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Intelligent Learning Techniques for Epileptic Seizure Prediction Using EEG Signals: A Comprehensive Review

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A B S T R A C T

Epileptic seizure prediction facilitates proactive rather than reactive medical treatment, thereby promoting patient safety and improved living conditions. One of the most prominent tools employed for epileptic seizure prediction purposes is electroencephalography, considering its temporal resolution and ability to detect brain activity. This paper offers an organized and tightly focused review on new intelligent learning methods applied for epileptic seizure prediction via EEG. This review discusses publicly and privately accessible datasets, preprocessing and segmentation, feature spaces, machine learning and deep neural networks, evaluation schemes, and postprocessing. It points out major bottlenecks preventing more effective implementation, including an overdependence on a few common datasets, preprocessing conventions, cross-validation on different patients, and poor interpretation and implementation strategies. This paper proposes future developments on more reliable seizure predictors.

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1.Introduction

Epilepsy is a chronic neurological disorder in the form of recurrent unprovoked seizures and has been a serious global health concern [1].A staggering estimate by the World Health Organisation says that there are over 50 million sufferers worldwide, imposing massive medical, psychological, and societal burdens on patients and their caregivers [2].Although considerable progress in antiepileptic drug therapy has been made, there is one patient in three with drug-resistant epilepsy, which increases injury and sudden unexpected death in epilepsy (SUDEP) risk considerably [3].Notably, early forewarning of epileptic seizure activity is now deemed one of the most important healthcare tasks that aim at enhancing patient safety and living standards [4].Unlike seizure detectors that identify the seizure after the seizure occurs, prediction tries to anticipate the seizure from minutes to hours before in order to act accordingly [4, 5].

However, reliable prediction of seizures has proven difficult due to the complex, nonstationary, and highly .patient-specific characteristics of epileptic brain dynamics [6].Electroencephalography (EEG) is largely utilized as the main tool for the prediction of seizures, thanks to the high temporal resolution and the ability to measure the neuronal activity directly [7].The scalp EEG and the intracranial EEG recordings have been extensively studied in the past, and although the intracranial EEG records better signals, it has limitations in terms of applications [8].For discriminative pre-ictal patterns to be captured in EEG-based seizure prediction systems, many signal processing and feature extraction approaches have been proposed [9].In traditional machine learning methods, feature extraction is performed based on time, frequency, and time-frequency domains, followed by traditional classifiers like support vector machines or ensemble methods [10].

Recently, the application of deep learning models such as convolutional neural networks and recurrent neural networks has received special attention for their potential to extract hierarchical features from raw or pre-processed EEG signals [11,12]. Despite the encouraging results, the deep learning-based approaches have been found to have high computational complexities and dependence on the preprocessing stage, which are non- interpretable [12].

In addition, current models show large variability in their data sets, processing approaches, representation of features and prediction intervals, what makes difficult their reproducibility and comparability in particular [13]. These challenges underscore the importance of conducting systematic reviews that synthesize contemporary advances, point out gaps in methodologies, and give organized insights to steer further research towards more reliable EEG-based seizure prediction systems [14].

2. Methodology

This review was carried out following the systematic review guidelines to achieve the analysis of published research on the intelligent learning techniques for predicting epileptic seizures via EEG to be complete, transparent, and reproducible. It consisted of an organized literature search, a selection of the study, an extraction of the data, and the qualitative examination explained in the following sub-sections.

2.1 Search Strategy

The literature review done yielded relevant peer-reviewed publications from January 2018 to May 1, 2025. This time frame was chosen to reflect the recent shift in the field of machine learning and deep learning and the advancements that ran in rapid, systematic order. This search was run on two major academic databases, Web of Science and PubMed.

2.2 Study Selection and Eligibility Criteria

Study selection was done using relevance and quality, in line with considerations of inclusion and exclusion criteria. These are detailed in a flowchart in Figure 1 below.

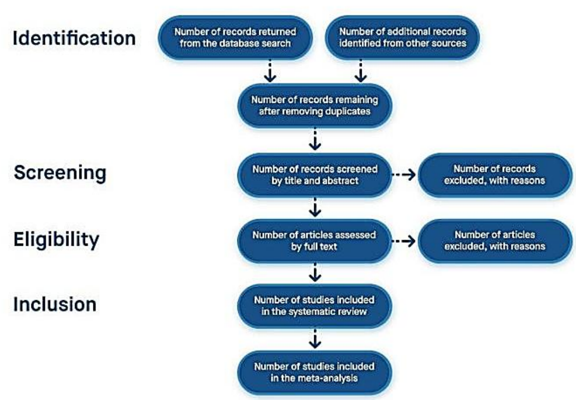

Fig. 1. Flowchart of literature review, sorting, and study selection.

Inclusion Criteria:

The following are the criteria which were used in identifying the studies:

1)Target group/area: The studies targeted individuals who were part of the study, which would foresee a seizure even before it occurred clinically.

2)Intervention/Method: The intervention for this research involved EEG or iEEG, which were considered the sources of intervention.

3)Methodology: The papers applied the methodologies of machine learning and deep learning.

4) Type of Study: The studies that were undertaken are those that have been published either in scientific journals or scientific conferences conducted in English language.

5) Dates of publication range from January 1, 2018, up to May.

Exclusion Criteria:

The following are the criteria which were used in excluding studies:

1)Scope: Studies that were used in identifying when an epileptic seizure occurred.

2)Approach: Studies that are only dependent on non-EEG signals, which are: ECG, MEG, etc.

3)Subject matter: Studies that are involved in other all other types of organisms, except humans. Which are, Animal models.

4)Content: Review articles, editorials, book chapter articles, articles that are retracted, and articles without full text.

5)Focus: Studies which focus on device design without significant algorithmic contribution to prediction.

Of the initial database searches conducted, 357 records were obtained: 256 from Web of Science and 102 from PubMed. The reference management software Zotero was used to remove duplicates. This left 298 unique records that would undergo sorting by title and abstract to check for relevance. Ultimately, 85 records were excluded based on their inability to meet the eligibility criteria. Then, the full texts of the remaining 213 studies were systematically assessed for their compliance with the inclusion criteria. At that point, 64 studies were excluded on various grounds that included: detection only, 31; review articles, 7; inappropriate subject matter, 7.use of non-EEG signals, 7; device-focused, 6; not conducted on humans, 3; and retracted, 3. Thus, 149 studies were accepted for the final qualitative analysis.

2.3 Data Extraction and Synthesis

The standardized data extraction model was optimized to systematically collect information relevant to each of the 149 studies included. Data extracted were categorized into major thematic groups corresponding to the seizure prediction pathway:

1. Dataset characteristics include: dataset name, accessibility-open/public or private, type of electroencephalography-sEEG or iEEG, sampling rate, number of channels, and how often the particular dataset has been used in studies.

2. Preprocessing Techniques: Signal segmentation, epoch length, preictal horizon definition, denoising methods including filtering and wavelet transforms, data balancing strategies such as undersampling or oversampling, SMOTE, and GANs.

3. Model Architectural Framework: Opted strategies including classical ML, deep learning, fusion, tactical.

1.For ML: Feature extraction disciplines, domain, frequency, non-linear, temporal interrelations; cornerstone algorithms such as SVM, Random Trees, XGBoost, etc

2. For DL: Type of model such as CNN, RNN, Transformer, GNN, representation of input in form such as raw EEG, spectrograms, hybrid architectures such as CNN-LSTM.

4. Validation and Evaluation: Definitions SOP and SPH, metrics of performance reported: Sensitivity, specificity, false positive rate per hour, AUC. Validation of data through at least one of the following: hold-out, k-fold cross validation, LOSO, LOPO.

5. Explainability and Deployment: Decisionmaking strategies - such as k-of-n voting and shareholding -, interchangeability methods, like SHAP or Grad-CAM, and reports of realworld deployment or hardware implementations.

A meta-analysis of these studies was not possible due to the heterogeneity in the methodologies, datasets, and metrics used. The study thus adopts a qualitative synthesis approach. The data extracted were then analyzed to identify prevailing trends, common practices, and methodological gaps, as well as emerging research directions, presented thematically in the sections below.

3. EEG Datasets for Seizure Prediction

The heavy reliance on a narrow data regime, mostly based on the CHB-MIT dataset, would therefore suggest that most of the "state-of-the-art" results reported are best-case estimates within the limited context of this dataset, rather than a reflection of broad clinical robustness. Indeed, the focus of future research should be toward collecting and using more diverse and representative datasets, inclusive of all age groups, different modalities-including EEG, intracranial EEG, and wearable devices-and an expanded range of seizure types to develop truly generalizable seizure prediction systems.

Any strong machine learning or deep learning model has its foundation in the data that it gets trained and tested on.In EEG-based seizure prediction, the choice of dataset has a profound impact on the features learned by the model, including its performance, where the importance of a dataset lies in its ability to generalize to a greater number of patients. Our analysis of 149 studies has identified a diverse yet highly skewed framework for using datasets, with high reliance on a few general sEEG repositories and significant underutilization of high-resolution iEEG data.

3.1 Modality and Accessibility

The technique of recording the EE produced even a higher number of variability among reviewed literature. The most frequently utilised one was scalp EEG across 87 studies (58.4%), stressing the ease with which public data for this noninvasive method is available. Intracranial EEG with improved SNR and spatial resolution for seizure focus localization would be applied in 29 studies. Nineteen percent of all reviewed articles (n = 32) employed a hybrid approach, utilizing both sEEG and iEEG in an attempt to exploit the best of each method for individual benefit. Lastly, only one of all analyzed articles used the wearable version of ear-EEG, which possibly marks a trend that should be further analyzed in upcoming studies.

For the sake of accessibility, 100 studies, 67.1%, utilized public data which improved reproducibility and cross-study comparisons.67.1% of the 100 studies used openly available data which has increased the facilities for reproducibility and benchmarking the studies across each other. To give a better demonstration of better accessibility, 100 studies were involving openly available data employed, which is 67.1%, thus improving reproducibility and benchmarking across different studies.

100 studies To make their approaches reproducible, 67.1% of studies used publicly available data, which increases reproducibility as it becomes easier to implement a cross-validation of their results.

To make it available, 100 studies adopted 67.1% open data. Open data enhances data reproducibility.

Regarding ease of access, 100 studies 67.1% relied on publicly available data, which increased reproducibility and ease of comparison, while 29 studies 19.5% solely used data from other, non-public sources such as some clinical data. These sources of data were obtained primarily from epilepsy monitoring units.

To make it accessible, 100 studies 67.1% relied on publicly available data, which improved traceability and facilitate comparative analysis. The remaining 29 studies 19.5% were completely reliant on non-public clinical data sources. These data sources were mostly gathered in specialist epilepsy monitoring units with a long-term high-quality REC Another 20 studies 13.4% used an integrative approach by including both benchmark public data and private clinical data for maximum model generalizability and relevance to clinical setup.

3.2 Major Public Datasets

This section summarizes some of the publicly available data dominating the research landscape in Table 1.

Table 1. Overview of datasets used in studies of EEG-based seizure prediction.

Dataset Name	Open Access	EEG Type	Sampling Rate (Hz)	Channels	Freq. (No. of Studies)
CHB-MIT	Yes	sEEG	256	23	107
AES-Kaggle	Yes	iEEG	500, 5000	16	24
Siena	Yes	sEEG	512	29	10
EPILIPSIAE	No	iEEG	256, 512	20–122	9
Freiburg	No	iEEG	256	64, 128	8

CHB-MIT Scalp EEG Dataset: By far, this is the most popularly used dataset, with citations in 107 studies. It includes the recordings of sEEG from 23 pediatric patients (1.5-19 years) that were obtained using 23 channels and a sampling rate of 256 Hz. This collection contains about 916 hours with 198 clinically annotated seizures. It is so popular because it was available early and was almost considered the de facto benchmark, but it focused on the pediatric population and a fixed channel montage, which introduces a big bias.

1. American Epilepsy Society Seizure Prediction Challenge (AES-Kaggle): The second most cited public dataset, utilized in 24 studies, presents long-term iEEG from 7 subjects-including 5 canines-with data sampled from 400 Hz to 5 kHz. It delivers more than 1333 hours of data, thus proving a rich contribution for research on iEEG-based prediction.

2. Siena Scalp EEG Dataset: This dataset is referenced by 10 studies and contains adult scalp recordings from 14 patients at 512 Hz, including 128 hours of video-EEG with 47 annotated seizures. It also serves as an important alternative to the rather pediatric-oriented CHB-MIT dataset.

3. SWEC-ETHZ Intracranial EEG Dataset: Used in 5 studies, this dataset provides continuous long-term iEEG of 18 drug-resistant epilepsy patients, including 2664 hours of data and 116 annotated seizures. Therefore, it is suitable for studies of long-term dynamics.

3.3 Notable Non-Public and Integrated Datasets

Nevertheless, non-public datasets remain indispensable in studies that need high-density, long-duration iEEG.

1. EPILEPSIAE-European Epilepsy Dataset: This is the most used non-public dataset with 9 studies, and it aggregates long-term surface and iEEG from 275 patients, giving over 30.000 hours of data and ~1,800 seizures. Some of these recordings have up to 122 channels.

2. Freiburg EEG Dataset: Used in 8 studies, it consists of depth electrode recordings from 21 drug-resistant epilepsy patients using 64 or 128 channels, with 509 hours of data annotated for 87 seizures.

Some studies verified the effectiveness of combining public and private data. Chen et al., for instance, tested their proposed method with CHB-MIT data and another private sEEG data source, and Guo et al. pre-trained their model with CHB-MIT and then further fine-tuned it with private iEEG data and got considerable advancement in terms of generalization.These integrative methods improve predictive performance and practical utility.

3.4 Critical Analysis and Identified Gaps

There are three critical challenges in the current dataset landscape that constrain clinical translation of seizure prediction models:

1. Strong Pediatric sEEG Bias: The field is heavily skewed, and the CHB-MIT dataset constitutes 71.8% of all dataset citations. Models performing well on this benchmark are often optimized for a narrow, age-specific feature space, for example, stronger delta activity in pediatric EEG, and do not generalize to adult populations or different recording montages.

2. Underutilization of Long-Term, High-Density iEEG: Despite being valuable, rich repositories of iEEG such as EPILEPSIAE and Freiburg feature in less than 12% of the publications. This underutilization can only limit the exploration of important biomarkers such as high-frequency oscillations between 80-250 Hz and fine-grained spatial synchrony, which are often occluded in sEEG but are very important for early localized seizure warnings.

3. Limited Real Cross-Source Integration:Only 13.4% of studies combine both public and private datasets. The lack of standardized protocols for cross-dataset evaluation makes reported transfer gains hard to interpret and impossible to disentangle genuine architectural advances from favorable domain alignment w.r.t a given dataset.

4. Preprocessing Techniques for EEG-based Seizure Prediction

In the overall sequence of the EEG-based seizure prediction pipeline, preprocessing is still the irreplaceable cornerstone and the most important determinant of the feature extraction quality and, as a consequence, the effectiveness of the subsequent prediction model. The universal goals of preprocessing are separating a continuous EEG time series into epochs amenable to analysis, specifying the prediction horizon, epoch artifact and noise removal, and class adjusting the preictal vs. interictal imbalances. Reviewing the 149 studies in this analysis showed a clear tendency to pre-processed in a standardized or perhaps overly constrained fashion.

4.1. Signal Segmentation and Preictal Definition

It is universally accepted that splitting continuous EEG data recordings into smaller segments (called epochs) is a way to balance computational manageability and temporal resolution during preprocessing:

1)Epoch Length: Of the 131 studies documenting this parameter, there was a notable skew toward smaller segments. The most frequently represented epoch lengths were 5 to 10 seconds (50 studies, 33.6%), and then <5 seconds (24.2%, 36 studies). 20 to 30 seconds was the length for 35 studies (23.5%), while longer epochs of >30 seconds were rare (8 studies, 5.4%). A small, though insightful, subset of six studies (4.0%) implemented a multi-scale approach, exploring several segment lengths to investigate the trade-off between capturing short-range and long-range dynamics.

2) Preictal Horizon: The preictal horizon is the time period immediately before the seizure onset that the target variable of the model is meant to predict. The 125 studies delineating this time period overwhelmingly chose the 30 to 60-minute range (91 studies, 61.1%), and for a 30-minute horizon only, that accounted for 61 studies (40.9%). This is a common clinical compromise, providing the time to issue a warning and predict with reliability. Shorter time horizons (≤10 min) were less so.

Table 2. Overview of denoising methods applied during EEG preprocessing.

Type	Cutoff Frequency (Hz)	Frequency (No. of Studies)	Representative References
Low-pass	≤ 30	3	[28], [101], [116]
	31–60	14	[31], [55], [71], [78], [79], [98], [99], [117], [104], [119], [134], [135],
	61–100	8	[25], [29], [39], [108], [109], [115], [133],
	> 100	13	[44], [47], [49], [61], [63], [105], [106], [115], [129], [131], [135],
High-pass	≤ 0.5	27	[25], [29], [39], [44], [55], [61], [63], [71], [79], [98], [99], [117], [108], [109], [101], [129], [115], [119], [131], [124], [135]
	0.6–1	7	[32], [72], [78], [81], [105], [106],
	1–3	2	[104], [107]
	> 3	3	[28], [47], [116]

Type	Cutoff Frequency (Hz)	Frequency (No. of Studies)	Representative References
Notch	50	22	[25], [32], [36], [31], [70], [72], [81], [105], [106], [108], [110]–[112], [107], [109], [122], [124]–[127], [118], [133]
	60	26	[36], [31], [40], [41], [43], [46], [50], [56], [60], [66], [70], [75], [80], [85], [90], [93], [108], [110]–[112], [114], [107], [120], [103], [131]

4.2 Artifact Removal and Denoising Techniques

1-Band-Pass Filtering: This was the most prevalent denoising strategy, usually implemented as separate high-pass and low-pass filters.

High-Pass Filtering: This filter was used to remove slow baseline drifts - otherwise known as DC offset. The most common cutoff was ≤ 0.5 Hz (27 studies), effectively preserving all clinically relevant EEG rhythms.

Low-Pass Filtering: This is used to remove high-frequency noise such as electromyography (EMG). The highest number of applications fell in the cutoff range 31–60 Hz (14 studies), representing a tradeoff between removing muscle artifacts and preserving potentially useable beta and gamma band activity. A significant proportion of studies (13 studies) also applied cutoffs > 100 Hz, especially in deep learning approaches where an attempt was made to leverage ultra-high-frequency components in iEEG.

1. Notch Filtering: Primarily used to suppress power-line interference. Notch filters at 50 Hz (22 studies) and 60 Hz (26 studies) were usual, reflecting geographical differences in mains electricity. Filters targeting harmonics at 100 Hz and 120 Hz were also common.

2. Advanced Techniques: The few other works had utilized more advanced techniques for noise removal. Among them, DWT soft-thresholding [36], SVMD[113], ICA [57] to separate sources of artefacts and Kalman filtering[59].

4.3 Data Balancing Strategies

The fundamental class imbalance between preictal and interictal recordings can be very severe in nature; the dataset is flooded with interictal rather than preictal data. Training a model on such an imbalanced dataset biases it towards the majority class, meaning interictal, and thus leads to high false negatives, meaning missed seizures.

Table 3. Overview of EEG seizure prediction data balancing strategies.

Strategy	Frequency (No. of Studies)	Representative Referents

Strategy	Frequency (No. of Studies)	Representative Referents
Interictal undersampling	57	[24], [30], [38], [39], [43], [47], [51], [58], [60], [61], [63]–[65], [67], [70], [71], [73], [76], [78], [84], [92], [98], [99], [104], [105], [109]–[111], [113], [115], [117], [109], [103], [104], [106], [107], [110], [111], [119], [116], [118], [121], [123], [125], [126], [128], [130], [132], [133], [135], [136],
Preictal overlapping oversampling	19	[27], [97], [28], [33], [34], [41], [56], [72], [85], [88], [93], [101], [102], [112], [114], [118], [118],
Preictal overlappg oversampl ing+ Interictal undersampling	14	[46], [55], [66], [74], [89], [91], [94]–[96], [120], [122], [125], [132],
SME	4	[32], [130]
Preictal duplicatin oversampling	4	[40], [75], [122], [127]
Synthetic preictal (GANs, TNDA)	4	[52], [86], [97], [108]
Preictal active upsampling	3	[57], [116]

Various approaches have been implemented to address this problem:

Interictal undersampling: This was the most common approach and was applied in 57 studies. It consists of randomly rejecting interictal segments in order to rebalance the class ratio with respect to the available preictal data. Although simple and practical for removal of classifier bias, it still throws away a lot of useful information.

a.Oversampling: Methods for oversampling the minority (preictal) class were also typically used.

b.Preictal Overlapping: We generate additional preictal samples by cross-fading .

Table 4. Handcrafted Feature Extraction Methods in Machine Learning Approaches.

Domain	Frequency	Common Methods
Time-Domain Features	14	Statistical analysis (mean, variance, skewness, kurtosis)
Frequency-Domain Features	15	FFT, PSD, Welch method, DWT
Time-frequency-domain features	9	DWT, WT, SWT, SET
Nonlinear features	4	Sample entropy, Approximate entropy, Lempel-Ziv complexity
Spatial structure / Connectivity features	5	PLV, PLI, graph-theoretical metrics

These features are mainly derived from several domains:

1-Time-Domain Features: The most basic features used in 14 studies are statistical measures that characterize the amplitude dynamics of the EEG signal, including mean, variance, skewness, kurtosis, and zero-crossing rate.

2-Frequency Domain Features: Slightly more in use, appearing in 15 studies, these features quantify the spectral composition of the signal. Standard approaches include the estimation of the PSD, for instance, using Welch's method, as well as calculation of band powers in frequency bands - δ, θ, α, β, γ.

3. Time-Frequency-Domain Features: Used in 9 studies, these features capture the non-stationary properties of the signal. The techniques involved include DWT and SWT, which decompose the signal into time-localized frequency components.

Nonlinear features include sample entropy and Lempel-Ziv complexity, calculated to quantify the chaotic dynamics and complexity of the preictal brain state in only 4 studies.

5-Connectivity Features: An emerging trend in 5 studies, these features model the interactions between different brain regions. Methods involve the calculation of phase synchrony indices, such as Phase-Locking Value (PLV), between channel pairs, and subsequently extracting graph-theoretical metrics, such as node degree and clustering coefficient, from the resulting functional brain networks.

5.1. Core Algorithms

Classifier selection becomes crucial for performance in the final prediction. In the light of details provided by Table 5,

Table 5. Overview of core algorithms in machine learning-based seizure prediction.

Algorithm	Frequecy
SVM	8
LR	4

Algorithm	Frequecy
k-NN	2
XGBoost	2
Others (RF, MLP, HMM)	6

The most commonly used algorithms include:

1. SVM: The most prevalent classifier represented in 8 studies. It is preferred mainly because of its capability to identify the optimal nonlinear decision boundary in high-dimensional feature space using kernel functions, for instance RBF.

2) Logistic Regression (LR): In total, 4 studies employed it as a lightweight interpretable linear baseline model.

3) k-Nearest Neighbors, XGBoost: Both applied to 2 studies. k-NN can actually be considered a simple case of distance-based classification, while XGBoost relies on boosting theory, by definition, doing so with a focus on handling nonlinear relationships, via incorporation of regularization.

There are other learning algorithms like RF, shallow MLP, and HMM that have been applied in the rest of the studies based on the specified feature set or constraints.

5.2 Deep Learning Architectures

Deep learning in seizure prediction has become the dominant paradigm, as 107 studies (71.8%) employed these models. This architecture can learn hierarchical features directly from data, reducing reliance on manual feature engineering.

5.2.1 Feature Extraction and Input Representation

Most of the DL studies reviewed (75 out of 107) employed an end-to-end approach, whereby the features are learned automatically. In particular, two types of input representation approaches:

1-Raw EEG Signals: The data of 31 studies directly feeds raw or just minimally preprocessed time-series to the model. Usually, 1-D CNNs or RNNs are used for this.

2-Time-Frequency Images: 44 studies first transform EEG segments into 2D representations, most commonly by STFT to obtain spectrograms (21 studies). Other transformations include CWT for obtaining scalograms and Pearson correlation matrices to represent functional connectivity. The obtained 2D images are then fed into 2D CNNs.

Of the remaining 32 studies, many have used a hybrid approach for feature learning, where handcrafted features (similar to traditional ML) are first identified and extracted before being fed into a deep network for secondary, automated representation learning.

5.2.2 Core Deep Learning Architectures

The landscape for deep learning models is diverse, though it is heavily biased for convolutional architectures as shown in **Table 6.**

Table 6. Overview of core algorithms in deep learning-based.

Algorithm	Frequency
CNN-based	44

Algorithm	Frequency
CNN + RNN-based	16
RNN-based	14
Transformer-based	7
GNN-based	5
Other Hybrids & Architectures	21

A CNN-based model is represented by 44 studies. Convolutional Neural Networks form the workhorse of this field. Their strength in extracting spatially local patterns makes them well-suited for identifying salient features in spectrograms or across EEG channels. The architectures range from the simple 1D CNN to deep multi-branch 2D and 3D-2D hybrid networks.

1. CNN + RNN-based Hybrids - 16: represents a strong and popular form of the hybrid architecture that pools strengths from CNN and RNNs. The CNN front-end extracts the spatial-spectral features, which are then fed into an RNN (typically LSTM or GRU) to model the temporal evolution of those features, thereby capturing long-range dependencies in the pre-ictal period.

2. Purely RNN-based Models (14): Those purely implemented by RNNs, including LSTMs and Gated Recurrent Units (GRUs), make direct modeling of EEG with a sequence structure as in time series to capture temporal dynamics without explicit spatial feature extractors.

3- Transformer-based Models (7 studies): An emergent trend, Transformer models take advantage of self-attention mechanisms that determine the importance between different time points in the EEG sequence and capture global context effectively. They are starting to rival RNNs in modeling long-term dependencies.

4- NN-based Models : In Graph Neural Networks, the brain is modeled explicitly as a functional network, with electrodes acting as nodes and their interactions as edges. GNNs use message-passing between nodes for learning from the connectivity structure in a biologically plausible way. Other architectures, like Temporal Convolutional Networks, Variational Autoencoders, or even more complex hybrids, such as CNN-Transformer and GNN-RNN, surface only in proof-of-concept studies, underlining the breadth of exploration in this field..

5.3 Comparative and Hybrid Machine Deep Learning Approachesosit of particular methodological interest in these studies (20 in total) is their direct comparative analysis or integration of traditional ML vs Deep Learning.

1- Comparative Studies (9 studies): These studies investigate the comparative analysis of traditional ML classifiers and Deep Learning approaches in a similar setting. The results were inconsistent, where in some studies, Deep Learning approaches outperformed, but in other studies, a wellformatted traditional ML model with a superior set of features would accomplish just as well, if not better than, a Deep Learning model, especially when data is limited, but a Deep Learning model, being a black box, where decisions are purely automated, with no direct human oversight. There is a glaring deficiency in that, among these studies, very few studies use even a simple model like Linear SVM, Logistic Regression, which would make for a proper comparative analysis in determining how good a Deep Learning model would be.

2- Hybrid Models (11 studies): These studies attempt to find a middle ground. The most common method used would involve a step-by-step mechanism where a Deep Learning model, such as a CNN, would use automatic feature extraction, then categorize it with a traditional model, such as SVM. Some studies would use this methodology as a better alternative than using either approaches on their own. Other methods for this would involve Deep Ensembles and Meta Learning. 5.4 Critical Analysis and Identified Gaps

The modeling world of today is expressed through maturity and conservatism, with a number of serious omissions:

1. Convolution Dominance and Exploration of the Fields: CNN-structured models are the dominant ones for CNN models in terms of time and frequency-image input and hence comprise 48.3% of studies in their domain, with highly promising ones like transformers for modeling global context and GNNs for network dynamics confided and relatively under-covered for proof of concepts.

2. "Black Box" of implicit dimensionality reduction: Most of the dimensionality reductions through architectural characteristics such as convolutions strides and pooling layers are implicit, and task-related characteristics in 8 studies are lacking. This lack of explicit control in this step is potentially bound to hamper the interpretations that, as a result, can lead to the loss of clinically important information.

3. The Missing Linear Baseline: A failure in proper analysis of complex models, such as those in deep learning, with a good, finely-tuned linear baseline-well, there is: without it, true modeling advancements are hard to disentangle from those that were due to added model complexity and a lot of hypers-parameter searching. It may be misleading for finding the “state-of-the-art” performance.

6. Model Evaluation and Validation

That is to say, to close the gap between performance in lab test settings and practical applications in the clinic, more stringent strategies regarding validation will have to be considered in future works. The evaluation needed concerns individual patient timing parameters, burden-focused metrics such as FPR/h, and cross-patient validation approaches such as LOPO if model robustness and generalizability were to be proved.

There ought to be a stringent validation and evaluation in order to establish the actual performance, reliability, and practical worth of seizure prediction models. There is a direct relation between these methodologies in both stages with the validity of models being used and with their qualification for practical use. This analysis of 149 studies suggests that there is a community of studies that are progressing towards developing standard approaches but are yet prone to compromises for experimental ease in clinically realistic scenarios.

6.1 Timing Parameters – SOP and SPH

Setting the temporal boundaries has a role in setting up the problem of seizure prediction. The SOP represents the temporal window of time that follows an alarm in which a seizure should occur for it to be a true positive. SPH represents the period between the alarm and the start of SOP. SPH acts as a buffer zone where it prevents the algorithm from detecting the beginning of a seizure.

Among the studies reviewed, there appears to be a substantial degree of agreement on certain defaults:

SOP refers to the period where seizures are likely to happen; most of the studies (37) apply a 30-minute SOP, while other periods, for example, 20, 40, 50, and 60 minutes, are uncommonly used.

SPH: The most common SPH used in 30 studies is 5 minutes, followed by 10-minute horizon shown in 9 studies.

This 30-min SOP plus 5-min SPH has effectively become a de facto standard in a practical clinical setting that satisfies certain regulatory conditions and provides a realistic amount of warning. However, this fixed setting tacitly implies that seizure anticipation always takes a certain amount of time for all patients and all seizures, which ignores individual differences when a longer lead time may be required for certain patients for certain seizures, which would be a shorter transition period from a preictal to an ictal state.

6.2 Evaluation Metrics

Performance of models is measured using a variety of different metrics, which all offer a different insight into model performance with regards to accuracy, timeliness, and workload. Figure 2 illustrates the use rate of these metrics in reviewed studies.

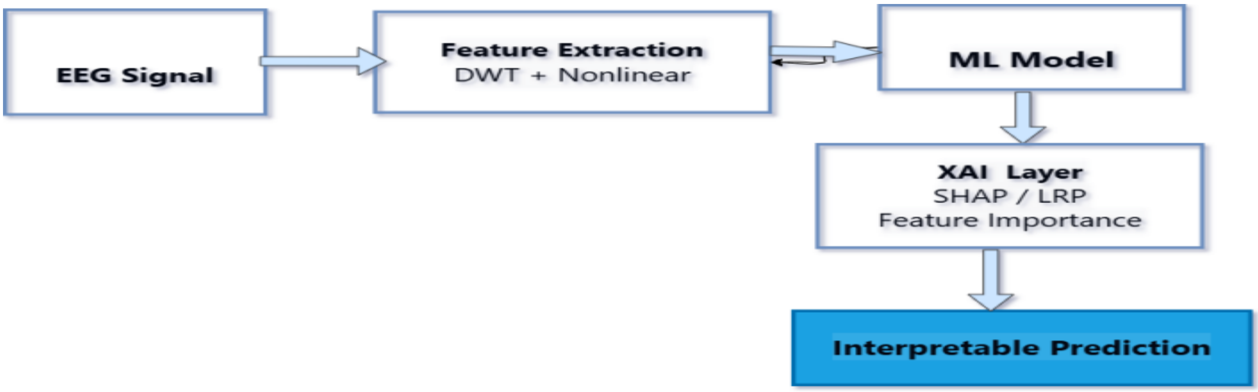

Fig. 2. EEG-Based Seizure Prediction Workflow.

1. Sensitivity (SEN) or Recall: This performance metric has been most frequently reported, with 133 studies, quantified as TP/(TP+FN). This index expresses the probability of correctly anticipating a seizure. High sensitivity shows considerable relevance in patient protection, as it reduces false negatives. A value of SEN ≥ 0.80 has been considered a threshold for acceptability.

2) Accuracy (ACC): This has been measured in 89 studies, and it gives a ratio of correct predictions as a proportion of all predictions. Intuitive though it seems, it is very misleading when working with imbalanced data in which data from interictal periods far exceeds data from preictal periods, since a model which predicts "no seizure" would result in high accuracy.

3) Specificity (SPE): This criterion appears in 75 studies, and it refers to the ratio of true negatives to true negatives plus false positives. This measure is related to the capability of identifying correctly the interictal periods. High values of specificity are very important in order to avoid false alarm situations, as it has been pointed out that a lack of alarm can cause a decrease in users' trust. A target value of >0.90

4) False Prediction Rate per Hour (FPR/h): An important diagnostic parameter, found in 69 studies, calculated as FPR/h= FP / Total monitoring hours. This parameter records the rate of occurrence of a wrong alert. A diagnostic threshold for FPR/h would be ≤ 0.1, which translates to no false alert in 10 hours.

5) Area Under the ROC Curve (ROC-AUC) : This metric has been utilized in 60 studies, which mostly estimates the performance of all models concerning their discrimination capabilities between ictal and interictal classes for all possible classification thresholds. A model with AUC value of 0.5 would usually report random performance, whereas 1.0 represents perfect discrimination.

6) F1-Score: A harmonic average of precision and sensitivity, in 30 studies. This has a practical role in finding a good trade-off between seizure detection (recall) and the validity of the alert productions (precision) in imbalanced datasets.

Other performance metrics like Precision are also helpful in understanding additional properties of model performance but are not measured as frequently; this implies a gap in analyzing the total user effort.

Several recent studies report classification accuracy as an auxiliary performance indicator for EEG-based seizure prediction. **Table 7** summarizes representative accuracy results from selected studies published between 2018 and 2025. Although accuracy alone is insufficient to reflect clinical applicability in highly imbalanced datasets, it provides a useful complementary measure when interpreted alongside sensitivity and false prediction rate.

Table 7. Classification accuracy reported in representative EEG-based seizure prediction studies.

Study	Year	Dataset	EEG Type	Model	Validatio n Strategy	Accuracy (%)	Ref.

Study	Year	Dataset	EEG Type	Model	Validation Strategy	Accuracy (%)	Ref.
Tsiouris et al.	2018	CHB-MIT	sEEG	LSTM	LOSO	95.6	[21]
Truong et al.	2019	CHB-MIT	sEEG	CNN	Hold-out	96.1	[9]
Hussein et al.	2020	CHB-MIT	sEEG	CNN–LSTM	LOSO	97.3	[24]
Raghu et al.	2021	AES-Kaggle	iEEG	CNN	K-Fold	94.8	[14]
Jemal et al.	2022	CHB-MIT	sEEG	Interpretable DL	LOSO	95.2	[22]
Gao et al.	2022	CHB-MIT	sEEG	Sample-weighted DL	LOSO	96.7	[25]
Shafiezadeh et al.	2023	Multi-dataset	sEEG/iEEG	Hybrid ML–DL	LOPO	93.9	[17]
Ghosh & Dey	2025	CHB-MIT	sEEG	CNN-BiLSTM + Attention	LOSO	97.8	[23]

Accuracy values are reported as presented in the original studies and are not directly comparable due to variations in datasets, preprocessing pipelines, class imbalance handling, and validation strategies.

6.3 Data Validation Strategy

The way the data is divided into training, validation, and test sets has a large impact on estimates of predictive model performance as well as generalisation of how well the model can predict. There are also different ways to split as it can be observed in the Table 8.

Table 8. Overview of data validation strategies in EEG-based seizure prediction studies.

Strategy	Frequency (No. of Studies)	Description
Hold-Out	57	Single, static split of data into training and testing sets.
Leave-One-Seizure-Out (LOSO)	44	Iteratively holds out each seizure for testing; trains on the remaining seizures from the same patient.
K-Fold Cross-Validation	32	Partitions data into K folds; model is trained and tested K times.
Leave-One-Patient-Out (LOPO)	9	Iteratively holds out all data from one patient for testing; trains on data from all other patients.
Others (e.g., LODO, LOO)	7	Includes Leave-One-Day-Out, sample-level Leave-One-Out, and other custom schemes.

1) Hold-Out Validation: This is the most common approach, used by 57 studies (38.2%). A single static split of the data is performed; for instance, 70%/30% for training/testing. This approach is quite easy to implement but has the serious disadvantage of running a high risk of overfitting to that particular split of data and will not be very robust for performance on unseen data.

2) LOSO: Used by 44/148 studies, this is a patient-specific approach in which all data from one seizure is iteratively left out for testing, while the remaining seizures are used for training. This is one of the most appropriate ways to assess how well a model generalizes a new seizure forecast from the same patient.

3) K-Fold Cross-Validation: This was used in 32 studies, or 21.5 percent, where the data are divided into K folds, repeatedly training on K-1 folds and testing on the held-out fold. It provides a more robust and stable performance estimate compared to a single hold-out split.

4) Leave-One-Patient-Out (LOPO): This represents the most conservative evaluation strategy for cross-patient generalization and is adopted by only 9 studies, 6.0% in total. In LOPO, data from one patient are left out for testing, and the remaining data across all other patients are used for model training. Its scant adoption suggests that the majority of the models are optimized and evaluated towards single-patient performance and not for broader applicability in a clinical setting.

6.4 Critical Analysis and Identified Gaps

The current status of validation and evaluation reflects various critical limitations that hamper clinical translation :

1. Over-reliance on Fixed, Convenient Parameters: This dominance of the 30-min SOP/5-min SPH configuration does not take into account patient-specific preictal dynamics; this may render models ineffective in patients whose seizures do not conform to this temporal configuration.

2.Incomplete Performance Reporting: The heavy emphasis on sensitivity and accuracy, without consistent reporting of FPR/h and Time-in-Warning, paints an incomplete picture. A model with 99% sensitivity is clinically useless if it generates a false alarm every few minutes, leading to alarm fatigue.

3. Lack of Assessment of Cross-Patient Generalizability: The general rarity of LOPO validation means that the overwhelming majority of "high-performance" models have only been validated on data that comes from patients already seen during their training. This provides very limited evidence that such a model will perform reliably for a new, unseen patient in a clinical setting—a prerequisite for large-scale clinical deployment.

7. Postprocessing and Decision Strategies

1) The raw output of a seizure prediction model - typically a sequence of probabilities or binary labels for short EEG segments - is frequently unstable or liable to spurious oscillations. If we were to directly use these outputs to trigger alarms, the false alarm rate would be too high. Thus the postprocessing decision strategy is an essential final step in the pipeline, converting these raw model outputs into robust, trustworthy and clinically useful seizure warnings. These mechanisms enforce temporal consistency, remove the isolated noise and boost the global robustness of predictive system. Of course, not every study has explicitly mentioned post-processes; however, at least 58 out of 149 studies in our review contained explicit postprocess steps that can be broadly grouped into the following four types of

2) whereas the deep learning modules at the front-end become increasingly complex, the decision logic in the back-end is still relatively simple. This reliance on fixed postprocessing is actually the main reason for the high rate of false alarms that prevents applications in the real world. In the future, our work will continue to focus on this high-priority need for dynamic, adaptive, and learnable postprocessing algorithms able to maintain their sensitivity while further reducing the burden of false predictions in continuous, longterm monitoring applications.

7.1 Voting Mechanisms

Voting mechanisms are the most commonly used postprocessing method, which can be found in 31 studies. They work based on examining a sequence of model predictions to take more firm decision in the end.

1)k-of-n Voting: This voting rule is the most widely used, appearing in 15 papers. This methodology considers a sliding windows with ‘n’ consecutive segments. If at least ‘k’ segments in that window are labeled as preictal, an alarm is sent.VoThis will ensure the seizure warning emanates from a sustained pattern of preictal activity rather than a transient and isolated prediction.

2) Segment-Ratio Method: This approach is utilized in 8 studies; it sends an alarm if the proportion of positive segments in a window is higher than a threshold (e.g., >60%).

3) Consecutive-Segment Method: Used in 6 studies, this technique utilizes the classification of a fixed number of successive segments as preictal for the confirmation of an alarm to enforce temporal continuity.

7.2 Thresholding Mechanisms

The thresholding mechanisms, reported in 22 studies, involve comparing the model output confidence to a set level in order to make a decision.

1.Fixed Thresholding: This is by far the most commonly used, with 21 studies adopting this practice. The fixed threshold, expressed, for example, by a probability of 0.8, is pre-specified, and an alarm goes off when the score exceeds it. While simple, there may be little flexibility regarding changes to patient status or signal quality.

2. Adaptive Thresholding: This dynamic approach has been investigated in only one paper thus far [162], adapting the warning threshold to recent background brain activity or patient-specific characteristics, which can provide a more flexible and potentially more robust alternative to static thresholds.

7.3 Temporal Smoothing and Debouncing

Many studies conduct temporal smoothing and debouncing techniques to further reduce volatility and prevent rapid re-triggering of alarms.

1. Moving-Average Smoothing: The most common, represented in 21 studies, includes averaging prediction scores or probabilities over a sliding window. This produces a smoother, more stable output signal with transient spikes attenuated.

2.Refractory Period: This scheme, reported in 10 studies, institutes a mandatory "silent" or "refractory" interval, e.g., 30 minutes, immediately after an alarm is issued. Any subsequent detections are automatically suppressed during this period. This is important to avoid multiple alarms for a single impending seizure and also to manage the clinical burden of alerts.

7.4 Advanced and Hybrid Strategies

Only a few works explore more advanced fusion strategies that would enhance generalization and long-term stability.

1. Combination Methods: The complex strategies most in use combine several of the basic techniques identified above. The most common combination is the k-of-n voting scheme (15 studies). Another popular workflow, described in 5 studies, first smooths model probabilities with a moving-average filter and then uses a fixed threshold. A further enhancement, described in 4 studies, adds a 30-minute refractory period to this pipeline.

2. Adaptive Ensemble Mechanisms: Four works discussed advanced fusion using MAML for ensemble classifiers or using simple multi-classifier voting methods.

3. Temporal Calibration and Scoring: Three studies used methods such as Platt calibration and circadian weighting, which sums prediction probabilities over time and consider diurnal rhythms in seizure likelihood.

4. Meta-Decision Frameworks: Only one work was identified that has proposed an LTT approach which dynamically updates the prediction after the initial learning to refine statistical robustness.

7.5 Critical Analysis and Identified Gaps

The current situation in postprocessing shows a big gap between algorithmic development and clinical deployment needs:

1) Reliance on Heuristic, Static Methods: The field remains heavily dependent upon simple, hard-coded heuristics like k-of-n voting and fixed thresholds. These methods are straightforward to implement but are not data-driven, lacking the flexibility in adapting to inter- and intra-patient variability, changes in medication, or shifts in background EEG dynamics.

2)Lack of Adaptive and Risk-Aware Calibration: The near-total absence of adaptive thresholding and the minimal exploration of context-aware calibration (e.g., based on time of day or patient activity) means that most systems cannot dynamically manage the trade-off between sensitivity and false alarm rate in response to a changing environment.

3)Underutilization of Learned Postprocessing: With only a few exceptions, the final decision layer is treated as a separate, manual tuning step rather than an integral, trainable component of the end-to-end prediction system. This represents a missed opportunity to optimize the entire pipeline for clinical utility.

Table 9. Overview of postprocessing decision strategies in EEG-based seizure prediction.

Category	Method	quency ɔ. of Studies)	Description
Voting Mechanisms	k-of-n	15	Alarm triggered if ≥ k out of n segments are preictal.
	Segment-Ratio	8	Alarm triggered if proportion of preictal segments in a window > threshold.

	Consecutive-Segments	6	Alarm triggered after a fixed number of successive preictal segments.
Thresholdin Mechanisms	Fixed Threshold	21	Alarm triggered if model output score > a static threshold.
	Adaptive Threshold	1	Threshold is dynamically adjusted based on signal or patient state.
Temporal Smoothing	Moving Average	21	Model outputs are averaged over a sliding window.
	Refractory Period	10	A silent period is enforced after an alarm to prevent re-triggering.
Advanced Strategies	Combination (e.g., Smoothing + Thresholding)	9	Multiple basic techniques are combined in a pipeline.
	Adaptive Ensemble	4	Uses learned or meta-learning approaches to fuse model outputs.
	Temporal Calibration	3	Integrates probabilities over time or with circadian context.
Categ or y	Method	quenc y of	Descri pt io n
Voting Mechanisms	k-of-n	15	Alarm triggered if ≥ k out of n segments are preictal.
	Segment-Ratio	8	Alarm triggered if proportion of preictal segments in a window > threshold.
	Consecutive-Segments	6	Alarm triggered after a fixed number of successive preictal segments.
Thresholding Mechanisms	Fixed Threshold	21	Alarm triggered if model output score > a static threshold.
	Adaptive Threshold	1	Threshold is dynamically adjusted based on signal or patient state.

Temporal Smoothing	Moving Average	21	Model outputs are averaged over a sliding window.
	Refractory Period	10	A silent period is enforced after an alarm to prevent re-triggering.
Advanced Strategies	Combination (e.g., Smoothing + Thresholding)	9	Multiple basic techniques are combined in a pipeline.
	Adaptive Ensemble	4	Uses learned or meta-learning approaches to fuse model outputs.
	Temporal Calibration	3	Integrates probabilities over time or with circadian context.

8. Interpretability and Clinical Deployment

Two intertwined factors are paramount to the translation of seizure prediction systems from experimental prototypes into reliable clinical tools: interpretability, providing an explanation of why a prediction was made and building clinician trust, and deployment, showing how the system works in the real world.This section explores the current state of the art regarding such key areas, and it notes the widening gap between progress on the algorithmic front and the integration of these techniques into clinical practice.

In reality, to move the field ahead, a paradigm shift is required. The next generation of research must integrate the concept of explainability, not after the fact but right from the beginning, in a way that allows the results to be clinically valid. At the same time, the next level of research must mature from the level of algorithmic theory and approach system-level work in the context of energy-efficient computation and, more importantly, clinical validation in the home and in the hospital. It is then that seizure prediction models will mature from a promising prototype to a trustworthy lifesaver.

8.1 Interpretability and Explainability

If clinicians are to adopt an AI-based decision support system, they must have trust in its outputs. This requires interpretability: the ability to understand the model's reasoning. Regardless of its great clinical need, explainability remains a very poorly addressed area in seizure prediction studies.

Of the 149 studies reviewed, only 11 ubi (7.4%) explicitly incorporated any form of explain-ability analysis. The methods employed can be categorized into three main approaches, as summarized in **Table 10.**

Table 10. Overview of post-hoe explain-ability mechanisms in seizure prediction studies.

Category	Representative Methods	Frequency	Representative References
Feature Attribution / Contribution Scoring	LRP, SHAP, LIME	4	[21], [24], [120], [128]

Category	Representative Methods	Frequency	Representative References
Statistical / Network Visual Analytics	Functional Connectivity Networks, KL Divergence, Feature-importance Ranking	4	[38], [87], [93], [115]
Gradient-based Activation Visualisation	Grad-CAM, Saliency Maps	3	[83], [106], [133]

1. Feature Attribution and Contribution Scoring (4 studies): These techniques generate seatmates highlighting the contribution of specific input features, such as EEG channels, time points, and frequency bands, to the model's final decision. Representative methods include

a) Layer-wise Relevance Propagation (LRP): Backpropagates relevance scores from the output to the input layer [21].

b)SHapley Additive exPlanations (SHAP): A game-theoretic approach to assign importance values for each feature [120, 128].

c) LIME: Local Interpretable Model-agnostic Explanations approximate a complex model locally with an interpretable one to explain individual predictions.

2. Statistical and Network Visual Analytics (4): This class utilizes domain expertise to understand model decisions through the visualization of changes in brain dynamics. Techniques range from the generation of functional connectivity networks based on features such as the directed transfer function [38] to the use of statistical divergence measures like Kullback-Leibler (KL) divergence to highlight preictal shifts [87, 93, 115].

3. Gradient-based Visualization of Activations: These are mainly applied to convolutional neural networks, where visual explanations are produced using the gradients flowing back into the final convolutional layer.

Also, Gradient-weighted Class Activation Mapping: It is the most frequent approach within this class that has been applied to generate coarse localization maps highlighting which regions are important in spectro-temporal inputs [83, 106, 133].

The harsh truth is that more than 92% of reports provide "black-box" models, in which no information concerning the electrophysiological rationale behind their predictions is given. This opacity undermines clinical confidence, since practitioners have no way to know whether an alarm originates from a real preictal pattern, a common artifact, or an irrelevant signal bias.

8.2 Clinical Deployment and Translation

The ultimate test of any seizure prediction system will come when its performance and usability are tested in real-world environments outside curated research datasets. Deployment involves implementing the already-trained model on hardware suitable for continuous, long-term monitoring, often with stringent constraints over power consumption, latency, and form factor.

Our study showed that most of the research studies stayed in the prototype phase with only model development and offline evaluation. The computational environments described usually consist of high-performance workstations with powerful GPUs, impractical for continuous bedside or ambulatory use. Only 9 studies (6.0%) went on towards any sort of physical deployment, which may be further classified as follows: Table 11

Table 11. Overview of deployment categories for EEG-based seizure prediction systems.

Category	Description	Frequency	Representative References
Hardware-Accelerated Deployment	Low-power, real-time inference on dedicated FPGA/ASIC hardware.	2	[105], [127]
IoT Edge, Cloud, LTE Deployment	Implementation on edge devices (e.g., Raspberry Pi), cloud platforms, or LTE testbeds.	3	[49], [119], [133]
Conceptual/Architectural Scheme	System architecture proposed without implementation or experimental data.	3	[48], [57], [92]
Clinical Prototype Validation	Hardware prototype tested in real patients or controlled hospital environments.	1	[134]

Hardware-Accelerated Deployment: This category includes work that has implemented their models on dedicated low-power hardware, which is requisite for any wearable or implantable device.

a) Khalil et al. [105] implemented a convectional autochanger–LSTM model on an Altera Arria 10 GX FPGA and synthesized it into a 45 nm ASIC. They reported just 1.53 mW of power consumption.

b)Massoud et al. [127] implemented a patient-specific MLP on Xilinx Virtex-7 FPGA using fixed-point arithmetic with very high energy efficiency against the GPU.

c) IoT Edge, Cloud, and LTE Deployment (3 studies): These works implemented their systems on devices suitable for consumer or hospital-grade monitoring.

d) Ahmad et al. [29] implemented a CNN-BiLSTM model on a Raspberry Pi 4B for continuous EEG acquisition with real-time detection, and sending SMS alerts via AWS IoT.

e) Hassoon et al. [119] executed a cloud-based pipeline on AWS for EEG acquisition in real time and inference of CAE-CNNs.

f) Hosseini et al. [133] presented performance testing on an LTE edge computing testbed using software-defined radios.

g) Conceptual/Architectural Schemes: The studies under this category introduced conceptual system architectures that would be deployed, including data flow and hardware interaction. However, no experimental implementation or validation was made [48, 57, 92]. h) Clinical Prototype Validation - 1 study: Only Zambrana-Vinaroz et al. [134] presented a real clinical prototype-a wearable system with ECG, PPG, and EEG-which was demonstrably tested with real patients, providing important preliminary data on usability and performance in realistic settings.

8.3 Critical Analysis and Identified Gaps

The interpretability analysis and deployment reveal a deep-seated translational gap:

1. The "Black Box" Problem: The near-absence of explanatory techniques is a major block to clinical adoption. Clinicians have no means with which to verify the physiological plausibility of predictions, troubleshoot false alarms, or build trust-the precursors to integrating these systems into clinical workflows.

2.The Prototype Chasm: After ten years of AI advancement, fewer than ten studies have demonstrated functional deployment, and only one has conducted preliminary patient testing. That would indicate that the field is still overwhelmingly focused on in-silico performance metrics rather than solving the practical engineering and clinical challenges of creating a usable product.

3. System-Level Challenges: There are many practical challenges which have been hitherto unresolved regarding continuous model adaptation for individual patients, power consumption for wearable devices, functioning in scenarios involving motion artifacts as well as data losses, compatibility with hospital information technology systems for alerts for healthcare professionals.

9. Challenges and Future Directions However

"the path to a clinically valid seizure prediction system is complex, requiring a paradigm shift away from where current research focuses exclusively on optimizing performance on leaderboard rankings towards a broader focus on system-level challenges.". This includes collaborative effort at the levels of data scientists, clinical neurologists, and hardware engineers. By being conscious of the biases in data, methodological limitations, and translational gaps pointed out in this review, the research community can turn seizure prediction from a promising technological demonstration into a trustworthy deployable solution that genuinely improves safety and quality of life for people living with epilepsy.

This state-of-the-art review of 149 studies on EEG-based epileptic seizure prediction unravels a field marked by rapid methodological advance at the same time as being held back by enduring translational gaps. Although deep learning has demonstrably pushed the boundary of in-silico performance, this aspirational path toward reliable clinical deployment is obstructed by a number of interconnected challenges. This section distills those key challenges into concrete, actionable future directions that address the gulf between experimental promise and clinical reality.

9.1 Synthesis of Key Challenges

1. Data Biases and Lack of Generalizability:

The field is built upon a narrow data foundation: the strong overreliance on the pediatric CHB-MIT sEEG dataset - an astonishing 71.8% of all dataset citations-have resulted in models optimized for a specific demographic and modality. This creates a large generalization crisis, as algorithms trained on short, low-channel pediatric recordings often fail when applied to adult populations, high-density intracranial EEG (iEEG), or long-term ambulatory data. Underutilization of rich iEEG repositories and rare cross-dataset benchmarking further limit the robustness and clinical breadth of developed models.

2. Methodological Inertia and Architectural Conservatism:

Dominated by a "convenience paradigm," the research pipeline is marked by rigid preprocessing, with a preference for short epochs ≤ 10 s and fixed preictal horizons, usually bounded between 30-60 min, which may truncate long-range preictal dynamics. The model landscape is overwhelmingly convolution-dominated, with CNNs and their hybrids occupying the majority in the architecture population. This sidelines promising alternatives, such as pure Transformers for global context modeling and GNNs for network dynamics, still in the proof-of-concept stage. Furthermore, the pervasive exclusion of well-tuned linear baselines renders it difficult to quantify the true incremental value introduced by complex deep models.

3. Clinically Unrealistic Validation and Evaluation:

Experimental protocols often prioritize convenience over clinical realism. The ubiquity of fixed SOP/SPH windows and naive validation strategies, such as hold-out or LOSO, in particular, ensures inflated performance estimates. The critical test of cross-patient generalizability via LOPO validation is rare at 6.0%. Similarly, performance reporting overemphasizes sensitivity and accuracy while under-reporting clinically crucial metrics such as the False Prediction Rate per hour (FPR/h), which directly measures patient burden from false alarms.

4. The Translational Chasm: Unexplained Models & Undeployed Systems:

A profound gap exists between algorithm development and clinical application. Interpretability is an afterthought, with more than 92% of the studies presenting "black-box" models. Without explanations for the predictions, clinician trust remains low. At the same time, real-world deployment is exceedingly rare: only 6.0% of studies moved forward with any hardware implementation, and a single study reported testing with real patients. The field has yet to address challenges in energy-efficient edge computing, continuous model adaptation, and integration into clinical workflows systematically.

9.2 Recommended Future Directions

This set of challenges we are facing has to be overcome, and it needs to steer the field toward clinical impact. Future research directions include:

1. Curate and Utilize Diverse, Representative Datasets.

The future research must be beyond the CHB-MIT benchmark. The priorities must be given to:

a) Assembling and leveraging multi-center datasets encompassing both pediatric and adult populations.

b) Integrating high-density iEEG with sEEG to capture complementary biomarkers.

c) The development and use of ambulatory, long-term data sets representative of real-world monitoring conditions. d) Creating standardized, cross-dataset benchmarks that stringently test model generalizability.

2. Pioneer Adaptive, Multi-Scale, and Architecturally diverse models.

The field needs to be liberated from methodological inertia.by:

a) Systematic investigation of adaptive and multi-scale preprocessing, evaluating variable epoch lengths and patient-specific preictal horizons to capture a fuller range of preictal dynamics.

b) Establishing common metrics for which CNN

The architectures proposed are RNN, Transformer, GNN, and TCN. against each other and crucially against well tuned linear models, e.g. Linear SVM, Logistic Regression to isolate true performance gains.

c) Requiring ablation studies that compare different defaults implicit dimensionality reduction with explicit perform task-aware feature selection to enhance interpretability and control.

3. Adopt Clinically Aligned and Rigorous

Evaluation Protocols.It is to ensure that reported performance translates to Clinical utility, researchers should:

a) Replace fixed timing parameters with patient-specific SOP/SPH windows where feasible.

b) require the use of cross-patient LOPO validation and external dataset testing as the The gold standard for the evaluation of generalisability.

c) Emphasize reporting clinical Burden metrics of particular interest include FPR/h and Time-in^{2}Warning, alongside the more classic metric sensitivity.

d) Creation and use of postprocessing dynamic, risk-aware strategies, shifting beyond simple k-of-n voting to methods that adapt to Signal quality and circadian rhythms

4. Bridging the Translational Gap via Explainability and Real-World Deployment The ultimate goal of clinical integration requires Two-fold focus on transparency and practicality:

a- Embed explainability by design. Apply methods:That is, methods like SHAP, LRP, and Grad-CAM not as post-hoc analysis rather than an intrinsic part of the model development cycle to validate physiological Plausibility and building clinician trust.

b- Prioritize research on the efficient model:architectures-such as knowledge distillation,quantization, pruning) tailored for low-power, low^{2}latency in-ference on wearable or implantable edge hardware.

c- Speed up real-life testing via industry-academia collaboration by targeting potential Controlled hospital epilepsy validation and Unstructured home environments and monitoring units.

10. Conclusion

This review has offered a brief and structured assessment of modern intelligent learning approaches for prediction of epileptic seizures using EEG. In addition to a discussion of prediction approaches, including data selection, modeling, and evaluations, it gives an idea of what can be achieved in this domain currently [13, 14].

It is clear from the analysis that despite the successful application of deep learning techniques, most of the existing solutions are limited in terms of a high dependency on limited public datasets, especially those in the pediatric scalp EEG channel. Furthermore, patient-specific validation methods also limit the scope. Additionally, the fixed preprocessing steps and under-investigation of different model designs and lack of reportage of appropriate metrics also limit the validity of results [8, 14].

Thus, in future works, there should be a focus on the application of varied representative databases, the employment of robust cross-patients verification methodologies, as well as the combination of explainability and energy efficiency methods. Overcoming these issues will be vital for applying seizure prediction models from research into clinically meaningful solutions in seizure prediction [1, 3].

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