Review Article

Deep Learning Approaches for EEG-Based Seizure Prediction in Pediatric Epilepsy: Current Advances, Challenges, and Future Directions

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ABSTRACT

Pediatric epilepsy is one of the most prevalent neurological disorders in children and is associated with significant cognitive, developmental, and psychosocial consequences. The unpredictable nature of seizures poses substantial challenges for patients, caregivers, and clinicians, emphasizing the need for accurate seizure prediction systems. Electroencephalography (EEG) remains the gold standard tool for seizure monitoring due to its high temporal resolution and ability to capture epileptiform activity. In recent years, deep learning approaches have demonstrated considerable potential in improving EEG-driven seizure prediction by automatically extracting complex spatiotemporal patterns from neural signals. This review summarizes current advances in deep learning-based seizure prediction in pediatric epilepsy, focusing on convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, hybrid CNN-LSTM architectures, and transformer-based models. The review also discusses pediatric-specific EEG characteristics, signal pre-processing methods, feature extraction techniques, and benchmark datasets commonly used for model evaluation. Although hybrid and transformer-based models have achieved promising predictive accuracies, several challenges continue to hinder clinical translation, including limited pediatric-specific EEG datasets, age-dependent EEG variability, poor cross-patient generalizability, black box model interpretability, wearable device limitations, and ethical concerns regarding pediatric data privacy. Emerging research directions such as explainable artificial intelligence, multimodal biomarker integration, federated learning, wearable EEG technologies, and edge AI systems are also highlighted. Overall, deep learning-driven seizure prediction holds substantial promise for personalized pediatric epilepsy management and may significantly improve long-term neurological outcomes through early intervention and real-time monitoring.

Key words: Pediatric epilepsy, EEG, Seizure prediction, Deep learning, Artificial intelligence, CNN, LSTM, Transformer models

Epilepsy is a chronic neurological condition characterized by recurrent, unprovoked seizures arising from abnormal electrical activity in the brain. It is among the most common neurological disorders of childhood, with an estimated global prevalence of 3.2 to 5.5 per 1,000 children under 15 years of age [1,2]. The International League Against Epilepsy (ILAE) defines epilepsy as having at least two unprovoked seizures more than 24 hours apart, one unprovoked seizure with a high recurrence risk, or a diagnosis of an epilepsy syndrome [3].

In pediatric patients, epilepsy carries a substantial burden, including increased risks of developmental delay, behavioral disorders, learning difficulties, and sudden unexpected death in epilepsy (SUDEP) [4,5]. The economic burden associated with pediatric epilepsy management is considerable, encompassing hospitalizations, antiseizure medications (ASMs), and long-term neurodevelopmental support [6].

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Seizures can occur abruptly and without warning, placing children at risk of injury, cognitive impairment, and life-threatening consequences. The unpredictability of seizure occurrence is a major source of anxiety for patients and caregivers alike [7]. Accurate seizure prediction, the ability to forecast an impending seizure in sufficient time to take preventive action, has the potential to revolutionize epilepsy management. Such systems could enable timely administration of fast-acting rescue medications, alert caregivers or medical personnel, or trigger responsive neurostimulation devices [8,9].

From a developmental perspective, minimizing seizure frequency in young children is critical, as repeated seizures during brain maturation may have disproportionate effects on cognitive and emotional development [10]. Electroencephalography (EEG) remains the gold standard diagnostic tool for epilepsy, providing non-invasive, high

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temporal resolution measurement of cortical electrical activity [11]. EEG can detect interictal epileptiform discharges (IEDs) such as spikes and sharp waves, delineate seizure onset zones, characterize seizure types, and monitor treatment responses [12]. In pediatric epilepsy, EEG interpretation is complicated by the dynamic changes in background rhythms associated with normal brain maturation, making it challenging to distinguish pathological from physiological patterns [13]. Long-term EEG monitoring, including ambulatory and video EEG, has enabled the capture of spontaneous seizures and the identification of preictal (pre-seizure) EEG changes that may precede clinical onset by minutes to hours [14].

The past decade has witnessed an exponential increase in the application of machine learning (ML) and deep learning (DL) to neurological data analysis. Unlike traditional ML methods that rely on handcrafted features, deep learning models autonomously extract hierarchical representations from raw data, making them particularly suited for complex biomedical signals [15,16]. The availability of large EEG datasets, advances in computational hardware, and improvements in neural network architectures have collectively accelerated the development of AI-based seizure detection and prediction systems [17].

In pediatric neurology, AI applications are emerging across domains, including autism spectrum disorder, attention deficit/hyperactivity disorder, and cerebral palsy, though epilepsy remains the most actively researched area [18,19]. This review summarizes recent advances in deep learning-based EEG seizure prediction in pediatric epilepsy, highlighting current model architectures, benchmark datasets, performance comparisons, key challenges, research gaps, and future clinical applications. It aims to serve as a comprehensive reference for clinicians, biomedical engineers, and AI researchers interested in this rapidly evolving field.

2. PEDIATRIC EPILEPSY AND EEG CHARACTERISTICS

2.1 Classification of Pediatric Seizures

The ILAE's 2017 revised classification divides seizures into focal onset, generalized onset, and unknown onset categories [20]. Focal seizures originate from a discrete cortical network in one hemisphere and may be further classified as aware or impaired awareness. Generalized seizures involve bilateral networks from onset and include tonic-clonic, absence, myoclonic, atonic, and tonic types. In pediatric practice, absence seizures are characterized by brief lapses of consciousness without postictal confusion, and are particularly common between the ages of 4 and 10 years [21]. Febrile seizures, the most frequent type in children aged 6 months to 5 years, are associated with fever in the absence of central nervous system infection [22]. Infantile spasms (West syndrome) and Lennox-Gastaut syndrome represent severe epileptic encephalopathies with characteristic EEG signatures [23].

2.2 EEG Characteristics in Pediatric Patients

Pediatric EEG exhibits significant age-dependent variation. In neonates, EEG activity is discontinuous and characterized by high-amplitude bursts alternating with periods of suppression. By early childhood, continuous background rhythms emerge, with the posterior dominant rhythm (PDR) gradually increasing from 3 to 4 Hz in infancy to the adult alpha frequency of 8 to 13 Hz by adolescence [24]. Sleep architecture also evolves substantially, with high-amplitude slow waves and prominent vertex waves appearing during non-REM sleep in children. These maturational changes necessitate age-specific reference norms for EEG interpretation and complicate the development of generalizable AI algorithms [25]. Pathological features such as focal slowing, interictal epileptiform discharges (IEDs), and hypsarrhythmia in infantile spasms can be identified, but their accurate automated detection requires models trained specifically on pediatric EEG data [26].

2.3 Challenges in Pediatric EEG Interpretation

Pediatric EEG recordings are susceptible to a range of non-neural artifacts, including movement artifacts from active children, electrode displacement, muscle activity, and cardio ballistic artifact from pulsating scalp vessels [27]. In neonates and infants, physiological patterns such as rhythmic movement artifact or sucking artifact can mimic seizure activity. The limited tolerance of young children for prolonged monitoring sessions further restricts the duration and quality of recordings [28]. Motion artifacts are especially problematic for wearable EEG systems. Additionally, the wide range of normal developmental EEG variants across age groups means that a single artifact removal or feature extraction approach may not be universally applicable [29].

3. EEG-BASED SEIZURE PREDICTION WORKFLOW

3.1 EEG Signal Acquisition

EEG acquisition in pediatric epilepsy can be performed using scalp electrodes placed according to the standard 10-20 international system, typically employing 19 to 256 electrodes [30]. Routine EEG recordings last 20 to 40 minutes, while long-term monitoring may extend for days using video EEG telemetry units. Ambulatory EEG systems allow patients to continue daily activities while recording, and modern wearable EEG devices, including behind-the-ear sensors, smart caps, and dry electrode headsets, are increasingly explored for continuous home-based monitoring [31]. Intracranial EEG (iEEG), although more invasive, offers higher signal quality and spatial resolution and is used in presurgical evaluation, though it is less applicable for routine pediatric seizure prediction [32].

3.2 Signal Pre-processing

Raw EEG signals are corrupted by artifacts that must be removed before feature extraction. Standard pre-processing pipelines include bandpass filtering (typically 0.5–70 Hz), notch filtering at 50 or 60 Hz to remove power line interference, re-referencing to average or linked mastoid electrodes, and epoch segmentation [33]. Independent component analysis (ICA) and artifact subspace reconstruction (ASR) are widely used to separate neural from non-neural components. In pediatric EEG, additional artifact rejection thresholds may be required due to higher baseline variability [34]. Automated pre-processing algorithms embedded in deep learning pipelines are increasingly reported, reducing the dependency on manual artifact identification [35].

3.3 Feature Extraction

Traditional seizure prediction systems relied on handcrafted features extracted from EEG signal segments. Time domain features include amplitude, variance, Hjorth parameters, and zero crossing rates [36]. Frequency domain features derived from fast Fourier transform (FFT) include delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz) band power. Wavelet transforms, particularly the discrete wavelet transform (DWT) and wavelet packet decomposition, provide joint time-frequency representations suitable for non-stationary EEG signals [37]. Coherence measures, phase synchrony, and nonlinear features such as Lyapunov exponents and approximate entropy have also been explored. In contrast, end-to-end deep learning models learn task-relevant features directly from raw or minimally processed EEG, bypassing the need for manual feature engineering [38].

3.4 Classification and Prediction

The seizure prediction task involves classifying EEG windows into preictal (preceding a seizure) and interictal (seizure-free) states. The preictal period is typically defined as a window of 5 to 60 minutes before seizure onset, while the interictal period is drawn from recordings remote from any seizure event [39]. AI-based classifiers receive pre-processed and feature-extracted EEG data and output a probability or binary prediction label. Performance is evaluated using sensitivity (true positive rate), specificity (true negative rate), area under the ROC curve (AUC), and time in warning metrics. Crucially, patient-specific models are trained and tested on data from the same individual, and typically outperform cross-patient models, though the latter are more scalable [40].

4. DEEP LEARNING APPROACHES IN PEDIATRIC SEIZURE PREDICTION

4.1 Convolutional Neural Networks (CNN)

CNNs were originally developed for image recognition tasks and have been adapted for EEG analysis by representing multichannel signals as 2D matrices or spectrograms [41]. CNNs learn spatial hierarchies of features through successive convolutional and pooling layers, enabling automatic extraction of local patterns from EEG without domain-specific feature engineering. Shallow Conv Net and Deep Conv Net are among the most frequently cited architectures in EEG classification [42]. In seizure prediction, CNNs applied to short-time Fourier transform (STFT) spectrograms or continuous wavelet transform (CWT) Scalo grams have demonstrated sensitivities exceeding 90% on benchmark datasets, including CHB-MIT and Bonn University EEG [43]. For pediatric applications, CNNs trained on the CHB-MIT scalp EEG dataset, which includes recordings from 22 pediatric patients, have achieved mean sensitivities of approximately 95% with false positive rates below 0.15 per hour [44]. Despite their performance, CNNs require large labelled datasets to generalize effectively and are computationally demanding during training.

4.2 Recurrent Neural Networks (RNN)

RNNs are designed for sequential data processing and model temporal dependencies through recurrent connections. In EEG-based seizure prediction, RNNs process EEG feature sequences to capture the temporal evolution of preictal dynamics [45]. Standard RNNs, however, suffer from the vanishing gradient problem, where gradients diminish exponentially during backpropagation through time, limiting their capacity to model long-range temporal dependencies. This limitation is particularly relevant for seizure prediction, where preictal changes may evolve over minutes. Despite these constraints, vanilla RNNs combined with frequency domain features have shown moderate performance in seizure onset detection tasks [46].

4.3 Long Short-Term Memory Networks (LSTM)

LSTM networks, introduced by Hochreiter and Schmidhuber in 1997, address the vanishing gradient limitation of standard RNNs through gated memory cells that selectively retain or discard information over time [47]. This architectural innovation makes LSTMs highly effective for modeling the slow, evolving temporal patterns characteristic of the preictal EEG state. Several studies have applied LSTM networks to pediatric seizure prediction, demonstrating the ability to capture preictal transitions occurring 30 to 60 minutes before seizure onset [48]. Bidirectional LSTM (Bi-LSTM) models, which process sequences in both forward and backward directions, have further improved sensitivity in classification tasks. On the CHB-MIT dataset, LSTM-based models have reported sensitivities ranging from 88% to 93% [49]. Attention augmented LSTM models, which assign variable importance to different time steps, represent an emerging refinement of this architecture [50].

4.4 Hybrid CNN and LSTM Models

Hybrid architectures combining CNN and LSTM modules leverage the complementary strengths of spatial feature

extraction and temporal sequence modeling [51]. In a typical design, CNN layers process raw EEG or spectrogram data to extract local spatial features, which are then fed into LSTM layers to model temporal dependencies across sequential windows. This architecture has consistently outperformed standalone CNN or LSTM models on EEG seizure prediction benchmarks. Studies utilizing pediatric ICU EEG data have reported accuracies up to 97% with hybrid CNN and LSTM models [52]. Variants such as temporal convolutional networks (TCNs) with LSTM integration have further enhanced performance by incorporating dilated causal convolutions for multi-scale temporal modeling [53]. The primary challenge of hybrid models is increased computational complexity and a higher risk of overfitting in small pediatric datasets.

4.5 Transformer-Based Models

Transformer architectures, initially developed for natural language processing, have recently been adapted for EEG signal analysis [54]. The self-attention mechanism of transformers enables simultaneous modeling of long-range dependencies across all positions in a sequence, overcoming the sequential processing bottleneck of RNNs. EEG Transformer, EEG Conformer, and related architectures have demonstrated competitive performance in EEG motor imagery classification and seizure detection tasks [55]. In the seizure prediction context, transformer models have been applied to temporal patch embeddings of multichannel EEG, achieving accuracies above 94% on benchmark datasets [56]. Their application to pediatric-specific data remains limited, with only a handful of studies published to date. The high computational requirements and relatively large data demands of transformers present challenges for deployment in resource-constrained pediatric monitoring settings [57].

5. COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS

Table 1 summarizes the performance characteristics of major deep learning architectures evaluated for EEG-based seizure prediction, with emphasis on their application to pediatric datasets.

Table 1. Comparative analysis of deep learning models for pediatric EEG-based seizure prediction

Model	Input Type	Primary Dataset	Reported Accuracy	Key Advantages	Main Limitations
CNN	EEG Spectrogram	CHB-MIT	~95%	Fast spatial feature extraction; high scalability	Requires large labeled datasets; limited temporal context
RNN	EEG Features	Various	~85%	Sequential data modeling	Vanishing gradient; poor long-range memory
LSTM	Raw/Feature EEG	CHB-MIT, Bonn	88–93%	Long-range temporal dependency modeling	High computational cost; slower training
CNN-LSTM Hybrid	Raw EEG	Pediatric ICU, CHB-MIT	~97%	Spatial + temporal learning; highest accuracy	Overfitting risk: high model complexity
Transformer	EEG Patches	Limited pediatric data	94–96%	Global attention; parallel processing	Very high data requirements; new in the EEG domain

CNN: Convolutional Neural Network; LSTM: Long Short-Term Memory; CHB-MIT: Children's Hospital Boston-Massachusetts Institute of Technology scalp EEG database; ICU: Intensive Care Unit.

6. CURRENT CHALLENGES AND RESEARCH GAPS

6.1 Limited Pediatric Specific EEG Datasets

One of the most pressing limitations in this field is the scarcity of large, well-annotated pediatric EEG datasets available for deep learning model training and validation [58]. The CHB MIT database, containing scalp EEG recordings from 22 pediatric patients, remains the most widely used benchmark but lacks the diversity of seizure types and age ranges representative of the broader pediatric epilepsy population [59]. Class imbalance is an inherent challenge: seizure epochs constitute a small fraction of total recording time, resulting in

highly skewed training sets that bias classifiers toward the majority interictal class. Oversampling techniques such as SMOTE, synthetic EEG generation via generative adversarial networks (GANs), and data augmentation strategies have been proposed to address this issue [60].

6.2 Poor Generalizability Across Patients

Most published deep learning models are trained and validated on data from single patients or single centers, raising serious concerns about generalizability [61]. Cross-patient seizure prediction models typically show a significant performance drop compared to patient-specific approaches. The high inter-individual variability in EEG morphology, seizure semiology, and epilepsy syndrome type is particularly pronounced in pediatric populations due to the wide age range and differential brain maturation trajectories [62]. Transfer learning approaches in which a model pre-trained on a large EEG corpus is fine-tuned with limited patient-specific data have shown promise in improving cross-patient performance [63].

6.3 Age-Dependent EEG Variability

The dynamic maturational changes in pediatric EEG constitute a fundamental challenge for algorithm development. The spectral composition, amplitude ranges, and spatiotemporal patterns of normal and abnormal EEG activity differ substantially across age groups from neonates to adolescents [64]. A model trained on EEG data from a 10-year-old child may perform poorly when applied to a 2-year-old with the same seizure type. Current deep learning models rarely account for age as an explicit covariate, limiting their clinical utility across the pediatric age spectrum [65].

6.4 Black Box Nature of AI Models

Deep learning models, despite their high predictive accuracy, are notoriously opaque in their decision-making processes, often described as "black boxes." [66]. This lack of interpretability is a major barrier to clinical adoption, as neurologists must understand and trust the basis of model predictions before incorporating them into patient care. Explainable AI (XAI) techniques such as gradient weighted class activation mapping (Grad CAM), layer-wise relevance propagation (LRP), and SHAP (Shapley Additive exPlanations) values have been applied to EEG models to identify which signal features drive predictions [67,68]. However, validation of these explanations against established neurophysiological knowledge remains limited.

6.5 Wearable Monitoring Challenges

The development of wearable EEG systems for pediatric home monitoring faces multiple practical challenges. Children often resist wearing EEG headsets due to discomfort, cosmetic concerns, or sensory sensitivities associated with neurodevelopmental comorbidities such as autism spectrum disorder [69]. Motion artifacts generated by play and physical activity substantially degrade signal quality. Battery life, wireless transmission latency, and data security are additional engineering constraints. Dry electrode systems, while improving comfort and setup time, generally exhibit higher contact impedance and greater susceptibility to artifact than gel electrode systems [70].

6.6 Ethical and Privacy Considerations

Continuous EEG monitoring of children raises important ethical, legal, and privacy issues. The collection, storage, and analysis of pediatric neurophysiological data require stringent adherence to data protection regulations, including the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States [71]. Obtaining informed assent from older children in addition to parental consent is an ethical imperative. Algorithmic bias, arising from the under-representation of certain demographic groups in training datasets, may result in disparate model performance across racial, ethnic, or socioeconomic subgroups, raising concerns about equitable access to AI-driven healthcare [72].

7. FUTURE DIRECTIONS

7.1 Explainable Artificial Intelligence (XAI)

The development of transparent, interpretable deep learning models is a research priority for clinical translation of AI-based seizure prediction [73]. Neurophysiologically grounded XAI methods that highlight specific EEG frequency bands, electrode locations, or temporal segments driving predictions can facilitate clinician AI collaboration and build trust. Causal inference frameworks and physics-informed neural networks represent frontier approaches that may improve model interpretability while maintaining predictive performance [74].

7.2 Multimodal Biomarker Integration

Seizure prediction accuracy may be improved through the integration of multiple physiological data streams beyond EEG. Electrocardiography (ECG) can provide autonomic nervous system correlates of seizure activity, while accelerometry captures motor manifestations [75]. Neuroimaging biomarkers, including structural MRI and functional connectivity derived from resting-state fMRI, can inform patient-specific baseline models. Genomic and metabolomic data may ultimately enable personalized epilepsy risk stratification [76]. Multimodal fusion architectures, combining convolutional, recurrent, and attention-based modules for different data types, represent an active area of model development.

7.3 Wearable Pediatric EEG Systems

Advances in flexible electronics, nanomaterial-based electrodes, and miniaturized signal processing chips are enabling the development of unobtrusive wearable EEG platforms suitable for children [77]. Smart headbands, behind-the-ear sensors, and scalp tattoo electrodes represent emerging

form factors. Integration with Internet of Things (IoT) ecosystems enables continuous data streaming to cloud-based analysis platforms, supporting remote monitoring by clinicians and caregivers. The development of pediatric-specific wearable form factors that accommodate smaller head sizes and higher activity levels is a critical engineering challenge [78].

7.4 Personalized Medicine Approaches

Patient-specific seizure prediction models, trained and continuously updated on individual patient data, represent the gold standard for clinical deployment [79]. Federated learning approaches, in which models are trained collaboratively across multiple institutions without sharing raw patient data, offer a privacy-preserving mechanism for developing robust, generalized models while respecting data sovereignty [80]. Adaptive learning algorithms that dynamically adjust model parameters in response to changes in a patient's EEG characteristics over time are particularly relevant for pediatric patients undergoing brain maturation or treatment changes.

7.5 Edge AI and Real-Time Monitoring

The deployment of deep learning inference at the edge, directly on wearable devices or bedside processors, eliminates the latency and bandwidth constraints of cloud-based systems, enabling truly real-time seizure prediction [81]. Model compression techniques, including pruning, quantization, and knowledge distillation, have demonstrated that compact deep learning models retaining greater than 90% of full model accuracy can be deployed on microcontrollers with milliwatt power budgets [82]. Closed-loop neurostimulation systems integrating edge AI for real-time seizure prediction with automated responsive stimulation delivery represent the most ambitious clinical application of this technology [83].

8. Clinical Translation and Practical Implications

The pathway from academic deep learning research to clinical deployment of pediatric seizure prediction systems involves multiple regulatory, validation, and implementation challenges [84]. Regulatory approval from agencies such as the US Food and Drug Administration (FDA) and the European Medicines Agency (EMA) requires demonstration of analytical validity, clinical validity, and clinical utility through prospective studies. Prospective multicenter studies enrolling diverse pediatric populations across multiple age groups and epilepsy syndromes are essential to establish the external validity of AI prediction models [85].

In the pediatric intensive care unit (ICU), continuous EEG monitoring is increasingly standard practice for patients at risk of subclinical seizures, including those with hypoxic ischemic encephalopathy, traumatic brain injury, and status epilepticus [86]. AI-assisted EEG review tools can reduce the burden on clinical neurophysiologists and enable timely seizure identification in resource-limited settings. For outpatient and home-based applications, integration of seizure prediction alerts into smartphone applications and caregiver notification platforms can empower families and improve safety during daily activities [87]. Decision support systems that present prediction confidence scores, explainability visualizations, and recommended interventions alongside clinical EEG data represent the most feasible near-term implementation model. Pediatric neurologists can then apply clinical judgment to contextualize AI outputs within the broader clinical picture, maintaining appropriate human oversight [88]. Long-term outcome studies are needed to demonstrate whether AI-guided seizure prediction leads to measurable improvements in seizure control, quality of life, and neurodevelopmental outcomes in pediatric epilepsy [89].

CONCLUSION

This review has synthesized the current state of deep learning-based EEG seizure prediction in pediatric epilepsy, encompassing signal acquisition and pre-processing, feature extraction methodologies, neural network architectures, and the unique challenges of the pediatric neurophysiological context. CNN, LSTM, hybrid CNN LSTM, and transformer-based models have each demonstrated strong predictive performance on existing benchmark datasets, with hybrid architectures currently achieving the highest reported accuracies approaching 97%.

Nevertheless, the field faces critical barriers, including the paucity of large, age-stratified pediatric EEG datasets, the developmental variability of the pediatric brain, the limited interpretability of deep learning models, and the practical challenges of wearable EEG monitoring in children. Addressing these limitations will require concerted efforts from neurologists, biomedical engineers, data scientists, ethicists, and regulatory authorities. Priority research directions include the creation of multicenter pediatric EEG repositories, the development of explainable AI frameworks validated against neurophysiological knowledge, the engineering of child-friendly wearable EEG platforms, and the conduct of prospective clinical trials evaluating AI-guided seizure prediction. With these advances, deep learning holds transformative potential to reduce the burden of epilepsy in children and improve long-term neurodevelopmental outcomes worldwide.

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