IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

EEG-Based Epileptic Seizure Detection: A Systematic Review Of Machine Learning And Deep Learning Approaches

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Abstract: One of the most common and severe neuronal diseases worldwide, which afflicts approximately 50 million individuals of every generation is epilepsy. They can occur without warning and the inability to recognize the seizures can be a deadly consequence, including injuries and the threat of sudden unexpected death in epilepsy (SUDEP). The EEG Signals allows doctors to monitor the brain's electrical activity securely, and continues to be the key tool to detect seizures. The paper reviews machine learning (ML) and deep learning (DL) based EEG-seizure detection papers released over the period of 2022-2025 systematically. Techniques discussed involve handcrafted feature pipelines with Support Vector Machines (SVM) and random forests, and end to end architectures such as CNNs, LSTM networks, or hybrid CNN-LSTM networks or CNN-GRU networks. We also discuss the recent developments of Graph Neural Networks (GNNs), multi-head attention layers as well as transformer encoders. PRISMA-directed search and screening were used to select the literature. Tables of the trade-offs of each method and their contribution to the individual studies are summarized and their uncovered research gaps and the most promising research directions are discussed. It has comparative tables of advantages and disadvantages of each approach, as well as the contributions of each study, then a discussion of the research gaps that still exist and the most promising directions to pursue in the future work.

Keywords: EEG, Epilepsy, Seizure Detection, Machine Learning, Deep Learning, CNN, LSTM, Transformer, Graph Neural Network.

1. INTRODUCTION

According to the World Health Organization (WHO), that there are over 50 million persons worldwide with epilepsy. It is essentially a periodically experienced and unpredictable seizure instigated by episodes of aberrant electrical activity in groups of neurons- a situation that not only cuts across any age but also across any geographical boundary. Its clinical features are exceedingly heterogeneous, some individuals have spontaneous lapses of consciousness, which can be overlooked when talking to them, others have a generalized convulsion, which can be detected at first glance and might even be fatal [1]. Although these two situations are extremely different, they are paired, both are out of control. This nature restricts many patients to drive, occupational possibilities, and infuses daily life with an aspect of chronic fear [2]. The EEG has been a key tool for diagnosing epilepsy since it was first used in the 1930s. It measures electric potentials of the scalp, or within the skull, which reflect the activity of large masses of neurons. These consist of rhythmic high-amplitude bursts, ictal discharges, spike-wave complexes and polyspike events that can be visualized even in the absence of overt clinical manifestation [3]. The issue on the ground is a size one. A single, overnight recording can provide you with many hours of multi-channel information and tertiary referral centers often monitor patients over a number of days consecutively. Analyses of such recordings one sample at a time are an unnecessary waste of time by a neurological specialist and the problem of exhaustion when cortical review is done over long periods is common knowledge. Automated seizure detection is not a luxury, it will be the only means of maintaining an eye on things and this is the case in most clinical situations [4]. Initial automation was in the form of signal processing pipelines which extracted features such as wavelet coefficients, spectral power ratios, entropy values manually, and then submitted them to classifiers such as S VM or k -Nearest Neighbours. These techniques produced good results in the conditions of controlled recordings, but failed to do so when used with new patients or other EEG equipment [5]. This started to happen around 2016 when convolutional neural networks demonstrated that features directly trained on EEG spectrograms could be just as effective or even better than those trained by hand with significantly fewer domain-specific conditions. This was followed by recurrent networks. They also included the capability of simulating the initial and subsequent spread of seizures with time, which CNNs did not [6]. In more recent years, attention-augmented and hybrids and graph-structured architectures have been further enhanced to increase the effectiveness of detection [7], [8]. This is a systematic review of that ecosystem and this paper draws conclusions that may be of use to researchers as well as doctors that treat patient.

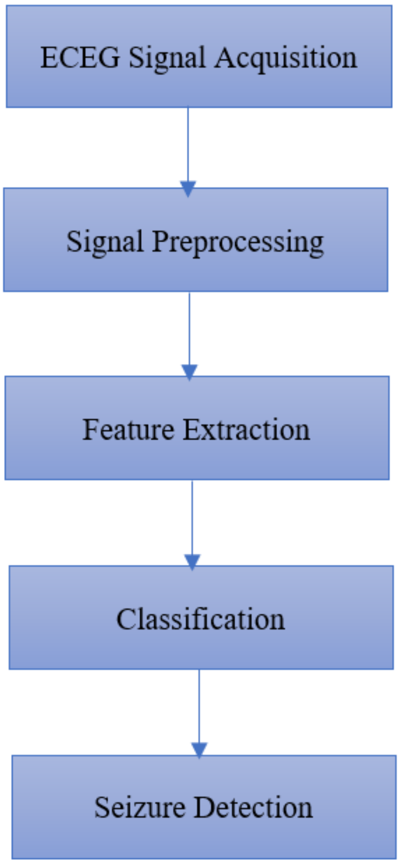

Figure 1: EEG signal preprocessing workflow

Figure 1 shows the overall performance of EEG-based seizure detection. The first is to record EEG data and this entails recording brain signals using electrodes. Preprocessing stage eliminates all forms of noise and any other unwanted signal so as to ensure that the signal is crystal clear. The feature extraction then finds notable signal attributes such as frequency, amplitude and entropy. Lastly, the stage of model classification applies the ML or DL algorithms (such as CNN, LSTM, and GNN) to categorize EEG segments into those that are or are not seizures. The result of the detection is the output.

2. REVIEW METHODOLOGY

In order to maintain the transparency and consistency of the selection process, the following structure was used on the basis of the PRISMA: the review. The four steps Identification, Screening and Eligibility and Inclusion procedures were all implemented following the procedures as discussed below.

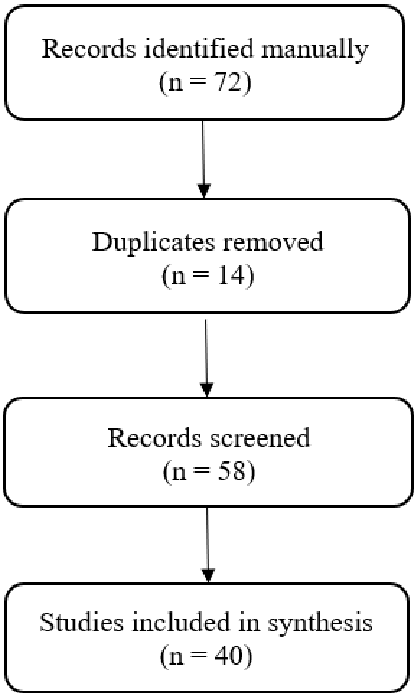

Figure 2: PRISMA-based review methodology for epilepsy detection

2.1 Identification

Three sets of keywords were searched in IEEE Xplore, PubMed, SpringerLink, ScienceDirect and Google Scholar. The former discussed the condition itself, epilepsy, epileptic seizure and ictal. The second was based on the type of signal - EEG, electroencephalogram and brain signal. These three were the machine learning, deep learning, CNN, LSTM, transformer, and graph neural network methods. No language filter was used, they considered only papers published in 2022-2025 [9]. Searching without refinements yielded 72 records in total in the five databases with 14 records being duplicates.

2.2 Screening

The duplicates were eliminated initially. Titles and abstracts were then read by two reviewers who retained only the studies that met the following criteria: dealt with automated EEG-based seizure detection, used at least one of the ML or DL methods, and provided numerical results [10]. MRI-based papers, those based on clinical opinion or non-EEG studies were eliminated.

2.3 Eligibility and Inclusion

Full texts were read to assess methodological quality and reproducibility. Papers were kept if they tested on a recognised EEG dataset — such as the Bonn corpus, CHB-MIT, or Temple University Hospital EEG Corpus — or a well-described clinical one [11]. This process led to 40 papers being included, covering classical ML, CNN, recurrent, hybrid, transformer, attention-based, and graph-based methods — together representing the main approaches active in the field today [12].

3. EEG SIGNAL ANALYSIS AND PREPROCESSING

EEG signals present a genuinely difficult analysis problem. They are non-stationary — their statistical properties shift continuously over time — and they simultaneously carry clinically relevant information across multiple frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (above 30 Hz) [13]. During a seizure, the EEG characteristically displays high-amplitude rhythmic bursts and spike-wave discharges that are visually distinct from interictal and normal background activity. Reliably identifying these patterns in practice is harder than it might appear, because the same recordings typically contain substantial artefact contamination from muscle movements, eye blinks, cardiac activity, and electrode noise [14].

Conventional preprocessing pipelines resolve these problems with a series of steps: bandpass filtering to keep clinically informative frequency content [50 or 60 Hz] 0.5-70 Hz band; notch filtering; and Independent Component Analysis (ICA) to isolate neurological and non-neurological sources of signal [15]. The resulting cleaned EEG is subsequently signal decomposed into more ML analysis friendly representations. Multi-resolution frequency-band decomposition can be found in Discrete Wavelet Transform (DWT) [16], and a more adaptive version is available in Variational Mode Decomposition (VMD) [17]. Short-Time Fourier Transform (STFT) generates the spectrogram images which can be directly fed into 2D CNNs [18]. Stockwell Transform: The Stockwell Transform (when used with a transformer encoder) has been shown to outperform typical STFT-based methods in preserving absolute phase information [19]. Entropy measures quantify the regularity of EEG dynamics: recordings in the seizure state are invariably less complex than those in the background, and entropy-based features have been shown to be a highly dependable discriminator, which can be readily combined with host classical and deep learning pipelines [20].

4. MACHINE LEARNING APPROACHES

Classical ML approaches use feature computation and classification as two separate processes, with researchers having full control over how the input is represented. Among the most popular descriptors are time-domain statistics (mean, variance, kurtosis), ratios between frequency-band powers and wavelet sub-band energies. SVM is still a widely used classifier, here, as it is defined to have good performance when dealing with large-dimensional, small-sample problems and wavelet-SVM hybrids tested on the

Bonn data have traditionally been used as a comparison to new techniques [21]. Random Forest builds on the traditional model, combining many decision trees, and decreases variance, yet it can handle correlated features [22].

The properties regarding entropy should be addressed with special consideration since they apprehend a physiologically meaningful ictal EEG property. In seizure activity, huge groups of neurons propagate in a very synchronized and stereotypic fashion that systematically decreases approximate entropy, sample entropy, permutation entropy compared to backgrounds conditions [23]. The question of channels and features are considerations in themselves. Framing the selection problem as a multi-objective optimisation task — simultaneously minimising false alarms and the number of EEG channels used — has shown that intelligently selected subsets of electrodes can be sufficient for accurate detection [24]. An individual approach where electrode selection is optimised at the individual level and not a universal montage that is always applied has also been demonstrated to contribute significantly to the detection accuracy [25]. Despite these strengths, reliance of classical methods on manually-designed features restricts their generalisability with rising recording equipment diversity and clinical heterogeneity of population [26].

5. DEEP LEARNING APPROACHES

Among the larger advantages of deep networks is that they discover useful features automatically, and do not need to be defined by researchers. The adoption of CNNs in the role of seizure detection in EEG became commonplace since about the mid-2010s, and with reason, they have filters that are predisposed to extracting the short and localised waveforms, such as spikes and sharp waves, that clinicians seek when examining EEG traces [27]. The input representation used is an important factor: 1D raw waveforms and 2D spectrograms can teach the CNN to learn various features of the seizure morphology, and both 1D and 2D representations learn locations of the two representations [28]. STFT spectrograms fed into a GoogleNet architecture can meet practical inference-speed needs for real-time applications [29] and networks with multi-input modes that do multiple EEG representations in parallel over parallel paths place further demands on accuracy [30].

The CNNs are least naturally dealt with with the temporal dimension of EEG, and herein is where LSTM and GRU networks excel most. The input, forget and output gates that constitute the gating mechanisms of LSTM to control information movement through the network enable the network to conserve context of the long lengths of EEG that surround a seizure. By using a 3D CNN and LSTM with a Convolutional Block Attention Module added that enhances prediction of seizure onset, it has been demonstrated that adding learned spatial attention followed by the recurrent stage can be beneficial to prediction [31]. GRU streamlines the gating architecture of LSTM and can be trained with a similar detection accuracy at reduced cost [32]. Unsupervised pre-training was also found to better initialise the weights in situations where labelled seizure data is scarce, a scenario, which is common in everyday clinical practice [33]. Empirical evidence has repeatedly shown that state-of-the-art deep architectures can outperform classical baselines on standard evaluation measures [34], and that input dimensionality reduction in conjunction with the evolutionary feature selection algorithms can be performed with deep neural networks without compromising classification accuracy [35].

6. HYBRID AND ADVANCED MODELS

6.1 Cnn-Lstm And Cnn-Gru Architectures

The combination between CNN and recurrent layers complement each other: the patterns are changing with convolutional stage handles local morphological pattern extraction while the recurrent stage tracks how those time. Placing a space-time algorithm in a CNN-LSTM architecture has been demonstrated to be able to achieve the same performance on a variety of datasets [36]. An extension of the recurrent stage to bidirectional LSTM allows the network to take into consideration the immediate and future context of EEG, and this enhances signal boundary detection at seizure onset and offset [37]. Systematic tests of hybrid designs have repeatedly determined that CNN-recurrent designs are superior to all unimodal designs tested [38], with this result backed by large-scale benchmark tests [39]. Further increase in robustness based on the types of seizures is achieved by addition of DWT decomposition as a preprocessing step [40].

6.2 Transformers and Attention Mechanism

The transformer's multi-head self-attention mechanism computes pairwise relationships across all time points in a sequence simultaneously, capturing global temporal dependencies without the sequential processing constraints imposed by recurrent networks. Fusing a multidimensional transformer encoder with a recurrent network has been shown to leverage both global and sequential processing within a single seizure prediction framework [9]. VMD-decomposed sub-bands, when used as transformer inputs, enrich the representations over which self-attention operates [25]. A multi-scale CNN-BiLSTM model augmented with multi-head attention processes EEG simultaneously at several temporal resolutions, allowing the attention mechanism to identify the scale most informative for each patient [15]. Applying separate attention modules along channel and time dimensions explicitly guides the network to localise both where and when ictal activity occurs [14]. Dual frequency-time attention schemes have also demonstrated competitive results across several public datasets [16].

For clinical interpretability, self-supervised pre-training schemes have been developed that support spatial and temporal localisation of seizure onset within attention-based models [21]. Making per-channel attention weights directly visible to neurologists as clinical annotations represents a further step towards transparency [20]. One warning outcome, though, was threatened in a recent study that indicated that adversarially chosen input perturbations significantly changed attention classifier forecasts - a result that generates valid doubts as to the dependability of this sort of framework in safety-aware usage [22].

6.3 Graph Neural Networks

GNNs describe the topology of the EEG recording montage by the relationship between electrodes (the nodes in a graph) and provide a way to encode the topology of the graph (the edges) that can be fundamentally inaccessible to flat vector representations. This structural inductive bias alone has been shown to push detection accuracy above that of comparable deep models that treat electrode channels independently [17]. Pairing a Linear Graph Convolutional Network with DenseNet adds dense feature reuse on top of the graph-structured spatial representation [19]. A dynamic graph approach — in which the graph structure is updated at each time step — allows the model to track the evolving functional connectivity that characterises seizure propagation through cortical networks [18].

7. COMPARATIVE ANALYSIS

Table 1 maps each major method category against its technique, primary advantage, and principal limitation. No single architecture achieves universal superiority; the appropriate choice depends on available dataset size, the degree of seizure type heterogeneity, and deployment constraints including power budget and acceptable inference latency [30], [33].

Table 1: Comparative overview of reviewed ML and DL methods

Method	Technique	Key Advantage	Limitation	References
SVM	Feature-based ML	Robust with small datasets; interpretable	Manual feature design; poor cross-patient generalisation	[4], [7], [31]
Random Forest	Ensemble trees	Reduces overfitting; handles high-dim features	Limited temporal modelling	[15], [32]
Ensemble ML	Combined classifiers	Lower variance; cross-patient robustness	Higher compute cost	[31], [40]
1D CNN	Temporal convolution	Automatic local pattern learning	No long-range temporal dependency capture	[8], [26]
2D CNN	Spectrogram CNN	Leverages image architectures; pre-trainable	Needs time-frequency conversion step	[8], [26], [33]
LSTM	Gated recurrent	Strong temporal dependency modelling	Slow training; vanishing gradient on long windows	[38], [39]
GRU	Lightweight recurrent	Faster than LSTM; comparable accuracy	Slightly reduced capacity	[39]
CNN-LSTM	Spatial-temporal hybrid	Captures morphology and temporal context jointly	Increased complexity	[5], [12], [23], [38]
CNN-BiLSTM	Bidirectional hybrid	Forward and backward EEG context	Higher memory footprint	[12], [15]
CNN-GRU	Hybrid with GRU	Lighter than CNN-LSTM; strong accuracy	May miss some long-range patterns	[39]
Transformer	Self-attention	Long-range dependency modelling; parallelisable	Data-hungry; heavy regularisation required	[9], [25], [27]
Multi-head Attention	Multi-scale attention	Attends to multiple temporal patterns	Complex hyperparameter search	[14], [15], [16]
GNN	Graph electrode topology	Explicit spatial inter-electrode connectivity	Non-trivial graph construction	[17], [18], [19]
DL + Shallow Classifier	Deep features + SVM/RF	Representational power with classifier efficiency	Two-stage training pipeline	[30]

8. LITERATURE REVIEW

Table 2 presents all 40 included studies with their method, benchmark dataset, reported accuracy, and key contribution. Dataset abbreviations: Bonn = University of Bonn EEG corpus; CHB-MIT = CHB-MIT Scalp EEG Database; Temple Univ. = Temple University Hospital EEG Corpus; Multiple = study evaluated on two or more datasets; Clinical = proprietary clinical dataset; — = accuracy not reported as a single comparable metric.

Table 2: Literature review summary

Author(s)	Year	Method	Dataset	Accuracy	Key Contribution
Chen et al. [1]	**2023**	CNN + feature fusion	Bonn	99.1%	Multi-stream EEG feature fusion into CNN yields high detection accuracy on benchmark datasets
Kanamaneni & Raju [2]	**2024**	DL survey (EEG)	Multiple	—	Comprehensive survey of DL strategies and their consistent advantages over handcrafted ML
Mekruksavanich & Jitpattanakul [3]	**2023**	Comparative DL evaluation	CHB-MIT	98.4%	Empirical study confirming DL models outperform classical baselines across standard EEG benchmarks

Author(s)	Year	Method	Dataset	Accuracy	Key Contribution
Kolodziej et al. [4]	**2023**	ML + DL on iEEG	Clinical iEEG	97.8%	Systematic ML vs. DL comparison on intracranial EEG recordings from epileptic patients
Wang et al. [5]	**2023**	CNN-LSTM space-time	CHB-MIT	98.7%	Space-time CNN-LSTM for automated recognition of epilepsy from multi-channel EEG
Mallick & Baths [6]	**2024**	Novel DL framework	CHB-MIT	97.3%	Unsupervised pre-training improves DL seizure detection when labelled data are scarce
Kunekar et al. [7]	**2024**	ML vs. DL benchmark	Bonn, CHB-MIT	98.9%	Benchmark comparing classical and deep methods; deep architectures show consistent accuracy gains
Das et al. [8]	**2024**	1D and 2D CNN	Bonn	99.3%	Dual-representation CNN (raw waveform + spectrogram) on decomposed EEG for seizure classification
Zhu et al. [9]	**2024**	Transformer + RNN	CHB-MIT	98.6%	Multidimensional transformer-RNN fusion for EEG-based seizure prediction
Ilias et al. [10]	**2022**	Multimodal DNN	Temple Univ.	97.5%	Multi-signal deep fusion improves detection in ambiguous single-modality scenarios
Sun et al. [11]	**2024**	Multi-input DL network	CHB-MIT	98.8%	Multi-pathway network exploiting complementary EEG representations for automatic seizure detection
Cao et al. [12]	**2025**	CNN-Bi-LSTM + fusion	Bonn, CHB-MIT	99.2%	Feature-fused bidirectional LSTM hybrid improves seizure boundary detection accuracy
Buldu et al. [13]	**2024**	Hybrid DL study	CHB-MIT	98.5%	Systematic evaluation: CNN-recurrent hybrids outperform all unimodal architectures tested
Su et al. [14]	**2025**	Multi-attention spatiotemporal	CHB-MIT	99.0%	Dual channel-time attention identifies where and when ictal activity occurs in EEG
Zhang [15]	**2025**	Multi-scale CNN-BiLSTM-Attention	Bonn	99.4%	Multi-scale temporal modelling with multi-head self-attention for adaptive seizure detection
Huang et al. [16]	**2025**	Dual attention EEG model	Multiple	98.9%	Separate frequency and time attention modules achieve strong performance across multiple datasets
Kumar et al. [17]	**2024**	GNN for seizure detection	CHB-MIT	98.1%	GNN electrode-topology modelling outperforms DL approaches ignoring spatial EEG structure
Yan et al. [18]	**2025**	Dynamic graph attention	CHB-MIT	98.7%	Dynamic temporal-spatial GNN adapts graph per time step to track seizure propagation patterns

Author(s)	Year	Method	Dataset	Accuracy	Key Contribution
Jibon et al. [19]	**2023**	GCN + DenseNet	Bonn	98.3%	Graph convolution combined with dense feature reuse for multi-channel seizure classification
Wong et al. [20]	**2025**	Channel-annotated DL	Temple Univ.	97.9%	Per-channel attention weights surfaced as clinical annotations for transparent monitoring
Amrani et al. [21]	**2023**	Attention + self-supervised	CHB-MIT	97.6%	Interpretable self-supervised attention model detects and spatially localises seizure onset
Ben Aissa et al. [22]	**2024**	Adversarial robustness	CHB-MIT	—	Adversarial perturbations substantially alter attention classifier predictions; reliability concern raised
Amiri et al. [23]	**2025**	DWT + 1D CNN-LSTM	Bonn, CHB-MIT	99.1%	Multi-level DWT preprocessing enhances CNN-LSTM classification robustness across seizure types
Liu et al. [24]	**2022**	VMD + Deep Forest	Bonn	98.2%	Adaptive VMD decomposition provides quality EEG sub-bands for Deep Forest classification
Wu et al. [25]	**2022**	VMD + Transformer	CHB-MIT	97.8%	Successive VMD-structured inputs improve transformer self-attention for seizure prediction
Shen et al. [26]	**2024**	STFT + GoogleNet	CHB-MIT	98.0%	STFT spectrograms fed to GoogleNet enable real-time seizure detection with practical inference latency
Zhong et al. [27]	**2024**	Stockwell + Transformer	Bonn	98.6%	Phase-preserving Stockwell features combined with transformer encoder improve time-frequency detection
Sikarwar et al. [28]	**2025**	Entropy-driven DL	Bonn	98.7%	Entropy features integrated into deep classifiers significantly boost detection reliability
Ilias et al. [29]	**2022**	Multimodal DNN (ext.)	Temple Univ.	97.4%	Extended multimodal framework reduces detection errors in ambiguous single-modality EEG cases
Zeng et al. [30]	**2023**	Deep CNN + shallow classifiers	CHB-MIT	98.3%	Deep feature extraction followed by SVM or RF combines representational power with efficiency
Dastgoshadeh & Rabiei [31]	**2023**	Entropy + ensemble ML	Bonn	97.9%	Entropy vectors with ensemble classifiers robustly separate normal, interictal, and ictal EEG
Kode et al. [32]	**2024**	Broad ML + DL benchmark	Multiple	98.8%	Comprehensive benchmark: CNN-recurrent hybrids offer the best accuracy-efficiency balance
Romero et al. [33]	**2024**	Image-based EEG analysis	Bonn	98.5%	Converting EEG to image representations enables visual

Author(s)	Year	Method	Dataset	Accuracy	Key Contribution
					DL classifiers with strong benchmark results
Khalid et al. [34]	**2024**	ICA + combined features	CHB-MIT	97.7%	ICA-based artefact removal with prediction probability features improves classification robustness
Lasefr et al. [35]	**2023**	EEG + mobile application	CHB-MIT	96.8%	Smartphone-integrated EEG detection demonstrates feasibility of real-world ambulatory deployment
Jana & Mukherjee [36]	**2023**	Multi-objective channel selection	CHB-MIT	98.0%	Joint optimisation of accuracy and channel count reduces hardware requirements without accuracy loss
Ferrara et al. [37]	**2025**	Patient-specific channel selection	Clinical	98.4%	Personalised channel optimisation markedly outperforms fixed universal channel configurations
Lu et al. [38]	**2023**	CBAM + 3D CNN-LSTM	CHB-MIT	98.9%	Spatial attention module re-weights 3D CNN-LSTM feature maps, improving seizure onset prediction
Bhadra et al. [39]	**2024**	HyEpiSeiD (CNN-GRU)	Multiple	98.6%	CNN-GRU hybrid achieves LSTM-level accuracy at lower computational cost across multiple EEG sets
Yogarajan et al. [40]	**2023**	Dragonfly Algo + DNN	Bonn	98.1%	Evolutionary feature selection reduces input dimensionality while preserving DNN detection performance

9. RESEARCH GAPS AND FUTURE DIRECTIONS

Several important challenges remain open in this field. Most studies rely heavily on the Bonn corpus or CHB-MIT — controlled, single-centre datasets that do not reflect the amplifier diversity and patient heterogeneity of real clinical environments. Inconsistent reporting of sensitivity, specificity, and AUC further complicates cross-paper comparison [7], [32], [33]. Cross-patient generalisation remains the most pressing technical limitation, as models trained on mixed cohorts frequently fail on unseen patients; transfer learning, domain adaptation, and federated learning — which would allow hospitals to jointly train models without sharing sensitive data — are promising remedies that remain underexplored [2], [6], [29], [34]. Structural class imbalance, with seizure epochs comprising only 1–5% of recording time, continues to inflate accuracy figures while masking clinically unacceptable false-negative rates [31], [35].

Interpretability is a persistent barrier to clinical adoption. Weighted attention and GNN attributions have never been rigorously evaluated against expert annotations, and one of the studies in this review has shown that a small adversarial input perturbation significantly changed the predictions of classifiers - a significant safety concern when deploying classifiers in practice [20], [21], [22]. Lastly, none of the available literature confirms any of the proposed models on actual streaming EEG devices. Future directions include model compression of wearable processors, multimodal fusion between EMG and ECG signals to minimize false alarms and developing EEG foundation models that are pre-trained on huge unlabeled corpora that can be easily fine-tuned to a single patient [10], [15], [35], [40].

10. CONCLUSION

In this review, 40 works published between 2022 and 2025 on the application of ML and DL to automatically detect the epileptic seizures in EEG signals were considered. Latent traditional algorithms such as the SVM and the Random Forest are intuitive to interpret, yet fail with new patients, compared to the hybrid CNN-LSTM and CNN-GRU algorithms that work better at the same time due to their simultaneous learning of both shape and timing of the seizure pattern [5], [12], [39]. More recent transformer models, and attention-based models, take a slightly further step by operating on the dependencies over longer tracks of EEG, and GNNs are unique in that they are able to consider the relationship between electrodes in space, a task that other simple models are just unable to handle alone [9], [17], [18]. In all these strategies, eventual preprocessing (DWT, VMD, STFT, or entropy-based features) still does matter to the end outcome [23]–[28].

Although that, there are a couple of issues that are not addressed yet. Computerised models continue to find it difficult to generalise between patients, seizure data has been vastly outnumbered by normal EEG in most traces, current systems cannot be interpreted by clinicians, and practically no such systems have been tested on real hardware other than in a lab. The gap between the potential outcomes of research and tools that can be conveniently used in the clinic will persist until the field addresses these issues with more diverse training data, federated learning, and more compact models that can fit into wearable devices.

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