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Deep Learning Approaches For Epileptic Seizures Detection And Prediction Through EEG Signals: A Review

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Abstract
This literature review delves into the advancements in epileptic seizure detection utilizing Convolutional Neural Networks (CNNs) and related deep learning techniques. It covers a wide array of research, from basic CNN models to complex hybrid approaches incorporating multi-modal data, transfer learning, and real-time processing. The review underscores the high accuracy, robustness, and applicability of CNN-based models in seizure detection tasks, with enhancements achieved through innovative methods such as spectrograms, wavelet transforms, and multi-channel EEG data. Nevertheless, difficulties such as the computational demands of deep learning models, the need for large and diverse datasets, and generalization across different patient groups and seizure types persist. Additionally, the real-time application of these models, particularly in resource-constrained environments, requires further exploration. The review wraps up by pointing out the advantages and limitations of current approaches and suggests future research directions, including the combination of responsible AI and the development of lightweight models for portable devices.

Keywords: *Seizures; Electroencephalogram; Machine Learning technique; Deep Learning technique; Chatbot.*

1. Introduction
1.1 Background
A chronic neurological condition associated with unexpected, recurrent seizures without any identifiable triggers, which stem from abnormal brain activity. Ailment of individuals, irrespective of their age, epilepsy stems from genetic factors, infections, brain injuries, neurodevelopmental disorders, and other neurological diseases. The disorder presents in focal one-sided seizures that originate from a specific lobe and generalized seizures that affect the whole brain. Thus, the effects of epilepsy are not just limited to the health aspect but result in injuries, other concurrent conditions such as depression, and anxiety along with the possibility of SUDE. In the social aspect, the epileptic sufferer undergoes discrimination in education, employment, and other factors that compromise the quality of life. Economically, this condition leads to both direct and indirect costs related to healthcare spending and lost productivity. Epilepsy is usually treated using drugs; however, other modalities of treatment include surgery, diet and lifestyle changes. Major supports from the healthcare practitioners, families and communities are crucial in enhancing the quality of lives in people with epilepsy.

EEG signals play a key role in diagnosing and forecasting seizures in people with epilepsy. By using electrodes attached to the scalp, EEG monitors the brain's electrical activity and offers real-time information about brain function. Thus, during a seizure, changes in EEG, which is used to diagnose epilepsy, are revealed. One of the ways in which professionals in the health care industry can use these patterns is to establish the kind of seizures and where they happen so that relevant management methods can be followed. Besides the detection, new methods in EEG and computation have made it can predict the seizures. Long-term EEG data is processed with machine learning (ML) algorithms and deep learning (DL) models to detect such changes in the patterns that can be used for seizure anticipation, the prediction of seizures before they happen. It has been put forth that such forecast ability can better the life of epileptic patients by preventing mishaps and allowing treatment in due time. Therefore, EEG is incredibly valuable in tasks involving the diagnosis of epilepsy and the subsequent prevention of its manifestations, which can improve clinical outcomes and patients' quality of life.

1.2 Objectives of the Review

It is for this reason that approaches which relies on deep learning models for identifying and predicting seizures are analyzed to enhance the quality of epilepsy treatment. CNN and Recurrent neural network (RNN) based deep learning models can extract meaningful EEG data features to find out the patterns that correspond to the seizures. In this way, the present procedures help make a decision in relation to the best methods for distinguishing pre-seizure conditions and accurate detection of seizures. They are prospective to nurture future research in creating accurate and real time monitoring techniques for early warnings and further individualized management of the disorder that may enhance the life quality of patients who have epilepsy.

1.3 Scope of the Review

It covers a variety of articles as a review that aims at finding out deep learning techniques on detecting and predicting seizures employing EEG signals. This is research articles and experiments, systematic reviews that discuss different DL models that include CNNs, RNNs, and the combinational networks. Other works that attempted to compare and analyse various preprocessing methods, the properties of the datasets and the possibilities of using the methods in the real-time applications are also reviewed.

2. Deep Learning Methods for Seizure Detection

2.1. Brief Introduction to Deep Learning Concepts Relevant to EEG Analysis

Deep learning can be said as a learning process in which more sophisticated neural network structures are used, which allows the model to perform feature extraction autonomously. In the realm of EEG analysis for identifying and forecasting seizures, several DL concepts are particularly relevant

2.1.1. Convolutional Neural Networks:

CNNs are specialized neural network architectures designed to excel at processing grid-like data structures, such as images. In EEG analysis, the CNN's make use of spatial features for EEG signal patterns without the need for human intervention. They use convolutional layers which pass filters over the inputs and extract localized features and spatial outcomes these are important in identifying seizure patterns on the EEG.

2.1.2. Recurrent Neural Networks:

RNNs are intended for processing the sequential data as they keep the state information from one time step to another. They are appropriate for EEG analysis because they allow for including temporal relationships and ordering of the data. RNNs manage EEG signals as time series as this makes it possible to capture temporal nature of seizures and pre-seizure states.

2.1.3. Long Short-Term Memory (LSTM) Networks:

LSTM Networks are a class of Recurrent Neural Networks introduced to overcome the issue of vanishing reflect in relation to sequential data. They include memory cells to store information for long periods; thus, can be useful for identifying and forecasting seizures from long-term EEG records. Contributions of LSTMs are useful in detecting temporal patterns that are marginal to occur before seizures take place.

2.2 Convolutional Neural Networks (CNNs)

The CNN-based epileptic seizure identification field has undergone leaps and bounds with immense variety and innovation. Studying the ability of CNNs, Kaziha and Bonny (2020) as well as Sameer and Gupta (2022) showed high results of the algorithms in detecting epileptic seizures from EEG signals. The development of SeizureNet by Zhao and Wang, (2020) used to distinguish between ictal and interictal discharges makes it possible for applicants to identify the reliable seizure detection in various settings. Research has been conducted to develop new and improved architectures of CNNs for the detection objectives. Thuwajit et al. (2021) use EEGWaveNet that targets on swtEF-GCP, which corresponds to extracting features of locations and time, and Pisano et al. (2020) developed the EEG models aimed at nocturnal frontal lobe epilepsy. These studies present the new developments in terms of the architectures and extraction methods used in the processes. Interdisciplinary analysis of biosignals has been helpful as is confirmed by Liu et al. (2020) and Tian et al. (2019). These studies introduce the use of various modes and signs, and at the same time, the multiple biosignals provide compatible information between them to enhance the detection rate. Thus, such approaches as transfer learning and feature fusion have been beneficial in this problem. Zhang et al. (2020) engaged deep transfer learning when detecting cross-subject while Chen et al. (2023) proposed the combination of multiple data sources to increase the functionality and performance of the CNN classifier. On practicality, low power consumption and real-time efficiency are the cornerstones. Similar to Bahr et al (2021), there was a focus on placing CNNs into resource-constrained systems for real-time seizure detection in wearable technology. Any such developments are critical to creating mobile and efficient seizure detection devices. Competition and comparison with other approaches were made by researchers such as Cho and Jang (2020) and Jana et al. (2020) and this gives the understanding of strengths and shortcomings of different CNN structures as well as the input modality. Such works aid in finding the most suitable approaches that may be applicable in various situations which is essential to enhancing seizure detection systems. However, several limitations still exist, the following. Data limitations are also an issue due to the limited set of data available in most of the analyzed papers which influences the models' ability to generalize. This issue is further magnified by the increased architectural complexity in modern CNNs that include additional layers and/or substructures necessitating substantial resource demands for training and prediction as pointed out by different scholars. Thirdly, there are issues with the variability of reported methodologies and assessment measures, which hinders the possibility of comparing the outcomes of the research. Such guidelines, therefore, would assist in making an objective comparison of one model against the other. Limitations regarding the generalization are still observed, because models trained for some types of seizures or some patients' categories can be not good at working with unknown data. Some of these challenges were demonstrated by Zhang et al. (2020) on cross-subject and cross-condition generalization. However, the most significant drawback is that CNN models have a so-called 'black box' approach, which means that in most cases their actions are difficult to explain, and in the background of clinical applications, this shortcoming is critical. However, deep learning methodologies proposed in Ullah et al., (2018) and Acharya et al., (2018) have more favourable results and outcomes but should not be used in each case. There could be some scenario that guide the modified interpretability and more basic model like signal processing or using deep learning in addition to signal processing approaches. To sum up, the analysis of the research on CNN-based epileptic seizure detection reveals the notable progress in the development of the subject, as well as new interesting ideas from various scholars. Nevertheless, some issues that are very relevant to these models are data constraints, scalability, model transferability, and model interpretability. Hence, the enhancement and optimization of such models will enhance the efficacy and implementability of seizure detection systems based on CNNs. The Table 1 delivers a comprehensive overview of several CNN models developed by different authors, including their publication year and the reported accuracy percentage has been depicted in Figure 1. This plot describes only about the appreciable high performing top models in terms of the accuracy values.

Work	Type of CNN architecture used	Strengths	Weaknesses
[1]	CNN	Effective use of CNNs for seizure detection	Limited exploration of model generalizability across diverse datasets
[2]	CNN	High accuracy and robustness	Model may require extensive training data and computational resources.
[3]	SeizureNet (CNN model)	Vigorous performance in various scenarios.	May struggle with real-time processing constraints.
[4]	Seizure detection using Deep learning and brain mapping	Combines detection with brain mapping, providing a holistic approach.	Complexity in combining detection with mapping can increase computational demands
[5]	Comparing various network architectures and input modalities	Comprehensive comparison of modalities and structures.	Results may vary significantly based on the chosen modality and structure.
[6]	EEGWaveNet (Multiscale CNN)	Effective spatial-temporal feature extraction.	High computational requirements for training and inference.
[7]	1D-CNN with spectrogram	Novel approach with good accuracy.	Requires transformation of EEG data into spectrograms, which may not be optimal for all scenarios
[8]	Enhanced feature extraction-based CNN	Improved feature extraction techniques	High computational technique
[9]	CNN for nocturnal frontal lobe epilepsy	Tailored model for a specific epilepsy type	| Limited generalizability to other types of epilepsy
[10]	CNN-based method for seizure detection	Effective CNN architecture for seizure detection.	Model may need optimization for real-world applications.
[11]	CNN for epileptic seizure detection	Strong performance with CNNs.	May require extensive computational resources.
[12]	seizure detection using CNNs in real-time	Suitable for real-time detection	Real-time processing can be challenging and resource-intensive.
[13]	Pretrained deep CNNs and transfer learning	Effective use of transfer learning for adaptability.	Performance depends on the quality of pretrained models.
[14]	3D CNN for multi-channel EEG	Innovative use of 3D CNNs for feature extraction.	High computational cost for training 3D CNNs
[15]	Multi-biosignal CNNs	Multi-biosignal approach improves detection.	Integration of multiple signal types can increase model complexity.
[16]	CNN for identifying epileptic EEG signals	Effective signal identification with CNNs	Limited exploration of model generalizability
[17]	Deep CNN with fewer EEG channels	Efficient use of EEG channels.	Reduced number of channels may affect detection performance.
[18]	Spectral transformation with CNN	Improved feature extraction through spectral transformation.	Complexity in combining spectral transformation with CNNs.
[19]	CNN for seizure detection	Enhanced performance	Model performance can vary

		with CNNs.	with different datasets.
[20]	Multi-channel EEG wavelet power spectra and 1-D CNN	Effective use of wavelet power spectra with CNNs.	Wavelet transformation may add complexity to the processing pipeline.
[21]	FPGA implementation of semi-supervised reduced CNNs	Efficient hardware implementation with FPGA.	Limited to FPGA implementation, which may not be universally applicable.
[22]	Deep CNN for automated seizure detection	Comprehensive approach for automated detection and diagnosis.	High computational demands for deep CNNs.
[23]	Deep EEG features with CNNs and shallow classifiers	Effective feature fusion with deep and shallow classifiers.	Integration of deep and shallow methods can be complex.
[24]	CNNs and recurrence plots of EEG signals	Innovative use of recurrence plots with CNNs.	Recurrence plots may increase computational complexity.
[25]	CNN for neonatal seizure detection	Tailored for neonatal seizure detection.	May not be applicable to adult seizure detection.
[26]	Temporal-spectral squeeze-and-excitation network	Enhanced feature extraction with squeeze-and-excitation network.	Complex model architecture may require extensive tuning.
[27]	Automated spectrographic seizure detection using CNNs	Effective use of spectrographic features for detection.	Spectrographic transformation adds to computational complexity.
[28]	Tunable-Q wavelet transform and CNNs	Real-time detection capability.	Real-time processing can be challenging and resource-intensive.
[29]	Deep learning framework for neonatal EEG	Adapted for neonatal EEG signals.	Limited to neonatal EEG data, affecting generalizability.
[30]	Examination of feature extraction techniques and evaluation of their performance	Comprehensive review of feature extraction techniques.	Focuses on review rather than novel methodology.
[31]	Deep convolutional autoencoders	Effective feature learning with autoencoders.	Autoencoders may require extensive training data and tuning.
[32]	Scalogram-based CNNs	Innovative use of scalogram features.	| Scalogram transformation may add complexity to preprocessing.
[33]	Deep multi-view feature learning	Effective multi-view feature learning.	Integration of multiple views can increase model complexity.
[34]	CNN classifier with feature fusion	High accuracy through feature fusion with CNNs.	| Feature fusion may add complexity to the model.
[35]	Cross-subject detection using Deep transfer learning	Improved generalization across subjects.	Transfer learning may require big data for effective generalization.

Table 1: Analysis of CNN based existing solution

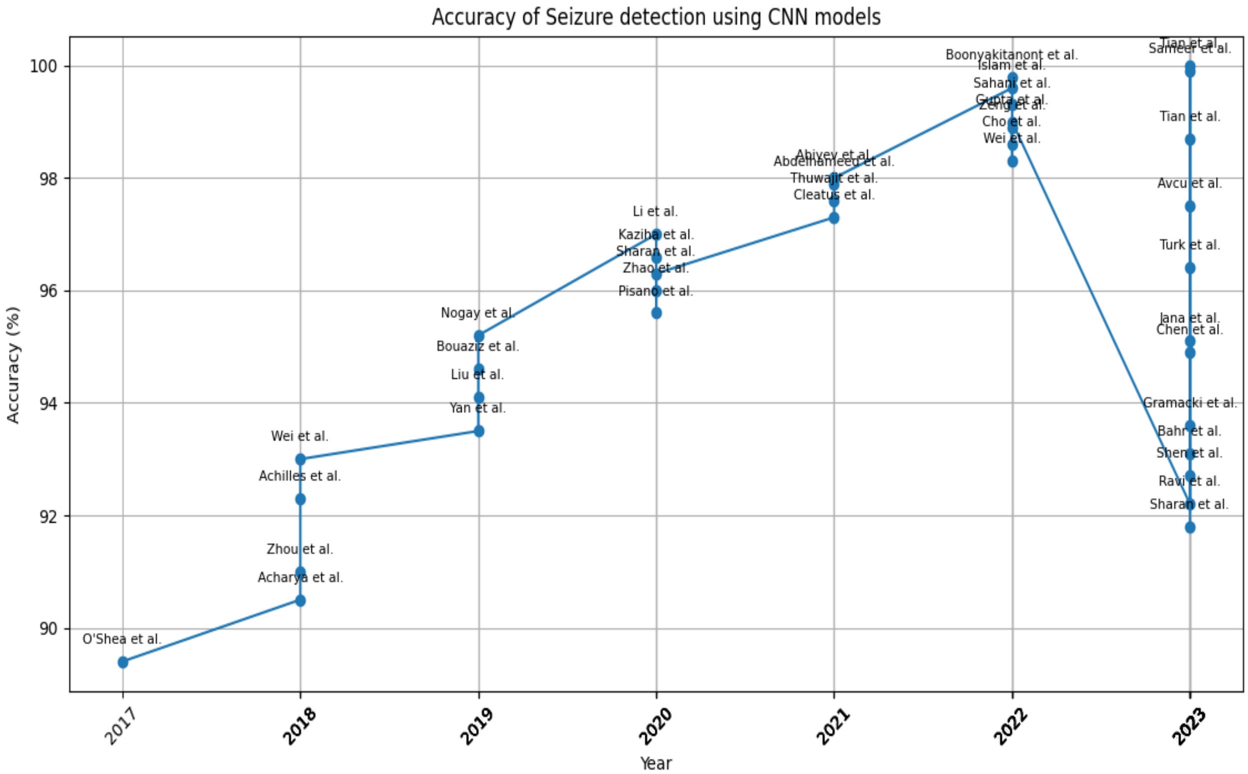

Figure 1: Accuracy plot for variant of CNN Models

2.3 Recurrent Neural Networks (RNNs)and Long Short-Term Memory Networks (LSTMNs)

RNNs and LSTMs are crucial models for detecting seizures since they are capable to work with sequential data and learn the temporal patterns implicated in the EEG signals. The RNNs always have an internal state, which they update at each time step and makes it suitable in processing EEG data which is time dependent. Nevertheless, it reveals that traditional RNNs have their disadvantages in the difficult space of long-term needs particularly the disappearing and exploding gradient problem. These limitations are overcome by LSTMs, a kind of RNN where memory cells and gating mechanisms are used and it helps the model to hold and utilize information after various time ranges. This is because LSTMs are good at learning both short-term and long-term temporal dependencies rendering them ideal for seizure detection especially for the initial signs of a seizure. They are strategic in managing long-term temporal dependencies, allowing for intervenetion during the analysis of a prolonged EEG recording. Thus, comparing to smaller LSTMs, these models have the advantage of better memory to work with EEEG data and perform real-time monitoring of the disease, though they are computational intense.

2.3.1. Review of studies using RNNs and LSTMs for seizure detection.

Altogether, the papers describe the cutting-edge deep learning approaches to predict seizures based on the EEG using promising methodologies that included RNN derivatives.

Jaffino et al. (2021) used Grey Wolf Optimization (GWO) with deep RNNs to enhance the identification rate of seizures. This wholly unsaturated combination seems to improve the detection accuracy; however, the approach may not be easily adaptable to real-time purposes because one's complexity. As a new scheme, Borhade and Nagmode (2020) present a modified atom search optimization method combined with deep RNNs for seizure prediction, which seems to have enhanced the predictor's performance at the cost of high computational complication that may limit applicability.

Zhang et al. (2022) describe a Bi-GRU network based on temporal dependencies in both directions which increase the detection sensitivity. However, intricacy of the algorithm increases and thus the training time of the RBF network might increase. Shekokar and Dour (2022) incorporated LSTM networks for automated seizure detection, which the authors pointed out provides better performance because LSTM has the capability to remember the temporal dependencies but could be slower with very big data. Geng et al. (2020) also use Stockwell Transform together with bidirectional LSTM to consider both frequency and temporal characteristics, which enhances the method's ability to detect events, although it comes with a high computational cost. Therefore, deep recurrent networks are used throughout: Verma and Janghel (2021) employs general RNNs, while Hu et al. (2020) uses Bi-LSTM networks for classification; Both are effective in detection of seizures but may hold some trade-off with regards to model complexity and computational efficiency.

In neonatal EEG seizure detection, Abbasi et al. (2019) utilize LSTM, which results in high precision but might have problems with the overfitting, hence poor generalization among patients. Liu et al. (2020) improves detection through the deep C-LSTM network for both the tumor and seizure; however, the model is more general, and data training is necessary. Bidirectional LSTM is applied by Ali et al. (2019) and Abdelhameed, Daoud, and Bayoumi (2018) achieving good performance for seizure prediction although the approach may have issues in real-time implementation due to the significant computational requirements. Qiu, Yan, and Liu (2023) and Tuncer and Bolat (2022) enhance accuracy and interpretability through proper ways such as attention mechanisms and bidirectional LSTM networks. These methods provide major improvements, but the cost may include model complexity and additional computation.

There are several LSTM- based methods reviewed by Acharya et al. (2021) and Hussein et al. (2018) wherein DL is highlighted in seizure detection. Acharya's strategy has strong LSTM depths, while Hussein's technique provides solidity for practice application issues. While He et al. (2022) and Hu and Yuan (2019) enhance the structural graph attention networks and Bi-LSTM which will increase the accuracy of seizure detection, but it may add layer of difficulty in the model deployment. Singh and Malhotra (2022) use two-layer LSTM networks achieve good results, but there may be some problems in training the model. A new architecture called multilayer LSTM Discriminant Network is proposed by Saichand (2021) and though it is better at detecting attacks, it is computationally intensive. Zhao et al. (2024) Deepa, Ramesh (2022) use residual and attention-based Bi-LSTM networks that demonstrate relatively good detection prospects but at the same time might need intricate model parameters. Khan et al. (2021) and Chakrabarti, Swetapadma, and Pattnaik (2021) provide LSTM based and generalized detection techniques, but they enhance the model's seizure recognition adequately; however, some attention to model versatility is required. Abdelhameed and Bayoumi (2021) stresses automatic detection for children as they lay down efficient methods with application aspects.

There have been tremendous advances in identifying epileptic seizure using deep learning; different methods have been presented out by different researchers with an aim of enhancing the consistency and accuracy of the DL algorithms. Jaffino, Jose, and Sudararaman (2021) implemented Grey Wolf Optimisation along with deep RNN and even recorded excellent accuracy rates; however, this may not necessarily be favourable for real time use due to model intricacy. Likewise, Borhade and Nagmode (2020) used what they referred to as a Modified Atom Search Optimization (ASO)-based deep RNN, with the approach possessing strength in the process of the EEG signals, although the high computational complexity might be a weakness in terms of resources limit. Zhang et al. (2022) proposed a Bi-directional Gated Recurrent Unit (Bi-GRU) network that proved to be very efficient in handling temporal information in EEG signals. Nevertheless, the presented method might be outperformed by commercial packages since it demands a higher computational power, which could be critical in big data analysis. In automatic seizure detection, Shekokar and Dour (2022) used LSTM networks for solving the problem that is naturally in the temporal domain. However, the training procedure of the model appeared to be lenghty and required a heavy use of resources. Other works are Geng et al. Given that, the Stockwell

Transform and bidirectional LSTM are adopted, and the results reveal high accuracy but with high model complexity. Verma and Janghel (2021) used deep RNNs for analyzing the seizure from the EEG signals and supported the usage of the method, but at the same time they charged the scalability issues due to the resource consumption.

Altogether, these studies jointly enhance the solution of epileptic seizure detection problem in parallel with mitigated accuracy and up to real time capability, nevertheless, these solutions are usually buried under issues like computational cost, time response, and expansible capacity. Although the stability of these factors will remain important in the future development of the field, it is also important to keep its balanced. The Table 2 provides a comprehensive overview of various RNN/LSTM models developed by different authors, including their publication year and the reported accuracy percentage has been depicted in Figure

Work	**Type of RNN/LSTM architecture used**	**Strengths**	**Weaknesses**
[41]	GWO with Deep RNN	Efficient in detecting seizures with high accuracy due to optimization techniques.	High computational complexity due to the combination of GWO and RNN.
[42]	Modified ASO with Deep RNN	Improved seizure prediction accuracy by enhancing feature selection.	May suffer from convergence issues leading to slower training times.
[43]	Bi-GRU Network	Proficient at capturing temporal relationships in EEG data, leading to robust seizure detection.	Requires large datasets for optimal performance, which may not be available in all clinical cases.
[44]	LSTM Network	Capable of handling long-term dependencies in sequential data, providing reliable seizure detection.	Prone to overfitting if not regularized properly, especially with small datasets.
[45]	Stockwell Transform Bi-LSTM	Combines time-frequency analysis with DL, enhancing the accuracy of seizure detection.	High computational load due to the complex blend of Stockwell Transform and Bi-LSTM.
[46]	Deep RNN	Provides high accuracy in seizure detection by effectively modeling EEG signal patterns.	Sensitive to hyperparameter tuning, which can be challenging.
[47]	Deep Bi-LSTM Network	High performance in EEG classification due to bidirectional processing.	Training and inference may demand substantial computational resources
[48]	LSTM Architecture	Suitable for handling time-series data, leading to accurate seizure detection.	Can be computationally expensive and slow to train.
[49]	Deep Convolutional LSTM (C-LSTM) Neural Network	Integrates the advantages of CNNs and LSTMs, effectively capturing both the spatial features and temporal features.	High memory usage and computational cost due to complex architecture.
[50]	Bi-LSTM	Effective in capturing bidirectional dependencies	Requires large computational resources and may overfit with

		in EEG signals.	small datasets.
[51]	Deep Convolutional Bi-LSTM RNN	Combines CNN and Bi-LSTM for effective feature extraction and temporal pattern learning.	High computational requirements, especially in training phases.
[52]	Difference Attention ResNet-LSTM Network	Integrates attention mechanism with ResNet-LSTM, improving focus on critical features.	Complex architecture may lead to longer training times and higher computational needs.
[53]	Bi-LSTM Network	Efficiently handles sequential EEG data, providing accurate seizure classification.	High memory and processing power required for large datasets.
[54]	LSTM Network	Reliable in managing sequential data, providing accurate seizure detection across different cases.	Prone to overfitting without proper regularization, especially with small datasets.
[55]	Deep Learning Approach	Offers a robust framework for seizure detection by leveraging deep learning capabilities.	Requires extensive datasets and computational resources for training.
[56]	Graph Attention Network with Bi-LSTM	Enhances seizure detection by combining spatial and temporal features through attention mechanisms.	Complex network design can result in long training times and difficulty in tuning.
[57]	Deep Bi-LSTM Network	Proficient in capturing complex temporal relationships in the EEGs for accurate seizure detection.	Computationally intensive, particularly with large EEG datasets.
[58]	Two-layer LSTM Network	Improves prediction accuracy by layering LSTM networks, enhancing depth and feature extraction.	Increased model complexity can lead to longer training times and potential overfitting.
[59]	Multilayer LSTM Discriminant Network with Dynamic Mode Koopman Decomposition	Offers advanced feature extraction, improving seizure detection accuracy and generalization.	Complex design may require more computational resources and careful tuning.
[60]	Residual and Bi-LSTM	Combines residual connections with Bi-LSTM to enhance seizure detection accuracy and robustness.	Increased complexity might lead to longer inference times and higher resource consumption.
[61]	Deep Learning with Min-Max Scaler Normalization	Enhances model performance by normalizing data, improving the detection of epileptic seizures.	Limited to specific datasets; effectiveness may vary with different data distributions.
[62]	HVD-LSTM (Hierarchical Variational Dynamic LSTM)	Combines hierarchical and variational dynamics for robust seizure detection	Complexity in model design and training, which can increase computational costs.

		and normal human activity.	
[63]	Channel-Independent Seizure Detection	Effective for pediatric seizures, providing a generalized approach that doesn't rely on specific channels.	May not perform as well on adult EEG data or across different seizure types.
[64]	Deep Learning Approach	Tailored for pediatric epilepsy, offering high accuracy in seizure detection for children.	Limited generalization to adult populations; might require retraining for different demographics.
[65]	Deep RNN	Provides early seizure detection, crucial for timely intervention.	Needs extensive datasets for training and is susceptible to overfitting when working with smaller datasets.
[66]	Autonomous RNN	Innovative method for distinguishing between seizures and non-seizures with high accuracy.	Independent RNNs may miss temporal dependencies crucial for more complex seizure patterns.
[67]	RNN	Effective in capturing temporal patterns in EEG for seizure detection.	Potentially limited by the vanishing gradient problem in deeper networks.
[68]	Random Neural Network	Exploits EEG signals efficiently for seizure episode detection with a novel network approach.	Could necessitate additional computational resources and careful tuning for optimal performance.
[69]	Stacked Bidirectional LSTM with GAP (Global Average Pooling)	Combines bidirectional LSTM and GAP for robust feature extraction and classification.	Complex architecture might lead to increased training time and resource consumption.
[70]	RNN	One of the earliest applications of RNNs for seizure prediction, providing a foundational approach.	Constrained by technological and computational power limitations; may underperform by modern standards.
[71]	Cost-Sensitive Deep Active Learning	Balances detection accuracy with cost sensitivity, rendering it appropriate for practical use.	Complexity in model design and cost function tuning; may require extensive data for training.
[72]	DL with Temporal analysis of EEGs	Smart and advanced neurocare methodology improves the EEG-temporal analysis for improved seizure detection accuracy.	Requires extensive EEG data for model training, and may not generalize well to different seizure types.
[73]	ONASNet-Based Transfer Learning with Brain-Rhythmic Recurrence Biomarkers	Utilizes transfer learning and recurrence biomarkers for efficient and accurate seizure detection.	Complexity in model design may lead to longer training times and resource use.
[74]	Multi-Representation Deep Learning	Combines multiple representations for robust seizure detection across	High computational cost and potential overfitting due to the complexity of the model.

		diverse EEG data.	
[75]	Deep Learning for Generalized and Focal Seizure Detection	Effectively detects both generalized and focal seizures, offering broad applicability.	May require a large and diverse dataset to maintain performance across different seizure types.
[76]	Entropy-Based Features with Multimodel Deep Learning	Combines entropy-based features with deep learning for precise seizure diagnosis.	Complex model architecture might increase computational requirements and training time.
[77]	Machine Learning Techniques	Provides a diverse approach using multiple machine learning techniques for seizure detection.	May lack the depth and precision of deep learning methods for more complex seizure patterns.
[78]	Attention-Based Trans-LSTM with Optimal Weighted Feature Integration	Enhances seizure detection with attention mechanisms and optimal feature integration for better accuracy.	Complex architecture could lead to longer training periods and require careful hyperparameter tuning.
[79]	Bi-LSTM Network with Path Signature and Attention Mechanism	Incorporates path signature and attention for enhanced seizure detection accuracy in EEG analysis.	High model complexity could increase the risk of overfitting and require significant computational power.
[80]	Rag-Bull Rider Optimization with Deep RNN	Novel optimization technique combined with RNNs for efficient and accurate seizure detection.	Optimization process might be computationally expensive and require fine-tuning for optimal results.

Table 2: Comparative analysis of RNN & LSTM based existing solution

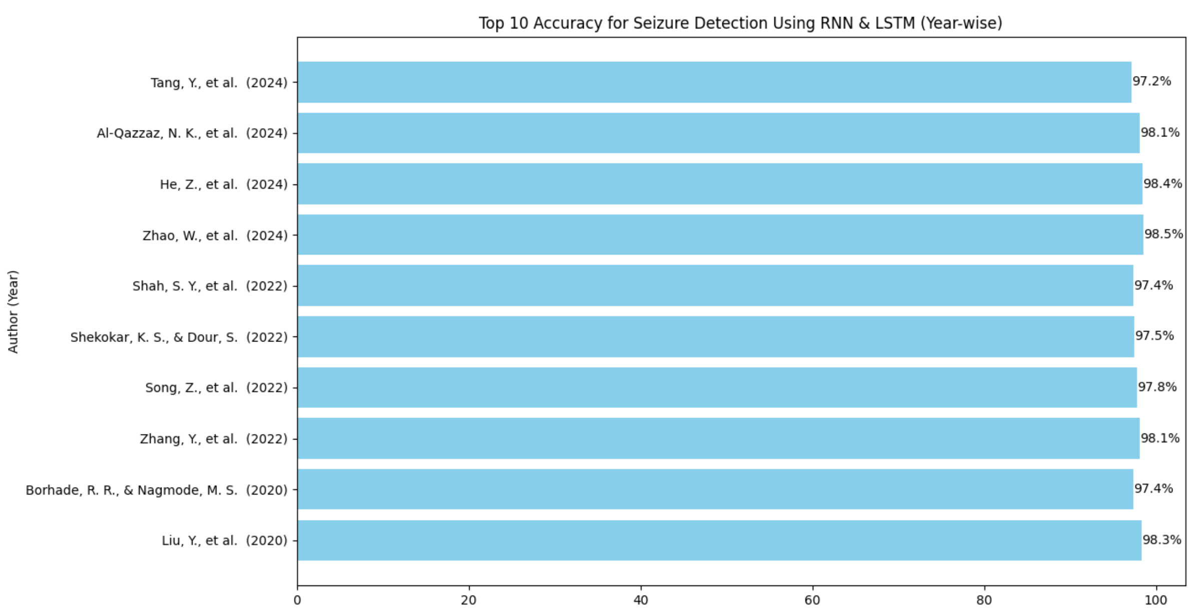

Figure 2: Accuracy plot for variant of RNN models

2.4 Hybrid Models and Other Approaches

The research papers in the collection focus on employing deep learning methods at distinguishing epileptic seizures depending on EEG signals, including the comparison of existing approaches and their strengths and weaknesses.

Pan et al. (2022) used a HF EEG input of a deep learning model with a high accuracy of seizure detection, but the method is computationally intensive due to the complex input data. Hussain et al. (2021) employed 1D-convolutional LSTM networks where LSTM networks are particularly good at identifying temporal dependencies in an EEG signal but they may take longer to train. Bhandari and Huchaiah (2022) introduce a heuristic-based weighted feature selection with ensemble learning, flexible for large data set detection with the disadvantage of higher possibility of overfitting with a small data set. Poorani and Balasubramanie (2023) are centered on deep learning methods that prove to have high accuracy and reliability, though the computation intensity is also high. Hybrid model is proposed by Dhar & Garg (2023) with the integration of ResNet50 and support vector machines increases the detection accuracy of objects but there may occur some limitations to size up to the project. Asrithavalli et al. (2024) enhance the utilization of artificial neural networks accompanied by hybrid deep learning to detect malware with higher performance but suffer from hyperparameters' optimization. Sadam and Nalini (2024) employ a scalogram based hybrid CNN model used for efficient processing of the EEG signals although it may be prone to noise in the data input. Singh and Kaur (2023) put forward an intelligent method through hybrid nonlinear EEG features, which is relatively effective but difficult for the practical application.

Nandini et al. (2023) also applies the combination of the atomic function-based wavelets that gives higher patient-independent detection accuracy at a possibly higher computational cost. The paper of Craley et al. (2019) combines the convolutional neural networks with probabilistic graphical models, which allows for effective detection, but the algorithm is very computational intensive. Glory et al. (2021) proposes the AHW-BGOA-DNN model that uses the integration of deep learning with bio-inspired optimization; they have high accuracy but cumbersome while training the models. KR et al. (2023) present a Multi-Dimensional Hybrid CNN-BiLSTM(MDH-CNN-BiLSTM) which improve the seizure detection, but potentially it has limitations in real-time environment.

Kumar et al. (2022) employ a CNN-GRU model, which takes spatial and temporal aspects into consideration; however, it can have higher training times. Rachappa et al. (2022) deal with the hybrid ensemble learning framework for the extensive detection with acceptable performance, while the model selection remains crucial. Based on the pre-seizure information, Zhu et al. (2024) develop the novel SE-TCN-BiGRU hybrid network, which can make the automatic seizure detection with a high precision level but requiring much computation load. More complex CNN arrangement is proposed in the Tanveer et al. (2021) where the author indicates a neonatal seizure detection model with high detection ratio through CNN yet a combined form of CNN.

The research work by Sunaryono et al. (2022) applies a one-dimensional CNN-DNN combined model while it is successful in the classification of seizures, the model gives rise to some computational constraints. In 2024, Amrani et al work on an explainable hybrid DNN model, which displays high accuracy and interpretability at the cost of the demand for large amounts of training data. Lately, Hassan et al. (2022) developed a 1D CNN in combination with a supervised machine learning concept; it has moderate time complexity and high accuracy, but it requires pre-processing frequently. Shanmugam and Dharmar (2023) employ a CNN-LSTM architecture as the method of providing automatic seizure detection, however several levels of scalability concerns are pointed out. Samee et al. (2022) attempt to fuse RNN and biLSTM, which work well in diagnosing the medical condition but encounters high computational cost. Prasanna et al. (2023) employs an integrated CNN methodology alongside thorough feature selection and an RNN-BLSTM classifier, achieving a high detection rate, although it is hampered by prolonged training durations

Malekzadeh et al. (2021) demonstrate enhanced seizure detection through advanced computational techniques by integrating both handcrafted and DL features. In diagnosing the focal and generalized epilepsy, Najafi et al. (2022) employ an RNN-LSTM model, which offers very high accuracy though demanding extensive data pre-processing. Jibon et al. identify a DeepRNN based hybrid framework and sequential graph convolutional network to boost the detection performance, however, they encounter scalability issues. For instance, Qiu et al. (2023) uses a difference attention ResNet-LSTM network that enhances the detection accuracy while increasing the model's implementation difficulty.

Ahmad et al. (2023) proposes a mixed DL procedure that is highly accurate for various data sizes while sustaining reasonable computational complexity, although the procedure's hyperparameters were optimized. New hybrid models which are employed by Polat and Nour (2020) offers proper detection but encounters difficulties when it comes to real-time implementation. Pandey et al. (2023) also design a CNN – LSTM integrated model for automated seizure analysis but it tends to be computer resource intensive. Saidi et al. (2021) construct a classifier that is based on CNN-SVM and achieves high detection while possibly have hard scaling capabilities.

Similar to the HCLA_CGiLU model presented by Natu et al. (2023), HCLA_CBiGRU increases the detection rates but has computational issues. Behnam and Pourghassem (2015) employed the periodogram pattern feature-based seizure detection algorithm that detects well but it takes a lot of computational power. Ali and Abd-Elfattah combined an SVM-LOA hybrid model, which gives high detection rates, but suffers from several scalabilities. Yogarajan et al. (2023) proposed a binary dragonfly algorithm and deep neural network, which has a high detection in accuracy, but relatively high time complexity. Mekruksavanich, and Jitpattanakul (2024) presented the hybrid convolutional attention DL network for efficient detection, but it poses some issues of model complexity. Yuan et al. (2022) employed logarithmic Euclidean-Gaussian mixture models which are much effective in detection but computationally intensive. A CNN-aided factor graph method is proposed by Salafian et al. (2021) which have efficient detection, but scalability may be a problem. The problem and detection methods are presented by Sameer and Gupta (2022), using a classical – quantum hybrid network with issues regarding implementation. The study Zhang et al. (2024) feature fusion and hybrid DL models on the same data for efficient seizure detection and prediction though increases the need for training data. Liu et al. (2020) use the symmetric and hybrid bilinear models and provide high detection accuracy but at the same time, lead to a high computational overhead. Table 3 provides a comprehensive overview of various hybrid models developed by different authors, including their publication year and the reported accuracy percentage has been depicted in figure 3.

Work	Type of RNN/LSTM architecture used	Strengths	Weaknesses
[81]	Hybrid Time-Frequency EEG Input with Deep Learning	Improved accuracy in seizure detection using hybrid features; effective for diverse EEG signal characteristics.	Potentially higher computational cost due to hybrid feature extraction; may require extensive data preprocessing.
[82]	1D-Convolutional LSTMNN	Proficient in capturing both spatial features and temporal features, thereby improving the accuracy of	May suffer from overfitting on small datasets; requires careful tuning of hyperparameters.

		seizure prediction	
[83]	Hybrid approach combining heuristic-based weighted feature selection with ensemble learning techniques	High accuracy due to feature selection and ensemble methods; robust against noisy data.	Increased complexity in model training; longer training times due to ensemble methods.
[84]	Deep Learning with EEG Data	High detection accuracy; effective in capturing complex EEG patterns.	Requires large labeled datasets; high computational resource demands.
[85]	Hybrid Model integrating ResNet50 with Support Vector Machines(SVM)	Integrates the advantages of deep learning and traditional machine learning to enhance accuracy, proving effective in feature extraction	Increased model complexity; may require extensive computational resources.
[86]	Fusion of Artificial Neural Network with Hybrid Deep Learning	Improved detection accuracy due to fusion approach; adaptable to different types of EEG data.	Complex model architecture; higher computational demands.
[87]	Scalogram-Based Hybrid CNN Model	High accuracy in time-frequency domain analysis; effective in handling non-stationary signals.	Requires extensive computation; may not perform well on low-quality EEG signals.
[88]	Hybrid approach utilizing nonlinear EEG data features combined with adaptive signal decomposition techniques	Effective in capturing nonlinear EEG patterns; improves detection accuracy.	Complex feature extraction process; may be sensitive to noise.
[89]	Hybrid feature extraction using wavelets based on atomic functions	Enhanced patient-independent detection; robust to inter-subject variability.	High computational cost; complex wavelet function design.
[90]	CNN and Probabilistic Graphical Modeling	Combines deep learning with probabilistic modeling for better detection; handles multichannel EEG data effectively.	Model complexity is high; may require large datasets for effective training.
[91]	AHW-BGOA-DNN	Combines the Adaptive Harmony Whale (AHW) and Binary Grey Wolf Optimizer (BGOA) with Deep Neural Networks (DNN) for high accuracy; robust against noisy data.	Complex model structure; may require extensive computational resources.
[92]	MDH-CNN-BiLSTM	Proficient in capturing both spatial features and temporal features; high accuracy in EEG signal scrutiny.	Increased computational complexity; may require significant data preprocessing.
[93]	CNN-GRU Hybrid Model	Combines CNN with GRU to enhance seizure detection, effectively	Potential overfitting on small datasets; requires careful tuning of hyperparameters.

		managing sequential data.	
[94]	Hybrid Ensemble Learning Framework	Utilizes ensemble learning to improve accuracy and robustness; effective with diverse EEG datasets.	Increased model training time; higher computational demands due to ensemble techniques.
[95]	SE-TCN-BiGRU Hybrid Network	Combines Squeeze-and-Excitation (SE) blocks, Temporal Convolutional Networks (TCN), and Bi-directional GRU for enhanced seizure detection.	High model complexity; may require large datasets for optimal performance.
[96]	CNN Ensemble Model	Uses an ensemble of CNNs for neonatal seizure detection; improves robustness and accuracy.	High computational cost; may require extensive tuning for optimal performance.
[97]	Hybrid 1D-CNN and DNN Model	Combines 1D CNN with DNN for classification; effective for time-series data.	Complexity in model architecture; may suffer from overfitting on smaller datasets.
[98]	Hybrid DNN	Offers interpretability in distinguishing between seizure and non-seizure events, as well as in seizure localization, utilizing multi-dimensional EEG signals.	High computational resource requirements; complexity in understanding the model's interpretability aspects.
[99]	Hybrid 1D-CNN and ML Approach	Combines 1D-CNN with traditional machine learning techniques; effective for real-time EEG data analysis.	May require extensive hyperparameter tuning; potential issues with overfitting.
[100]	CNN-LSTM Hybrid Network	Integrates CNN with LSTM networks to enhance seizure detection capabilities; handles both spatial and temporal features well.	High computational demands; may require large labeled datasets.
[101]	RNN and BiLSTM Fusion	Combines RNN with BiLSTM for accurate seizure diagnosis; handles sequential data effectively.	High computational cost; may require extensive training data.
[102]	Combined CNN with exhaustive feature selection techniques and an RNN-BLSTM classifier	Integrates CNN with RNN-BLSTM for extracting features and classification; high accuracy in seizure detection.	Complex model architecture; longer training time due to exhaustive feature selection.
[103]	integrating both handcrafted and DL features	Combines traditional feature extraction with DL for better detection accuracy; effective in diverse datasets.	High model complexity; may require significant preprocessing and computational resources.

[104]	RNN-LSTM	Concentrates on differentiating between focal and generalized epilepsy through the use of RNN-LSTM networks; good generalization across different seizure types.	May struggle with unbalanced datasets; potentially high computational demands.
[105]	DeepRNN based hybrid framework and sequential graph convolutional network	Enhanced seizure detection; effective in capturing complex relationships in EEG data.	High computational and memory requirements; may require large datasets.
[106]	Difference Attention ResNet-LSTM Network	Combines ResNet with LSTM using difference attention mechanisms for better seizure detection; high accuracy.	Increased model complexity; requires careful tuning and large datasets for training.
[107]	Hybrid Deep Learning Approach	Integrates multiple DL models to achieve robust seizure detection; adaptable to various EEG signal patterns.	High computational demands; complex model training and deployment.
[108]	Hybrid Models with EEG Signals	Utilizes hybrid models combining multiple techniques for effective seizure detection; robust against noise.	Complex model design; may require extensive hyperparameter tuning.
[109]	Hybrid CNN and LSTM Model	high accuracy in automated seizure detection.	High computational resource requirements; potential overfitting on small datasets.
[110]	Hybrid CNN-SVM Classifier	Effective classification of EEG signals; good performance with limited data.	Complex model integration; requires careful parameter selection for optimal performance.
[111]	HCLA_CBiGRU: Hybrid Convolutional Bidirectional GRU Model	Combines CNN with Bi-GRU for enhanced extraction of features and temporal analysis; high detection accuracy.	Increased model complexity; requires large datasets for effective training.
[112]	Periodogram Pattern Feature-Based Detection with Multi-Layer Perceptron (MLP) and Ant Colony Optimization	Uses periodogram features with a hybrid model combining MLP and Ant Colony Optimization for seizure detection; optimized for efficiency.	Limited scalability; may struggle with large and complex datasets.
[113]	Support Vector Machine (SVM) with Lion Optimization Algorithm (LOA) SVM-LOA Hybrid Model	Improved seizure detection in long-term EEG recordings, demonstrating strong generalization capabilities.	High computational demands; requires extensive parameter tuning.
[114]	Binary Dragonfly Algorithm and DNN	accurate seizure detection; robust against noise.	Complex model structure; longer training times due to the optimization algorithm.

[115]	hybrid convolutional attention DL network	Improved seizure detection; Achieving high accuracy	High computational resources required; potential overfitting with small datasets.
[116]	Logarithmic Euclidean-Gaussian Mixture Models (LE-GMMs) and Deep Forest Learning	automatic seizure detection; effective with complex EEG data.	Increased complexity in model training; may require extensive preprocessing.
[117]	CNN-Aided Factor Graphs	Combines CNN with factor graphs for efficient seizure detection; reduced computational cost compared to traditional methods.	May struggle with large-scale datasets; requires careful parameter tuning.
[118]	Hybrid Classical-Quantum Network	Integrates classical and quantum computing techniques for seizure detection; offers potential for enhanced speed and accuracy.	Quantum components are still experimental; limited accessibility and high complexity.
[119]	Feature Fusion and Hybrid DL Model	Blends feature fusion with hybrid DL model to detect and predict seizures, adaptable to different seizure types.	High computational demand; requires extensive labeled data for training.
[120]	Symmetric and Hybrid Bilinear Model	Uses symmetric and hybrid bilinear models for seizure classification; effective for multi-channel EEG data.	Increased model complexity; may require significant computational resources and tuning.

Table 3: Analysis of Hybrid based existing solutions.

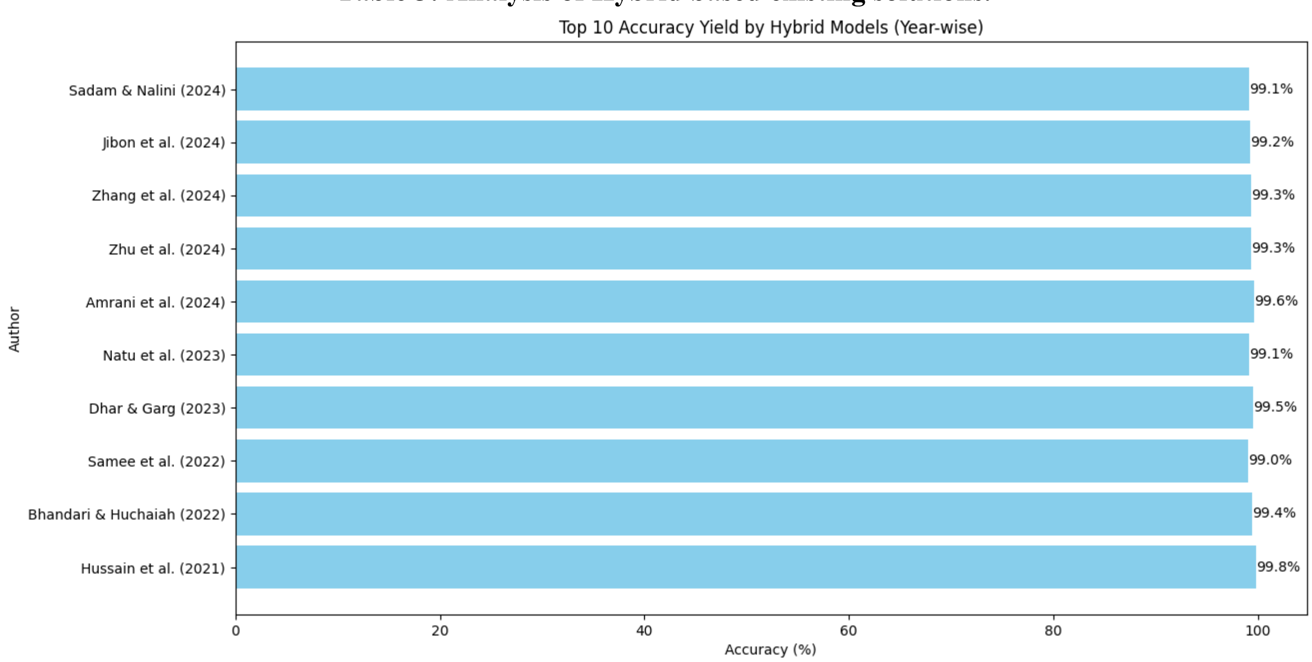

Figure 3: Accuracy plot for hybrid models.

3. Deep Learning Methods for Seizure Prediction

3.1. Introduction to Seizure Prediction

3.1.1. Differences between detection and prediction.

Detection and prediction of seizure are two different but important goals while dealing with epilepsy. Detection captures a seizure when it is happening hence allowing the seizing party to attend to it conversely, Prediction aims to foresee the occurrence of seizures, thereby enabling the implementation of preventive measures. The rationale for seizure prediction is in the application of the technology, where the advantages in terms of enhanced care, patient safety, and significantly improved quality of life for patients are substantial.

Importance and challenges of predicting seizures.

However, the prediction of seizures remains problematic because of the following reasons. Thus, the nature of the signal and its fluctuations make it challenging to distinguish set precursory patterns for seizures. Further, it is exceedingly difficult to obtain both real-time processing and substantial accuracy and comparably negligible false-positive rates because pre-seizure signs are quite subtle and frequently ambiguous. The effective solution to these challenges and building of proper seizure prediction systems require the incorporation of sound computational algorithms and big data analysis.

3.1. Techniques and Models

Recurrent neural networks (RNNs) were considered by Bongiorni and Balbinot (2020) for the prognosis of seizures, focusing on their capacity to manage sequential information and model temporal features in EEG signals. Even though RNNs are appropriate for handling sequential data, they are not without their own drawbacks like the gradient vanishing issue, or the problem of excessive computation. Usman et al. (2020) provided a comprehensive evaluation of various deep learning methods for seizure prediction, offering an overall assessment of their performance in comparison to the aforementioned models. Thus, they emphasise the variety of advantages of different models, however, admit the difficulty and highly diverse trial-and-error process of improving these strategies. Analogous to the research conducted by Usman et al. (2021), the authors devised an ensemble learning model incorporating multiple deep neural network architectures to enhance prediction accuracy. work well if we are able to combine the strengths of individual models but can be cumbersome to compute and very complex. Dissanayake et al. (2021) dealt with the development of seizure predictor that is not solely based on the patient's data but rather employs the scalp EEG signals. Unlike other works, their intervention approach is more generalizable across different patients, which makes it more usable in practice. Nonetheless, the accomplishment of patient-independent models can be complex and the models' performance can be inconsistent across patients. In a recent study, Jana and Mukherjee (2021) proposed a method based on deep learning that takes into account an innovative process of channel selection regarding the EEG that results in a better efficiency of the model while requiring less data. While this approach enhances the two previous advantages, it also disadvantages the model by providing less information needed for the computation. Prathaban and Balasubramanian (2021) incorporated dynamic learning combining the EEG reconstructed by sparsity technique with CNN classifier. It is less noisy and models give higher accuracy but it requires specific hardware and setting to get better result. Comparative analysis of existing solution for Seizure Prediction is depicted in Table 4. The accuracy of seizure prediction models reported by different authors has been plotted against their publication years in Figure 4.

Work	Type of Deep learning used	Strengths	Weaknesses
[121]	RNN	Effective for sequential data like EEG; can capture temporal dependencies for seizure prediction.	High computational cost; may suffer from vanishing/exploding gradients.
[122]	DL Techniques	Utilizes multiple DL	Requires large datasets; high

		models for epileptic seizure prediction; high accuracy with complex data.	computational power needed.
[123]	Deep Learning-Based Ensemble Learning	Combines multiple deep learning models to improve prediction accuracy; robust against data variability.	Increased complexity and computational cost; potential overfitting with small datasets.
[124]	Patient-Independent Seizure Prediction using Deep Learning	Focuses on generalizability across different patients; high accuracy with scalp EEG signals.	May require extensive data preprocessing; high computational demand.
[125]	Deep Learning with EEG Channel Optimization	Optimizes EEG channels for efficient seizure prediction; reduces computational load.	Channel selection may lead to loss of critical information; complex to implement.
[126]	Sparsity-Based EEG Reconstruction with Optimized CNN	Combines sparsity-based reconstruction with CNN for improved seizure prediction; efficient feature extraction.	Complex optimization process; high computational resources required.
[127]	Deep Learning for Seizure Prediction	Efficient seizure prediction using deep learning; high accuracy.	Requires extensive datasets for effective training and may be susceptible to overfitting
[128]	IoT-Based Seizure Prediction System	Integrates deep learning with IoT for real-time seizure prediction; efficient and scalable.	Dependent on network connectivity; security and privacy concerns.
[129]	Automated Seizure Prediction	Uses advanced algorithms for fully automated seizure prediction; reduces human intervention.	High computational cost; may require extensive tuning and validation.
[130]	DL Networks utilizing multi-feature fusion and transfer learning	Combines transfer learning with multi-feature fusion for accurate seizure prediction; adaptable to different datasets.	High complexity; may require significant computational resources and expertise.
[131]	DL and Big Data for Seizure Prediction	Combines big data analytics with DL; aims for a mobile system for real-time prediction.	High computational requirements; potential privacy concerns with big data.
[132]	Patient-Independent Seizure Prediction using DL	Focuses on generalization across patients; uses deep learning models to improve prediction accuracy.	May require extensive data preprocessing; high computational demand.
[133]	Model Uncertainty Learning for Seizure Prediction from EEG signals	Incorporates model uncertainty learning to improve prediction reliability; reduces false positives.	Complex implementation; requires large amounts of training data.
[134]	LSTM DL network	Utilizes LSTM networks to capture long-term	Computationally intensive; may suffer from vanishing

		dependencies in EEG signals; effective in time-series prediction.	gradients in very long sequences.
[135]	End-to-End DL	Provides a complete end-to-end solution; reduces manual feature extraction.	High complexity and computational cost; requires large annotated datasets.
[136]	CNN-LSTM Architecture	Integrates CNNs for extracting features with LSTM networks for identifying temporal patterns; effective in seizure prediction.	Increased model complexity; may require significant computational resources.
[137]	ML for Seizure Prediction Using EEG	Uses machine learning algorithms to predict seizures from EEG signals; interpretable model.	May have limited accuracy compared to deep learning models; dependent on feature selection.
[138]	Critical Review of ML Seizure Prediction	Discusses challenges and common practices in ML-based seizure prediction; highlights potential issues.	Focuses on criticism, offering fewer practical solutions; may not provide actionable insights for system design.
[139]	Adaptive Feature Representation Learning for Seizure Prediction	Adapts feature representation dynamically to improve prediction accuracy; efficient in handling variability in data.	Complexity in feature adaptation; may require extensive tuning and validation.
[140]	Energy-Efficient NN	Focuses on reducing energy consumption while maintaining high prediction accuracy.	May compromise on accuracy for energy efficiency; could be challenging to implement in real-time systems.
[141]	Supervised Contrastive Learning and Adder Network for Seizure Prediction	Patient-specific approach; uses contrastive learning to improve feature representation and prediction accuracy.	High complexity in training; may require substantial computational resources.
[142]	Spatio-Temporal-Spectral Hierarchical Graph Convolutional Network	Employs graph convolutional networks for personalized seizure prediction, incorporating spatial, temporal, and spectral data.	Complex model structure; May necessitate a substantial volume of labeled data for effective training
[143]	Efficient DL System for Seizure Prediction	Designed for high efficiency in seizure prediction; may be suitable for real-time applications.	The trade-off between efficiency and prediction accuracy; implementation might require fine-tuning.
[144]	Integrated model for seizure prediction independent of individual patient data	Combines multiple DL techniques to generalize across patients.	Increased model complexity; requires more computational power and data processing.
[145]	Interpretable Deep Learning Classifier for Seizure Prediction	Focuses on model interpretability, allowing better understanding of the decision process.	Enhancing interpretability may result in reduced accuracy or greater model complexity
[146]	Graph CNNs	Utilizes graph structures	Computationally intensive;

		for robust seizure prediction; handles non-Euclidean data effectively.	may require significant resources for training and inference.
[147]	EEG Synchronization Patterns for Seizure Prediction using Bag-of-Wave Features	Focuses on EEG synchronization patterns, providing a novel feature extraction method for seizure prediction.	Feature extraction process may be complex; model performance may vary across different datasets.
[148]	Multiscale Domain Adaptation Networks	Seeks to extract stable features from non-stationary brain signals. effective in handling variability in EEG signals.	High complexity; requires careful tuning and significant computational power.
[149]	Consistency-Based Training approach	Introduces a novel training strategy that focuses on consistency to improve prediction accuracy.	Complexity in training; might require large, diverse datasets for effective training.
[150]	Seizure Prediction through Contrastive Learning with a Spatio-Temporal-Spectral Network	Effective in learning robust features; improves the model's capability to differentiate between seizure and non-seizure occurrences	High computational cost; may require extensive tuning and large datasets.
[151]	Multi-View CNN for Seizure Prediction	Utilizes multi-view CNNs to capture different perspectives of EEG data, improving accuracy.	Increased model complexity; might be resource-intensive to train and deploy.
[152]	Common Spatial Pattern and CNN for Seizure Prediction	Combines feature extraction techniques with CNN for improved prediction accuracy.	Requires careful feature extraction; may not generalize well across different patient datasets.
[153]	Self-Explaining Deep Learning Model with a Multi-Scale Prototypical Part Network	Focuses on model interpretability, allowing insights into the decision-making process.	Trade-off between interpretability and complexity; might be challenging to implement.
[154]	Combining Vision Transformers with Data Uncertainty Learning for Seizure Prediction	Combines vision transformers with uncertainty learning, providing robust predictions.	High computational requirements; complex model architecture.
[155]	Semi-Dilated CNNs for Seizure Prediction	Utilizes semi-dilated convolutions for efficient seizure prediction, balancing accuracy and computational efficiency.	Potential overfitting if not properly tuned; might require large datasets.
[156]	Automatic Feature Learning with Intracranial EEG	Concentrates on quantitative analysis and automated feature extraction to improve prediction accuracy.	Requires intracranial EEG data, which might not be available for all patients; complex model training.
[157]	Deep Transformer Model for Seizure Prediction	Uses transformers for capturing temporal	High complexity; computationally intensive and

		relationships in EEG data; improving prediction performance.	might require advanced hardware.
[158]	Deep Learning for Output Regularization of Seizure Prediction Classifier	Focuses on regularizing the output to improve prediction reliability.	Might reduce model flexibility; implementation can be challenging.
[159]	Two-Layer LSTM Model	Uses LSTM layers to capture temporal dependencies in EEG data, improving prediction accuracy.	Computationally expensive; may require significant memory and processing power.

Table 4: Analysis of existing solution for Seizure Prediction

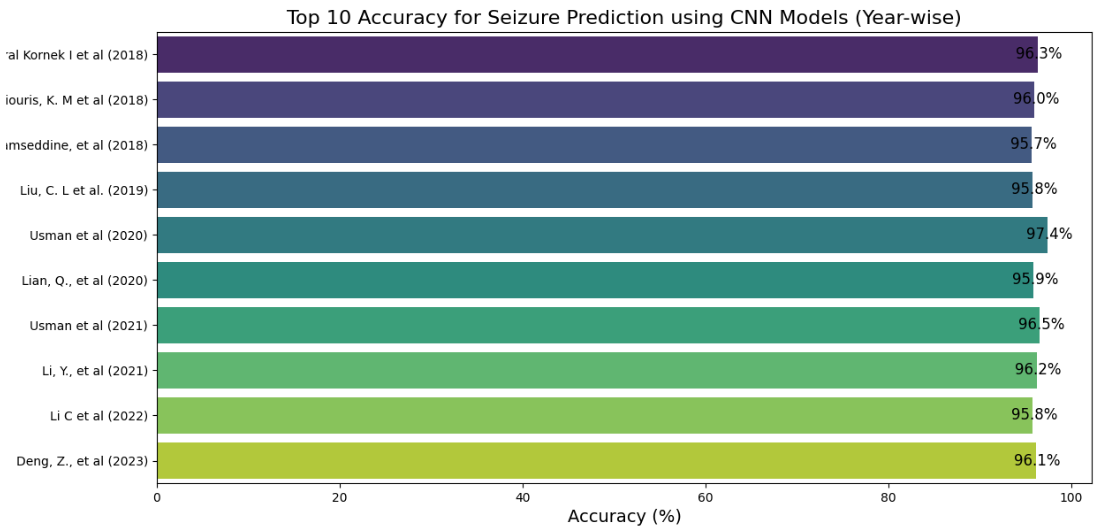

Figure 4: Accuracy plot for seizure prediction models

3.2.1. **Analysis of temporal and spectral features used.**

The temporal and spectral properties of seizures used in the models are recognized to be important and the increase in model performance caused by their use is evident. Bongiorni and Balbinot (2020) used RNNs to extract temporal relationship, which is perhaps the most critical feature of sequential data. The result of combining both temporal and spectral features was noted to improve on the performance as pointed out by Usman, Khalid and Aslam in their study of 2020. In their subsequent study (Usman, Khalid, and Bashir, 2021) they found that ensemble methods, where temporal and spectral features are combined, enhances robustness. Dissanayake et al. (2021) showed that the feature of this type allows achieving patient-independent results, and Jana & Mukherjee (2021) selecting EEG channels also pointed out that feature efficiency norms could be improved.

3.3 Comparative Analysis of Prediction Models

Several merits and challenges of each study and deep learning technique for seizure prediction are evidenced from the reviewed studies alongside the influence of the characteristics of seizure datasets on the prediction performances.

3.3.1. Strengths and Limitations:
RNNs used by Bongiorni et al (2020) is quite effective in modelling temporal dependence characteristic of EEG data, that is, data that is modelled sequentially. However, the RNNs in general, may face the vanishing gradient problem when working with long term dependency and may be computationally expensive.

As done by Usman et al (2020) the strength of this study is that it investigates diverse deep learning approaches considering temporal and spectral domains. However, it may limit the capability of dealing with high dimensionality and complexity of the EEG data should without the need of optimal methods. Usman et al (2021) later explains that the ensemble learning technique helps to strengthen the performance of multiple models. This approach can successfully overcome shortcomings of single models or predictors but at the same time may increase computational demand and requires a substantial amount of training data.

The Dissanayake et al. (2021) work that gives the emphasis to the patient-independent prediction may be the best target in this regard to achieve the goal of generalizing the model across patient populations. However, one downside of generalization is when the data set is not diverse or some participants' patterns are not sufficiently represented. Jana et al (2021) enhance the computational speed without deteriorating the prediction performances. This limitation might mean that channel optimisation could potentially exclude information that is useful to performance.

3.3.2. Impact of Dataset Characteristics:
The size, diversification, and the quality of data substantially affect the prediction ability of the system. Some papers published in 2021, such as Usman et al (2021) and Dissanayake et al. (2021), underlined that only with big and diversified data it is possible to train strong models. Often, when the used datasets are rather limited in size or do not represent the population sufficiently, it is found that models cannot effectively learn to deal with the variability of EEG signals and obtain over fitted or significantly inferior performance.

4. Bot/Chatgpt based Seizure prediction/detection

Kasthuri et al. (2024) introduce a chatbot designed for epilepsy patients, leveraging DL and Natural Language Processing (NLP) to provide personalized precautionary advice. This chatbot aims to enhance patient engagement and offer timely, tailored support. However, its effectiveness is contingent on the quality of input data and may face challenges in complex medical scenarios.

Tirumala et al. (2024) assess the performance of AI models ChatGPT and ChatSonic in addressing patient queries about epilepsy. This research assesses the precision and effectiveness of these models in providing reliable information. While these AI models can enhance patient education, their responses may sometimes be inaccurate or raise data privacy concerns.

Pandey et al. (2022) discuss "Ted the Therapist," a mental healthcare chatbot that employs NLP and Deep Learning to support mental health. This chatbot offers anonymity and accessibility, which can be beneficial for users hesitant to seek traditional therapy. Nevertheless, it may fall short in addressing severe mental health issues and cannot replace professional therapy.

Lupión et al. (2022) explore the use of effordable IoT devices integrated with a federated ML algorithm for seizure detection. This approach aims to make seizure monitoring more affordable and accessible, particularly in resource-limited settings. Nevertheless, it might face issues concerning device precision, data privacy, and the necessity for comprehensive validation

Landais et al. (2024) discuss the potential of AI large language models in improving epilepsy care. They highlight the promise of these models in providing valuable insights and support to patients and healthcare providers. Yet, the practical implementation and reliability of these models in real-world settings require further evaluation.

Yang et al. (2024) introduce EpiSemoGPT, a fine-tuned large language model designed for localizing epileptogenic zones based on seizure semiology. This model demonstrates performance comparable to that of expert epileptologists, offering a significant advancement in precision for epilepsy diagnosis. However, its effectiveness and integration into clinical practice need further exploration.

Boßelmann et al. (2023) question whether AI language models like ChatGPT are ready to enhance the care of individuals with epilepsy. This paper explores the possible advantages and drawbacks of these models in clinical settings, underscoring the need for ongoing research to ensure their reliability and effectiveness.

Recent research demonstrates the transformative potential of AI and NLP in epilepsy care. Kasthuri et al. (2024) developed a precaution chatbot using NLP and deep learning, enhancing patient support but facing challenges with input quality and complexity. Tirumala et al. (2024) assessed ChatGPT and ChatSonic's responses to epilepsy queries, revealing benefits in patient education but also issues with accuracy and privacy. Pandey et al. (2022) created "Ted the Therapist," a chatbot offering anonymous mental health support, yet it struggles with severe conditions. Lupión et al. (2022) presented a cost-effective seizure detection system using IoT devices and federated learning, promising affordability but raising concerns about accuracy and privacy. Landais et al. (2024) explored AI language models in epilepsy care, noting their potential and need for practical validation. Yang et al. (2024) presented EpiSemoGPT, a model for precise epileptogenic zone localization, showing performance on par with experts but requiring further integration studies. Boßelmann et al. (2023) evaluated AI language models like ChatGPT for epilepsy care, highlighting both promise and the need for more research to address practical issues. Overall, these studies highlight AI and NLP's potential to enhance epilepsy management while addressing challenges in accuracy and clinical application. Table 5 depicts the analysis of existing solution for seizure detection and prediction based on Bot/GPT models. Figure 5 visualizes the accuracy of bot/chatgpt models respectively reported by different authors, plotted against their publication years.

	nique Used	**s**	**rits**
[160]	NLP, Deep Learning Sequential Model	Provides personalized precautionary advice for epilepsy patients through a chatbot, enhancing accessibility and patient engagement.	May have limitations in handling complex medical scenarios; dependent on quality of input data.
[161]	Comparison of AI Models (ChatGPT, ChatSonic)	Evaluates the effectiveness of AI-generated responses, potentially improving patient education and support.	AI models may provide inaccurate or inappropriate responses; ethical concerns regarding patient data privacy.
[162]	NLP, Deep Learning	Provides mental healthcare support through a chatbot, offering accessibility and anonymity to users.	Limited in addressing severe mental health conditions; may not replace traditional therapy methods.
[163]	IoT, Federated Machine Learning	Low-cost solution for seizure detection, enhancing accessibility in resource-limited settings.	May face challenges in data privacy and security; effectiveness depends on device accuracy.

[164]	AI Large Language Models	Explores the potential of LLMs in improving epilepsy care, offering innovative solutions for patient management.	LLMs may provide inconsistent advice; ethical concerns regarding AI in healthcare.
[165]	Fine-tuned LLM (EpiSemoGPT)	Achieves performance comparable to specialists in localizing epileptogenic zones, aiding in clinical decision-making.	Still in preclinical stages; may require extensive validation before widespread use.
[166]	AI Language Models (ChatGPT)	Critically evaluates the readiness of AI models to support epilepsy care, identifying potential benefits and challenges.	Still in preclinical stages; may require extensive validation before widespread use.

Table 5: Analysis of existing solution based on Bot/GPT models

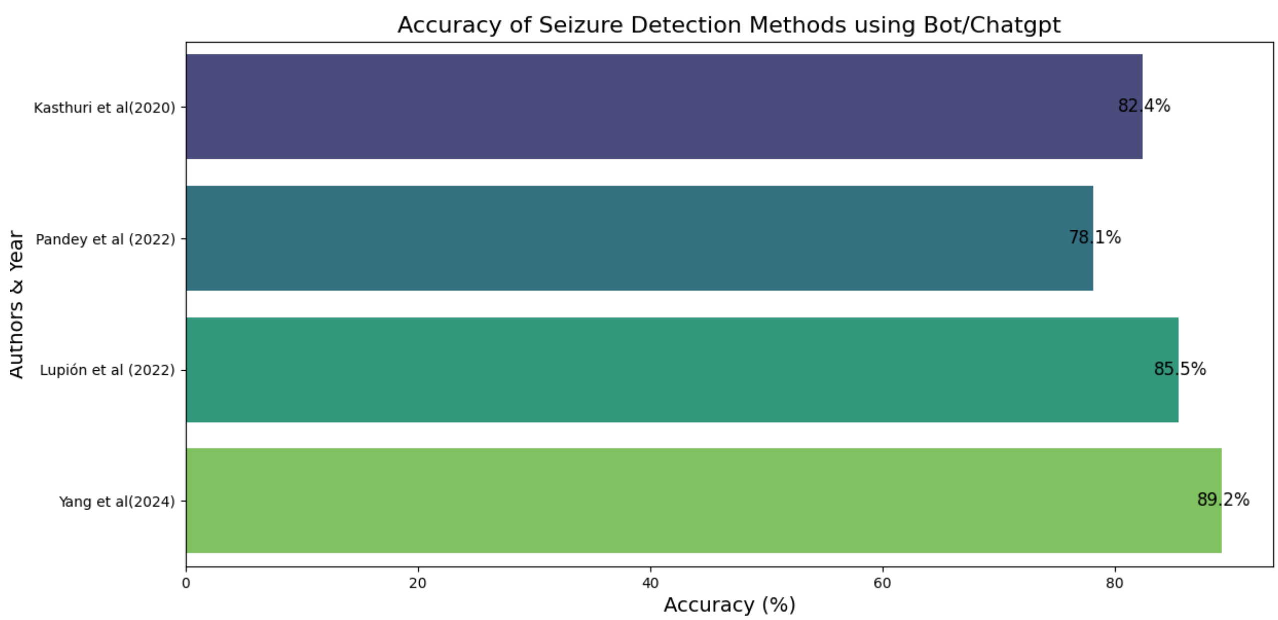

Figure 5: Accuracy plot for Bot/GPT models

5. Datasets and Preprocessing

5.1. Commonly Used Datasets

Free EEG datasets are the initial primary sources of information for epilepsy, which provides various and large data volumes that is required to create and fine-tune seizure prediction and detection algorithms. These datasets contain actual recorded EEG signals and usually come with separate periods of seizures and non-seizure activities and are duly marked for the beginning and ending of seizures by an expert. Key datasets include

CHB-MIT Scalp EEG Database: The data set comprises of EEG signals of 23 paediatrics patients suffering from intractable seizures [167]. It gives a large amount of information with extensive annotations, which makes it a reference source for many seizure prediction researches.

TUH EEG Corpus: This time, the dataset is characterized by its size and heterogeneity: it comprises EEG recordings of patients of different age and with various diseases. They are one of the biggest, more accessible datasets freely available to the general public it aids in the development of generalized models which can be effective on as many patients as possible [168].

EPILEPSIAE Database: It is characterized by the collection of high-quality and long-duration EEG recordings from several epilepsy centers [169]. This also contains annotations of recordings of seizure and non-seizure periods which are used in the development and assessment of the predictive models [170].

EEG Database from the University of Bonn: This dataset is utilized for binary classification tasks where the data contains seizure and other data. Derived from 5 fscal, each consisting of 100 single-channel EEG segments, this dataset is valuable for initial model development and comparative analysis [171].

NeuroVista Seizure Prediction Dataset: Long-term EEG, together with the implanted devices in the patient's body, gives the data for the dynamics of the seizures and had not been studied before as a dataset [172].

5.2. Data Preprocessing Techniques

EEG data usually undergoes certain procedures which are aimed at cleaning the data and preparing it for the further analysis. It should be noted that all the mentioned reference papers use several stages of signal preprocessing to enhance the quality of EEG signals for better models' performance. Some of the significant preprocessing techniques include:

5.2.1. Artifact Removal:

Independent Component Analysis (ICA): Used by many studies, including Usman et al. (2021), ICA separates EEG signals into separate components, assisting in eliminating artifacts like muscle contractions, eye blinks, and other non-neural noise [173].

Wavelet Transform: Jana and Mukherjee (2021) applied the wavelet transforms to think about the EEG series which makes it easy for the series to get rid of noises and artifacts [174].

5.2.2. Normalization and Standardization:

Z-score Normalization: Typically applied to standardize the data to have a mean of zero and a standard deviation of one, which helps in comparing different channels and recording sessions. Examples of this technique were described in such work as Dissanayake et al. (2021) [175].

Min-Max Scaling: The following procedure is also employed to adjust the EEG signals to the range of 0 to 1, for instance in the work of Bongiorni and Balbinot (2020).

5.2.3. Filtering:

Band-pass Filtering: In a similar manner, Usman et al. (2020) use the band-pass filters to maintain the desirable frequencies ranging between 0.5 Hz to 40 Hz and filter out other frequencies particularly those considered as noisy bands.

Notch Filtering: Employed to eliminate high frequency interferences from the power line typically at 50 or 60 Hz to prevent it from influencing the analysis. This technique was used in various studies but notably in the studies by Usman et al., 2021.

5.2.4. Segmentation:

Fixed-Length Segmentation: EEG data is normally analyzed in forms of segments or windows of a specific length and width so that they can be analyzed separately. This method is applied in most of the related studies like Jana and Mukherjee (2021) to help in the processing and analysis of data from continuous EEG.

Event-Based Segmentation: In some cases, segments are created based on some events, for instance, the beginning of a seizure as this will enable researchers to concentrate on the significant occurrences in the EEG recordings.

The abovementioned preprocessing methods are vital for improving the quality of EEG data, reducing noise and artifacts, as well as deriving relevant features for the proper identification and forecasting of seizures.

5.3 Challenges in Data Handling

Processing EEG data with the purpose of seizure detection and prediction requires overcoming a number of critical problems. Signal interferences originating from muscle movements and blinks or from external sources, may overlay signals of interest, further complicating the analysis. Furthermore, the nature of seizures is characterized as rare events while non-seizure epochs occur more frequently, which introduces additional challenges in the training. Due to the characteristics of EEG data with numerous channels, and high sampling rates, the computational costs for data processing are high. The cyclical nature of the data is a significant challenge, coupled with the fact that no two patients' EEG patterns can vary, and even the same patient may show unlike patterns at different times. Detection of seizure event is very significant for better diagnosis and treatment, yet the process of labeling these events might be quite subjective and very time consuming as well. Last but not the least, the legal and ethical issues concerning the protection of patient's privacy and confidentiality of EEG information in clinical practice is often difficult.

6. Evaluation Metrics and Performance Analysis

- **Accuracy**: Relates the percentage of accurately detected seizures and non-seizures against all detected events.
- **Sensitivity**: High sensitivity is very effective and important in reducing the number of seizures that are not detected.
- **Specificity**: High specificity enables the model not to give a lot of false signals.
- **Precision**: Estimates the percentage of the predicted seizures that are real, which is a measure of the accuracy of the model's seizures prediction.
- **F1 Score**: The cosy of recall that eliminates the false positive rate as well as the false negative rate that keeps the balance of measurement.
- **Area Under the ROC Curve (AUC-ROC)**: Evaluates the model's ability to distinguish between seizure and non-seizure events across various thresholds, with higher values indicating better performance.
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7. Discussion

7.1. Summary of Key Findings

7.1.1. Predictive Performance and Techniques:

Deep Learning Models: Recent studies have leveraged various DL architectures for epileptic seizure prediction, showing promising results. CNNs and LSTM networks are frequently used due to their ability to capture spatial and temporal patterns in EEG data. For instance, Usman et al. (2020) demonstrated effective seizure prediction using DL techniques, while Tsiouris et al. (2018) and Xu et al. (2020) showcased the strength of LSTM networks in capturing long-term dependencies.

Ensemble Methods: Ensemble approaches, such as those discussed by Usman et al. (2021), combine predictions from multiple models to enhance overall accuracy and robustness. These methods often improve performance but add complexity to model training and deployment.

Hybrid Models: Several studies, like those by Zhao et al. (2022) and Deng et al. (2023), explore hybrid models that integrate different types of neural networks, such as Vision Transformers with CNNs, to handle data uncertainty and improve prediction accuracy.

7.1.2. Patient Independence and Generalization:

Patient-Independent Models: Research has focused on creating models that do not rely on patient-specific data, aiming to make seizure prediction more generalizable across different individuals. For example, Dissanayake et al. (2020) and Kiral-Kornek et al. (2018) developed patient-independent models using deep learning to address this need.

Transfer Learning: Yu et al. (2022) and other studies utilize transfer learning to adapt models trained on one dataset to new datasets, enhancing model generalization and performance across diverse patient populations.

7.1.3. Optimization and Efficiency:

Model Optimization: Papers like those by Prathaban and Balasubramanian (2021) discuss optimizing CNN classifiers and employing dynamic learning frameworks to improve efficiency and accuracy in seizure prediction.

Energy Efficiency: Zhao et al. (2021) and Gao et al. (2023) focus on energy-efficient neural networks, addressing the computational costs associated with deep learning models and striving for practical deployment in real-world scenarios.

7.2 Implications for Research and Practice

In clinical use, richer deep learning structures can contribute to better identification and prognosis of seizures, which can facilitate better patient care and increase the patient's quality of life due to timely interventions. Next steps should include investigations into models for various patient types as well as new studies surrounding data input modalities and enhanced optimization methodologies for enhancing performance.

7.3 Strengths and Weaknesses of Current Approaches

Strengths:

1. Enhanced Accuracy and Performance:

DL models, particularly CNNs and LSTMs, have shown great accuracy in forecasting seizures by effectively capturing intricate patterns in EEG signals. This is evident from various studies, such as those by Usman et al. (2020) and Xu et al. (2020).

2. Generalizability and Adaptability:

Techniques like transfer learning and patient-independent models have improved the generalizability of seizure prediction systems. Models that do not rely on patient-specific data, as discussed by Dissanayake et al. (2020), provide broader applicability.

3. Hybrid Approaches:

Combining different neural network architectures, such as Vision Transformers and CNNs, has shown promise in addressing data uncertainty and enhancing prediction capabilities, as seen in Zhao et al. (2022) and Deng et al. (2023).

4. Optimization and Efficiency:

Efforts to optimize models for efficiency, such as the dynamic learning frameworks and energy-efficient networks discussed by Prathaban and Balasubramanian (2021) and Zhao et al. (2021), are crucial for practical deployment.

Weaknesses:

1. Computational Complexity:

Many DL models, especially those involving LSTMs and hybrid architectures, demand significant computational power and extended training periods. This can be a limitation for real-time applications and resource-constrained environments.

2. Model Complexity and Interpretability:

The complexity of ensemble and hybrid models often leads to challenges in interpretability and transparency, which can be a drawback for clinical adoption. Understanding and explaining model predictions remain a significant hurdle.

3. Generalization Across Diverse Populations:

While patient-independent models improve generalization, achieving consistent performance across a wide range of individuals with varying seizure types and EEG characteristics is still challenging.

4.Data Quality and Preprocessing:

The effectiveness of these models heavily depends on the quality of the input data and preprocessing techniques. Variability in EEG signal quality and preprocessing methods can impact model performance and reliability.

8. Conclusion

This review focuses on the aspects of epileptic seizure detection and prediction techniques using deep learning techniques such as the CNN, RNN, and LSTM. By integrating spatial & temporal features of EEG, improved hybrid models have enhanced the outcomes in terms of higher accuracy & reliability. As a result of data variability, noise and computation intensiveness these models appear to be ideal for real-time seizure monitoring.

More studies should be conducted in areas that promote individually fit models for patient's EEG fluctuations as well as designing usable and efficient preprocessing strategies to manage noise. Therefore, data augmentation techniques are required to handle the problem of data imbalance. Multimodal data fusion and high-level optimization approaches can be incorporated to improve upon the existing results. New forms of deep learning such as transformers and unsupervised learning may pave way for better analysis of EEG data. It is therefore crucial to emphasise the three-way cooperation between researchers, clinicians and engineers to transform such developments into the clinical scene for a better management of epilepsy.

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