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OPTIMIZING EEG CHANNEL SELECTION AND DEEP LEARNING MODELS FOR RELIABLE EPILEPTIC SEIZURE PREDICTION: A STATE-OF-THE-ART REVIEW AND ROADMAP FOR FUTURE RESEARCH

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Abstract : Epilepsy is one of the most prevalent neurological disorders worldwide, characterized by recurrent and unpredictable seizures resulting from abnormal electrical activity in the brain. Accurate seizure prediction using electroencephalogram (EEG) signals holds tremendous potential to improve patient safety and quality of life by enabling timely interventions. In recent years, substantial progress has been made in developing automated seizure detection and prediction systems, driven by advances in publicly available EEG datasets, optimized channel selection techniques, and powerful machine learning (ML) and deep learning (DL) models. This review provides a comprehensive analysis of key open-access EEG datasets, comparing their characteristics such as recording type, number of channels, sampling frequencies, and annotation quality. It examines state-of-the-art channel selection strategies, including statistical measures, information-theoretic approaches, and multi-objective optimization algorithms like NSGA-II and particle swarm optimization, which reduce computational complexity and enable efficient wearable systems. Furthermore, we critically evaluate recent ML and DL architectures — including convolutional neural networks (CNNs), long short-term memory (LSTM) networks, transformer-based models, and ensemble methods — highlighting their performance, strengths, and limitations in seizure prediction tasks. This review also discusses challenges that remain unsolved, including patient-specific EEG variability, class imbalance between seizure and non-seizure data, generalizability of models across populations, and integration into real-time, low-power devices suitable for clinical or wearable applications. Finally, we outline future research directions focusing on personalized seizure prediction, explainable AI, federated learning for collaborative data utilization, and the design of energy-efficient systems for continuous brain monitoring. By synthesizing current knowledge and identifying open issues, this review aims to provide a valuable reference for researchers and practitioners working towards reliable, practical, and patient-centered seizure prediction technologies.

***IndexTerms* -** EEG, Epilepsy, Seizure prediction, Channel selection, Machine learning, Deep learning, Optimization

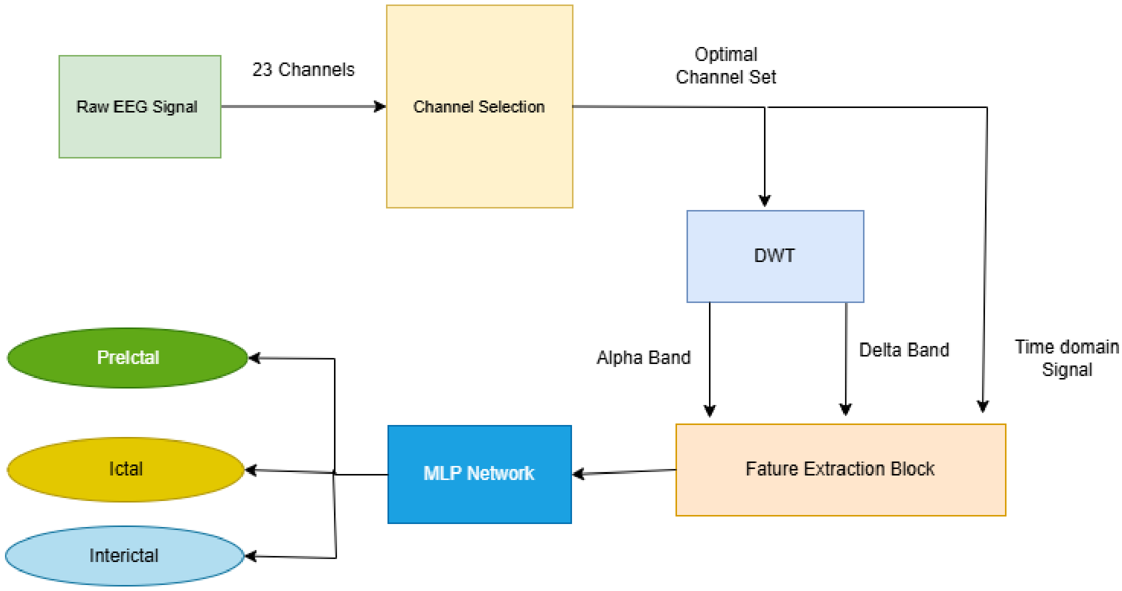
I. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures caused by abnormal and excessive synchronous neuronal activity in the brain. According to the World Health Organization, it affects more than 50 million people globally, making it one of the most common neurological diseases. Uncontrolled seizures can cause physical injuries, cognitive decline, social stigma, and a severely reduced quality of life, especially in drug-resistant epilepsy, which affects nearly 30% of patients who do not respond to anti-epileptic drugs.

Predicting seizures in advance offers a transformative opportunity for epilepsy management: timely warnings can allow patients or caregivers to take preventive actions, administer rescue medications, or move to a safe environment. Seizure prediction systems could enable closed-loop therapeutic devices that deliver interventions (e.g., neurostimulation) only when needed, reducing side effects of continuous treatment. Electroencephalography (EEG) — the non-invasive recording of electrical activity from the scalp or intracranial electrodes — remains the gold standard for monitoring brain dynamics due to its excellent temporal resolution, direct measurement of neuronal activity, and relative affordability compared to imaging techniques.

However, designing reliable seizure prediction systems is highly challenging. EEG signals are inherently nonlinear, non-stationary, and exhibit significant inter- and intra-patient variability in seizure onset patterns. Moreover, the rarity of seizures in long EEG recordings leads to severe class imbalance, complicating machine learning (ML) model training. High-density EEG systems with dozens of electrodes generate massive amounts of redundant data, necessitating effective channel selection and dimensionality reduction techniques.

The block schematic of seizure prediction system is as follows.



Over the past two decades, substantial progress has been made with the availability of publicly accessible EEG datasets, innovative channel selection strategies, and the adoption of state-of-the-art ML and deep learning (DL) architectures, including CNNs, RNNs, and transformers.

This review provides a comprehensive synthesis of EEG-based seizure detection and prediction, focusing on three critical areas:

1. EEG datasets enabling reproducible and comparable research
2. channel selection methods that balance model performance and computational efficiency
3. ML and DL algorithms advancing seizure prediction performance.

We also discuss key challenges that hinder clinical translation, including data variability, class imbalance, and real-time deployment constraints, and outline future research directions toward personalized, explainable, and energy-efficient seizure prediction systems.

II. Data sets for Seizure Prediction

Robust, diverse, and well-annotated datasets are essential for training and evaluating seizure prediction algorithms. Several open-access datasets have emerged over the past two decades, each offering unique features in terms of patient population, recording type, channel configuration, sampling frequency, and seizure annotation quality.

These datasets provide complementary opportunities to benchmark algorithms under diverse conditions. A cornerstone of progress in seizure prediction research is the availability of open-access, annotated EEG datasets that enable reproducible experiments and fair performance comparisons across methods. Early studies relied on private datasets with limited recordings, restricting generalization and hindering progress. Over time, several widely used datasets have emerged, each offering unique properties that make them suitable for different research needs.

2.1. CHB-MIT Scalp EEG Database

Recorded at Boston Children's Hospital, the CHB-MIT dataset consists of scalp EEG from 24 pediatric patients with drug-resistant epilepsy. It includes over 980 hours of recordings across 23 channels sampled at 256 Hz, with 173 annotated seizures. Each recording is accompanied by seizure start and end times, making it a benchmark for training and evaluating seizure detection algorithms. Its public availability and wide use in literature make it a de facto standard for seizure prediction research.

2.2. TUH EEG Seizure Corpus

From Temple University Hospital, the TUH EEG is the largest publicly available clinical EEG dataset. It covers over 14,000 EEG recordings, including various seizure types (focal, generalized, absence) across adult and pediatric populations, with sampling rates from 250 Hz to 500 Hz. Unlike CHB-MIT, TUH reflects real-world clinical heterogeneity with variable recording lengths, noise artifacts, and different electrode montages. This diversity makes it ideal for developing models robust to practical challenges.

2.3. EPILEPSIAE Database

This multicenter European dataset includes continuous scalp and intracranial EEG from 275 drug-resistant epilepsy patients, with most recordings sampled at ≥256 Hz. Each seizure event is annotated with precise metadata (onset, offset, seizure type), and patients are monitored over weeks, offering unique opportunities for long-term prediction and personalized modeling studies.

2.4. Bonn University Dataset

Although limited in size, the Bonn dataset has been extensively used for proof-of-concept seizure detection studies. It contains five sets of single-channel EEG segments (Z, O, N, F, S), each 23.6 seconds long and sampled at 173.61 Hz. Sets Z and O include healthy volunteers' EEG, while N, F, and S represent interictal and ictal recordings from epileptic patients. Its simplicity makes it suitable for algorithm benchmarking.

2.5. Freiburg Intracranial EEG Dataset

Focused on presurgical evaluation of drug-resistant epilepsy, Freiburg includes intracranial EEG from 21 patients with up to 128 electrodes. Recordings are sampled at ≥256 Hz and contain precise seizure onset annotations, allowing high spatial resolution analysis critical for seizure onset zone localization.

2.6. Comparison Summary

Sampling Rates: Range from 173.61 Hz (Bonn) to 500 Hz (TUH), affecting frequency resolution.
Channel Count: Varies from single-channel (Bonn) to dense 128-channel intracranial EEG (Freiburg).
Seizure Types: TUH covers multiple seizure types; CHB-MIT primarily focal seizures; Bonn includes healthy control data.
Data Quality: CHB-MIT is cleaner, while TUH reflects real-world noise and variability.

Dataset	Recording Type	Channels	Sampling Rate	Annotation
CHB-MIT	Scalp EEG	23	256 Hz	Seizure events
TUH EEG	Scalp EEG	21–25	250–500 Hz	Seizure types
EPILEPSIAE	Scalp/Intracranial	Variable	≥256 Hz	Seizure metadata
Bonn University	Single-channel EEG	1	173.61 Hz	Ictal/interictal states
Freiburg EEG	Intracranial EEG	32+	≥256 Hz	Seizure onset

Table 1: Comparison Summary of Datasets

2.7. Key Remarks

1. CHB-MIT and TUH remain the most common benchmarks for scalp EEG-based seizure prediction.
2. Datasets like EPILEPSIAE and Freiburg enable personalized and intracranial EEG studies but require specialized expertise.
3. Cross-dataset validation is rare in current research; future work should evaluate models across multiple datasets for better generalizability.

III. Review on Channel Selection Techniques

EEG recordings often involve many channels (up to 128), but not all contribute relevant information for seizure detection. Using redundant channels increases computational complexity and power requirements, especially for portable devices. Channel selection identifies a subset of informative electrodes, balancing model performance with efficiency.

Channel selection plays a critical role in EEG-based seizure prediction by reducing computational complexity, minimizing noise from irrelevant signals, and enabling practical deployment on wearable or portable devices. EEG systems can record from over 100 electrodes, but many channels provide redundant or non-informative data for seizure detection. Using fewer but highly informative channels improves energy efficiency and reduces processing time — essential for real-time applications.

Statistical methods assess each channel independently, calculating metrics such as Signal Quality Index (SQI) and Absolute Strictly Standardized Mean Difference (ASSMD) to quantify the relevance of each electrode. For example, Wang et al. (2019) used SQI and ASSMD on CHB-MIT data to select seven optimal channels, including T5, T6, F3, F2, F4, C3, and C4, resulting in 60% power savings with minimal accuracy loss compared to full-channel models.

Heuristic approaches, like sequential forward or backward selection, eliminate or add channels based on incremental performance improvement. However, these methods often converge to sub-optimal solutions because they make greedy, local decisions, motivating the shift toward metaheuristic algorithms.

Population-based optimization algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), search the space of channel subsets more globally. Sun et al. (2019) combined information gain ranking with PSO to select a compact set of channels that improved classifier performance. These methods balance exploration and exploitation, making them better suited for non-convex optimization problems like channel selection.

Multi-objective evolutionary algorithms, such as NSGA-II, simultaneously optimize competing objectives (e.g., maximizing accuracy and minimizing channel count). Jana et al. (2023) demonstrated the power of this approach by reducing 22 channels to just 3 while maintaining over 96% accuracy with a 1D-CNN classifier on CHB-MIT data. Their Pareto-optimal solutions highlighted trade-offs between model performance and electrode reduction.

Information-theoretic measures, including mutual information (MI) and Fisher Score, rank channels by their contribution to class separability. These ranking filters are computationally efficient for large-scale data but don’t consider redundancy among channels, which can limit performance improvements.

Wrapper methods evaluate subsets of channels by training a classifier on each subset and directly measuring predictive performance. While wrappers often achieve better results than filters, they require significant computational resources, making them suitable mainly for offline optimization rather than real-time adaptation.

Method	Approach Type	Key Idea / Description	Notable Papers / Highlights
Entropy Measures	Statistical	Uses entropy measures (e.g., Shannon, approximate entropy) to assess channel complexity and relevance.	Widely used in statistical feature ranking.
Mutual Information	Information-theoretic	Calculates shared information between channel signals and labels to rank relevance.	Common in filter-based selection pipelines.
Signal Quality Index (SQI)	Statistical	Evaluates signal quality per channel to remove noisy electrodes.	Wang et al. (2019) reduced CHB-MIT channels.
ASSMD	Statistical	Computes standardized differences between preictal and interictal EEG to identify discriminative channels.	Used with SQI for effective selection.
Sequential Forward/Backward Selection	Heuristic	Greedily adds or removes channels to improve classifier performance.	Simple but may get stuck in local optima.
Genetic Algorithm (GA)	Evolutionary	Encodes channel subsets as chromosomes; evolves optimal sets via crossover and mutation.	Sayeed et al. (2018) applied GA on Freiburg dataset.
Particle Swarm Optimization (PSO)	Evolutionary	Models candidate channel sets as particles moving in search space with velocity updates.	Sun et al. (2019) combined PSO with info gain.
NSGA-II	Multi-objective Evolutionary	Optimizes both accuracy and number of channels using Pareto-optimal solutions.	Jana et al. (2023) achieved 96%+ accuracy with 3 channels.
Wrapper Methods	Supervised	Directly evaluates channel subsets using classifier performance to guide selection.	High accuracy but computationally intensive.
Correlation-Based Feature Selection	Filter	Minimizes redundancy by excluding highly correlated channels while maximizing relevance.	Yang et al. (2020) demonstrated effective reduction.
Fisher Score Ranking	Statistical	Uses class separation statistics to rank each channel's discriminative power.	Fast, but ignores inter-channel dependencies.
Mutual Information Maximization	Filter	Selects channels maximizing information with labels while reducing redundancy.	Popular in offline channel selection.

3.1. Key Challenges

Despite advances, key challenges remain:

- Inter-patient variability in seizure onset regions makes universal channel selection difficult.
- Different EEG systems use varying electrode montages, complicating the transferability of selected channels across datasets.
- Most studies use patient-dependent evaluations; robust patient-independent or cross-dataset validations are rare but necessary for clinical applicability.
- Future research should explore adaptive channel selection methods that dynamically adjust channels based on individual EEG patterns, potentially leveraging reinforcement learning or online optimization. Personalized channel selection could enable both robust prediction and energy-efficient operation in practical systems.

Overall, the choice of channel selection method depends on the specific requirements of the EEG application. Statistical measures-based methods are simple and efficient, while machine learning-based methods can capture complex relationships. Frequency or time-frequency analysis-based methods focus on specific frequency components, and information theory-based methods consider the information content. Hybrid methods offer flexibility but come with additional complexity. It is recommended to consider the characteristics of the EEG data, computational resources, interpretability requirements, and the specific goals of the analysis when selecting an appropriate technique.

IV. REVIEW ON SEIZURE PREDICTION & DETECTION METHODS USING ML & DL TECHNIQUES

Accurate detection and prediction of epileptic seizures using EEG signals have increasingly relied on the power of machine learning (ML) and deep learning (DL) methods. Traditional seizure detection methods based on thresholding, visual inspection, or simple statistical features often lack robustness, generalizability, and adaptability to the complex temporal and spatial patterns inherent in EEG. ML and DL models overcome these limitations by automatically learning informative representations from data, significantly improving performance across many studies.

In this section, we categorize and discuss ML and DL-based seizure prediction approaches, critically analyzing their architecture, performance, advantages, and shortcomings

Table 2: Comparison of Various Literature Works

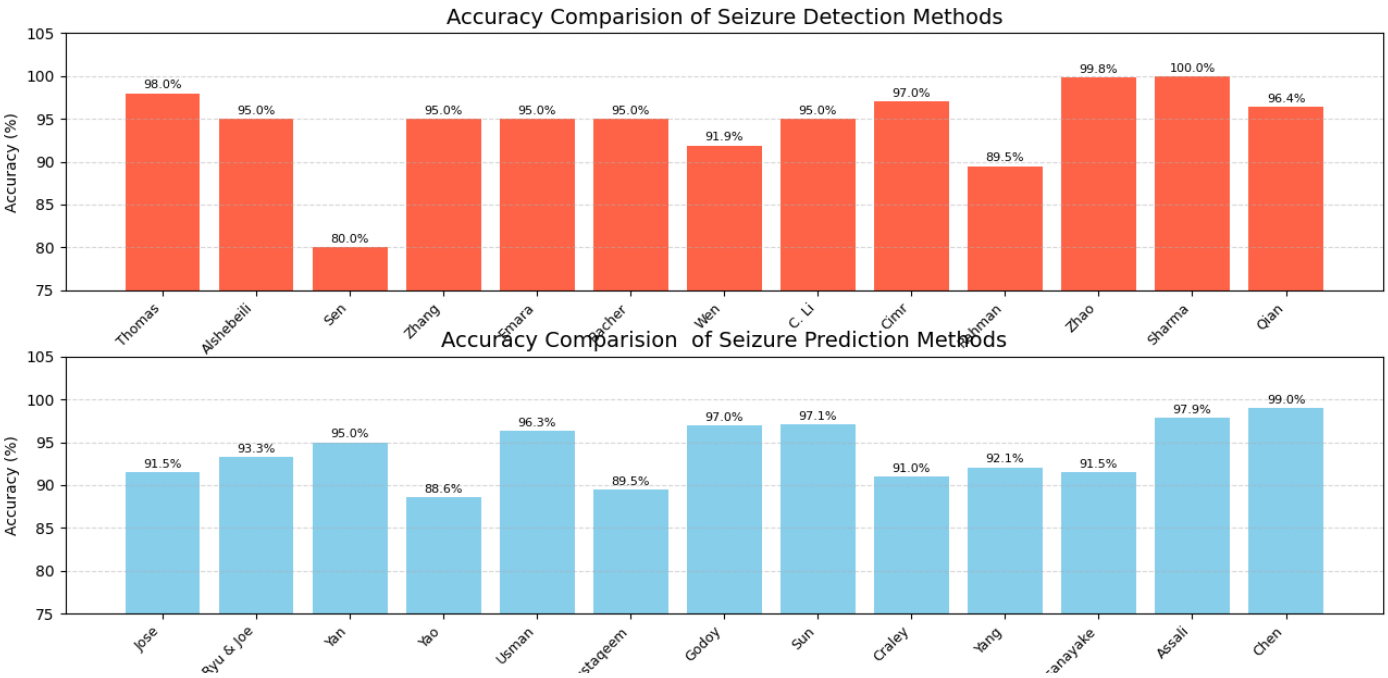
Authors	Year	Dataset	Use Case	Method / Model	Key Results	Notable Points
Prabin Jose et al.	2021	CHB-MIT	Seizure Prediction	Adaptive rag-ROA + Deep SAE	91.5% / 85.2% / 86%	Adaptive optimizer improved deep SAE
Ryu & Joe	2021	CHB-MIT	Seizure Prediction	DenseNet + LSTM	93.3% / 92.9% / 93.6%	Time-frequency analysis with DWT
J. Yan et al.	2022	CHB-MIT	Seizure Prediction	Transformer towers	Superior accuracy reported	Attention mechanisms leveraged
Yao et al.	2021	CHB-MIT	Seizure Prediction	Attention + BiLSTM	88.6% avg accuracy	Enhanced spatial-temporal modeling
Muhammad Usman et al.	2021	CHB-MIT + AES-Kaggle	Seizure Prediction	GAN + CNN-LSTM ensemble	96.3% / 96.2% / 95.7%	Synthetic data improved class balance
Mustaqeem et al.	2023	CHB-MIT	Seizure Prediction	2D CNN	89.5% / 89.7% / AUC: 89.5%	Generalized preictal phase prediction
Thomas	2020	Public dataset	Seizure Detection	EMD + MLPNN	Up to 98% accuracy	IMFs extracted for AR modeling
Vilela de Godoy et al.	2022	CHB-MIT	Seizure Prediction	TMC-T & TMC-ViT	Outperformed CNN	Analyzed impact of preictal durations
Alshebeili et al.	2020	Not specified	Seizure Detection	Band-limiting + MLP/k-means	High accuracy, low false alarms	Mobile seizure alert system potential
Sen et al.	2020	UCI	Seizure Detection	Various ML classifiers	80% detection rate	Multiclass classification with overlapping features
Sun et al.	2021	CHB-MIT	Seizure Prediction	CADCNN	97.1% sensitivity, AUC 0.917	Dual input with STFT and raw signals
Craley et al.	2021	CHB-MIT	Seizure Prediction	CNN-BLSTM	Sensitivity ~0.91	Leave-one-patient-out validation
S. Zhang et al.	2021	CHB-MIT	Seizure Detection	Correlation matrix + CNN	High performance	Synchronization-based prediction
X. Yang et al.	2021	CHB-MIT	Seizure Prediction	RDANet	92.07% accuracy	Dual self-attention residual network
Dissanayake et al.	2022	CHB-MIT	Seizure Prediction	Siamese models	88.8%-91.5% accuracy	Cross-patient generalization
Emara et al.	2022	Not specified	Seizure Detection	FFT + ANN	Strong performance	Automated detection frameworks
Assali et al.	2022	Public + simulated	Seizure Prediction	AR + stability analysis	97.9%-100% accuracy	Virtual patient simulations
Bacher et al.	2021	Subcutaneous EEG	Seizure Detection	Simple algorithm	High precision	Implantable device validation
Wen et al.	2022	CHB-MIT	Seizure Detection	Parallel SVM on hardware	91.9% sensitivity	Chip design for wearable devices
C. Li et al.	2023	Not specified	Seizure Detection	End-to-end MLP	High performance	Denoising-weighted MLP blocks
Cimr et al.	2023	CHB-MIT, Bonn	Seizure Detection	8-layer CNN	97%+ accuracy	Avoids explicit feature extraction
Chen et al.	2022	CHB-MIT	Seizure Detection	AutoML + CTGAN	Up to 99% accuracy	Balances classes with synthetic data
Rahman et al.	2022	CHB-MIT	Seizure Detection	2D CNN + Butterworth	89.5% accuracy	Generalized method
Zhao et al.	2021	CHB-MIT, others	Seizure Detection	NAS + compression	99.8% sensitivity	Tiny models for wearable devices

Sharma et al.	2020	Bonn	Seizure Detection	Autoencoder + Softmax	Up to 100% accuracy	Nonlinear deep model
Qian et al.	2023	Bonn	Seizure Detection	1D CNN + compressed learning	96.4% accuracy	Microcontroller deployment

Siamese networks enable patient-independent models by learning feature representations invariant to individual differences. Dissanayake et al. used a Siamese architecture trained across multiple patients to achieve \~89–91% accuracy on CHB-MIT, offering a path toward generalized seizure prediction.

AutoML frameworks automate hyperparameter and architecture search. Chen et al. combined AutoML with generative adversarial networks (GANs) to address class imbalance, achieving up to 99% accuracy and outperforming manual architectures. Neural architecture search (NAS) has also been applied to derive compact, hardware-friendly models for low-power deployment.

The results comparison of the papers can be given as follows



4.1. Key Challenges & Opportunities

Despite impressive performance, challenges remain:

- Generalizability: Many models are trained and evaluated on patient-specific or single-dataset scenarios. Cross-patient and cross-dataset evaluations often show performance degradation due to inter-individual EEG variability.
- Interpretability: Deep models, especially CNNs and transformers, function as black boxes, limiting clinical acceptance without clear explanations of predictions.
- Data Imbalance: Most datasets are dominated by non-seizure data, making models prone to overfitting and generating false positives.
- Computational Demand: High complexity of deep architectures challenges real-time deployment on wearable or implantable devices.
- Limited Diversity: Existing datasets may not adequately cover diverse seizure types or patient demographics.

Future research can address these limitations by:

- Developing interpretable AI methods such as layer-wise relevance propagation or attention heatmaps to visualize model focus.
- Applying transfer learning from large EEG datasets or other bio signals to reduce data requirements.
- Exploring federated learning for multi-center data without compromising privacy.
- Creating lightweight architectures via model compression or quantization for wearable devices.
- Establishing standardized benchmarks with unified metrics for fair comparison of models.

V. RESULTS AND DISCUSSION

This review highlighted advances in EEG-based seizure prediction, driven by novel datasets, optimized channel selection, and cutting-edge deep learning models. Transformer networks and ensemble approaches demonstrate superior performance but challenges in personalization, real-time deployment, and interpretability remain. Addressing these will be key to translating AI-based seizure prediction systems into clinical practice.

Despite progress, obstacles persist. EEG patterns vary greatly between individuals, making generalization difficult. Seizure prediction datasets suffer from class imbalance due to the rarity of seizures compared to long interictal periods. Real-time applications require models with low latency and false alarm rates. Developing energy-efficient models suitable for wearable devices remains challenging. Furthermore, scarcity of data for rare seizure types limits training robust models. Addressing these challenges is essential for clinical translation of AI-based seizure prediction.

Future research should focus on personalized medicine through patient-specific models, cross-dataset validation for improved generalizability, and energy-efficient architectures for wearable devices. Explainable AI will build clinician trust in automated predictions. Collaborative federated learning frameworks can help overcome data privacy concerns and expand dataset diversity for training robust models.

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