 (23), 50–55.

[91] San-Segundo, R., Gil-Martín, M., D'Haro-Enríquez,L. F., & Pardo, J. M. (2019). Classification of epileptic eeg recordings using signal transforms and convolutional neural networks. Computers in biology and medicine, 109 , 148–158.

[92] Satapathy, S. K., Jagadev, A. K., & Dehuri, S. (2017a). Weighted majority voting based en- semble of classifiers using different machine learning techniques for classification of eeg sig- nal to detect epileptic seizure. Informatica (03505596), 41 (1).

[93] Satapathy, S. K., Jagadev, A. K., & Dehuri, S. (2017b). Weighted majority voting based en- semble of classifiers using different machine learning techniques for classification of eeg sig- nal to detect epileptic seizure. Informatica (03505596), 41 (1).

[94] Sazgar, M., & Young, M. G. (2019). Absolute epilepsy and eeg rotation review: Essentials for trainees. Springer.

[95] Selvakumari, R. S., Mahalakshmi, M., & Prashalee,P. (2019). Patient-specific seizure detection method using hybrid classifier with optimized electrodes. Journal of medical systems, 43 , 1– 7.

[96] Senders, J. T., Zaki, M. M., Karhade, A. V., Chang,B., Gormley, W. B., Broekman, M. L., . . . Ar- naout, O. (2018). An introduction and overview of machine learning in neurosurgical care. Acta neurochirurgica, 160 , 29–38.

[97] Sharif, B., & Jafari, A. H. (2017). Prediction of epileptic seizures from eeg using analysis of ictal rules on poincaré plane. Computer methods and programs in biomedicine, 145 , 11–22.

[98] Sharma, M., Sharma, P., Pachori, R. B., & Acharya, U. R. (2018). Dual-tree complex wavelet transform-based features for automated alco- holism identification. International Journal of Fuzzy Systems, 20 , 1297–1308.

[99] Shiao, H.-T., Cherkassky, V., Lee, J., Veber, B., Patterson, E. E., Brinkmann, B. H., & Wor- rell, G. A. (2016). Svm-based system for pre- diction of epileptic seizures from ieeg signal. IEEE Transactions on Biomedical Engineering, 64 (5), 1011–1022.

[100] Siddiqui, M. K., Islam, M. Z., & Kabir, M. A. (2019). A novel quick seizure detection and localiza- tion through brain data mining on ecog dataset. Neural Computing and Applications, 31 , 5595– 5608.

[101] Singh, A., Thakur, N., & Sharma, A. (2016). A re- view of supervised machine learning algorithms. In 2016 3rd international conference on com- puting for sustainable global development (indi- acom) (pp. 1310–1315).

[102] Singh, K., & Malhotra, J. (2019). Iot and cloud com- puting based automatic epileptic seizure detec- tion using hos features based random forest classification. Journal of Ambient Intelligence and Humanized Computing, 1–16.

[103] Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. Statistics and com- puting, 14 , 199–222.

[104] Stelzle, D., Schmidt, V., Ngowi, B. J., Matuja, W., Schmutzhard, E., & Winkler, A. S. (2021). Life- time prevalence of epilepsy in urban tanzania–a door-to-door random cluster survey. Eneurolog- icalsci , 24 , 100352.

[105] Subasi, A., Kevric, J., & Abdullah Canbaz, M. (2019). Epileptic seizure detection using hybrid machine learning methods. Neural Computing and Applications, 31 , 317–325.

[106] Sui, L., Zhao, X., Zhao, Q., Tanaka, T., & Cao, J. (2019). Localization of epileptic foci by using

convolutional neural network based on ieeg. In Artificial intelligence applications and innova- tions: 15th ifip wg 12.5 international conference, aiai 2019, hersonissos, crete, greece, may 24–26, 2019, proceedings 15 (pp. 331–339).

[107] Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

[108] Talathi, S. S., & Vartak, A. (2015). Improving performance of recurrent neural network with relu nonlinearity. arXiv preprint arXiv:1511.03771 . Tharayil, J. J., Chiang, S., Moss, R., Stern, J. M., Theodore, W. H., & Goldenholz, D. M. (2017).

[109] A big data approach to the development of mixed-effects models for seizure count data. Epilepsia, 58 (5), 835–844.

[110] Tian, X., Deng, Z., Ying, W., Choi, K.-S., Wu, D.,Qin, B., . . . Wang, S. (2019). Deep multi-view feature learning for eeg-based epileptic seizure detection. IEEE Transactions on Neural Sys- tems and Rehabilitation Engineering, 27 (10),

[111] 1962–1972.

[112] Tiwari, A. K., Pachori, R. B., Kanhangad, V., & Panigrahi, B. K. (2016). Automated diagnosis of epilepsy using key-point-based local binary pat- tern of eeg signals. IEEE journal of biomedical and health informatics, 21 (4), 888–896.

[113] Torse, D. A., Desai, V., & Khanai, R. (2017). Eeg signal classification into seizure and non-seizure class using empirical mode decomposition and artificial neural network. IJIR, 3 (1), 2454–1362.

[114] Tsiouris, K. M., Markoula, S., Konitsiotis, S., Koutsouris, D. D., & Fotiadis, D. I. (2018). A robust unsupervised epileptic seizure detection methodology to accelerate large eeg database evaluation. Biomedical Signal Processing and Control , 40 , 275–285.

[115] Türk, Ö., & Özerdem, M. S. (2019). Epilepsy detection by using scalogram based convolutional neural network from eeg signals. Brain sci- ences, 9 (5), 115.

[116] Tzimourta, K. D., Tzallas, A. T., Giannakeas, N., Astrakas, L. G., Tsalikakis, D. G., Angelidis, P., & Tsipouras, M. G. (2019). A robust methodol- ogy for classification of epileptic seizures in eeg signals. Health and Technology , 9 , 135–142.

[117] Usman, S. M., & Hassan, A. (2018). Efficient prediction and classification of epileptic seizures using eeg data based on univariate linear features. J. Comput., 13 (6), 616–621.

[118] Usman, S. M., Usman, M., & Fong, S. (2017a). Epileptic seizures prediction using machine learning methods. Computational and mathe- matical methods in medicine, 2017 .

[119] Usman, S. M., Usman, M., & Fong, S. (2017b). Epileptic seizures prediction using machine learning methods. Computational and mathe- matical methods in medicine, 2017 .

[120] Wang, D., Ren, D., Li, K., Feng, Y., Ma, D., Yan, X., & Wang, G. (2018). Epileptic seizure detection in long-term eeg recordings by us- ing wavelet-based directed transfer function. IEEE Transactions on Biomedical Engineering, 65 (11), 2591–2599.

[121] Wang, J., Li, Y., Wang, Y., & Huang, W. (2018). Multimodal data and machine learning for de- tecting specific biomarkers in pediatric epilepsy patients with generalized tonic-clonic seizures. Frontiers in neurology , 9 , 1038.

[122] Wang, X., Gong, G., Li, N., & Qiu, S. (2019). Detection analysis of epileptic eeg using a novel random forest model combined with grid search optimization. Frontiers in human neuroscience, 13 , 52.

[123] Wu, M., Qin, H., Wan, X., & Du, Y. (2021). Hfo detection in epilepsy: a stacked denoising au- toencoder and sample weight adjusting factors- based method. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29 , 1965–1976.

[124] Yan, B., Wang, Y., Li, Y., Gong, Y., Guan, L., & Yu,S. (2016). An eeg signal classification method based on sparse auto-encoders and support vec- tor machine. In 2016 ieee/cic international con- ference on communications in china (iccc) (pp. 1–6).

[125] Yang, Y., Zhou, M., Niu, Y., Li, C., Cao, R., Wang, B., . . . Xiang, J. (2018). Epileptic seizure pre- diction based on permutation entropy. Fron- tiers in computational neuroscience, 12 , 55.

[126] Yao, X., Cheng, Q., & Zhang, G.-Q. (2019a). Automated classification of seizures against non- seizures: A deep learning approach. arXiv preprint arXiv:1906.02745 .

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

[128] Yuan, Y., Xun, G., Ma, F., Suo, Q., Xue, H., Jia, K., & Zhang, A. (2018). A novel channel-aware at- tention framework for multi-channel eeg seizure detection via multi-view deep learning. In 2018 ieee embs international conference on biomedi- cal & health informatics (bhi) (pp. 206–209).

[129] Yuan, Y., Xun, G., Suo, Q., Jia, K., & Zhang, A. (2019). Wave2vec: Deep representation learn- ing for clinical temporal data. Neurocomputing, 324 , 31–42.

[130] Zhang, T., Chen, W., & Li, M. (2017). Ar based quadratic feature extraction in the vmd domain for the automated seizure detection of eeg us- ing random forest classifier. Biomedical Signal Processing and Control , 31 , 550–559.

[131] Zhang, Y., Zhang, Y., Wang, J., & Zheng, X. (2015). Comparison of classification methods on eeg signals based on wavelet packet decomposition. Neural Computing and Applications, 26 , 1217– 1225.

[132] Zhao, Y. (2017). Addressing bias and subjectivity in machine learning (Unpublished doctoral disser- tation). Tufts University.