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Artificial Intelligence in Epilepsy: A Systemic Review

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Diagnosing and managing epilepsy is difficult for doctors. Surgery can help some patients, but it often takes a long time to get there. This research looks at scientific studies to see if artificial intelligence and machine learning (ML) can be used to improve epilepsy treatment. In-depth research was conducted across PubMed, Google Scholar, Scopus, Wiley, Web of Science, and Microsoft Academia. This search focused on studies exploring the use of ML for diagnosing epilepsy, predicting treatment response, and predicting outcomes of epilepsy surgery. The search was limited to original English-language articles published between 2015 and 2022. This review examined 36 studies on using ML to predict epilepsy. The studies fell into four categories: general diagnosis (27), treatment outcome (3), identifying surgical candidates (2), and predicting surgical results (4). Researchers employed a diverse set of data, including symptoms and brain scans, alongside machine learning algorithms like support vector machines and convolutional neural networks, to construct their models. Some models achieved impressive results with areas under the curve reaching up to 0.99, but most studies were limited by small sample sizes and a lack of independent validation. ML shows potential for epilepsy treatment based on initial studies, but real-world use is restricted due to small sample sizes and the need for more validation from other studies. Large collaborative research efforts and data on long-term outcomes are essential before ML can be widely adopted by doctors and make a positive difference for epilepsy patients. **(2025;15:2-22)**

Key words: Artificial intelligence, Machine learning, Epilepsy, Seizure, EEG, Convolutional neural network

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Introduction

Epilepsy had a combined incidence rate of 61.4 per 100,000 people-years. Incidence was higher in nations with low and middle countries compared to high-income countries, 139.0 vs. 48.9. Studies consistently show that about half of the cases tend to achieve long-term seizure remission. Although epilepsy itself has a low risk of death, we would expect large differences in mortality when comparing incidence and prevalence studies, children and adults, and individuals with idiopathic and symptomatic seizures.[1]

A group of neurons discharge excessively synchronously and continuously during epileptic convulsions. Neuronal excitability is consistently elevated, and this is the only characteristic shared by all epileptic disorders. Numerous conditions, including trauma, oxygen deprivation, malignancies, infections, and metabolic disturbances, can cause abnormal cellular discharges. However, in roughly 50% of epilepsy patients, there are no clear-cut causes identified.[2]

Patients with epilepsy are managed with three significant aims: managing seizures, preventing adverse therapeutic effects, and preserving or recovering quality of life.[3] Antiepileptic medications are the primary approach to epilepsy therapy, with around two-thirds of patients achieving seizure independence.[3] Generally, less than 15% of patients who continue to have seizures following two adequate antiepileptic drugs (AEDs) trials become seizure-free with additional AEDs.[4]

Epilepsy surgery can eliminate seizures in a fraction of drug-resistant people, and it should be explored when two AEDs have failed.[5] Epilepsy surgery, which includes excision or, less typically, disconnection or elimination of epileptic tissue, is the most effective treatment for selected people with drug-resistant epilepsy.[5] Among the nonpharmacological therapies available for individuals with drug-resistant epilepsy, vagus nerve stimulation has been shown to reduce seizures by 50% in half of the patients. However, only 5% achieve seizure-free status.[6] Deep brain stimulation of the anterior nucleus of the thalamus and responsive cortical stimulation, which administers electrical stimulation when abnormal electrocorticographic activity is detected via a closed-loop implanted device, are two additional neuromodulatory treatments that can be used in patients with drug-resistant epilepsy.[3]

Artificial intelligence (AI) is defined as using aspects of human intellect as computer algorithms to help machines solve problems more naturally.[7] The term AI was used by Nair et al.[7] and he defined AI as "the combination of science and engineering to produce intelligent devices for human welfare". Learning, perception, problem-solving, language logic, and reasoning are all possible components of AI. As a result, numerous fields, including philosophy, logic and mathematics, psychology, cognitive science, computer, neurology, etc., have contributed to AI.[7] Machine learning (ML) is a branch of artificial intelligence that studies computer systems that learn via experience without explicit instructions using different programming languages to code and pilot algorithms.[7]

It can take some time to identify an epileptic irregularity in an electroencephalogram (EEG), which necessitates direct examination by highly qualified neurologists and epileptologists. Moreover, experts varying diagnostic encounters could result in varying thoughts regarding the diagnostic outcomes.[8] The creation of an automated computerized system for the diagnosis of epilepsy is therefore of the utmost importance. By extracting entropy characteristics from EEG recordings, several ML techniques have been developed for the diagnosis of epilepsy, including the fuzzy Sugeno classifier, support vector machine (SVM), k-nearest neighbor (KNNC), probabilistic neural network, decision tree (DT), Gaussian mixture model, naive Bayes classifier, and pre-trained deep two-dimensional convolutional neural network (CNN).[8]

AI helps in various aspects of the recognition of newborns' seizures by identifying the type and starting point.[9] AI plays an important role in localizing the seizure points. The results of an artificial intelligence-based technique in a cohort of 82 patients who underwent examination for drug-resistant epilepsy suggest that the time needed to accurately pinpoint the seizure onset zone is between 90 minutes and 2 hours.[10] AI also has an important role in the prediction of surgery outcomes in patients with epilepsy.[11] In patients with atypical mesial temporal lobe epilepsy (MTLE), supervised ML using multimodal data compared to unimodal data accurately using a maximum relevance minimum redundancy feature selection identifier in combination with a least square support vector machine classifier, produced very high surgical outcome prediction accuracy (95%) in predicted postsurgical outcome. This study assesses the peer-reviewed scientific and medical evidence related to the application and impact of AI and ML in the epilepsy field.

Methods and materials

Search strategy

We performed a search on the terms ("Artificial intelligence"[All Fields] OR ("AI"[All Fields] AND "epilepsy"[All Fields] AND "surgery"[All Fields] [All Fields]) OR "AI"[All Fields] AND "seizure disorder"[All Fields] AND "machine learning"[All Fields]) OR "AI"[All Fields]) AND ("surgery"[All Fields] AND "epilepsy"[All Fields] OR "AI"[All Fields] OR "surgery"[All Fields] AND "seizure disorder"[All Fields] OR "Artificial intelligence"[All Fields]) AND ("seizure disorder"[All Fields] AND "machine learning"[All Fields] OR "Artificial intelligence"[All Fields]) AND ("surgery"[All Fields] AND ("epilepsy"[All Fields]). The search was limited to articles published between 2015 and 2022, excluding those from 2017, using all relevant phrases and Medical Subject Heading terms in four medical literature databases, including PubMed, Google Scholar, Scopus, Wiley, Web of Science, and Microsoft Academia. We consider only English-written articles. Furthermore, this systemic review follows the Preferred Reporting Items for Systematic Review approach.

Inclusion and exclusion criteria

Studies that satisfied the subsequent criteria were possibly included. A study on coexisting illnesses associated with seizures and artificial intelligence intervention. Studies that met the eligibility criteria were incorporated, and references were examined to find other relevant research. To make sure that no pertinent papers were overlooked, the references of the included articles were manually searched. Excluded materials included unpublished research, conference presentations, abstracts, non-English articles, articles with no participants stated in the study, and publication without peer review. Following an initial search approach, duplicate articles were eliminated. All records collected from potentially eligible studies were subjected to an independent screening process for titles and abstracts. Subsequently, each full-text record was evaluated independently. Eligibility criteria determined whether the articles should be included or excluded.

Table 1. Describes different AI modalities that can be used for seizure detection and predicting treatment outcome, along with the validation methods and seizure detection methods that are commonly used with each modality

Study	AI type/modalities	Methods used for data or epilepsy detection	Validation methods
Hou et al. (2022)[18]	Graph CNN	Video stereo electroencephalography	Leave-one-subject out
Fergus et al. (2016)[17]	KNNC	Electroencephalogram (EEG)	k-fold cross-validation
Lee et al. (2021)[23]	SVM	EEG	k-fold cross-validation
Yamamoto et al. (2021)[27]		Intracranial EEG	Nested cross-validation
Gleichgerrcht et al. (2018)[24]	CNN	EEG and MRI	5-fold cross-validation
Ito et al. (2021)[14]	CNN	MRI and EEG	5-fold cross-validation
Tjepkema-Cloostermans et al. (2018)[28]	Convolutional and recurrent neural networks	EEG	Validation: used another independent set consisting of 12 EEGs from patients without epilepsy (divided into 11,782 epochs of 2s) and seven EEGs from patients with epilepsy, where all interictal epileptiform discharge were annotated
Zhang et al. (2021)[29]	CNN	EEG and two neurologists	5-fold cross validation
Geng et al. (2021)[30]	Generative adversarial network	EEG and MRI	Leave-one patient, out cross-validation
Abou Jaoude et al. (2020)[12]	CNN	EEG, MRI, and clinical	Nested 5-fold cross-validation
Wissel et al. (2021)[22]	Machine learning not specified	EEG, MRI, and clinical	10-fold cross-validation
Wei et al. (2019)[16]	Long-term recurrent convolutional network	EEG	10-fold cross-validation
da Silva Lourenço et al. (2021)[31]	CNN	EEG	5-fold cross-validation
Zheng et al. (2020)[13]	CNN	Magnetoencephalography	Leave k-subject-out validation, leave-one-subject-out validation test
Munsell et al. (2015)[26]	SVM	Criteria defined by the International League Against Epilepsy	10-fold cross-validation
Kang et al. (2022)[19]	SVM	EEG	Leave-one-out cross-validation
Varatharajah et al. (2018)[10]	CNN	EEG and clinical	Leave-one-out cross-validation
Wissel et al. (2021)[22]	Natural language processing	EEG and clinical	10-fold cross-validation
Zhang et al. (2021)[29]	CNN	EEG and MRI	10-fold cross-validation
Muhammad Usman et al. (2021)[32]	CNN	Intracranial EEG/scalp EEG	k-fold cross validation
Fergus et al. (2016)[17]	KNNC	EEG	Leave-one-subject-out cross-validation, k-fold cross-validation
Yuvaraj et al. (2018)[33]	CNN	EEG	Leave-one-subject-out cross-validation, k-fold cross-validation
Yuan et al. (2019)[34]	CNN	EEG	Leave-one-subject-out cross-validation, k-fold cross-validation
Kural et al. (2022)[35]	CNN	EEG	10-fold cross-validation
Fürbass et al. (2020)[36]	CNN	EEG	10-fold cross-validation
Kong et al. (2022)[37]	SVM	Two neuroradiologists+and two nuclear medicine physicians	Not mentioned clearly
Gleichgerrcht et al. (2021)[15]	CNN	MRI	10-fold cross-validation
Asadi-Pooya et al. (2022)[21]	SVM, random forests, and decision trees	EEG and MRI	10-fold cross-validation
Yamamoto et al.[27]	Random forest	EEG	10-fold cross-validation
Vakharia et al. (2019)[38]	SVM	MRI	Not mentioned clearly

Table 1. continued

Study	AI type/modalities	Methods used for data or epilepsy detection et	Validation methods
Memarian et al. (2015)[11]	SVM	EEG	10-fold cross-validation
Jeong et al. (2021)[39]	CNN	EEG and MRI	Leave-one-out cross-validation
Jiang and He (2022)[40]	CNN	EEG, MRI, and CT	k-fold cross validation
Grattarola et al. (2022)[41]	Graph neural networks	EEG	k-fold cross-validation, leave-one-out cross-validation
Gleichgerrcht et al. (2020)[42]	Random forest	EEG and MRI	k-fold cross validation
Ali et al. (2016)[43]	SVM	EEG	k-fold cross validation

AI, artificial intelligence; CNN, convolutional neural networks; KNNC, k-nearest neighbor; SVM, support vector machines; MRI, magnetic resonance imaging; CT, computed tomography.

Data extraction

We extracted data separately in four Excel sheets, which were then cross-checked against each other and the source material. The data collected included study type, AI type or modalities, methods used/EEG data or epilepsy detection, age group, AI group, control group, brief description on the methods of AI, validation methods, outcomes, statistical analysis used, recommendations, and limitations. In the case of unresolved discordance, the senior author would adjudicate.

Data analysis

A narrative synthesis and graphical representation of data were performed to summarize and present the findings from the included studies. This involved synthesizing the data qualitatively and identifying patterns, similarities, and differences across the studies.

Results

Twenty-seven of the 36 articles were about predicting and diagnosing seizures. Three articles were about predicting the outcome of epilepsy treatment. Two articles were about identifying candidates for epilepsy surgery. Four articles were about predicting the outcome of surgery. The methods and results of these articles are summarized in Table 1, Table 2. EEG was the method used to diagnose epilepsy in 31 studies (81%). The largest sample size was 2,030 participants while the smallest was 20 participants divided equally between the control and AI groups. CNN was the most common AI method used in around 55.6% of the studies. k-fold cross-validation was used in 27 out of 36 studies. The receiver operator curve as a statistical method was used in 75% of the studies. The most shared limitation between studies was a small sample size followed by a single-center study.

In Fig 1, we can see that publications started from 2015 till 2022, with no articles in 2017. We can also see that the highest number of publications was in 2021. Fig. 2 presents a comprehensive overview of the studies conducted on epileptic patients, each color-coded line represents a specific study, offering a visual illustration of each age group. The X-axis denotes the age groups, while the Y-axis illustrates the author's name of each study. From the visual representation, we can see that most of the studies were conducted on adult age groups ranging from 20 to 75 years of age.

The systematic review included a total of 36 studies. The most common study type was observational retrospective studies (21 studies). Other study types included cross-sectional studies (four studies), retrospective cohort studies (six studies), prospective cohort studies (two studies), and other methodological studies (three studies). Fig. 3 shows a bar chart describing the types of studies that were included.

Conclusion

ML in diagnosis of epilepsy

We identified 27 studies that used an ML approach to aid in the diagnosis of epilepsy and a variety of ML algorithms were employed. The majority were trained on EEG data, EEG along with magnetic resonance imaging (MRI), and few on MRI and other images. Eighteen studies used algorithms based on CNN, which are well-suited for image and signal processing tasks, the CNNs can learn complex patterns in data by using a series of convolutional layers (used to detect interictal epileptiform discharges in EEG recordings). The highest performance rate in detecting epileptic discharge was achieved AUC, 0.99; and this was achieved by Abou Jaoude et al.[12] and Zheng et al.,[13] demonstrating the im-

Table 2. Demonstrated a detailed informations about each include studies, included outcome, description of AI methods, limitations ans future work

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Automated video analysis of emotion and dystonia in epileptic seizures	Graph convolutional neural networks (CNN)	Video stereo electroencephalography	19 subject electroencephalogram (EEG) videos	19 subject EEG videos (visual analysis based on international league against epilepsy [ILAE] criteria)	A deep learning multi-stream model with appearance and skeletal key points, face and body information, using graph CNN (neural networks that can learn from graph data, which is data that is structured as a network of nodes and edges: nodes represent the different body parts and the edges represent the relationships between them)	Deep learning multi-stream model (TCN, AGCN)	Leave-one-subject out	Dystonia accuracy: AGCN (body/pose), 0.81; temporal convolutional network (body/pose), 0.73; emotional detection accuracy: AGCN (face), 0.78; TCN (face), 0.80	Receiver operator curve (ROC)	Increasing the size of the dataset, improving the accuracy of the models by (increasing detection features like (altered behavior or motor function)	Small sample size, two features only to detect seizure (dystonia, emotion)
Automatic epileptic seizure detection using scalp EEG and advanced artificial intelligence techniques	Supervised machine learning (ML) using (k-class nearest neighbor classifier (KNNC)	EEG	342 EEG recording (50% seizure and 50% non-seizure)	686 EEG recordings from 22 subject	Non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point, by finding the k most similar EEG records to a new EEG record	KNNC	k-fold cross-validation	Sensitivity of 93%; specificity of 94%; area under the curve, 98%	ROC	Using regression analysis, larger datasets, advanced classification algorithms (advanced artificial neural network architectures)	Small sample size
Can we predict anti-seizure medication response in focal epilepsy using machine learning?	Support vector machines (SVM)	EEG	160 subjects with focal epilepsy	92 healthy	Classifies data by finding the best hyperplane that separates all data points of one class from those of the other class (analyzed the patients' clinical characteristics, conventional diffusion tensor imaging measurements, and structural connectomic profiles to predict anti-seizure medication [ASM] response)	SVM algorithm	k-fold cross-validation	Accuracy, 87.5%; area under curve, 0.882	Chi-squared test, student's *t*-test, and Mann-Whitney *U*-test	Multicenter studies with a large sample size, enrolled patients with a different type of seizure	Short duration to evaluate the ASM response (12 months), 16 patient have remitting-relapsing fluctuating course of seizures, single-center study

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Data-driven electro-physiological feature based on deep learning to detect epileptic seizures	CNN	Intracranial (EEG)	21 subjects (12 women and nine men) with multiple types of refractory epilepsy (CNN group)	21 subjects (12 women and nine men) with multiple types of refractory epilepsy (SVM group)	CNN well-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used EEG image data to detect epilepsy)	CNN (Epi-Net)	Nested cross-validation	Area under the ROC curve (AUC) (Epi-Net, 0.944; SVM, 0.808; p=0.025), sensitivity (Epi-Net, 0.878; SVM, 0.680; p<0.05)	Paired t-tests	Further studies using larger prospective cohorts and multicenter	The single-center study, a high proportion of temporal loop epilepsy patients, Epi-Net might extract unknown features to help identify seizures
Deep learning applied to whole-brain connectome to determine seizure control after epilepsy surgery	CNN	EEG and magnetic resonance imaging (MRI)	50 post temporal lobectomy free seizure and nonfree (neural network)	50 post temporal lobectomy free seizure and non-free (clinical evaluation and follow up 1 year)	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used to predict seizure outcome based on presurgical connectome data from diffusion tensor imaging	Trained neural network using binarized input	5-fold cross-validation	Accuracy (model [PPV; seizure freedom], 88±7; [NPV; seizure refractoriness], 79±8), clinical variables alone, <50%	Chi-squared test	Dense neural network design, prospective data collected from multiple sites	Retrospective study, a small sample of patients
Deep learning-based diagnosis of temporal lobe epilepsy (TLE) associated with hippocampal sclerosis: an MRI study	Convolutional neural network	MRI and EEG	85 with clinically diagnosed mesial temporal lobe epilepsy (MTLE)	56 normal group	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used MRI and EEG images data to diagnose MTLE)	VGG-16 CNN	5-fold cross-validation	Sensitivity, 91.1% (85% and 96%); specificity, 83.5% (75% and 91%). Area under the curve, 0.94	Receiver operating characteristic (ROC), analysis in terms of the AUC	Using MRI at multiple facilities to resolve the problem of domain shift, training it with whole-brain MRI	Learning and testing from different distributions results in "domain shift" causes a drop in classification accuracy of the CNN, cropped images to prioritize just a few brain structures (primarily the temporal lobe)

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Deep learning for detection of focal epileptiform discharges from scalp EEG recordings	Convolutional and recurrent neural networks	EEG	50 EEGs from focal epilepsy subject	50 normal EEGs	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used to detect focal epileptiform discharges from scalp EEG recordings)	346 neural networks (convolutions [1D and 2D] and long short-term memory [LSTM])	Validation: used another independent set consisting of 12 EEGs from patients without epilepsy (divided into 11,782 epochs of 2s) and 7 EEGs from patients with epilepsy, where all interictal epileptiform discharge (IEDs) were annotated	AUC, 0.94; detection of epilepsy (sensitivity, 47.4%; specificity, 98.0%), detection of normal (specificity, 99.9%)	Receiver operating characteristiccurves	Include more patients	Small sample size
Deep learning for interictal epileptiform spike detection from scalp EEG frequency sub-bands	CNN	EEG and two neurologists	93 epileptic 30-minute EEG (84 subjects)	461 non-epileptic 30-minute EEG (84 subjects)	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used to learn patterns in the EEG frequency subbands that are associated with IEDs)	CNN classifiers	5-fold cross validation	p-values <0.05; AUC, 0.988; AUROC, 0.902; sensitivity, 90% (percsion, 0.79; false+rate [FP] rate/minutes, 0.23)	Mean precision and FP rate/minutes for fixed sensitivity value at 90%. Area-related measures such as the area under the curve and area under the precision-recall curve	Build EEG classification system (using CNN) based on datasets collected from multiple centers	Single-center study

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Deep learning for robust detection of interictal epileptiform discharges	Generative adversarial network	EEG and MRI	12 patient EEG recorded divided into two data sets (auxiliary classifier generative adversarial network [AC-GAN] group)	12 patient EEG recorded divided into two data sets (SVM and random forest [RF] classifiers group)	A LSTM network architecture with an AC-GAN, used to learn the temporal features of the EEG signals and the AC-GAN was used to generate synthetic spike samples to improve the model's performance on unseen data from intracranial electroencephalography (iEEG) recordings of epilepsy patients	AC-GAN (IEDnet)	Leave-one patient, out cross-validation	AUROC, 96.4%; compared to AUROC, 95.6% by RF, 77.7% by SVM (p<0.05)	Rreceiver operating characteristic	Include more patient and more data set to be included in training the IEDnet	Small sample size, lack of validation of independent cross-institutional iEEG datasets with annotated IED events
Detection of mesial temporal lobe epileptiform discharges on intracranial electrodes using deep learning	CNN	EEG, MRI, and clinical	13,959 epileptiform discharges from 46 patient	Standard diagnosis of 46 subject	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used to classify iEEG signals into two categories: mesial temporal lope epileptiform discharges and non-epileptiform discharges)	CNN-bipolar	Nested 5-fold cross-validation	AUC, 0.996; sensitivity, 84%	ROC curve	Modifications to the network architecture, and hyper-parameters to potentially improve detector performance in the future	Spike detection by one expert epileptologist, detecting IEDs specifically from the mesial temporal lope
Early identification of epilepsy surgery candidates: a multicenter, machine learning study	ML not specified	EEG, MRI, and clinical	The experimental group consisted of 47 subjects with TLE who did undergo surgery	Subject with epilepsy with no history of surgery	ML algorithms were trained on n-grams extracted from free-text neurology notes, EEG, and MRI reports, to predict which patients were most likely to benefit from epilepsy surgery	n-gram (ML)	10-fold cross-validation	Pediatrics: standard method AUC, 0.76/mL; AUC, 0.93 adults: standard method AUC, 0.85/mL; AUC, 0.95	ROC curve	Develop a generalizable modeling process to connect algorithms between centers	Lack of electronic health record connection between centers, algorithms identified, surgical candidates before entering the presurgical evaluation, limited features from the system identified

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Early prediction of epileptic seizures using a long-term recurrent convolutional network	Long-term recurrent convolutional network (LRCN)	EEG	15 epileptic patients using the LRCN classifier	15 epileptic patients using traditional CNN classifier	LRCN: a spatiotemporal deep learning model for predicting epileptic seizures, by using two-dimensional images from EEG for multichannel fusion	LRCN classifier	10-fold cross-validation	LRCN (accuracy, 93.40%; sensitivity, 91.88%; specificity, 86.13%; CNN (accuracy, 88.17%; sensitivity, 83.33%; specificity, 81.85%)		Increase experimental data from multiple centers	Single-center study, small sample size
Efficient use of clinical EEG data for deep learning in epilepsy	Convolutional neural network	EEG	99 epileptic patients	67 healthy controls	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (used to detect IEDs in EEG recordings)	VGG convolutional neural network	5-fold cross-validation	False positive rate, 0.73; sensitivity, 96%; specificity, 99%	ROC curve	Train a model to eliminate epileptiform variants, eliminated by a specialist	Detect epileptiform variants (i.e., patterns that look like IEDs but are not significant for the diagnosis, such as wicket waves or small sharp spikes) as a spike
EMS-Net: a deep learning method for autodetecting epileptic magnetoencephalography (MEG) spikes	CNN	MEG	20 clinical subject spikes of focal epilepsy (EMS-Net group)	20 clinical subject spikes of focal epilepsy (traditional EMG)	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (multiview epileptic MEG spikes detection)	EMS-Net	Leave k-subject-out validation, leave-one-subject-out validation test	Accuracy, 91.82-99.89%; precision, 91.90-99.45%; sensitivity, 91.61-99.53%; specificity, 91.60-99.96%; area under the curve, 0.9688-0.9998	ROC curve	Include large data of epileptic MEG signals, more types of epilepsy	Small data of epileptic MEG signals, one type of epilepsy included

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Evaluation of ML algorithms for treatment outcome prediction in patients with epilepsy based on structural connectome data	SVM	Criteria defined by the ILAE	70 subjects with refractory TLE	48 normal controls	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (used to predict the surgical treatment outcome of patients with TLE)	SVM classifier	10-fold cross-validation	PPV, 90%; NPV, 70%; and ACC, 80%	*t*-test	Increase sample size	Small sample size
Identifying epilepsy based on ML technique with diffusion kurtosis tensor	SVM	EEG	59 children with hippocampus epilepsy, 70 subjects with sex-matched AI	59 children with hippocampus epilepsy, 70 subjects age-and sex-matched standard methods	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (classify participants as either having epilepsy or not having epilepsy based on the kurtosis tensor features extracted from their DKI images)	SVM classifier	Leave-one-out cross-validation	Accuracy, 95.24%; SEN, 98%; SPS, 80%; AUC, 96%	ROC curve	Larger sample of patients with different types of epilepsy, in combination with other diagnostic tests	A small sample size, patients with hippocampus epilepsy, and no long-term follow-up to assess the clinical utility of the method
Integrating artificial intelligence with real-time intracranial EEG monitoring to automate interictal identification of seizure onset zones (SOZs) in focal epilepsy	CNN	EEG and clinical	20 patients received the new AI-based method in addition to standard care	20 subjects received standard care, which involved clinical evaluation and scalp EEG monitoring	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (identifying SOZs in focal epilepsy patients using interictal EEG data)	CNN-algorithm	Leave-one-out cross-validation	AI detects 18 out of 20, standard methods detect 10 out of 20	ROC curve	Further studies in a larger population of patients with focal epilepsy	Small sample size

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Investigation of bias in an epilepsy ML algorithm trained on physician notes	NLP	EEG and clinical	1,097 notes from 175 epilepsy subjects with respective epilepsy surgery, 268 subjects achieved seizure freedom without surgery AI methods	1,097 notes from 175 epilepsy subjects with respective epilepsy surgery, 268 subjects achieved seizure freedom without surgery, standard methods	The algorithm extracted semantic features from free-text physician notes using unigrams, bigrams, and trigrams, to identify potential surgical candidates for epilepsy	NLP algorithm	10-fold cross-validation	Specificity, 0.91 (95% CI, 0.87 to 0.95); AUC, 0.94 (95% CI, 0.92 to 0.96)	Multiple linear regression, ROC curve	To trained in MRI and EEG data	Trained on free-text notes
A deep learning framework for ^{18}F-FDG PET imaging diagnosis in pediatric patients with TLE	CNN	EEG and MRI	136 with TLE were included in the analysis	24 participants, specifically 6 girls and 18 boys	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (to classify each voxel in the PET images as either epileptic focus or normal tissue)	Pair-of-cube-based siamese CNN	10-fold cross-validation	AUC, 0.92; accuracy, 0.81; sensitivity, 0.80; specificity, 0.89	ROC	Can be used as a complementary tool for epilepsy diagnosis, using larger datasets and incorporating other imaging modalities	Small sample size, single center, the proposed method was not compared with other deep learning methods
A deep learning-based ensemble learning method for epileptic seizure prediction	CNN	Intracranial EEG/scalp EEG	23	20	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (preprocessing of EEG signals images, comprehensive feature extraction, and classification between interictal state and preictal state)	Model agnostic meta learning classifier	k-fold cross validation	Sensitivity, 96.28%; specificity, 95.65%; average anticipation time, 33 minutes	ROC	Exploring different feature extraction techniques and classification algorithms, use of larger datasets, and developing a real-time epileptic seizure prediction	Small database, not suitable for real-time prediction of epileptic seizures

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
A ML system for automated whole-brain seizure detection	KNNC	EEG	171 seizure records	171 non-seizure records	Non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point, by finding the k most similar EEG records to a new EEG record	Algorithm KNNC classifier	Leave-one-subject-out cross-validation, k-fold cross-validation	Sensitivity, 88%; specificity, 88%; AUC, 93%	ROC	Use of a bigger dataset, a region-by-region approach is better at discriminating between seizure and non-seizure events, using real-time signals	Small data, offline data used, considers a limited set of features and ML algorithms
A deep learning scheme for automatic seizure detection from long-term scalp EEG	CNN	EEG	100 subjects with epilepsy	100 without epilepsy	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (automatic seizure detection from long-term scalp EEG)	CNN	Leave-one-subject-out cross-validation, k-fold cross-validation	Sensitivity, 86.29%; average false detection rate, 0.74 houres-1; average detection latency, 2.1 seconds		Integrate with other clinical decision support systems to provide real-time seizure detection and prediction for patients with epilepsy	Small dataset, relatively high latency of 3.75 seconds, no details about the statistical analysis used, proposed system may produce false positive or false negative results
A multi-view deep learning framework for EEG seizure detection	CNN	EEG	50 subjects with epilepsy	50 subjects with epilepsy	CNN: an end-to-end model that can jointly learn multi-view features from both unsupervised multi-channel EEG reconstruction and supervised seizure detection via spectrogram representation	STFT-m Conv A	Leave-one-subject-out cross-validation, k-fold cross-validation	Accuracy, 94.37%; F1-score, 85.34%	ROC and precision-recall, AUC to validate, F1-score and accuracy to evaluate	Can be extended to other biomedical signal processing tasks, such as electrocardiogram and EMG signal analysis, increasing datasets	Single clinical scalp multi-channel EEG epilepsy dataset, small datasets, no comparison between other deep learning models
Accurate identification of EEG recordings with IEDs using a hybrid approach: artificial intelligence supervised by human experts	CNN	EEG	100 subjects with epilepsy	100 without epilepsy	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (to detect IEDs in EEG recordings)	Encevis, spike-net, and persyst	10-fold cross-validation	Sensitivity, 66.67-100.0%; specificity, 3.33-63.33%; accuracy, 51.67-65%	Wilson´s method, McNemar's test, *t*-test, ROC (AUROC) curve	Use of a hybrid approach to achieve high specificity, increase sample size	Small sample size, inclusion criteria are too restrictive and may not be representative of the wide variety of IED morphologies encountered in practice

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
An artificial intelligence-based EEG algorithm for detection of epileptiform EEG discharges: validation against the diagnostic gold standard	CNN	EEG	54 subjects with epilepsy	46 with non-epileptic paroxysmal events	A CNN-based algorithm was used to find the most promising regions of sharp distractors or spikes in a 2s EEG segment, and second to rate these regions with a continuous value between 0 and 1 corresponding to the probability of including a spike	CNN	10-fold cross-validation	Sensitivity, 89%; specificity, 70%; accuracy, 80%	ROC	Evaluate the algorithm in larger populations	Low specificity for unsupervised clinical application needs for human expert confirmation of detected clusters, small sample size
Application of combined multimodal neuroimaging and video-electroencephalography in intractable epilepsy patients for improved outcome prediction	SVM	2 neuroradiologists+2 nuclear medicine physicians	58 subjects (28 males and 30 females)	58 subjects (28 males and 30 females)	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (used data from neuroimaging with v-EEG in predicting post-surgical seizure outcomes in patients with intractable epilepsy)	SVM classifier	Not mentioned clearly	Accuracy, 82%; hazard ratio, 11.4; 95% confidence interval, 2.249 to 57.787; $p=0.003$	Cox proportional hazard analysis	Increase sample size	Retrospective study, small sample size, validation technique was not mentioned clearly/not used
Artificial intelligence for classification of TLE with ROI-level MRI data: a worldwide ENIGMA-epilepsy study	CNN	MRI	1,030 subjects with TLE	1,000 subjects without epilepsy	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (to detect IEDs in EEG recordings)	CNN	10-fold cross-validation	Accuracy, 70% to 90%	Mean and standard deviation	Increased datasets, further research is needed to validate and extend these findings	Single center

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
ML applications to differentiate comorbid functional seizures and epilepsy from pure functional seizures	SVM, random forests (RF), and decision trees (DT)	EEG and MRI	64 subjects with comorbid functional seizures and epilepsy (PNES+E)	65 subjects with pure functional seizures PNES	Supervised learning algorithm that can be used for classification and regression tasks to classify different types of epilepsy	s SVM, RF, and DT	10-fold cross-validation	Accuracy, 82.5%, 81.3%, and 78.7%; respectively	ROC	Further research is needed to validate the findings of the study in a larger, multicenter study	Single-center study, relatively small sample size
ML approaches for imaging-based prognostication of the outcome of surgery for mesial TLE	Random forest	EEG	200 subjects (who underwent surgery for MLTE)	200 subjects (who not undergone surgery for MLTE)	Random forest algorithm is a ML algorithm that uses an ensemble of decision trees to make predictions. It is a popular algorithm for classification and regression tasks, and it is known for its robustness and accuracy (to predict surgical outcome)	Random forest classifier	10-fold cross-validation	Accuracy, 80%	ROC	Larger dataset of patients with MTLE, the model be evaluated in a long-term follow-up study	Small sample size, lack of a long-term follow-up, and training on patients with MTLE

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Multicenter validation of automated trajectories for selective laser amygdalo-hippocampectomy	SVM	MRI	100 subjects with MTLE were scheduled to undergo selective laser amygdalo-hippocampectomy (SLIA). The subjects were randomly assigned to one of two groups: the automated trajectory planning group (n=50) or the manual trajectory planning group (n=50)	100 subjects with MTLE were SLIA. The subjects were randomly assigned to one of two groups: the automated trajectory planning group (n=50) or the manual trajectory planning group (n=50)	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (to classify data or predict outcomes)	EpiNav	Not mentioned clearly	Automated trajectory planning group had a significantly shorter distance from the planned trajectory to the brainstem than the manual trajectory planning group (*p*<0.001). The automated trajectory planning group also had a significantly higher extent of ablation of the mesial temporal structures than the manual trajectory planning group (*p*<0.001)	Wilcoxon signed-rank test	Further studies in larger populations and at multiple centers	Small sample size, single center
Multimodal data and ML for surgery outcome prediction in complicated cases of mesial TLE	SVM	EEG	20 subjects who had undergone standard anteromesial temporal lobectomy (AMTS) for MTLE	Same 20 subjects, but their data was also used to train a ML model to predict the outcome of their surgery	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (used to learn the relationship between the patient's MRI images and the optimal trajectory for SLIA)	SVM classifier	10-fold cross-validation	Predict the surgical outcome accuracy, 95%	ROC	Further studies in larger populations and at multiple centers	Small sample size, retrospective study

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
Prediction of baseline expressive and receptive language function in children with focal epilepsy using diffusion tractography-based deep learning network	CNN	EEG and MRI	110 children with focal epilepsy, divided into two groups: DRE, and drug-responsive epilepsy	50 healthy controls, matched to the epilepsy groups by age, sex, and handedness	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (learn the patterns of connectivity between different brain regions that were associated with language function)	Diffusion tractography-based deep learning network	Leave-one-out cross-validation	Predict baseline expressive and receptive language function accuracy of 78% and 76%, respectively	ROC	Further studies in larger populations and at multiple centers, follow-up	Small sample size, single center, not follow the children over time
Prediction value of epilepsy secondary to inferior cavity hemorrhage (ICH) based on scalp EEG wave pattern in deep learning	CNN	EEG, MRI, and CT	The experimental group consisted of 78 subjects with ICH who developed epilepsy	78 subjects with ICH who did not develop epilepsy	CNNwell-suited for image and signal processing tasks, CNNs can learn complex patterns in data by using a series of convolutional layers (to detect IEDs in EEG recordings)	CNN-classifier	k-fold cross validation	Classify the EEGs accuracy, 94.9%	ROC	Further studies in larger populations and at multiple centers	Small sample size, single center
Seizure localization with attention-based graph neural networks	Graph neural networks (GNNs)	EEG	10 subjects with epilepsy who had not undergone iEEG monitoring	10 subjects with epilepsy who had undergone iEEG	Localizing the SOZ in patients with epilepsy, graph CNN (GCNN) with an attention layer. The GCNN was trained to distinguish between functional networks associated with interictal and ictal phases of epilepsy	GCNN	k-fold cross-validation, leave-one-out cross-validation	GNN localizes the SOZ (AUC, 0.92 in the control group), (AUC, 0.88 in the experimental group)	ROC	Further studies with larger sample sizes, and prospective data collection	Small sample size, retrospective study

Table 2. continued

Study title	AI type/ modalities	Methods used for data or epilepsy detection	AI group	Control group	Brief description of the AI method	AI	Validation methods	Outcome	Statistical analysis used	Recommendations	Limitations
TLE surgical outcomes can be inferred based on structural connectome hubs: a ML study	Random forest	EEG and MRI	47 subjects with TLE who did undergo surgery	47 subjects with TLE who did not undergo surgery	Random forest algorithm is a ML algorithm that uses an ensemble of decision trees to make predictions. It is a popular algorithm for classification and regression tasks, and it is known for its robustness and accuracy	Random forest classifier	k-fold cross validation	The experimental group had significantly lower betweenness centrality in the medial and lateral temporal regions than patients in the control group (AUC, 0.88)	ROC	Further studies with larger sample sizes, and prospective data collection	Small sample size, retrospective study
Using artificial intelligence techniques for epilepsy treatment	SVM	EEG	50 subjects with severe	50 subjects without seizure	SVMs work by finding a hyperplane in the input space that separates the data points into two classes (to predict whether a patient will have a seizure within the next 5 minutes)	SVM classifier	k-fold cross validation	Accuracy, 81.7%	ROC	Further studies with larger sample sizes in multiple centers	Small sample size, single center

AI, artificial intelligence; TCN, temporal convolutional network; AGCN, adaptive graph convolutional neural networks; AUC, area under the curve; PPV, positive predictive value; NPV, negative predictive value; VGG, visual geometry group; 1D, 1 dimensional; 2D, 2 dimensiona; AUROC, area under receiver operator curve; EMS, electromyogram; EMG, electromyogram; DKI, diffusion kurtosis imaging; SEN, sensitivity; SPS, specificity; NLP, natural language processing; CI, confidence interval; 18F-FDG, F-18 fluorodeoxyglucose; PET, positron emission tomography; ROI, region of interest; PNES, psychognic non epileptic seizure; AMTS, anteromesial temporal lobectomy; DRE, drug-responsive epilepsy; MLTE, mesial lobe temporal epilepsy.

portance of assessing external validity in model evaluation. In those studies, the CNN was trained on epileptiform discharges from 46 subjects, which were detected by one epileptologist and were from one type of epilepsy (mesial temporal lope), and on epileptic magnetoencephalography signals from 20 subjects with only one type of epilepsy. Using MRI images as input to train CNN algorithms for the diagnosis of temporal lobe epilepsy was identified in two studies, which revealed a sensitivity of 91.1% and an AUC of 0.94,[14] as well as an accuracy of 70-90%.[15] The long-term recurrent convolutional network (LRCN) classifier, which is a spatiotemporal deep learning approach, utilizing two-dimensional images from EEG for multichannel fusion for the early prediction of epileptic seizures. Compared to the traditional CNN classifier, the LRCN classifier achieved an accuracy of 93.40%, while the CNN achieved an accuracy of 88.17% Wei et al.[16] Moreover, the LRCN classifier's runtime was shorter; however, it was trained on EEG data from 15 epilepsy patients, and this insisted on fusing experimental image data from different centers.

Fergus et al.[17] used EEG data from the CHB-MIT dataset of 22 pa-

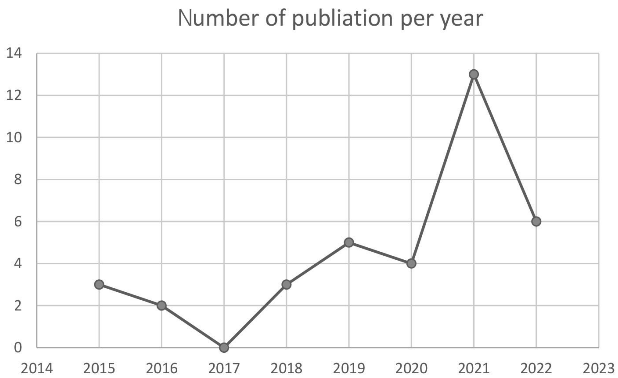

Figure 1. Nnumber of publications per year, we can see that publications started in 2015 and ended in 2022, with no articles in 2017. We can also see that the highest number of publications was in 2021.

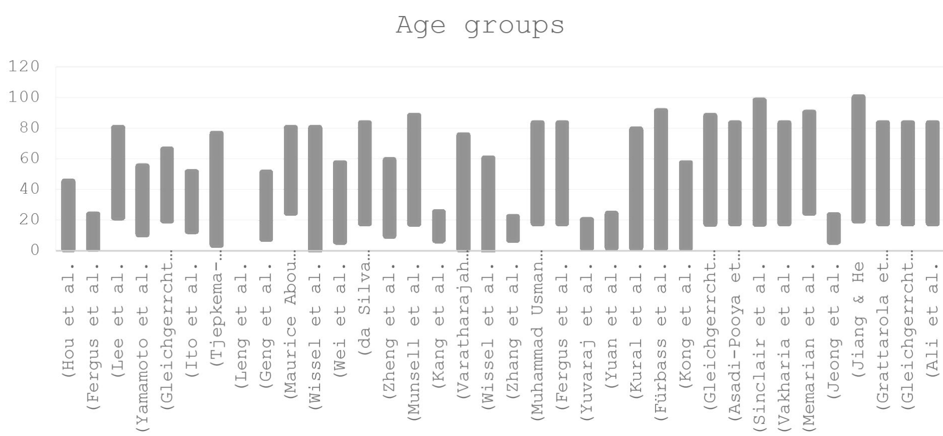

Figure 2. Age distribution across the published articles.

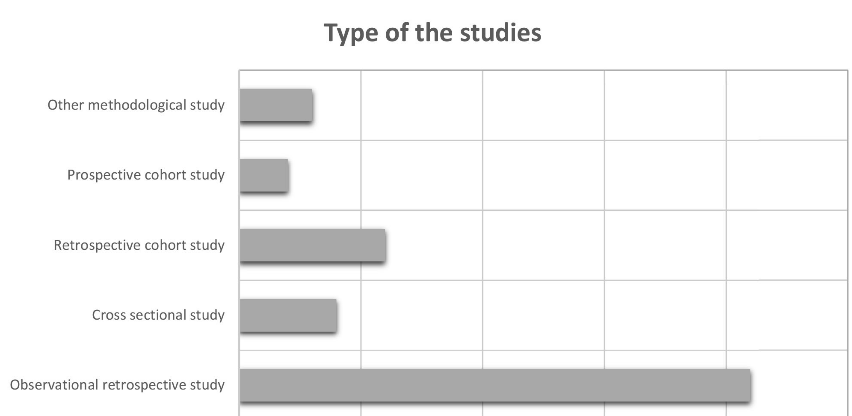

Figure 3. Types of the studies.

tients for seizure detection by a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point by finding the k most similar EEG records to a new EEG record KNNC the models achieved a sensitivity of 93% and AUC, 0.98; similar study was conducted by almost same investigators using KNNC on 342 individuals divided into two groups seizure and no seizure, the models achieved a good result by a sensitivity of 88% and AUC, 0.93. The data fed to the model had already been processed and filtered, so it needs to be trained on real-time EEG and MRI data.[17] Body and face key points detectors were applied on patients with hyperkinetic seizures to detect the presence or absence of emotional features and dystonia,[18] designed a deep learning multi-stream model with appearance and skeletal key points, face and body information, using graph convolutional neural networks (neural networks that can learn from graph data, which is data that is structured as a network of nodes and edge), the model was applied on EEG of 19 patients, it achieved accuracy of 81%, 78% for detection of dystonia and emotion respectively. Detecting key points in the body and face is important not only for diagnosing this type of disease but also for aiding in the diagnosis of many other diseases. However, it needs to be trained on other different features, such as abnormal gait and movement.

Differentiated normal subjects from those with hippocampus epilepsy by using diffusion kurtosis imaging (DKI) with kurtosis tensor[19] fed an SVM algorithm with a kurtosis tensor obtained from DKI of 59 pediatrics hippocampus epilepsy and 70 normal subjects, SVM witch work to find a hyperplane in the input space that separates the data points into two classes by classifying participants as either having epilepsy or not having epilepsy based on the kurtosis tensor features extracted from their DKI images, the classier accuracy in differentiating between normal and the effected subject was 95.2% and AUC, 0.96 compared to studies mentioned by Smolyansky et al.[20] using SVM fed with clinical and EEG data and almost was achieved similar AUC, 0.96 and accuracy of 90%. Functional seizure also has been studied in the AI era. Asadi-Pooya et al.[21] used different types of ML to classify patients with functional seizures with comorbid epilepsy and functional seizures without comorbid epilepsy. SVM, random forests, and DT have been used and achieved an accuracy of 82.5%, 81.3%, and 78.7%; respectively.

Predicting surgical candidates for epilepsy surgery

This study dives into the application of AI and ML algorithms in the context of epilepsy treatment, specifically focusing on their capacity to identify potential surgical candidates. The natural language processing algorithm was trained on free-text physicians' notes. It's encouraging to see that the surgical candidacy scores weren't influenced by patient demographics, suggesting a level of fairness in the algorithm.[22] It is also interesting how factors such as travel from outside the local area, continuation of care past 18, and socioeconomic variables played a role in the scores. This illustrates the significance of unbiased surgical candidacy scores, highlighting their potential as a valuable tool for clinicians. In another study by Wissel et al.,[22] the use of ML algorithms to identify potential candidates for resective epilepsy surgery seems promising. The predictive capabilities for both pediatric and adult surgical patients, especially with AUC scores of 0.93 and 0.95, are quite impressive. It is very important and promising how the early identification of surgical candidates could significantly impact treatment planning and potentially lead to better outcomes. Emphasizing the lead time provided by the ML algorithms-2.0 years for pediatric patients and 1.0 years for adults-could highlight the potential for timely intervention and improved patient care.

Prediction response to antiepileptic medications

Predicting the response to anti-seizure medications (ASMs) is crucial for optimizing epilepsy treatment. AI has shown promise in this area as well. One study, using an SVM classifier, achieved an accuracy of 87.5% in predicting ASM response in focal epilepsy patients.[23] This suggests that AI could guide personalized medication selection, reducing trial-and-error approaches and improving seizure control.

Predicting the outcome of surgery

Several studies have explored the use of AI in predicting the outcome of epilepsy surgery. These studies have employed various AI techniques, ML, SVM, and random forest algorithms. The data used for AI training has included clinical characteristics, EEG recordings, MRI images, and structural connectome data. A study employing a neural network achieved a remarkable success rate of 88% in forecasting seizure remission following surgery for MTLE patients, as evidenced by its positive predictive value of 88% and mean neg ative predictive value of 79%. This significantly surpassed the performance of a traditional classification model relying solely on clinical variables, which yielded an accuracy of less than 50%.[24]

Another study, using SVMs, demonstrated an accuracy of 95% in predicting surgical outcomes in complicated cases of MTLE Asadi-Pooya et al.[21] One more study found that a random forest algorithm could accurately predict seizure freedom after surgery for MTLE patients in 80% of cases (Sinclair et al.[25]). SVMs have shown promise in predicting treatment outcomes in patients with refractory epilepsy; one study using SVMs achieved a positive predictive value of 90%, a negative predictive value of 70%, and an accuracy of 80% in predicting the surgical treatment outcomes of patients with temporal lobe epilepsy.[26] These findings suggest that AI could be a valuable tool in surgical planning and improving patient outcomes.

Challenging and future directions

Despite the promising results, AI in epilepsy management faces challenges, including small sample sizes, retrospective study designs, and the need for further validation in larger, prospective studies. Additionally, integrating AI into clinical practice requires collaboration between clinicians and data scientists to ensure the interpretability and applicability of AI tools.

Future research directions include developing AI-powered tools for real-time seizure prediction and monitoring treatment efficacy. Combining AI with other emerging technologies, such as wearable devices and genomics, holds the potential for further enhancing epilepsy treatment.

Multiple studies conducted on patients with epilepsy using ML algorithms were able to aid in the diagnosis, treatment, and prognosis of epilepsy patients with great accuracy and specificity. Although initial studies show promise for ML in epilepsy, its clinical adoption is hampered by limited sample sizes and a lack of external validation. Large-scale collaborative research and prospective outcome evidence are necessary before ML models can become part of daily clinical workflows and positively impact the lives of epilepsy patients.

Conflicts of Interest

The authors declare no conflict of interest.

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