# The Emerging Role of Artificial Intelligence in Identifying Epileptogenic Zone: A Systematic Literature Review

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*Abstract*—**Identifying epileptogenic zones (EZs) is a crucial step in the pre-surgical evaluation of drug-resistant epilepsy patients. Conventional methods, including EEG/SEEG visual inspection and neurofunctional imaging, often face challenges in accuracy, reproducibility, and subjectivity. The rapid development of artificial intelligence (AI) technologies in signal processing and neuroscience has enabled their growing use in detecting epileptogenic zones. This systematic review aims to explore recent developments in AI applications for localizing epileptogenic zones, focusing on algorithm types, dataset characteristics, and performance outcomes. A comprehensive literature search was conducted in 2025 across databases such as ScienceDirect, Springer Nature, and IEEE Xplore using relevant keyword combinations. The study selection followed PRISMA guidelines, resulting in 34 scientific articles published between 2020 and 2024. Extracted data included AI methods, algorithm types, dataset modalities, and performance metrics (accuracy, AUC, sensitivity, and F1-score). Results showed that deep learning was the most used approach (44%), followed by machine learning (35%), multi-methods (18%), and knowledge-based systems (3%). CNN and ANN were the most commonly applied algorithms, particularly in scalp EEG and SEEG-based studies. Datasets ranged from public sources (Bonn, CHB-MIT) to high-resolution clinical SEEG recordings. Multimodal and hybrid models demonstrated superior performance, with several studies achieving accuracy rates above 98%. This review confirms that AI (especially deep learning with SEEG and multimodal integration) has strong potential to improve the precision, efficiency, and scalability of EZ detection. To facilitate clinical adoption, future research should focus on standardizing data pipelines, validating AI models in real-world settings, and developing explainable, ethically responsible AI systems.**

***Keywords*—*Epileptogenic Zone; Artificial Intelligence; Deep Learning; Machine Learning; Stereo-EEG.***

## I. Introduction

Epilepsy is a neurological disorder characterised by a tendency to experience recurrent seizures, caused by abnormal electrical activity in the brain. One important approach in the management of refractory epilepsy, which is epilepsy that does not respond to pharmacological treatment, is to accurately determine the epileptogenic zone (EZ) through clinical and electrophysiological evaluation [1]-[5]. Accurate identification of the EZ is crucial in determining the success of surgical intervention, which aims to significantly reduce or eliminate seizure frequency. Currently, approximately 30% of epilepsy patients experience refractory conditions, where the quality of life of patients heavily depends on the accuracy of the medical or surgical interventions applied [6]-[8]. Data from the World Health Organisation (WHO) indicate that over 50 million people worldwide have epilepsy, with approximately 30-40% of them experiencing refractory epilepsy [9]-[11]. This number is projected to continue rising, given the various diagnostic and therapeutic challenges still faced in the field of epilepsy neurology [12], [13].

Conventional diagnostic techniques such as electroencephalography (EEG), magnetic resonance imaging (MRI), positron emission tomography (PET), and single photon emission computed tomography (SPECT) have been widely used in clinical practice to identify EZ. However, these methods have limitations in terms of inconsistent sensitivity and specificity among patients. Additionally, interpreting the results of these techniques is often complex and highly dependent on the clinician's experience. These challenges lead to variations in diagnostic outcomes and may result in suboptimal identification of EZ. These challenges underscore the need for more advanced and accurate diagnostic approaches. The development of alternative methods based on cutting-edge technology, particularly AI, is expected to address the limitations of conventional diagnostic methods [14]-[17].

Artificial intelligence (AI) offers potential and transformative solutions to address various challenges in the field of neurology, particularly in identifying epileptogenic zones (EZ) in patients with drug-resistant epilepsy. AI is broadly defined as a branch of computer science focused on developing algorithms and systems capable of mimicking human intelligent behaviour, including the ability to understand, learn, and make data-driven decisions. In the medical context, AI has advantages in handling large and complex datasets, such as electroencephalography (EEG), magnetoencephalography (MEG), and various neuroimaging modalities like MRI and PET scans [18]–[21]. Through processes such as prediction, classification, segmentation, and feature extraction, AI algorithms can improve diagnostic accuracy, accelerate clinical decision-making processes, and reduce reliance on subjective interpretations by medical professionals [22]–[25].

A range of artificial intelligence (AI) techniques has been applied in epilepsy research, including machine learning (ML), deep learning (DL), expert systems (ES), and integrated multimodal frameworks that combine multiple data types and analytical methods [26]–[29]. ML and DL, in particular, have shown strong capabilities in detecting intricate patterns within electrophysiological recordings and neuroimaging data, patterns that are often challenging to discern through manual analysis. Techniques such as ANN, SVM, Decision Trees, CNN, and ensemble models like random forest and gradient boosting have achieved notable accuracy in localizing epileptic foci [30]–[35]. These strengths highlight the potential of AI to enhance and streamline the pre-surgical assessment of epilepsy, offering more precise and efficient diagnostic support.

Furthermore, AI is not only used for diagnosis but also plays a growing role in guiding therapeutic decisions, such as identifying suitable candidates for surgical resection, neuromodulation, or laser ablation. Accurate identification of EZs can lower the failure rate of invasive interventions and significantly enhance patients' quality of life. However, despite its promise, the application of AI in this domain still faces several challenges, including variability in data quality, limited interpretability, and inconsistent validation across clinical settings. Given these gaps, it is essential to conduct a systematic review of existing AI methods used for EZ localization. This includes analyzing the types of algorithms implemented, the nature and sources of datasets, and reported performance metrics. A clearer understanding of these components will help formulate strategic recommendations for real-world clinical integration and guide future development of more robust, interpretable, and clinically reliable AI technologies for managing refractory epilepsy.

## II. METHODOLOGY

### A. Research Question

This study aims to identify the application of artificial intelligence (AI) in determining the epileptogenic zone (EZ). We reviewed various scientific articles that have reported AI methods and techniques specifically applied to identify the EZ in epilepsy patients. The population in this study consists of individuals with epilepsy. The intervention of focus is the use of various AI algorithms and methods to support the accurate identification of EZ. In this study, no comparative analysis was conducted, as the review's focus was on a comprehensive exploration of available AI methods and algorithms. The main goal of this review is to deliver an in-depth overview of the AI methodologies applied, including machine learning (ML), deep learning (DL), and multimodal strategies, while assessing their performance in localizing the epileptogenic zone (EZ).

### B. Search Strategy

This systematic review was conducted in 2025, employing a structured literature search across major scientific databases such as ScienceDirect, Springer Nature, and Taylor & Francis. The search strategy utilized combinations of relevant keywords derived from MeSH, as outlined in Table I. The entire process followed the PRISMA guidelines to ensure methodological rigor. To minimize selection bias, two independent reviewers performed the screening and selection of articles. In instances where discrepancies arose between the reviewers, a third independent evaluator was consulted to reach a consensus. The inclusion criteria were limited to English-language publications from the past five years (2020–2024).

TABLE I. SEARCH STRATEGY OF THE RESEARCH

| **Search strategy** | |
|---|---|
| Database | ScienceDirect, Springer Nature, and Taylor & Francis (2020-2024) |
| Limits | Inclusion criteria included English-language sources and studies in human populations. |
| Data | January 1, 2020 to December 31, 2024 |
| Search Query | ("Epileptogenic Zone") AND ("Detection" OR "Diagnosis") AND ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") |

### C. Inclusion and Exclusion Criteria

The inclusion criteria for this review include original research articles, experimental studies, and meta-analysis reports discussing the application of artificial intelligence (AI) for the identification of epileptogenic zones (EZ) in epilepsy patients. Only articles reporting evaluations of AI model performance, such as accuracy, sensitivity, specificity, precision, F1 score, or area under the curve (AUC), were included in the analysis. Selected studies must have used AI-based methods, including machine learning, deep learning, or other computational techniques applied for the classification or prediction of EZ locations. Exclusion criteria included articles not written in English, articles that did not provide full-text access, and non-original research publications such as narrative reviews, comments, opinions, letters to the editor, brief communications, and conference proceedings abstracts. Additionally, studies not conducted on human subjects or those that did not present quantitative data on AI model performance were also excluded from this review.

### D. Selection Process

The article selection process in this review followed the PRISMA guidelines as shown in Fig. 1. After screening the titles, abstracts, and full texts, 34 articles were finally selected for further analysis. The entire selection and quality evaluation process was conducted independently by two researchers to ensure objectivity and avoid selection bias. If there were differences of opinion between the two researchers, the final decision was made through discussion with a third independent reviewer. For data analysis purposes, each article that met the inclusion criteria was extracted using a standard form covering seven main categories, namely (1) author name, (2) year of publication, (3) artificial intelligence (AI) method applied, (4) type of algorithm used, (5) type of data used to identify epileptogenic zones, including EEG data, MRI images, PET, or multimodal combinations, (6) characteristics of the study population or sample, and (7) best model performance based on evaluation metrics such as accuracy, sensitivity, specificity, F1 score, and AUC. All successfully extracted data were systematically analysed and synthesised, then presented in the form of tables and graphical visualisations to illustrate the main findings of this review.

## III. RESULTS

Based on the study search terms, 34 articles were reviewed in detail and presented in Table II. Meanwhile, Fig. 2 shows the distribution of articles published in the 2020–2024 period, related to the topic of epileptogenic zone identification. Based on the data, it is evident that 2021 and 2024 were the years with the highest number of publications, each contributing 26%, or approximately 9 articles per year. Meanwhile, 2022 and 2023 each contributed 18% (6 articles per year), indicating a relatively stable publication trend but not as intense as the two peak years prior. The year 2020 had the fewest publications, at only 12%, or equivalent to 4 articles, likely influenced by the initial impact of the COVID-19 pandemic on clinical research activities. This trend indicates an increasing interest and need for approaches to identify epileptogenic zones in clinical and research contexts, particularly in recent years (2021 and 2024), which may be linked to the development of technologies such as SEEG, HFO analysis, and the application of AI in neurodiagnostics.

Fig. 3 shows the distribution of artificial intelligence (AI) methods used in studies identifying epileptogenic zones. Of the total 34 articles described, Deep Learning was the most dominant method, used in 44% of publications (15 articles). This indicates that Deep Learning is increasingly relied upon due to its ability to extract complex patterns from brain signals such as EEG and SEEG. Additionally, classical Machine Learning was used in 35% of studies (12 articles), indicating that this approach remains relevant, particularly for smaller datasets or those based on manual features. Multi Methods (combining two or more AI techniques) were used in 18% of publications (6 articles), reflecting an integrative trend in epileptogenic research. Meanwhile, Knowledge-Based AI, such as expert systems or inference based on brain network theory, was only used in 1 article (3%), indicating that symbolic approaches are increasingly rare in modern AI epileptology. These findings reflect a shift in research from conventional approaches toward more automated, high-precision, and measurable deep learning to support clinical decision-making in identifying epileptogenic zones.

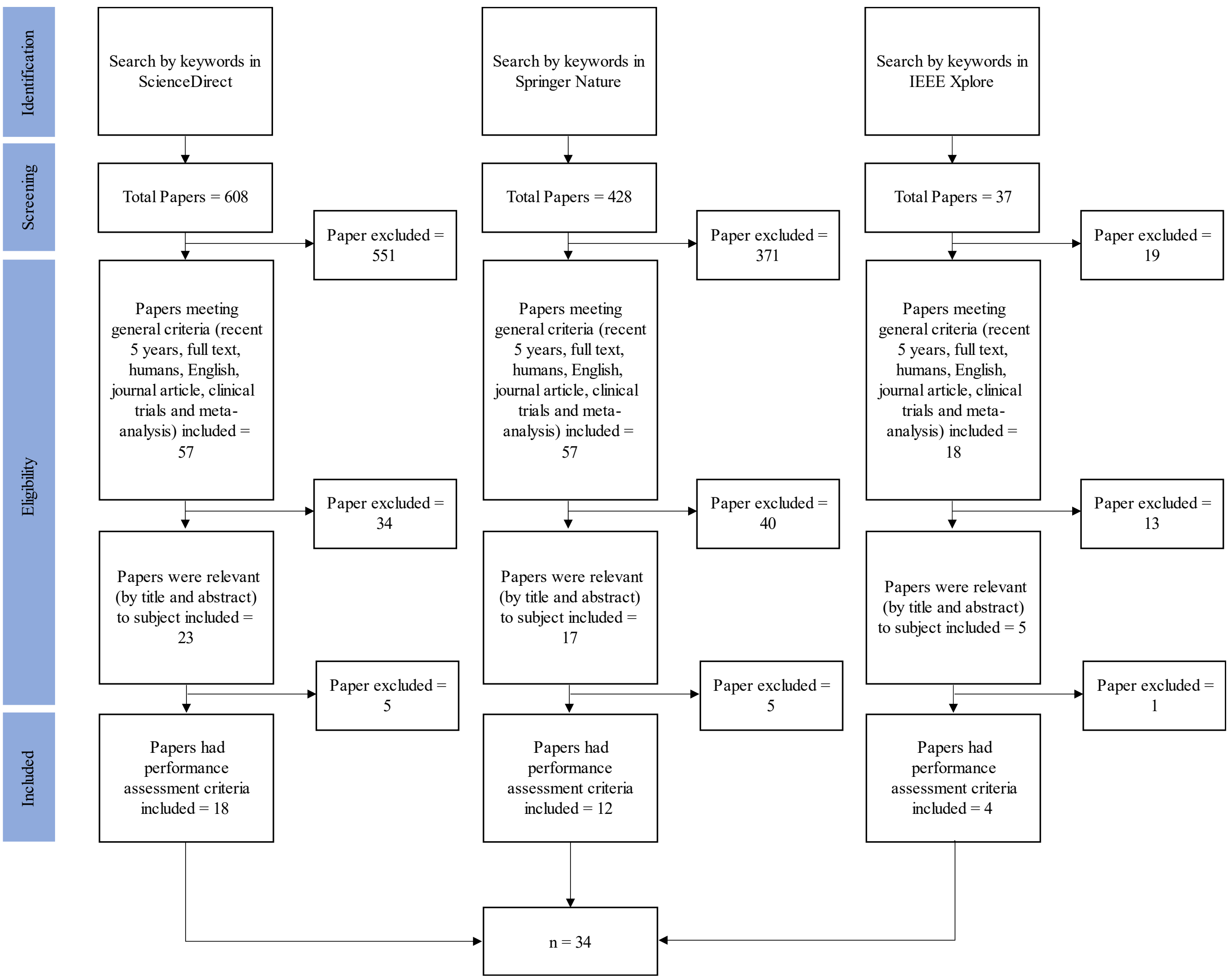


Fig. 1. PRISMA process for data collection

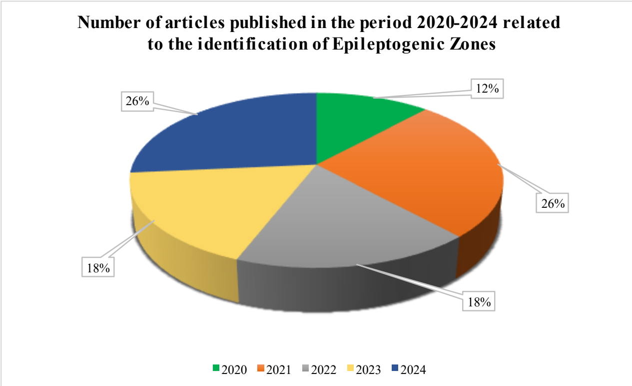


Fig. 2. Number of articles published in the period 2020-2024 related to the identification of Epileptogenic Zones

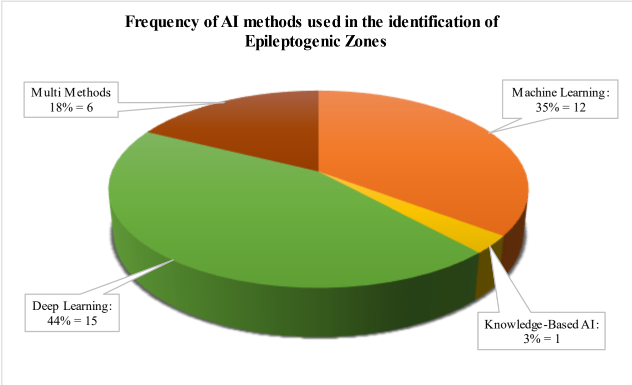


Fig. 3. Frequency of AI methods used in the identification of Epileptogenic Zones

TABLE II. SELECTED PAPERS ACCORDING TO THE SPECIFIED CRITERIA

| Authors & Year | AI methods | Algorithm used | Dataset | Characteristics of dataset | The best algorithm | Performance |
|---|---|---|---|---|---|---|
| Roger *et al.*, 2020 [36] | Machine Learning | Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost) | The "original" dataset of 57 unilateral mTLE patients and the "reduced and working" dataset of 46 patients | Drug-resistant patients; pre-surgical evaluation (NPE, EEG, MRI); divided into L-mTLE and R-mTLE | XGBoost | AUROC: 90.2%, Accuracy: 77.70% |
| Hashemi *et al.*, 2020 [37] | Knowledge-Based AI | No-U-Turn Sampler (NUTS), Automatic Differentiation Variational Inference (ADVI) | Simulated synthetic data using The Virtual Brain (TVB); patient-specific MRI and DTI data; SEEG data | Personalized, structural connectome-based data derived from non-invasive imaging (MRI, DTI); used to simulate brain seizure propagation | No-U-Turn Sampler (NUTS) | Accuracy: 100% |
| Guo *et al.*, 2020 [38] | Deep Learning | Attention Neural Network (AttNN) | MEG data from 20 epilepsy patients (50 ripples and 50 fast ripples) | MEG 306-channel, 4000 Hz frequency sampling, Manual labeling by experts | Attention Neural Network (AttNN) | Accuracy: 89.3%, AUC: 0.88, Sensitivity: 84.2%, Specificity: 92.3%, F1 Score: 88.7% |
| Zheng *et al.*, 2020 [39] | Deep Learning | EMS-Net (CNN multiview: 1D + 2D + feature fusion) | MEG data from 20 epilepsy patients recorded at Sanbo Hospital, Beijing | 306-channel, 1000 Hz, 300 ms epochs, spike & non-spike, data augmentasi | EMS-Net | Accuracy: 99.48%, Precision: 99.45%, Sensitivity: 99.53%, Specificity: 99.43%, F1 Score: 99.48%, AUC: 0.9998 |
| Nkengfack *et al.*, 2021 [40] | Machine Learning | Simple multilayer perceptron neural network (sMLPNN), least-square support vector machine (LS-SVM) | Bonn University EEG dataset | 500 EEG segments, 5 subsets (A–E), 100 segments per set, 173.61 Hz sampling, 0.5–40 Hz filtered | GDA + sMLPNN | Accuracy: 100%, Sensitivity: 100%, Specificity: 100%, Precision: 100%, AUC: 1 |
| Xia *et al.*, 2021 [41] | Deep Learning | Convolutional neural network (CNN) | Bern-Barcelona EEG Database (3750 pairs of Focal and Non-Focal signals from 5 epilepsy patients) | intracranial EEG, 512 Hz, 20 seconds, 10240 data points per signal; signals from epileptogenic & non-epileptogenic zones; Data has been normalized & de-noise | CNN-based STFT+CWT feature combination | Accuracy: 91.3% |
| Aliyu *et al.*, 2021 [42] | Deep Learning | Long short-term memory (LSTM) | EEG Bonn University | 5 EEG subsets, 100 segments each, duration 23.6 seconds, sampling rate 173.61 Hz | LSTM with optimal wavelet feature (CCP) | Accuracy: 99%, Precision: 95%, Recall: 100%, F1-score: 98% |

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|---|---|---|---|---|---|---|
| García *et al.*, 2021 [43] | Deep Learning | 3D convolutional neural network (3D CNN) | EPISURG (Postoperative MRI dataset of refractory epilepsy brain from various institutions, total of 430 postoperative subjects) | 3D MRI T1-weighted (T1w), resolusi isotropik 1 mm, 193 × 229 × 193 voxel | 3D CNN | Dice Score (DSC): 89.2 |
| Nkengfack *et al.*, 2021 [44] | Machine Learning | Least Squares Support Vector Machine (LS-SVM) dengan RBF kernel | Publicly available EEG dataset from the University of Bonn | 5 sets (A–E), each of 100 EEG data of 23.6 seconds; Condition: healthy (with eyes open/closed), epileptic patients without seizures, and epileptic patients during seizures | LS-SVM berbasis Jacobi Polynomial Transform (JPT) | Accuracy: 88.75% - 100%, AUC: 0.983 - 1.0 |
| Torabi *et al.*, 2021 [45] | Machine Learning | Multilayer Perceptron Neural Network (MLPNN), Support Vector Machine (Linear SVM dan RBF SVM) | Bonn University EEG Dataset | Epilepsy EEG, 5 sets (A-E), 100 segments each, duration 23.6 seconds, sampling frequency 173.61 Hz | Multilayer Perceptron Neural Network (MLPNN) | Accuracy ABCD/E: 99.91%, Accuracy AB/CD/E: 98.19%, Accuracy A/D/E: 98.5%, Accuracy A/E: 100%, Accuracy D/E: 99.84% |
| Saeedinia *et al.*, 2021 [46] | Deep Learning | Spiking Neural Network | EEG and MRI of epilepsy patients (two subjects) | Multi-channel EEG (15 channels), personal MRI, data duration ≥24 hours (patient 1) and 40 minutes (patient 2) | Spiking Neural Network | Mean Square Error (MSE): $0.197 \times 10^{-6}$ |
| Guo *et al.*, 2021 [47] | Machine Learning | Hypergraph Learning | SEEG data from 19 refractory focal epilepsy patients (total 4000 segment signals: 1640 HFO and 2360 baseline controls) | SEEG 256-channel, sampling rate 2000 Hz, segmentation per 1000 ms, includes interictal and ictal data, gold standard determined by clinical epileptologists | Hypergraph SEEG HFOs (HSO) detector | Accuracy: 90.7%, Sensitivity: 80.9%, Specificity: 96.9% |
| Vattikonda *et al.*, 2021 [48] | Machine Learning | Epileptor model (dynamical system) + Hierarchical Bayesian inference | Retrospective SEEG data from 25 focal epilepsy patients; includes synthetic and empirical patient data | SEEG data, individualized structural connectome, synthetic seizure generation, real patient outcome labels (Engel I–IV) | Epileptor-based probabilistic hierarchical model using Bayesian inference | Precision: 80%, Recall: 85% |
| Wang *et al.*, 2022 [49] | Machine Learning | Random Forest, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) | Temple University Hospital EEG Seizure Corpus (TUSZ) | EEG of patients with epilepsy, multi-channel scalp EEG, sampling rate (250–512 Hz) | Random Forest | Accuracy: 97.8%, AUC: 99.7%, Sensitivity (Recall/TPR): 83.0%, Specificity (TNR): 99.6% |
| Liu *et al.*, 2022 [50] | Deep Learning | Deep convolutional neural network using NAS and EEGNet | EEG dataset (Sets A–E), total 500 segmen | Each set consisted of 100 fixed-duration EEG segments, from healthy and epileptic subjects | Neural Architecture Search (NAS) | Accuracy: 76.61%, F1-score: 76.49%, Kappa coefficient: 70.76% |
| Sunaryono *et al.*, 2022 [51] | Machine Learning | Gradient Boosting Machines (GBM) fusion + Genetic Algorithm (GA) for feature selection | EEG dataset from University of Bonn (Set A–E, total 500 trials) | 3-class EEG (normal, interictal, ictal); 4096 samples per trial; sampling rate 173.61 Hz | Gradient boosting machines (GBM) fusion + genetic algorithm (GA) for feature selection | Accuracy = 100% |
| Miao *et al.*, 2022 [52] | Multi methods | SVM (Linear & RBF Kernel), LightGBM, 2-D convolutional | Interictal ECoG from 7 patients with refractory epilepsy (Focal Cortical Dysplasia) | 1 hour of interactive ECoG recording, 2000 Hz sampling rate, adult and pediatric | SVM with RBF Kernel | AUC: 0.915 |

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|---|---|---|---|---|---|---|
| | | neural network (CNN) | | patients, number of channels 36–76 | | |
| Mohammed *et al.*, 2022 [53] | Machine Learning | Artificial Neural Networks (ANNs), Multi-Layer Perceptron (MLP) | Scalp EEG recordings of 21 adult patients with focal epilepsy (data from Baptist Hospital of Miami, 19 electrodes, 10-20 system) | 3-second EEG segments (IED vs NIED), band-pass filtered 0.5–70 Hz, sampling rates of 200/256/512 Hz, PCA+ICA preprocessing, manually annotated IEDs | FC-NNPruned (a pruned neural network using features from 4 sub-bands) | ROC-AUC: 0.8807 |
| Wang *et al.*, 2022 [54] | Deep Learning | Multiscale convolutional neural network (MSCNN), Bidirectional LSTM (BiLSTM-AM), Grad-CAM++ | Public multicenter SEEG dataset (MAYO, FNUSA) and Private clinical SEEG dataset | Multicenter SEEG data from epilepsy patients, including pathological, physiological, and artifact signals; high-frequency SEEG data; cross-subject variation. | SEEG-Net (MSCNN + BiLSTM-AM + FDG-loss) | Accuracy: 93.85%, TPR: 87.61%, TNR: 95.09%, FPR: 6.24% |
| Mohsen *et al.*, 2023 [55] | Multi Methods | LSTM, SVM (with Fast Walsh-Hadamard Transform) | EEG dari University of Bonn | 500 EEG signals, single-channel, duration 23.6 s, sampling 173.61 Hz; only class C&D (non-seizure and seizure) is used | LSTM | Accuracy: 99.32%, Precision: 99.29%, Recall: 99.45%, F1-score: 99.52% |
| Sun *et al.*, 2023 [56] | Deep Learning | Deep Source Imaging Framework (PDeepSIF) | MEG data from 29 focal epilepsy patients | MEG interictal spike; head model from MRI; validation with iEEG/surgical results | PDeepSIF | Sensitivity: 77%, Specificity: 99% |
| Dou *et al.*, 2023 [57] | Deep Learning | Autoencoder + Adaptive Graph Convolutional Network (GCN) | SEEG (Stereoelectroencephalography) & CCEP (Cortico-Cortical Evoked Potentials) | Time-frequency SEEG data from 18 patients, 3 behavioral states (awake, sleep, seizure) | Adaptive Graph Convolutional Network | Accuracy: 83.38%, F1-score: 76.24% |
| Li *et al.*, 2023 [58] | Machine Learning | RUSBoost (Random Under Sampling + Boosting) | HFO data from 26 epilepsy patients (2 hospitals: Tiantan & Fengtai Hospital, Beijing) | 113,457 HFO (training: 89,844 pathoHFO + 23,613 phyHFO), testing: 12,695 pathoHFO + 5,599 phyHFO | RUSBoost | AUC: 0.90, Accuracy: 0.863, Sensitivity: 0.903, Specificity: 0.773, F1-score: 0.901 |
| Ilias *et al.*, 2023 [59] | Deep Learning | EfficientNet-B7, CNN, Gated Multimodal Unit | EEG database dari University of Bonn | Single-channel EEG, consisting of healthy, interictal, and ictal classes, is processed with STFT to produce 3-channel images (spectrogram, delta, etc.) | Multimodal CNN + EfficientNet-B7 + Gated Multimodal Unit | Accuracy: 95.33% - 98.75% |
| Weiss *et al.*, 2023 [60] | Multi methods | Graph metrics (FR rate-distance radius, mutual information) | iEEG from 23 epilepsy patients (UCLA & Thomas Jefferson Univ.) | SEEG, non-REM sleep, fast ripples >350 Hz, 2 kHz sampling | FR rate-distance radius | AUC: 0.75, Accuracy: 78.3%, Sensitivity: 100%, Specificity: 61.5%, NPV: 100% |
| Kim *et al.*, 2024 [61] | Multi Methods | Convolutional neural network, random forest, SVM, XGBoost | EEG from 150 patients (50 NCSE, 50 ME, 50 BI), 19 channel, 20 seconds epoch | EEG 32-channel: 19 channel, 200 Hz, bandpass 0.1–70 Hz, 20s optimal epoch | CNN uses FC adjacency matrices | AUC = 0.905 |
| Murugan *et al.*, 2024 [62] | Deep Learning | Convolutional Neural Network (CNN) | The public EEG dataset, consisting of 500 EEG recordings, each 23.6 seconds long, is divided into 23 segments per recording | EEG 1D signals (178 data points/segments), consisting of seizure and non-seizure classes, recorded from various individuals | Convolutional Neural Network (CNN) | Accuracy: 98.08%, Precision: 0.99, Recall (Sensitivity): 0.91, F1 Score: 0.95 |

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|---|---|---|---|---|---|---|
| Stergiadis *et al.*, 2024 [63] | Machine Learning | Logistic Regression | iEEG recordings from 20 MRE patients (sumber: CRCNS.org) | Intracranial EEG (subdural & depth electrodes), interictal sleep recordings, sampling window per night, freely available, anonymized | Logistic Regression | Accuracy: 82.5% (ripple), 75.4% (fast ripple) |
| Payman *et al.*, 2024 [64] | Deep Learning | Convolutional Neural Network (CNN) | 3,560 annotated skull base images (from 34 dry human skulls) | Multi-angle, high-resolution images of 10 types of foramina; annotated with bounding boxes | Convolutional Neural Network (CNN) | Precision: 90.4%, Recall: 89.6% |
| Huang *et al.*, 2024 [65] | Deep Learning | Temporal Convolutional Neural Network dengan Self-Attention Layer (TCN-SA) | Own EEG dataset (pediatric patients with epilepsy), Bonn EEG dataset | multi-channel EEG (own dataset, 500 Hz sampling rate, 2-second segment); single-channel (Bonn, 173.61 Hz, 23.6 sec segment) | TCN-SA | Self-dataset accuracy: 95.50%; Sensitivity: 91.22%; Specificity: 98.72%; AUC: 0.95 and Bonn A-E dataset accuracy: 97.37%; Sensitivity: 94.88%; Specificity: 99.91%; F1 Score: 97.30% |
| Kantipudi *et al.*, 2024 [66] | Multi Methods | GBSO-TAENN (Gradient-based Spider Optimization + Temporal Aware Ensemble Neural Network) | Bonn EEG dataset & CHB-MIT EEG dataset | EEG signals classified as normal or seizure, multichannel, benchmark sets | GBSO-TAENN | Accuracy: 99.1%, Specificity: 99.5%, Sensitivity: 99% |
| Mora *et al.*, 2024 [67] | Multi Methods | Logistic Regression, SVM (linear, RBF, polynomial), NLP | 536 seizure descriptions from 122 patients (retrospective from Italian epilepsy surgery center) | Text-based seizure semiology descriptions in Italian, labeled by EZ side & region; highly curated clinical EMR | SVM with RBF kernel using TF-IDF representation | F1-score: 85.6% (temporal vs extra-temporal classification) |
| Mercier *et al.*, 2024 [68] | Machine Learning | Artificial Neural Network (ANN), Logistic Regression (LR) | 123 paediatric patients, EEG data (wakefulness & sleep), 246 1-minute interictal scalp EEG segments | Clean EEGs without artefacts or epileptiform discharges, using standard 10–20 montage, sampling rate 256/512 Hz | ANN | Accuracy: 64.8%, Sensitivity: 76.7%, Specificity: 43.0% |
| Krishnamoorthy *et al.*, 2024 [69] | Deep Learning | Optimized Deep Convolutional Neural Network (DCNN) | Bonn EEG dataset, New Delhi EEG dataset | Bonn EEG dataset is categorized into 3 (Normal, Interictal, Seizure); and New Delhi dataset is categorized into 3 classes (ictal, preictal, interictal). | DCNN + Genetic Algorithm (GA) + Cross-Validation (CV) | Accuracy: 93.2%, Precision: 90%, Recall/Sensitivity: 90%, Specificity: 93%, F1-score: 0.90, AUC: 0.939 |

Based on a systematic review of 34 scientific articles, various artificial intelligence (AI) approaches have been used to detect epileptogenic zones (EZs) with varying performance and characteristics. These methods include deep learning, conventional machine learning, multi-method (hybrid) approaches, and knowledge-based AI systems. Each has its own advantages in specific aspects, such as accuracy, scalability, interpretability, and robustness to data variability. However, each approach also faces limitations, ranging from data requirements, modelling complexity, to clinical validity. Table III summarises the types of AI methods used in studies identifying epileptogenic zones, along with the main advantages and limitations of each approach.

Fig. 4 shows the frequency of AI algorithm use in identifying epileptogenic zones based on all articles reviewed (34 articles). The two most dominant algorithms are convolutional neural network (CNN) and artificial neural network (ANN), each used in 26% of studies (9 articles). This reflects researchers' tendency to rely on neural network models, both in the form of convolutional networks for extracting spatial-temporal features from brain signals and classical feedforward networks for classification. Furthermore, Support Vector Machine (SVM) and ensemble algorithms (such as XGBoost or GBM) were used in 9% of studies (3 articles) each, indicating that conventional machine learning approaches remain relevant, especially in situations with limited data. Long short-term memory (LSTM), which focuses on temporal dynamics, was used in 6% (2 articles) of studies, while random forest and logistic regression were each used in only 3% of studies (1 article). Another 18% of studies (6 articles) used other methods such as NUTS, NAS, or adaptive graph algorithms that were not explicitly categorised. This distribution reflects the trend that while neural network algorithms dominate, combination or alternative approaches remain necessary to address the complexity of SEEG/EEG data in the context of epilepsy.

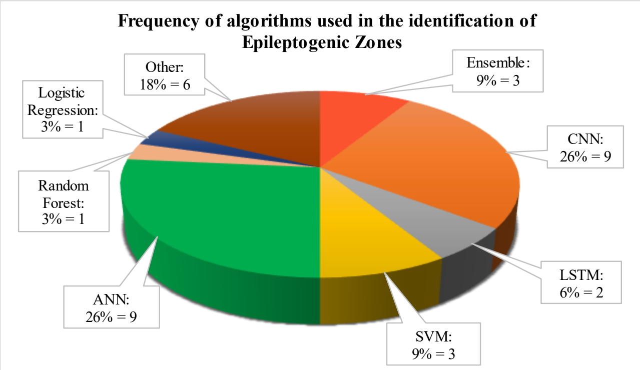


Fig. 4. Frequency of algorithms used in the identification of Epileptogenic Zones

In addition, Fig. 5 presents the frequency distribution of the use of various types of datasets in studies identifying epileptogenic zones, based on an analysis of a number of scientific articles. It can be seen that scalp EEG is the most widely used dataset, accounting for 53% of all studies. This reflects that scalp EEG remains the primary and most accessible method in both research and clinical practice, despite its limitations in spatial resolution. On the other hand, SEEG (Stereo-EEG), an invasive technique with high spatial and temporal resolution, was used in 12% of studies, followed by MRI (11%) and MEG (9%), both of which play a crucial role in non-invasive mapping of brain anatomy and function. iEEG (Intracranial EEG) datasets were also used in 6% of studies, indicating a trend toward increased use of data from subdural or intracortical electrodes. Meanwhile, high-frequency oscillation (HFO), Electrocorticography (ECoG), and clinical descriptions were each used in only 3% of studies, indicating that although highly informative, such data remain limited in use due to access constraints, costs, and the need for invasive procedures. This pattern highlights that while scalp EEG remains dominant due to its non-invasive and easily accessible nature, there is an increasing utilisation of multimodal datasets (such as SEEG, MRI, and MEG) to achieve more precise identification of epileptogenic zones, particularly in the context of refractory epilepsy requiring surgical intervention.

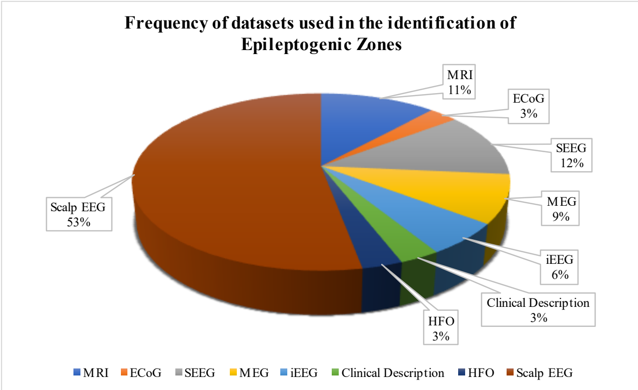


Fig. 5. Frequency of datasets used in the identification of Epileptogenic Zones

## IV. Discussion

This systematic review shows a growing number of publications between 2020 and 2024 discussing the application of artificial intelligence (AI) in identifying epileptogenic zones, a crucial area in the management of refractory epilepsy. A total of 34 articles were analysed, with a significant increase in publications in 2021 and 2024. This reflects advancements in AI technology and the urgency to improve the accuracy of epileptogenic zone identification, particularly in the context of pre-surgical evaluation. The review also highlights a shift in approach from conventional methods toward deep learning techniques, as well as increased use of high-resolution Stereo-EEG (SEEG) data. Deep learning methods are the most dominant AI approach used, appearing in 44% of studies. Architectures such as CNN, LSTM, and TCN have proven highly effective in extracting spatio-temporal features from EEG/SEEG signals. For example, the SEEG-Net model (Wang *et al.*, 2022), which combines CNN, BiLSTM, and Grad-CAM++, achieved an accuracy of 93.85% on a multicenter dataset [54]. Similarly, the TCN-SA model (Huang *et al.*, 2024) demonstrated high performance on both internal and external datasets [65]. These results reinforce the potential value of deep learning in mapping epileptogenic zones with high precision.

TABLE III. Summary of Types of AI Methods, Their Advantages and Limitations in the Context of Epileptogenic Zone Identification

| AI Method | Advantages in Epileptogenic Zone Identification | Limitations in Epileptogenic Zone Identification |
|---|---|---|
| Deep Learning | 1. Automatically extracts spatial-temporal features from EEG/SEEG data.<br>2. Highly accurate (accuracy >90%) with SEEG.<br>3. Suitable for large and complex datasets. | 1. Requires large, well-annotated datasets.<br>2. Low interpretability (black-box).<br>3. Prone to overfitting on small datasets. |
| Machine Learning | 1. Suitable for small to medium-sized datasets.<br>2. Faster to train and more interpretable.<br>3. Can be optimized through feature selection or transformation. | 1. Relies on manually extracted features.<br>2. Less effective for raw EEG signal.<br>3. Lower performance than DL overall. |
| Multi-method (Hybrid) | 1. Combines strengths of multiple models (e.g., CNN + SVM).<br>2. More robust and adaptive.<br>3. Can enhance generalization to noisy or varied data. | 1. More complex to design and validate.<br>2. Harder to reproduce without detailed documentation.<br>3. Requires tuning many parameters. |
| Knowledge-Based AI | 1. Can integrate clinical knowledge and brain network theory.<br>2. More transparent and interpretable (rule-based systems). | 1. Less flexible for real-world data variability.<br>2. Not suitable for raw EEG signals.<br>3. Rarely used and less scalable. |

On the other hand, conventional machine learning methods such as SVM, Random Forest, and XGBoost are still used in certain conditions, particularly when the dataset size is limited or when better interpretability is required. A study by Roger *et al.* (2020) used a combination of SVM and XGBoost to classify mTLE laterality, achieving an AUROC of 90.2% [36]. Although simpler, this approach remains highly relevant, especially in clinical settings with data limitations or the need for transparent interpretation. Some studies also explore multi-method and hybrid approaches, such as Miao *et al.* (2022), who combined SVM, LightGBM, and CNN [52], and Kantipudi *et al.* (2024) with the GBSO-TAENN model, which integrates spider algorithm optimisation (GBSO) with temporal neural networks [66]. Such hybrid models can leverage the strengths of each algorithm and demonstrate superior performance in handling the complexity of brain signals.

This review also highlights trends in dataset usage. Scalp EEG is the most commonly used dataset type (53%), primarily due to its non-invasive nature and availability in open-access formats (e.g., Bonn EEG, CHB-MIT). However, the most accurate results are generally found in studies using SEEG or iEEG datasets (12%), which have high spatial and temporal resolution. This is evident in the study by Zheng *et al.* (2020) using MEG, which achieved an accuracy of 99.48% and nearly perfect AUC (0.9998) [39]. Studies using SEEG data produce very high performance because they are able to record brain electrical activity in depth and with precision. Guo *et al.* (2021) using an HSO Detector based on hypergraph learning achieved an accuracy of 90.7% and specificity of 96.9% [47]. SEEG data offers advantages over scalp EEG in revealing hidden epileptogenic activity patterns within brain structures, particularly in patients with complex focal epilepsy. Recent approaches also demonstrate the use of graph models, such as graph convolutional networks (GCN) in the study by Dou *et al.* (2023), which model the relationships between SEEG channels as an adaptive graph [57]. This approach treats the brain as a complex interconnected network, reflecting the new perspective that epileptogenic zones are not fixed locations but part of the brain's dynamic network system.

Although the models generally perform well, many studies still face limitations, particularly in terms of small sample sizes, reliance on synthetic data (such as TVB), and lack of validation on external datasets or clinical outcomes (such as post-surgical Engel classification). This limits the application of these models in real-world contexts and needs to be addressed in future studies. Another challenge is the lack of standardisation in EEG/SEEG preprocessing across studies. Filtering, segmentation, and HFO annotation techniques vary, making it difficult to replicate or compare studies. Differences in HFO definitions (pathological vs. physiological) also add complexity. Therefore, clinical consensus and open standards for invasive EEG signal processing are needed. From a clinical perspective, these findings hold great potential. AI can accelerate the identification of epileptogenic zones, reduce SEEG monitoring time, and assist in electrode placement and epilepsy surgery planning. Models such as SEEG-Net and HSO Detector have the potential to be integrated into clinical decision support systems (CDSS) at epilepsy surgery centres [70]-[72].

However, to date, the application of AI in clinical settings remains limited. Most models have not been prospectively tested in real-world practice, and there are still ethical, regulatory, and interpretability challenges [73]-[76]. Transparent and explainable AI models are crucial in the context of high-stakes surgical decision-making [77]-[81]. For future development, research should focus on integrating multimodal data (SEEG + MRI + DTI + clinical), tracking long-term outcomes, and conducting prospective multi-centre clinical trials. Collaboration between neurologists, epileptologists, and AI scientists is essential to develop robust, clinically valid systems ready for implementation [82]-[85]. Additionally, future research should also emphasize transparent documentation of the AI model structure, preprocessing procedures, and patient demographic details. Moreover, it is important to report post-surgical clinical outcomes, such as those measured by the Engel scale, to assess the practical efficacy of EZ predictions beyond statistical metrics alone.

## V. CONCLUSIONS

This review confirms that artificial intelligence (AI), particularly deep learning methods based on SEEG and multimodal approaches, has great potential to revolutionise the process of identifying epileptogenic zones. Models such as CNN, LSTM, and hybrid networks that combine spatial-temporal features have demonstrated high accuracy in detecting abnormal patterns in EEG and SEEG data. This advantage is reinforced by consistent results across various studies, especially those using high-quality data such as SEEG and MEG, as well as validation against clinical outcomes. AI enables more objective, efficient, and scalable exploration of epileptogenic zones across diverse patient populations. However, for AI to be widely implemented in clinical practice, a series of important prerequisites are required, including: multi-centre validation, standardisation of preprocessing and data annotation processes, and transparent reporting of model structures and clinical outcomes. Key challenges also include the need for explainable AI models, integration with clinical decision support systems (CDSS), and attention to ethical and medical data privacy aspects. Bridging the gap between research and clinical practice requires coordinated efforts from scientists, clinicians, and tech developers. With the right direction of development, AI has the potential to become a cornerstone of future precision epileptology practice. The combination of AI's capabilities in large-scale and complex data analysis, along with clinicians' expertise in contextual interpretation and medical decision-making, will create a strong synergy in the management of refractory epilepsy. In the long term, AI systems integrated into clinical workflows can contribute to improved diagnostic accuracy, pre-surgical evaluation efficiency, surgical success, and overall quality of life for epilepsy patients.

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