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Research Article

Advancements and Challenges in Epileptic Seizure Detection Techniques: A Survey

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ABSTRACT

Epileptic seizure detection is a crucial area of research aimed at identifying and predicting seizure events through advanced techniques, primarily utilizing electroencephalogram (EEG) signal. Despite significant progress, the field faces numerous challenges, including the need for diverse and comprehensive datasets, high computational complexity, and difficulties in generalizing models across various patient populations. This survey systematically reviews approximately 30 research articles, focusing on the methodologies employed, the challenges encountered, and the results obtained in seizure detection. By critically analyzing the strengths and limitations of existing approaches such as deep learning, machine learning, and hybrid models this research provides valuable insights into current practices and identifies opportunities for enhancing the effectiveness and reliability of seizure detection systems in clinical settings. Ultimately, the research aims to inform future developments in this vital domain, facilitating improved patient outcomes through timely and accurate seizure prediction.

Keywords: Epileptic seizure detection, Machine learning, deep learning, hybrid models and feature extraction.

INTRODUCTION

Epilepsy is a neurological disorder that affects approximately 50 million people globally, making it one of the most prevalent neurological conditions, as reported by the World Health Organization. Characterized by recurrent and unpredictable seizures, epilepsy can significantly diminish the quality of life for those living with the condition. These seizures can vary widely in type and severity, often leading to challenges in daily activities, social interactions, and overall well-being [1]. It is characterized by a propensity for repeated episodes throughout one's life. Seizures can occur due to various triggers, including skull fractures, genetic factors, tumors, and other influences [2]. Research indicates that epilepsy can affect individuals at any age, although it most commonly begins in childhood or after the age of 65. An epileptic seizure is a sudden, temporary disruption in the brain's normal functions, marked by excessive and abnormal electrical activity [3-4]. This electrical discharge can lead to a range of physical and psychological symptoms, from mild sensations to convulsions and loss of awareness, and can occasionally result in unexpected death. It is crucial to accurately identify seizures in individuals with epilepsy for proper diagnosis and to formulate personalized treatment plans [5-6]. Early detection and ongoing monitoring of seizures can improve quality of life and lower risks. The analysis of EEG signals, which capture the brain's electrical activity, aims to assess patients with known seizures to identify the specific type of seizure they are experiencing. Epileptic EEG signals offer a dynamic portrayal of neural activity, reflecting the complex patterns linked to seizures [7-8]. These signals are detected using electrodes positioned on the scalp, which record the electrical impulses generated by the brain's neurons [9]. The raw EEG data often includes noise and extraneous information, necessitating preprocessing steps like filtering, artifact removal, and baseline correction to refine the signals and improve their quality. After preprocessing, selecting and extracting features becomes essential for detecting epileptic seizures through EEG signal classification. By deriving relevant features from the signal data, one gains more distinctive insights compared to using the raw signal alone [10-11].

Machine learning and deep learning methods have demonstrated significant effectiveness in extracting pertinent features and classifying them across a range of medical applications, including the diagnosis of epilepsy. Epileptic seizures can vary greatly in how they manifest, their intensity, and their duration. The brain's normal functioning arises from complex interactions among neurons via electrical impulses. In people with epilepsy, there's a propensity for neurons to become overactive and fire inappropriately, resulting in a seizure. Seizures can be categorized into various types depending on their features and the specific brain regions involved [12-13]. In healthy areas of the brain, we generally see uniform, rhythmic patterns with stable frequency and amplitude, indicating typical electrical activity. However, at the site of a tumor, the EEG signals show changes when compared to those from healthy brain regions. These can appear in different forms based on the type and position of the tumor [14-15]. However, during a seizure, the EEG signals display unique patterns indicative of abnormal neuronal activity characterized by high frequency and amplitude. Predicting seizures presents a significant challenge, primarily due to the need to identify specific symptoms and assess whether a patient is likely to experience an impending seizure. In terms of phase differentiation, recognizing these symptoms parallels the classification of interictal and preictal phases. Consequently, a range of seizure prediction methods has been developed, drawing on feature extraction and classification techniques similar to conventional signal analysis [16-17]. However, two critical factors greatly influence the effectiveness of these prediction methods. First, the differences between interictal and preictal signals are often subtle, making it challenging to detect variations through brief observations. Second, the signals can vary significantly over time due to fluctuations in brain activity, further complicating accurate predictions [18-20].

This survey aims to identify and evaluate various approaches to epileptic seizure detection, emphasizing assessment metrics, benefits, and drawbacks in different contexts. It examines key limitations such as data requirements, computational complexity, persistent challenges in generalization, and feature extraction issues. The analysis is based on approximately 30 studies, focusing on the techniques employed, challenges encountered, results achieved, and relevant parameters. The aim of this research is to offer a thorough overview of contemporary methodologies in seizure detection, focusing on the strengths and weaknesses of deep learning, machine learning, and hybrid approaches.

This discussion centers on the various sections of the survey aimed at evaluating the literature on epileptic seizure prediction methods. Section 2 provides a clear taxonomy that categorizes the different approaches employed in this field. In Section 3, summarize the methods used, the assessment metrics applied, the achievements realized, and the limitations encountered in existing studies. Section 4 offers a detailed evaluation of these metrics, highlighting their effectiveness in measuring predictive performance. Section 5 delves into the research gaps identified throughout the review, pointing out areas that require further exploration. Finally, Section 6 concludes the survey, summarizing key findings and proposing future directions for research to enhance the accuracy and reliability of seizure prediction systems.

2. Methodology for article selection process:

The next section presents the methodological details, focusing on the systematic approach used in selecting articles. This comprehensive literature review summarizes various seizure detection techniques and highlights the methodologies involved in current research. By clearly delineating the selection criteria and processes, this section seeks to establish a robust framework for comprehending the advancements and challenges in the detection of epileptic seizures.

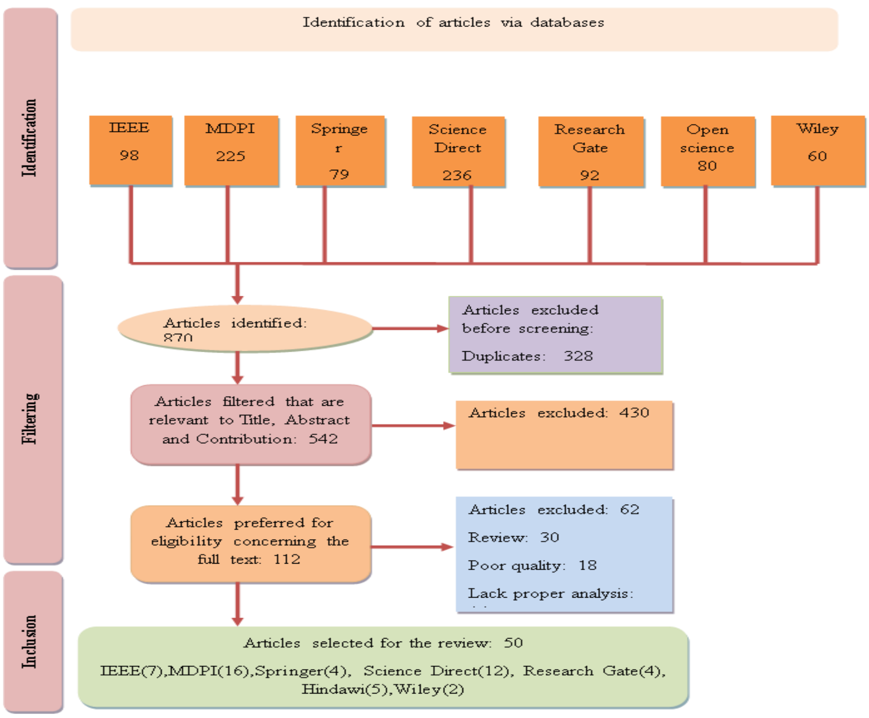

Figure 1: Process flow diagram for the Systematic literature review **Figure 1:** Schematic representation for the article selection process

The proposed review utilizes a systematic literature review methodology to ensure a comprehensive and reproducible approach, aligning with PRISMA guidelines. As illustrated in Figure 1, the PRISMA-based review process outlines the steps taken in selecting relevant articles. Initially, a comprehensive search of data sources yielded 870 documents published between 2020 and 2024, focusing on the latest advancements in Epileptic seizure prediction. Each publication's full text, abstract, and title undergo meticulous assessment to determine their relevance to the research topic. During this evaluation, we exclude review articles, those of low quality, and publications lacking adequate analysis based on specific eligibility criteria. Ultimately, 30 papers are selected for in-depth examination. By implementing a rigorous and systematic approach to the literature review, we ensure that the chosen studies adhere to high standards of research integrity and fulfill inclusion criteria. The PRISMA flow diagram provides a visual representation of the search and selection process, illustrating the number of records identified, included, and excluded, along with clear justifications for each exclusion. This structured methodology greatly enhances the credibility and reliability of our evaluation. By focusing on recent literature, the review aims to uncover existing research gaps while also highlighting the latest advancements and trends in the field.

A. Taxonomy of for Epileptic seizure prediction techniques:

Figure 2 features a taxonomy diagram that illustrates the array of methods used in epileptic seizure prediction, including DL, ML, and hybrid models. This diagram effectively categorizes these techniques, highlighting their specific applications and providing a detailed overview of how these technologies converge and enhance the field of seizure detection. By mapping out the relationships among various approaches, the diagram serves as a valuable tool for understanding the complexities and innovations within seizure prediction methodologies.

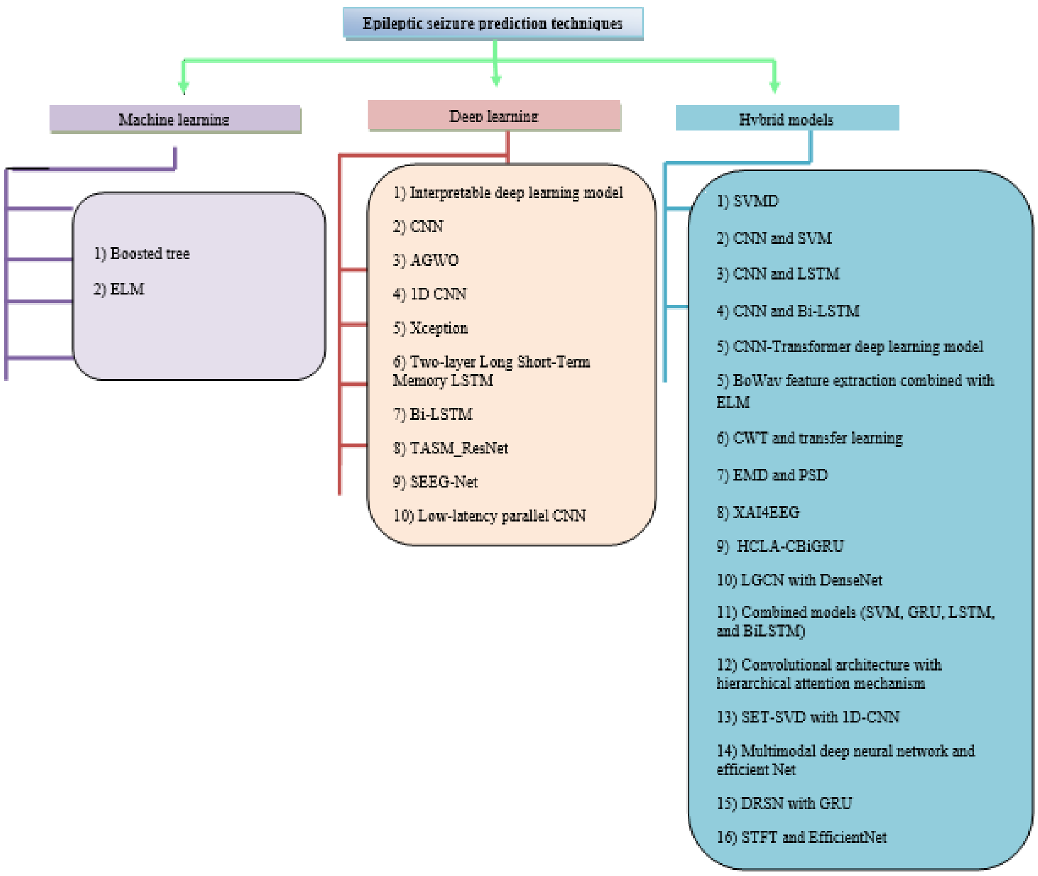

Figure 2: Taxonomy diagram of Epileptic seizure detection techniques

i) Deep learning model: Imene Jemal et al. [1] introduced an understandable deep learning model aimed at predicting epileptic seizures through the analysis of EEG signals. The model incorporates signal processing techniques like frequency sub-band and spatial filters, making the learned weights align with meaningful, clinically relevant EEG features. Layer-wise relevance propagation further enhances transparency by revealing important features that influence predictions. Its key advantage is interpretability, making it suitable for clinical use, though it may face challenges with complex or noisy data and limited adaptability due to its reliance on predefined signal processing methods. Omaima Ouichka et al. [2] introduced five deep learning models designed to forecast epileptic seizures based on intracranial electroencephalogram (iEEG) data. The models include a standard Convolutional

Neural Network (CNN), as well as fusion models combining two, three, and four and a transfer learning model using ResNet50. The main advantage of these models is their high accuracy, which is crucial for providing timely interventions in epilepsy management. However, the fusion models may require substantial computational resources and need further validation across different datasets to assess generalizability and robustness. B. Jaishankar et al. [4] developed a deep learning model for predicting epileptic seizures using EEG recordings from 23 individuals of varying ages, consisting of 17 females and 5 males, sampled at 256 samples per second. This model leverages raw EEG signals for feature extraction, effectively minimizing computational complexity and execution time. To further enhance the model's performance, an Adaptive Grey Wolf Optimizer (AGWO) is employed to refine discriminative features, thereby improving prediction accuracy. Key advantages include high accuracy, reduced false alarms, and lower computational demands, although its reliance on specific datasets may limit generalizability and pose implementation challenges for real-time applications. Hepseeba Kode et al. [5] introduced a seizure detection model that employs deep learning algorithms, particularly focusing on a One-Dimensional Convolutional Neural Network (1D CNN) to classify time-series EEG signals. The 1D CNN achieved an impressive accuracy of 99% among the tested classifiers, significantly enhancing real-time seizure detection by directly analyzing EEG signals without the need for extensive preprocessing. However, the model's dependence on specific datasets may limit its generalizability across diverse patient populations and varying seizure types. Additionally, its inherent complexity and the requirement for extensive parameter tuning could present challenges for clinical implementation. Dhouha Sagga et al. [11] presented a seizure detection method using two models CNN and Xception, focusing on analyzing EEG signals to improve epilepsy diagnosis. The results demonstrate that the proposed CNN model surpasses the performance of the Xception model, achieving superior accuracy, precision, recall, and F1 score. The advantages of the CNN model include its superior performance metrics, making it effective for seizure detection. However, potential disadvantages may include the requirement for substantial training data and computational resources, as well as limitations in generalizing to other datasets or populations outside the study's scope. Kuldeep Singh1 and Jyoteesh Malhotra2 [12] introduced a two-layer Long Short-Term Memory (LSTM) network model designed to forecast epileptic seizures by utilizing multichannel EEG signals. This model takes advantage of spectral power and average spectrum amplitude characteristics obtained from different EEG frequency bands. The model's performance is validated against several classifiers, achieving high classification accuracy, sensitivity, and specificity. This approach can significantly improve the quality of life for epileptic patients by enabling real-time seizure prediction. However, potential challenges include model complexity, the requirement for extensive training data, and difficulties in real-time clinical implementation. Puranam Revanth Kumar et al. [16] developed a Bi-LSTM network for seizure detection that effectively manages the nonstationary nature of EEG data while reducing processing costs through local mean decomposition (LMD) and statistical feature extraction. The model utilizes two LSTM networks that process information in opposite directions, enhancing prediction accuracy by incorporating both past and future data. It demonstrated high performance metrics, including accuracy, sensitivity, and specificity, making it a valuable tool for early seizure detection. However, it faces challenges such as the need for extensive training datasets and the complexity of real-time implementation. Ranjan Jana and Imon Mukherjee [21] introduced a compact, wearable device for predicting seizures, which employs a 1D CNN to extract features and classify raw EEG signals. The device is designed to attain high classification accuracy while decreasing the number of EEG channels from twenty-two to three, achieving an 86.36% reduction. The NSGA-II algorithm identifies the optimal EEG channel set, enhancing efficiency for low-power applications. The proposed method demonstrates excellent performance and accuracy, making it suitable for practical seizure prediction while ensuring energy efficiency and portability. However, the reliance on a limited number of channels may impact the robustness and generalizability of the model in diverse patient populations and varying seizure types. Yating Jiang et al. [22] presented a seizure prediction model called TASM_ResNet. This model combines a time-wise attention simulation module with a pre-trained ResNet, making use of intracranial EEG signals The use of an improved focal loss function addresses data imbalance issues, enhancing the model's performance. Compared to existing CNN models, TASM_ResNet achieves a higher average AUC, demonstrating its effectiveness. However, the model's reliance on converting EEG data to image-like formats may lead to information loss and its performance in real-world clinical settings requires further validation. Jamal Nazari et al. [23] introduced a CNN designed to predict the preictal period in epileptic patients, especially those with infrequent seizures that complicate the recording of preictal signals. By employing few-shot learning, the model can adapt and learn from a limited number of samples while utilizing prior knowledge from generalized methods. The findings indicate a strong sensitivity and minimal false prediction rates, emphasizing the model's success in predicting seizures. However, the reliance on few samples may restrict its robustness and generalizability across a wider patient population, and further validation in larger clinical settings is needed. Yiping Wang et al. [24] introduced the SEEG-Net model, a multiscale convolutional neural network designed to detect pathological activities in invasive stereo electroencephalography (SEEG) for drug-resistant epilepsy (DRE). This model effectively tackles challenges such as sample imbalance and cross-subject domain shifts by employing a focal domain generalization loss function. This approach enhances sensitivity and facilitates the learning of consistent domain features, improving the overall detection capabilities for individuals with DRE. The model demonstrates state-of-the-art performance in sensitivity and robustness across various datasets, while also offering interpretability through methods like Grad-CAM++. However, its reliance on specific clinical datasets may limit generalizability, necessitating further validation in broader clinical contexts. Chenqi Li [25] developed a low-latency parallel CNN architecture for the detection and prediction of epileptic seizures, achieving a dramatic reduction in the number of network parameters, ranging from 2 to 2,800 times fewer than leading models. This architecture demonstrates high accuracy for seizure detection and prediction across various datasets and is executed on analog crossbar arrays utilizing Resistive Random-Access Memory (RRAM) devices, leading to a significant reduction in latency. Advantages include efficient power consumption and a compact design. However, challenges related to hardware scalability and real-world data variability remain potential concerns.

ii) Machine learning model: David Zambrana-Vinaroz et al. [7] introduced a seizure prediction model that uses Ear EEG, ECG, and PPG signals collected from a wearable device, making it applicable in both static and outpatient environments. When evaluated in a clinical setting, the model applies supervised machine learning methods to categorize a patient's condition as normal, pre-seizure, or in the midst of a seizure. A confirmed simplified version of the model, which is based on Boosted Trees, demonstrated impressive prediction accuracy and sensitivity. However, challenges include the need for accurate data collection, variability in patient responses, and the necessity for extensive clinical validation prior to widespread use. Ummara Ayman et al. [17] presented an Extreme Learning Machine (ELM) designed for the automated identification of epileptic seizures from EEG signals. The process involves three steps: preprocessing the EEG dataset, training the ELM model to address overfitting, and automatically extracting features for classification. The advantages include high classification performance and reduced reliance on manual feature extraction, enhancing usability in clinical settings. However, challenges may include generalizability across diverse patient populations and the need for extensive training data for real-world applications.

iii) Hybrid models:

Song Cui et al. [8] introduced a framework for predicting epileptic seizures by analyzing synchronization patterns in EEG signals through the use of bag-of-wave (BoWav) feature extraction. It constructs interictal and preictal codebooks through a clustering algorithm to model local EEG segments, projecting these segments onto the codebooks to express synchronization patterns with histogram features. An extreme learning machine (ELM) is utilized for classification. The model's advantages include improved prediction accuracy through synchronization pattern analysis, while disadvantages involve reliance on high-quality EEG data and the need for further validation across diverse patient populations. Xiao Wu et al. [3] proposed a method for predicting epileptic seizures that integrates Successive Variational Mode Decomposition (SVMD) with transformer models. They expanded SVMD into a multidimensional framework to perform time-frequency analysis on multi-channel EEG signals, which facilitates the adaptive extraction of shared band-limited intrinsic modes across different channels. This integration improves the model's accuracy in forecasting seizures. While the use of SVMD improves the precision of signal decomposition and transformers strengthen temporal pattern recognition, the approach has some disadvantages. It is computationally intensive and may require significant resources, and its performance across diverse EEG datasets needs further validation to ensure robustness in real-world applications. Marcin Kołodziej et al. [6] presented an automated seizure detection system utilizing artificial intelligence techniques on intracranial electroencephalographic (iEEG) signals. It investigates different methodologies, encompassing both conventional machine learning techniques like support vector machines and sophisticated deep learning architectures such as CNN and LSTM networks. The CNN model delivered exceptional results, boasting an accuracy of 99%, a precision of 98%, a sensitivity of 100%, and a specificity of 99%. While the model shows great potential for accurate seizure detection, challenges include the complexity of feature extraction, the need for extensive training data, and issues related to interpretability. Wenbin Hu et al. [10] presented an algorithm for classifying epileptic states that segments the preictal period into several subintervals, differentiating these from ictal (seizure) and interictal states. Their approach includes computing amplitude spectrums of EEG signals across 18 channels, generating a mean amplitude spectrum (MAS) map, and employing a CNN for feature extraction, followed by an SVM for classification. The approach aims to improve seizure prediction accuracy by providing a more detailed classification of the preictal state. However, it may be complex and dependent on specific datasets, which could limit its generalizability. Yahong MA and et al. [20] introduced a multi-channel feature fusion model that integrates CNN and Bi-LSTM for classifying and forecasting seizures in individuals with epilepsy. This model successfully captures spatial features via CNN and temporal features through Bi-LSTM, while an attention mechanism assigns weights to various electrode channels to improve prediction accuracy. The method requires minimal preprocessing and demonstrates superior performance compared to existing techniques. However, it faces challenges in automatic screening of electrode channels and may require further refinement for real-time application. Taranjit Kaur and Tapan Kumar Gandhi [26] introduced an automated seizure detection system that utilizes EEG image representations generated from continuous wavelet transform (CWT) and transfer learning. The model fine-tunes a pre-trained deep learning network on these EEG images and uses a SVM for classification. Key advantages include high classification accuracy, sensitivity, and specificity, surpassing state-of-the-art systems and decreasing the analysis time for neurophysiologists. However, challenges include ensuring generalization across diverse clinical scenarios and the model's reliance on the quality of EEG image representations. Yayan Pan et al. [27] introduced two novel methods for automating seizure detection, which leverage empirical mode decomposition (EMD) and power spectral density (PSD) of EEG signals. Their goal is to improve detection accuracy in situations where data is restricted. By employing EMD components as inputs for multiple specially designed convolutional neural networks (CNNs), the methods significantly outperform traditional deep learning techniques in few-shot learning situations. Experimental results demonstrate substantial improvements in accuracy, sensitivity, and specificity, particularly when the number of training samples is reduced. However, the complexity of EMD preprocessing and the dependency on the quality of EEG data could impact the model's effectiveness. Dominik Raab et al. [28] introduced XAI4EEG, a hybrid deep learning framework that is explainable and designed for detecting epileptic seizures through the analysis of multivariate EEG time series. The framework enhances interpretability by highlighting decision-relevant areas in EEG data. A user study demonstrated that XAI4EEG notably shortened the validation time for predictions while enhancing interpretability, trust, and confidence in comparison to conventional SHAP plots. However, the complexity of integrating domain knowledge and differing user interpretations may present challenges in clinical applications. Milind Natu et al. [29] introduced the Hybrid Cross Layer Attention Based Convolutional Bidirectional Gated Recurrent Unit (HCLA_CBiGRU) model for detecting seizures from EEG signals. This innovative model integrates convolutional and recurrent neural networks, allowing it to effectively capture both spatial and temporal features within complex EEG data. To enhance its performance, a combined dataset was curated from public sources, with noise and artifacts meticulously removed during preprocessing, ensuring cleaner input for more accurate seizure detection. The HCLA_CBiGRU achieved impressive performance metrics: 98.5% accuracy, 98.5% sensitivity, and 98.9% specificity, surpassing existing methods. However, its complexity may pose challenges in interpretability and require significant computational resources for clinical deployment. Ferdaus Anam Jibon et al. [30] introduced a hybrid framework designed for detecting epileptic seizures, which combines a linear graph convolutional network (LGCN) with DenseNet. This approach tackles the difficulties associated with the irregular and unordered nature of EEG recordings. The model demonstrates an impressive accuracy of 98% and a specificity of 98.60% on the CHB-MIT EEG dataset, outperforming current leading techniques. While the model shows significant performance improvements, it may also present challenges such as complexity, requiring substantial computational resources and expertise, as well as interpretability issues inherent to advanced deep learning techniques. Noor Kamal Al-Qazzaz et al. [15] introduced an automated seizure prediction model that utilizes EEG signals. This model extracts features based on time-domain analysis and entropy, including the Hurst exponent and Tsallis Entropy. It consists of two sessions: the first utilizes machine learning classifiers (SVM) for feature classification, while the second employs deep learning recurrent neural networks (GRU, LSTM, and BiLSTM) for enhanced classification accuracy. The strategy seeks to accurately distinguish between children with epilepsy and those without, emphasizing the benefits of deep learning in enhancing performance. That said, obstacles such as the need for extensive datasets and the difficulty of deploying these models in real-time clinical settings remain. Petros Koutsouvelis et al. [9] introduced a CNN-Transformer model for predicting epileptic seizures by detecting preictal spatiotemporal dynamics in EEG signals. The model features a Continuous Input-Output Performance Ratio (CIOPR) metric for evaluating predictive performance and identifying the optimal preictal period for labeling EEG segments. It achieves high sensitivity, specificity, and AUC values, while also examining how different preictal period definitions affect prediction accuracy. However, challenges include reliance on large datasets for training and evaluation, as well as the complexity of integrating multiple data types for clinical implementation. Sateesh Kumar Reddy Chirasani1 and Suchetha Manikandan [13] introduced a convolutional architecture integrated with a hierarchical attention mechanism for EEG signal classification to detect seizures. The model comprises three parts: a feature extraction layer for generating convoluted feature maps, a hierarchical attention layer for obtaining weighted features, and a classification layer for distinguishing between healthy and seizure subjects. The advantages of this approach include high classification accuracy and reduced computational complexity compared to existing methods. However, challenges may arise in generalizing the model to diverse EEG datasets and implementing the hierarchical attention mechanism in real-time applications. Jee Sook Ra et al. [14], developed a model for predicting epileptic seizures that integrates synchroextracting transformation with singular value decomposition (SET-SVD) to improve the time-frequency resolution of EEG signals. This model employs a one-dimensional convolutional neural network (1D-CNN) for classifying pre-seizure activity, showing enhanced accuracy, sensitivity, and specificity over conventional short-term Fourier transform (STFT) approaches. The advantages of this approach include the ability to extract more detailed information from EEG signals, while potential disadvantages may involve the complexity of the SET-SVD method, which could impact computational efficiency and real-time clinical application. Loukas Ilias et al. [18] introduced two innovative methods for classifying healthy, interictal, and ictal cases of epilepsy without extensive feature extraction. The first method uses STFT to convert single-channel EEG signals into a three-channel image, analyzed with pretrained models like EfficientNet. The second method features a multimodal deep neural network that processes EEG signals through two branches of CNN to capture low and high-frequency features, alongside the STFT-derived image. A gated multimodal unit assesses the significance of each modality. This approach aims to improve classification accuracy while reducing the need for time-consuming feature extraction, though it may depend on the availability of sufficient labeled data for effective training. Xin Xu et al. [19] proposed a personalized seizure prediction technique that combines a Deep Residual Shrinkage Network (DRSN) with a Gated Recurrent Unit (GRU) to analyze EEG signals during the pre-ictal phase, segmented into multiple temporal windows. This innovative approach leverages automatic feature extraction through soft threshold denoising and incorporates an attention mechanism within the neural network, enhancing its ability to focus on relevant patterns in the data for more accurate seizure prediction. The method demonstrates effective performance when tested on selected patients and presents innovative ideas, although it has some gaps compared to the best existing epilepsy prediction methods.

3. Analysis of Epileptic seizure detection techniques: This survey reviews recent advancements in utilizing ML and DL models for epileptic seizure detection. It discusses various methodologies, including CNN and LSTM networks, alongside hybrid approaches that combine these architectures for enhanced predictive accuracy. The review emphasizes the use of various feature extraction methods to enhance the performance and efficiency of models, illustrating their importance in the real-time prediction and detection of seizures from EEG signals. Furthermore, it emphasizes how these models contribute to clinical decision-making and patient safety, providing a comprehensive overview of their methodologies and their impact on advancing seizure detection technology.

Table 1: Summarized Analysis of Epileptic seizure detection techniques

Author	**Achievements**	**Dataset**	**Method**	**Challenges**
Imene jemal et al. [1]	Accuracy of 90.9%, sensitivity of 96.1%, specificity of 84.7%, FPR of 0.040 and 0.918	CHB-MIT dataset	Interpretable deep learning model	Deep learning models are not very transparent, which complicates the process of understanding how classification choices are determined.
Omaima Ouichka et al. [2]	The CNN model achieved an accuracy of 95%. Significantly improved seizure prediction performance compared to previous studies.	Intracranial Electroencephalogram (iEEG) datasets	CNN	However, the fusion models may require substantial computational resources and need further validation across different datasets to assess generalizability and robustness.
Xiao Wu et al. [3]	It demonstrates strong predictive performance on an intracranial EEG dataset, achieving an average sensitivity of 0.86 and a false positive rate of 0.18 per hour.	Intracranial EEG dataset	SVMD combined with transformers	Computationally intensive, Requires significant resources, Performance across diverse EEG datasets needs further validation, Essential for robustness in real-world applications
B. Jaishankar et al. [4]	Attains an accuracy rate of 99%. Lowers the False Alarm Rate (FAR) and the time needed for predictions. Shows an improved balance compared to current methods.	CHB-MIT EEG dataset	AGWO with integrated auto-encoder and GA	Its reliance on specific datasets may limit generalizability and pose implementation challenges for real-time applications.
Hepseeba kode et al. [5]	Achieved accuracies of 98% (XGBoost), 96% (TabNet), 98% (Random Forest), and 99% (1D CNN).	UCI Epileptic Seizure Recognition dataset	1D CNN	Reliance on specific datasets limits generalizability, May not apply to diverse patient populations and seizure types, Complexity and extensive parameter tuning challenge clinical deployment
Marcin Kołodziej et al. [6]	Optimal outcomes for seizure detection using CNN: Accuracy of 0.99, Precision of 0.98, Sensitivity of 1, Specificity of 0.99. For LSTM: Accuracy of 0.98, Precision of 0.96, Sensitivity of 1, Specificity of 0.99.	Publicly available iEEG database	CNN and LSTM	Challenges include the complexity of feature extraction, the need for extensive training data, and issues related to interpretability
David Zambrana-	Afterward, a simplified model utilizing Boosted Trees was validated, achieving a	Ear EEG, ECG, and PPG signals collected from individuals with	Boosted	Need for accurate data collection,

Vinaroz [7]	prediction accuracy of 91.5% and a sensitivity of 85.4%.	epilepsy in a clinical setting.	Trees	Variability in patient responses, Extensive clinical validation required before widespread use
Song Cui et al. [8]	Sensitivity stands at 88.24%, and the false prediction rate is 0.25 per hour.	Kaggle Seizure Forecasting Challenge Dataset and CHB-MIT Dataset	BoWav feature extraction combined with ELM	While disadvantages involve reliance on high-quality EEG data and the need for further validation across diverse patient populations.
Petros Koutsouvelis et al. [9]	Average Sensitivity 99.31%, Average Specificity: 95.34%, Area Under Curve (AUC) 99.35%, F1-Score: 97.46% and Average Prediction Time 76.8 minutes before onset	CHB-MIT Dataset	CNN-Transformer Deep Learning Model	Reliance on large datasets for training and evaluation, complexity in integrating multiple data types for clinical implementation
Wenbin Hu et al. [10]	Classification Accuracy 86.25%	CHB-MIT Database	CNN and SVM	However, it may be complex and dependent on specific datasets, which could limit its generalizability
Dhouha Sagga et al. [11]	Accuracy 98.47%, Precision 99.79%, Recall 98.93% and F1 Score 98.51%.	CHB-MIT Database	CNN	Requires substantial training data, high computational resources needed and limitations in generalizing to other datasets or populations
Kuldeep Singh and Jyoteesh Malhotra [12]	Average Classification Accuracy is 98.14%, Average Sensitivity is 98.51%, and Average Specificity is 97.78%.	CHBMIT EEG database	Two-layer LSTM Network Model	However, potential challenges include model complexity, the requirement for extensive training data, and difficulties in real-time clinical implementation.
Sateesh Kumar Reddy Chirasani and Suchetha Manikandan [13]	The proposed model achieves an accuracy of 97.03%, with 0.9747% sensitivity, 0.9604% specificity, 0.9634 precision, 0.9694 f-measure, and 0.9385 MCC.	Bonn University EEG Database	Convolutional Architecture with Hierarchical Attention Mechanism	Challenges in generalizing to diverse EEG datasets and difficulty implementing hierarchical attention mechanism in real-time applications

Jee Sook Ra and Tianning Li, YanLi [14]	Achieved an accuracy of 99.71% on CHB-MIT and 100% on Bonn University. Improvements over STFT. Accuracy increased by 8.12% Sensitivity increased by 6.24% Specificity increased by 13.91%.	CHB-MIT Database And Bonn University Database	1D-CNN	Complexity of the method, potential impact on computational efficiency and challenges for real-time clinical application
Noor Kamal Al-Qazzaz et al. [15]	Attained a peak classification accuracy of 90% by employing RNN deep learning classifiers on the All-time-entropy fusion feature.	EEG dataset	ML and DL models	Requirement for large datasets and Complexity of real-time clinical implementation.
Puranam Re vanth Kumar 1 and B. Shilpa [16]	Accuracy 97%, Sensitivity 95.70%, Specificity 93.90%, G-Mean 94.80% and Anticipation Time 10 minutes	Long-term scalp EEG database.	Bi-LSTM	Nonetheless, possible obstacles involve the requirement for large training datasets and the intricacies of executing in real time.
Ummara Ayman et al. [17]	Accuracy: 100% AUC (Area Under Curve): 0.99	Bonn University EEG dataset	ELM	However, challenges may include generalizability across diverse patient populations and the need for extensive training data for real-world applications.
Loukas Ilias et al. [18]	Accuracy of 97.00%	EEG database of the University of Bonn.	STFT with Pretrained Model	Though it may depend on the availability of sufficient labeled data for effective training
Xin Xu et al. [19]	Sensitivity: 90.54% AUC (Area Under the Curve) Value: 0.88 False Prediction Rate: 0.11/h	CHB-MIT Scalp EEG Dataset	DRSN with GRU	Although it has some gaps compared to the best existing epilepsy prediction methods.
Yahong ma et al. [20]	Average accuracy from ten-fold cross-validation for CHB-MIT is 94.83%, with a precision of 94.84%, a recall of 94.84%, and an F1-score of 94.83%. The Matthews Correlation Coefficient (MCC) for CHB-MIT is 92.26%. For the UCI Dataset, the average accuracy from ten-fold cross-validation is 77.62%, with precision at 77.66%, recall at 77.62%, and an F1-score of 77.60%. The MCC	CHB-MIT EEG Dataset and UCI Dataset	CNN-Bi-LSTM	However, it faces challenges in automatic screening of electrode channels and may require further refinement for real-time application.

	for the UCI dataset stands at 72.03%.			
Ranjan Jana and imon mukherjee [21]	Classification Accuracy 0.9651, Sensitivity 0.9655, Specificity 0.9647 and Channel Reduction from 22 channels to 3 channels (86.36% reduction).	CHB-MIT database	1D-CNN	Reliance on a limited number of channels , impact on robustness and generalizability and concerns for diverse patient populations and seizure types
Yating Jiang et al. [22]	Average AUC 0.877	UPenn-Mayo Clinic Seizure Prediction Challenge Dataset	TASM_ResNet	However, the model's reliance on converting EEG data to image-like formats may lead to information loss and its performance in real-world clinical settings requires further validation.
Jamal Nazari et al. [23]	Average Sensitivity 95.70%, False Prediction Rate (FPR, 10-min Seizure Prediction Horizon): 0.057/h Average Sensitivity (5-min Seizure Prediction Horizon): 98.52% FPR, 5-min Seizure Prediction Horizon): 0.045/h	CHB-MIT Database	Few-Shot Learning Method using CNN	Reliance on few samples restricts robustness and generalizability Further validation needed in larger clinical settings
Yiping Wang et al. [24]	Accuracy 93.85, TPR 87.61, FPR 6.24 and TNR 95.09.	Public Benchmark Multicenter SEEG Dataset Private Clinical SEEG Dataset	SEEG-Net	However, its reliance on specific clinical datasets may limit generalizability, necessitating further validation in broader clinical contexts
Chenqi Li [25]	Decrease in network parameters by a factor of 2 to 2,800 compared to top-tier architectures, Power usage is around 2.791W, Area occupied measures 31.255 mm² in a 22nm FDSOI CMOS process, Latency reduction: Attained a reduction in latency by two orders of magnitude relative to leading hybrid Memristive-CMOS deep learning accelerators.	University of Bonn EEG Dataset CHB-MIT Dataset SWEC-ETHZ Seizure Dataset	Low-Latency Parallel CNN	However, challenges related to hardware scalability and real-world data variability remain potential concerns.
Taranjit Kaur and Tapan	Classification Accuracy of 98.67% , Sensitivity 100% and Specificity of 96%.	University of Bonn EEG Dataset	SVM	Ensuring generalization across diverse clinical scenarios, reliance on the quality of EEG image

Kumar Gandhi [26]				representations
Yayan pan et al. [27]	Improvement in Accuracy: +23% when training samples are reduced to 10% Improvement in Sensitivity: +19% Improvement in Specificity: +26%	Publicly Available Epilepsy Detection Dataset	EMD with CNN	However, the complexity of EMD preprocessing and the dependency on the quality of EEG data could impact the model's effectiveness.
Dominik Raab et al. [28]	Balanced accuracy 90.06%, sensitivity 84.24%, specificity 97.55% and precision 84.24%	Neonatal EEG Seizure Database	XAI4EEG	However, the complexity of integrating domain knowledge and differing user interpretations may present challenges in clinical applications
Milind Natu et al. [29]	The proposed model, HCLA_CBiGRU reached an accuracy of 98.5%, demonstrating a sensitivity of 98.5% and a specificity of 98.9% in detecting seizures.	CHB-MIT EEG Database, University of Bonn EEG Dataset and UCI Machine Learning Repository (EEG Eye State)	HCLA_CBiGRU	However, its complexity may pose challenges in interpretability and require significant computational resources for clinical deployment
Ferdaus Anam Jibon et al. [30]	An accuracy rate of 98% and a specificity rate of 98.60%.	CHB-MIT EEG dataset	LGCN and Dense Net	The complexity of the model demands significant computational power and specialized knowledge. Additionally, there are challenges in interpreting advanced deep learning methods.

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4 Analysis and discussion

This section evaluates models for epileptic seizure detection techniques by focusing on key assessment metrics, techniques used, as well as the publications and datasets employed. The evaluation metrics quantify model performance, while a review of the publications provides context on methodologies used.

A. Evaluation of dataset: The analysis of datasets utilized by various researchers in this domain is presented in Figure 3 and table 2. This figure highlights that the CHB-MIT dataset is the most frequently used dataset in epileptic seizure detection techniques.

Table 2: Analysis concerning dataset

Dataset	Reviewed papers
CHB-MIT dataset	[1][4][7][8][9][10][11][12][14][15][19][20][21][23][25][29][30]
iEEG datasets	[2][3][6]
UCI Epileptic Seizure Recognition dataset	[5][20][29]
Kaggle Seizure Prediction Challenge Dataset	[8]
Bonn University EEG Database	[13][14][17][18][25][26][29]
Long-term scalp EEG database.	[16]
UPenn-Mayo Clinic Seizure Prediction Challenge Dataset	[22]
Public Benchmark Multicenter SEEG Dataset	[24]
Private Clinical SEEG Dataset	[24]
SWEC-ETHZ	[25]
Publicly Available Epilepsy Detection Dataset	[27]
Neonatal EEG Seizure Database	[28]

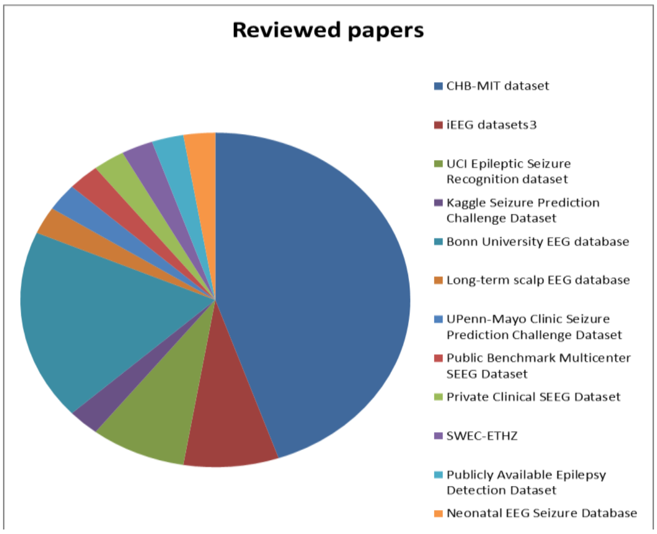

Figure 3: Analysis concerning dataset

B. Evaluation of methods: Figure 4 illustrates that CNN are the most commonly employed method in epileptic seizure detection techniques. This emphasizes the growing reliance on CNNs for analyzing EEG data in the identification of seizures. Additionally, Table 3 presents an overview of the various methods used in this field, highlighting the diversity of approaches in seizure detection.

Table 3: Analysis concerning methods

Methods	Reviewed papers
CNN	[1][2][6][10][11]
SVMD combined with transformers	[3]
AGWO with integrated auto-encoder and GA	[4]
1D CNN	[5][14][21]
LSTM	[6][15]
Reduced model based on Boosted Trees	[7]
BoWav feature extraction combined with ELM	[8]
SVM	[10][15][26]
CNN-Transformer Deep Learning Model	[9]
Two-layer LSTM Network Model	[12]
Convolutional Architecture with Hierarchical Attention Mechanism	[13]
ELM	[17]
Bi-LSTM	[15][16]
STFT with Pretrained Model	[18]
DRSN with GRU	[19]
CNN-Bi-LSTM	[20]
TASM_ResNet	[22]
Few-Shot Learning Method using CNN	[23]
SEEG-Net	[24]
Low-Latency Parallel CNN	[25]
EMD with CNN	[27]
XAI4EEG	[28]
HCLA_CBiGRU	[29]
LGCN and Dense Net	[30]
GRU	[15][19]

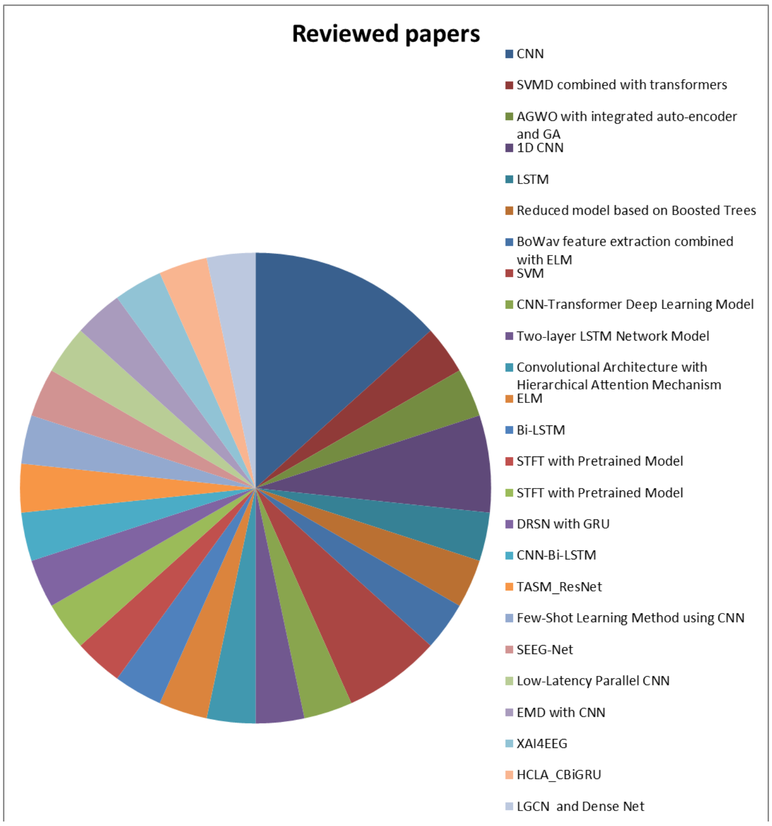

Figure 4: Analysis concerning methods

C. Evaluation of Metrics Achievements:

As shown in Figure 5, the primary metrics commonly employed in epileptic seizure detection models include accuracy, sensitivity, and specificity. These metrics are essential for evaluating the performance of various detection techniques. Furthermore, Table 4 presents a comprehensive assessment of these metrics, offering valuable insights into the effectiveness of different models in accurately identifying seizures. This evaluation highlights the strengths and limitations of each approach, facilitating a deeper understanding of their performance in clinical applications.

Table 4: Analysis concerning metrics

Metrics	Reviewed papers
Accuracy	[1][2][4][5][6][7][10][11][12][13][14][15][16][17][18][20][21][24][26][27][28][29][30]
Sensitivity	[1][3][6][7][8][9][12][13][14][16][19][21][23][26][27][28][29]
Specificity	[1][6][9][12][13][14][16][21][26][27][28][29][30]
FPR	[1][3][8][19][23][24]
Precision	[6][11][13][20][28]
AUC	[9][17][19][22]
F1-score	[9][11][13][20]
Average prediction time	[9]
Recall	[11][20]
G-mean	[16]
Anticipation time	[16]
MCC	[20]
TPR	[24]
TNR	[24]

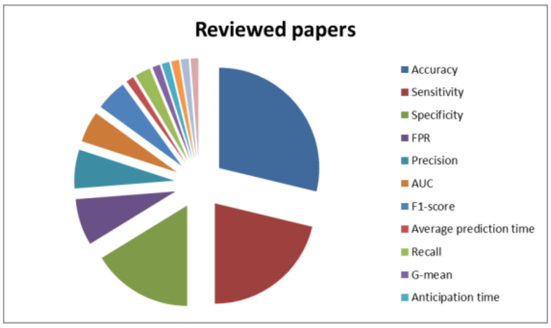

Figure 5: Analysis concerning achievements

D. Analysis based on year of publication

In this section, the analysis focuses on the publication year of the journals reviewed, covering works from 2022 to 2024, as detailed in Table 5. Notably, the majority of literature related to epileptic seizure detection analysis has emerged in 2022. This trend highlights the increasing interest and advancements in the field during that year, with further insights presented in Figure 6, which illustrates the distribution of publications over time.

Table 5: Analysis concerning year of publication

Publications	Reviewed papers
2022	[1][2][3][7][11][12][13][22][23][28]
2023	[4][6][8][10][14][16][17][18][19][20][21][26][29][30]
2024	[5][9][15][22][22][27]

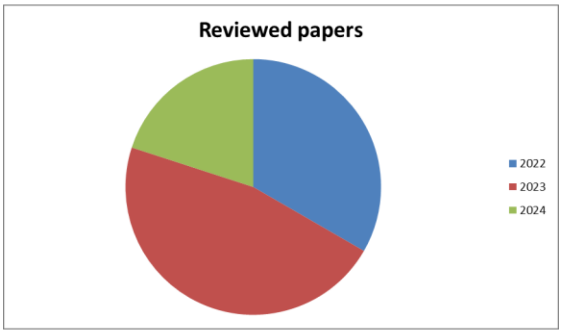

Figure 6: Analysis concerning publication

5. Research gaps and future works:

This section identifies key research gaps in the field of epileptic seizure detection, highlighting the limitations of current models, such as inadequate datasets, challenges in generalization, and issues with real-time implementation. It also outlines future directions for research, emphasizing the need for improved model interpretability, integration of multi-modal data, and enhanced clinical validation. Addressing these gaps will pave the way for more effective and reliable seizure detection systems.

➢ Numerous current models often overfit to the training data, particularly when they are trained on limited datasets. This leads to high accuracy during the training phase, but they struggle to generalize when faced with new, unseen data an essential requirement for clinical applications [2].

➢ Advanced deep learning models frequently demand substantial computational resources, which makes their deployment in real-time clinical environments challenging. High computational demands can limit accessibility and increase costs associated with implementing these technologies in healthcare [2].

➢ While some models perform well on specific seizure types, they may struggle with other variations or atypical presentations. This can lead to missed detections or false alarms, undermining the reliability of the systems in clinical practice [3].

- The complexity of feature extraction in deep learning models can obscure the clinical relevance of the features being utilized. Clinicians may find it challenging to connect model predictions to specific EEG features, hampering trust and usability [4].
- Many models are designed for specific use cases or datasets and may not scale effectively to larger populations or different clinical environments. This can limit their utility in broader healthcare settings [4].
- Variations in how patients experience seizures, differences in their physiological responses, and environmental factors can lead to inconsistent model performance. Existing models may not account for this variability, impacting their effectiveness [5].
- There is often a lack of consensus on the best evaluation metrics for assessing model performance in seizure detection. This can result in misleading comparisons between studies and hinder progress in the field [5].
- Many models rely on extensive feature sets, leading to increased training times and complexity. Inefficient feature selection can also result in models that do not prioritize the most clinically relevant indicators [6].
- Current models may not adequately consider the needs and preferences of patients or healthcare providers. This oversight can affect acceptance and usability in real-world settings [7].
- High-quality, annotated datasets are essential for training effective models. However, data annotation can be time-consuming and prone to human error, leading to potential inconsistencies that impact model training [8].
- Many existing models do not seamlessly integrate with current clinical workflows, making it difficult for healthcare providers to adopt these technologies into their practice without disrupting existing processes [9].
- Seizure detection models frequently encounter the issue of imbalanced datasets, where seizures are infrequent when compared to non-seizure conditions. This disparity can result in biased predictions and decreased accuracy in identifying seizures [10].
- Current models might not fully represent the timing dynamics of seizure events, as these can greatly differ in both duration and characteristics. This limitation can affect the predictive accuracy and timing of detections [11].
- Many models do not personalize predictions based on individual patient characteristics, such as seizure history or comorbidities. This lack of personalization can lead to generalized recommendations that may not be effective for all patients [11].
- Data used to train models may reflect biases related to specific populations, potentially leading to disparities in performance across different demographic groups. This can exacerbate existing inequalities in healthcare [12].

Future works:

- Create comprehensive datasets that encompass various seizure types, demographics, and physiological conditions. This can improve model robustness and generalization across different patient populations.
- Implement techniques such as domain adaptation and transfer learning to improve model performance across diverse populations and clinical settings. This will help in making models more versatile and applicable in real-world scenarios.
- Focus on developing models optimized for real-time processing to ensure immediate seizure detection. This involves reducing computational complexity while maintaining accuracy, enabling timely interventions.
- Explore the use of multi-modal data, such as combining EEG with ECG, PPG, and behavioral data, to enhance predictive accuracy and provide a more holistic view of the patient's condition.
- Develop explainable AI (XAI) methods that provide insights into model decisions, helping clinicians understand the reasoning behind predictions. This can foster trust and encourage adoption in clinical settings.
- Find ways to enhance model robustness in noisy environments by developing preprocessing techniques that filter out artifacts without losing critical information.
- Conduct longitudinal studies that focus on predicting seizures based on historical data, enhancing proactive management strategies for epilepsy care.
- Establish clear ethical guidelines for data collection, privacy, and security to address concerns surrounding patient data and ensure patient trust in using these technologies.
- Perform rigorous clinical trials to validate the effectiveness of seizure detection models in real-world settings. This will aid in establishing their reliability and increase clinician acceptance.
- Involve clinicians and patients in the model design process to ensure that tools are user-friendly and meet the needs of end-users. This can improve usability and adoption rates in clinical environments.
- Explore and apply regularization methods, like dropout or early stopping, to help reduce overfitting. Additionally, explore model compression and optimization methods to reduce computational overhead.
- Develop standardized evaluation metrics tailored specifically for seizure detection models to facilitate better comparisons across studies and improve overall model assessment.
- Investigate personalized models that adapt to individual patient characteristics and seizure histories, enhancing prediction accuracy and relevance in clinical practice.
- Employ techniques like synthetic data generation or advanced sampling methods to address class imbalance in seizure datasets, improving model training and performance.

➢ Design models that can seamlessly integrate into existing clinical workflows, ensuring that they enhance rather than disrupt healthcare processes.
➢ Conduct studies to identify and mitigate biases in training datasets, ensuring that models are fair and equitable across different demographic groups.
➢ Investigate and test new deep learning architectures, such as attention mechanisms or graph neural networks, to capture complex relationships within EEG data more effectively.
➢ Develop models capable of continuous learning from new patient data over time, adapting to changing seizure patterns and improving predictive accuracy.

6. Conclusion:

In conclusion, this survey underscores the critical importance of epileptic seizure detection as a research domain focused on leveraging advanced techniques, particularly through the analysis of EEG data. While significant advancements have been made, challenges such as the need for diverse datasets, computational complexity, and the generalizability of models remain pressing issues. By systematically reviewing around 30 research articles, this study highlights both the strengths and limitations of existing methodologies, including deep learning, machine learning, and hybrid models. The findings from this analysis provide a more profound understanding of existing practices and also highlight opportunities for improving the effectiveness and reliability of seizure detection systems in clinical environments. Ultimately, this research aims to drive future developments in the field, ensuring improved patient outcomes through timely and accurate seizure prediction.

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