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Epileptic Seizure Detection using an Advanced Deep Learning Model Applied to Epileptic EEG Signals: A Survey and Analysis

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ABSTRACT
The chronic neurological disorder known as epilepsy is characterized by frequent, unprovoked seizures that impacts millions of people globally. In order to effectively treatment and management epilepsy, early and accurate diagnosis is essential. Automated detection and categorization of epilepsy using Electroencephalogram (EEG) signals has been made possible by Deep Learning (DL) models. Several DL models, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid models, have been used for epilepsy detection. The research also evaluates and contrasts the models according to their structures, data processing methods, and performance indicators like specificity, sensitivity, and accuracy. Furthermore, the survey delves into the pros and cons of each method, highlighting the potential for future improvements in terms of model interpretability and real-time application.
Keywords: Epilepsy detection, Deep Learning, Electroencephalogram signals, Ictal, Classification

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I. INTRODUCTION

The neurological condition known as epilepsy is characterized by frequent, unprovoked seizures caused by irregular brain electrical activity [1]. It encompasses various types of seizures including generalized seizures, which affect both hemispheres and focal seizures, which originate in one area [2]. The first class premonitory symptoms include sudden, momentary symptoms recurring frequently, dreamy state, sense of strangeness, dyspnea, palpitation, epigastric pain, while the second class include irritability, lethargy and somnolence [3]. In order to improve quality of life by reducing the frequency and severity of seizures, early detection of epilepsy is essential.

Accurate detection also helps prevent potential complications associated with uncontrolled seizures, such as injury during a seizure, psychological distress and social stigma. Moreover, identifying specific seizure types enables healthcare providers to tailor treatment strategies effectively, ensuring that patients receive the most appropriate care for their condition. Electroencephalograms (EEGs) and brain imaging are among the diagnostic tests that are commonly used to confirm a diagnosis, along with a comprehensive medical history and neurological examinations [4]. Treatment options include antiepileptic medications, lifestyle modifications and in some cases, surgical interventions, tailored to the individual's needs and seizure type [5, 6, 7].

Although several systematic treatments for individuals with epilepsy have been conducted, the response to these therapies can vary significantly among patients leading to a subset classified as having drug-resistant epilepsy. This resistance highlights the importance of incorporating advanced technologies including Artificial Intelligence (AI) into the diagnostic and treatment processes. AI can assist in analysing vast amounts of clinical data to identify patterns that may predict seizure occurrences, enabling personalized treatment strategies and optimizing patient management [8].

Machine Learning (ML) significantly enhances the detection and management of epilepsy. By employing algorithms that learn from data, ML can identify complex patterns in patient information that may not be apparent through traditional analysis. This capability allows for the development of predictive models that can forecast seizure onset based on individual patient histories, environmental factors and physiological signals. A Support Vector

Machine (SVM) based model [9] was proposed which is optimized using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) using EEG signals. A fuzzy- based feature extraction method [10] was introduced for enhancing the detection of epilepsy. However, ML models require high-quality, diverse datasets to train these algorithms effectively.

To address these limitations, DL, a subset of ML has emerged as an effective tool for analysing complex data patterns in epilepsy care. DL models ability to automatically learn hierarchical features from raw data, without the need for manual feature extraction. Figure. 1 shows the process of classification task both in ML and DL.

There are many researches done to detect epilepsy using DL models such as CNN, RNN, Deep Belief Network (DBN) and AE. These models help pathologists in evaluating EEG signals faster and more accurately and thereby help in reducing time spent in diagnosis of the images and enhance reliability.

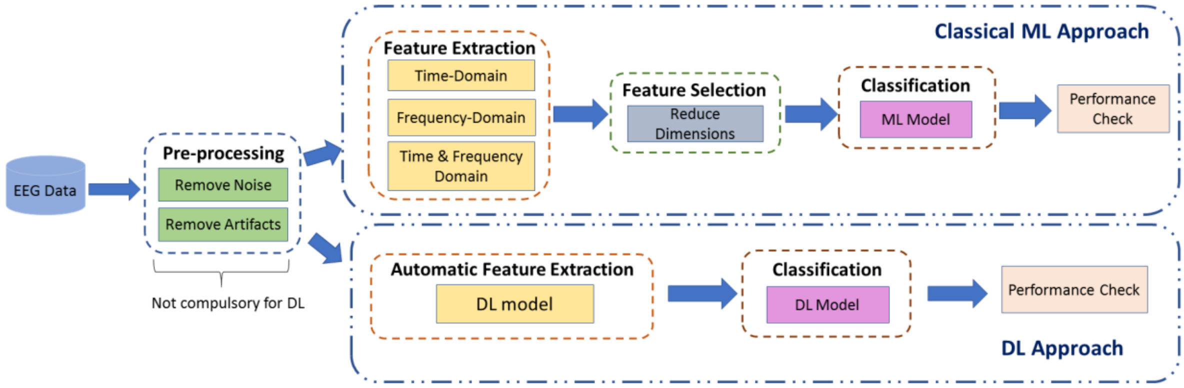

Figure. 1 Process of epilepsy prediction using EEG data and classification algorithm [8]

1.1 Epilepsy Prediction using Deep Learning Techniques

DL has significantly advanced the field of epilepsy detection particularly through its ability to automatically learn and identify complex patterns in EEG signals without the need for manual feature extraction. Acquiring data, pre-processing, extracting features, selecting them and finally classifying them are the usual steps in a deep learning process.

Data Acquisition: The initial step is the collection of raw EEG signals, typically sourced from clinical datasets or recorded in real-time using EEG devices. These signals are then digitized and stored in standard formats such as EDF [11] or HDF5 for further processing.

Pre-processing: Pre-processing is crucial for reducing noise and artifacts that may interfere with the learning process. In EEG analysis for epilepsy detection, this stage often involves filtering techniques to remove unwanted frequencies (like noise or muscle activity) and normalizing the signal. Some popular methods include:

- **Bandpass Filtering**: Utilized to concentrate on particular frequency ranges associated with seizure activity [12].
- **Artifact Removal**: The goal is to detect and remove any artifacts or noise using techniques such as Independent Component Analysis (ICA).

Feature Extraction: Feature extraction is critical for identifying and quantifying characteristics of the EEG signals that correlate with seizures. This process involves extracting quantitative measurements related to the signal's time and frequency characteristics. Commonly used features include:

- **Time-Domain Features:** Variance, Mean and standard deviation are examples of statistics that summarize the signal's overall behavior.
- **Frequency-Domain Features:** Derived from techniques like Fast Fourier Transform (FFT), which capture power spectral densities in specific frequency bands associated with seizure activity.
- **Wavelet Transform Features:** Utilizing Discrete Wavelet Transform (DWT) to capture time-frequency representations, enabling the identification of transient patterns in the EEG signal [13].

Feature Learning: In some cases, DL models are able to automatically learn pertinent features from raw EEG signals through hierarchical representations. The most commonly used DL architectures in epilepsy detection include:

- **CNN**: CNNs excel at extracting spatial features from 2D representations of EEG signals (e.g., spectrograms or topographic maps). They utilize convolutional layers to detect local patterns, enabling the model to learn features such as waveforms and spatial distributions related to seizure activity.

- **Recurrent Neural Network (RNN)**: RNNs, particularly LSTM networks capture temporal dependencies and are capable of learning patterns over time, making them effective for detecting the onset of seizures and classifying seizure types [14].
- **Auto-Encoder**: These unsupervised learning models can be used for feature extraction and dimensionality reduction. By training on normal EEG data, autoencoders learn to reconstruct the input data, allowing them to identify anomalies indicative of seizure activity when applied to unseen data.

Classification: After training, the DL model can classify incoming EEG signals in real-time. The classification process involves predicting whether a given segment of the EEG signal contains a seizure and identifying its type if applicable.

This manuscript aims to provide a comprehensive review of different frameworks for epilepsy prediction and classification using EEG signals. In addition, provide a comparative analysis that addresses the benefits and drawbacks of those frameworks in order to propose future scope. Here is how the rest of the sections are prepared: In Section II, different DL frameworks that use EEG signals to forecast and categorize epileptic seizures are covered. A comparison of those models is given in Section III. The complete survey is summarized in Section IV, along with recommendations for the future scope.

2. REVIW ON VARIOUS DEEP LEARNING MODELS FOR EPILEPTIC SEIZURE DETECTION

Ma et al. [15] presented a Mentor-Student architecture (MS4PS) for the purpose of detecting seizures in individual patients. Without transferring patient data or pre-trained model parameters, the MS4PS system's mentor-select-for-student knowledge transfer method could choose training data for a student model. Mentor and student models worked together to find high-quality samples that doctors could label as part of the architecture's active learning method. The mentor selected category-certain EEG segments, while the student chose category-uncertain ones. This approach enabled efficient training of seizure detectors for newly diagnosed patients.

An optimized neural network (ONASNet) model and Brain-Rhythmic Recurrence Biomarkers (BRRM) were used to develop a single-channel seizure detection system by Song et al. [16]. The nonlinear dynamics of EEG signals are reflected in BRRM's phase-space mapping of brain rhythm recurrence patterns. The architecture of ONASNet was developed using a modified neural network search strategy. To improve its performance on EEG data, transfer learning was applied. Combining BRRM with ONASNet enables the simultaneous extraction of features from numerous brain rhythms. When compared to complex feature engineering algorithms, the BRRM-ONASNet framework has a better chance of retaining crucial nonlinear features.

Hu et al. [17] proposed an EEG hybrid transformer for the purpose of epilepsy detection. The model made up of four components: rhythm embedding block for extracting multi-view spatio-temporal features, positional encoding for learning the dependencies between the features, self-attention block for further feature calculation and classifier block for binary classification. Also, a feature engineering method was introduced using Short-Time Fourier Transform (STFT). In order to further enhance the model's performance based on patient-specific information, two TL approaches were used: one that only fine-tuned inter-ictal samples, and another that fine-tuned both inter-ictal and pre-ictal samples.

Ilias et al. [18] suggested dual approaches for epilepsy detection using EEG signals. The first method utilized STFT to convert single-channel EEG signals into three-channel images, which were then processed through various pretrained CNN models, including AlexNet and EfficientNet for classification. The second method features a multimodal deep neural network that processes the EEG signals through two branches of CNNs to capture low and high-frequency features. These signals were also transformed into images via STFT and analyzed using the EfficientNet-B7 model. A gated multimodal unit is incorporated to prioritize relevant modalities, ultimately yielding competitive performance.

Jaishankar et al. [19] developed a DL-based approach for epilepsy seizure prediction using EEG data. The model aimed to analyse brain states and detect early signs of seizures, enabling timely intervention. For learning and enhancing discriminative features, the spatio-temporal features extracted from the raw EEG signals were fed into an Adaptive Grey Wolf Optimizer (AGWO). For classification, an adaptive Auto-Encoder with a Genetic Algorithm (aADGA) was employed.

Prasanna et al. [20] developed a Brain Epilepsy Seizure-Detection Network (BESD-Net) that detects seizures automatically using DL and recurrent learning techniques. The EEG signals were first pre-processed to eliminate background noise and extraneous information. As a next step, features associated with diseases were extracted from the pre-processed EEG data using a Customized CNN (CCNN). In order to maximize the extracted features' disease relevance, we used the ML-based Exhaustive Random Forest (ERF) feature selection. Selected features from the ERF were then used to train an RNN with BiLSTM to identify seizures.

Salafian et al. [21] developed a method for detecting epileptic seizures using Mutual Information-based CNN-Aided Learned factor graphs (MICAL). A one-dimensional CNN, factor graph inference, and a neural Mutual Information (MI) estimator were the three components of this method. During seizures, the algorithm was able to detect correlated electrical brain activity by using neural MI estimators to measure inter-channel statistical dependence. By using factor graphs informed by both components' soft estimates, the 1D CNN was able to improve detection accuracy by extracting features from raw EEG signals and capitalizing on temporal correlations. Results showed superior generalizability and performance when tested on the CHB-MIT dataset.

Shi & Liu [22] introduced a Vision Transformer Network with Broad Attention (B2-ViT Net), a two-tiered model for seizure detection. Its purpose is to automatically predict seizures by extracting generalized spatio-temporal long-range correlation features. It featured a robust generalized feature search capability, enabling comprehensive learning of generalized spatiotemporal correlations across extensive data spaces, thereby enhancing feature representation. Furthermore, the attention mechanism used in this model calculated interaction weights between channels, effectively determining the importance of every channel at given time.

Shoka et al. [23] developed an encrypted EEG classification system for epilepsy detection. To encrypt EEG spectrograms, the system used Arnold Transform and Chaotic Baker Map algorithms. Subsequently, CNN-based transfer learning models were used for classification. Before being fed into pretrained CNNs like ResNet50, AlexNet, and GoogleNet, EEG time series were encrypted and transformed into 2D spectrograms. The encrypted images were resized and classified into seizure and non-seizure states.

Wang et al. [24] developed a lightweight PCNN-BiLSTM architecture for epilepsy detection. To tackle challenges related to EEG dataset imbalance, small window segmentation was employed alongside the Synthetic Minority Oversampling Technique (SMOTE) to augment and balance the data. In order to maximize the number of samples, the initial EEG data was initially segmented using a sliding window algorithm. This algorithm transformed longer time series data into multiple shorter segments. Following this, the SMOTE algorithm was used to evenly distribute the sample sizes among the smaller classes by expanding them proportionally. Lastly, the PCNN-BiLSTM model was fed the processed data. which automatically extracted features and performed triple classification, distinguishing between normal, interictal, and ictal states.

de Sousa et al. [25] devised an automated framework for detecting Interictal Discharges (IEDs) in EEG recordings, addressing the limitations of manual analysis, which is laborious and mistake-prone manual analysis. The framework employs unsupervised deep learning models, specifically AE and Variational AE (VAE), to learn normal patterns in EEG data and reconstruct samples for epilepsy detection.

Grubov et al. [26] presented a dual-phase algorithm for seizure detection and classification. In the first phase, one-class SVM (OCSVM) was employed for identifying outliers i.e., data pre-processing in the EEG signal. It was inspired from the extreme value theory. The second phase employed CNN to improve prediction accuracy in the classification of epileptic seizures. The combined OCSVM-CNN model incorporated knowledge from different fields which generates approximately ten times fewer false positive predictions than the two initial approaches.

Hosseinzadeh et al. [27] introduced a hybrid technique that combines DL and Ensemble Learning (EL) to improve the accuracy of epileptic seizure detection utilizing EEG signals. The methodology encompassed dual pre-processing stages. Initially, each EEG recording underwent segmentation into smaller segments, facilitating the models' analysis of shorter time windows thereby enhancing the feasibility of the classification task. In the second step, the dataset underwent normalization through techniques including standardization and min-max normalization, resulting in the transformation of data points into a standard range between 0 and 1. Following the pre-processing phase, a Bidirectional LSTM (Bi-LSTM) network was utilized for the purpose of feature extraction. The ensemble model, which incorporates Bi-LSTM, SVM, XGBoost and Random Forest (RF), significantly improved the overall detection accuracy.

Liang et al. [28] proposed a Double Discrete Variational Auto-Encoder (D^2-VAE) network for unsupervised representation learning of generic patterns in EEG signals. This model achieved a local-global compressed representation of EEG signals through learnable quantization coding and distributional discretization based on histogram statistics, significantly enhancing the quality of feature learning for long signals. Additionally, a Vector Quantized Variational Auto-Encoder (VQ-VAE) was introduced to extract and characterize local patterns in EEG signals. This component employed vector quantization techniques to map continuous data to a discrete representation space, allowing for more effective capture of important features. Furthermore, local pattern discretization was achieved by assigning discrete indexes to signal segments using the trained VQ-VAE.

Data augmentation and hybrid DL models were presented by Palanisamy & Rengaraj [29] as a method of early detection of epileptic seizures induced by stress and anxiety. In order to create synthetic seizure signals from the BONN EEG dataset, Position Data Augmentation (PDA) and Random Data Augmentation (RDA) were executed. After that, two newly-proposed methods, Particle Swarm Optimization of LSTM (PSO-LSTM) and Fuzzy C-Means clustering (FCM) with PSO-LSTM (FCM-PSO-LSTM) were used to examine the enhanced signals. In order to optimize the feature extraction and classification hyperparameters of LSTM models, the FCM-PSO-LSTM approach combines FCM clustering with PSO. The PSO-LSTM method uses PSO for optimizing the LSTM directly.

Qi et al. [30] suggested a EEG data augmentation network (EDAN) using Semi-Supervised Seizure Prediction Model (SSSPM). The model aims to utilize the auxiliary information of limited labelled samples for guiding the learning and training towards massive unlabelled samples to predict seizures. Initially, the EEG signals were made consistent with their distribution based on the original EEG signals to prevent model overfitting. Then, the SSSPM model performed data augmentation, label guessing, interpolation and deep pairwise representation alignment based on the time–frequency representations of EEG signals. This method required labeling only a small amount of data to achieve satisfactory results in patient-specific seizure prediction.

Sadiq et al. [31] developed a novel approach for epilepsy detection based on a Hellinger distance classifier combined with PSO. The first phase involved using PSO to select relevant features from EEG signals, optimizing the feature set for better accuracy. In the second phase, the Hellinger distance metric was applied to classify the selected features. The process iteratively refined the feature selection to enhance model performance.

A real-time method for detecting epilepsy seizures was developed by Shen et al. [32] using Google-Net CNN and STFT. The analysis was performed in real-time using a sliding window technique. Each 2-second EEG episode took 0.02 seconds to process, and on average, it took 9.85 seconds to detect the beginning of a seizure. After applying a 6th-order Butterworth band-pass filter, six EEG channels were subjected to time-frequency analysis using STFT. The extracted time-frequency spectra were used as input for a 29 layer Google-Net CNN model, which was trained using the leave-one-out method. The CNN model achieved high validation accuracy in distinguishing seizure states from seizure-free ones.

Tang et al. [33] introduces an automatic epilepsy detection. It involved combining path signature with Bi-LSTM networks that were enhanced by an attention mechanism. While the Bi-LSTM delves further into the signals' temporal patterns, the path signature algorithm analyzes the dynamic interdependencies between the EEG channels. The attention mechanism improves model focus by assigning weights to essential features. The model was tested on both public and private EEG datasets, demonstrating superior performance and robustness in cross-patient evaluations.

Zhu et al. [34] suggested a fusion method that integrated Squeeze and Excitation Network (SE-Net), Temporal Convolutional Network (TCN) and Bidirectional Gated Recurrent Unit (BiGRU) models, termed SE-TCN-BiGRU for automatic seizure detection. Initially, the filtered multi-channel EEG signals were fed into SE-Net to select the most relevant channels. The selected signals were then passed to TCN for temporal-spatial feature extraction. The temporal information from these features was further refined by BiGRU, enhancing the model's classification capability. Finally, the output from BiGRU was sent to a Fully Connected (FC) layer and post-processed to generate the final classification results.

Pan et al. [35] introduced a dual-method framework based on Empirical Mode Decomposition (EMD) for epilepsy detection. The first approach, referred to as EMD-EEG, decomposed EEG signals using EMD, which were then arranged into a matrix and input into a CNN for detection and classification. The second method, EMD-PSD, followed a similar process but employed the Discrete Fourier Transform (DFT). After decomposing the signals via EMD, DFT was applied to each component and the Power Spectral Density (PSD) was computed using amplitude values. Similar to the first approach, the resulting PSD was then fed into the CNN for epilepsy detection.

II. COMPARATIVE ANALYSIS

Table 1 provides a comparison of the aforementioned models derived for epileptic seizure prediction using EEG signals, and this section presents a comparative study according to the advantages and disadvantages of these models.

Table 1. Comparison of different epileptic seizure prediction models

Ref No.	Techniques	Advantages	Disadvantages	Dataset	Performance Metrics
[15]	MS4PS	The model uses an active learning approach that combines mentor and student models that reduces labeling burden on doctors	The primary goal of the model fails to improve seizure detection performance but rather to confirm that MS4PS is feasible.	CHB-MIT dataset	Average F1= 0.69, Average Seizure = 24
[16]	BRRM, ONASNet	The multi-channel model analyses color images that eliminates need for complex 3D CNNs to process sub-bands, thereby simplifying the computational process.	Transferring ONASNet from image classification to epileptic pattern detection, potentially limiting its effectiveness.	Bonn EEG dataset	Accuracy = 99.67%, Precision = 99.68%, Latency = 66 ms, Model Size = 47.16 MB
[17]	STFT, CNN, Hybrid Transformer, TL	The use of parallel attention heads allows the model to focus on patterns across different rhythms, enhancing the interpretability of the detection process	Two-fold reduction in wavelet transform decomposition can cause minor boundary errors between rhythm frequency bands, leading to the loss of useful rhythm information	CHB-MIT sEEG dataset	Sensitivity = 91.7%
[18]	STFT, CNN	The model has the ability to selectively filter and suppress irrelevant information from the two different input modalities. thereby enhances the model's focus on the most critical features,	The dataset demonstrates an imbalance, which may impact the performance of the model	Bonn EEG dataset	Precision = 98.03%, Recall = 97.33%, F1-score = 97.65%, Accuracy = 97.20%
[19]	AGWO, aADGA	The model demonstrates reduced computational complexity during the validation process, improving efficiency.	The sensitivity is lower than the state-of-the-art approaches	CHB-MIT sEEG dataset	Accuracy = 97.49%, F-score = 98.2%, Sensitivity = 95.90%, Precision = 96.90%, Specificity = 96.90%, MCC = 0.5232, Execution time = 82.72 min
[20]	BESD-Net, ERF, RNN, BiLSTM	The model circumvents the issue of overfitting.	The lack of real-time implementation may limit the practical applicability of the model in clinical settings.	CHB-MIT sEEG dataset	Precision = 98.36%, Sensitivity = 97.54%, F1-score = 97.91%, Accuracy = 98%, Specificity = 95.08%
[21]	MICAL, CNN	MI can detect higher-order statistical	The neural MI estimator increases the algorithm's	CHB-MIT dataset	Accuracy = 95.39%, Precision = 56.

		dependencies between recordings.	computational complexity.		09%, Recall = 78.75%, F1-score = 65.4%, AUC-ROC = 95.6%, AUC-PR = 74%
[22]	B2-ViT Net	The model employs an attention mechanism to clarify spatial interactions and temporal dependencies in seizure prediction, enhancing interpretability.	If the training and test sets have different distributions, the model will not be able to handle it.	CHB-MIT dataset	For 40s, window, AUC = 86%, S_n = 79.5 %
[23]	CNN, Arnold, Chaotic	This model is one way to enhance performance while protecting EEG signals over an unsecured network.	The model demonstrates considerable computational complexity, which may hinder its efficiency and scalability in practical applications	CHB-MIT dataset	With Arnold, Accuracy = 86.11%, Precision = 84.21%, Recall= 88.89%
[24]	PCNN-BiLSTM, SMOTE, Small window	The low resource requirements, it is ideal for clinical medical devices and wearables, offering it a significant edge over recent research advancements.	Utilizing data augmentation techniques does not improve the generated data's quality to the level of real-world data.	CHB-MIT dataset	Accuracy = 98.52%, Precision =98.44%, Sensitivity = 97.99%, Specificity = 99.35%
[25]	AE, VAE	The abnormality score demonstrated a clear difference between controls and patients with epilepsy	Long-term EEG data labeling poses significant challenges due to the extensive time required for accurate labeling	Twente dataset	Sensitivity = 81.9% Specificity = 91.7%
[26]	OCSVM, CNN	The two-stage algorithm has ten times fewer false positives	The algorithms used in this approach are not optimized.	Pirogov dataset	Precision = 57.33%, Recall = 84.31%, F1-score = 68.25%
[27]	BiLSTM, SVM, XGBoost, RF	Integrating the model with clinical systems like EHRs and decision support systems will facilitate its adoption in medical practice.	Segmenting recordings into 1-second chunks may lose temporal context, affecting the detection of longer-term EEG patterns.	Bonn EEG dataset	Accuracy = 98.58%, Precision = 97.37%
[28]	D^2-VAE, VQ-VAE	The model focuses on the characteristics of epileptic seizures, aligning more closely with the transmission characteristics of EEG signals for different types of information.	The model involves complex operations that can lead to increased computational costs, making it less suitable for real-time applications	Bonn, Bern-Barcelona, New Delhi EEG datasets	Accuracy = 99.52%

[29]	FCM-PSO-LSTM, Fuzzy logic,	LSTM is effective for sequence prediction due to learning long-term dependencies property	The time complexity remains a significant concern	Bonn, CHB-MIT, SIENA EEG datasets	Accuracy = 98%
[30]	SSSPM, EDAN	SSL requires labeling only a small amount of data to achieve satisfactory results in patient-specific seizure prediction.	The model trained on EEG data from one patient will perform poorly when tested on data from another patient.	CHB-MIT dataset	Sensitivity = 87.65%,
[31]	PSO	The effectiveness of the Hellinger distance classifier combined with PSO results in a highly accurate and reliable diagnostic tool	The computational complexity of the model reduces the performance	Bonn EEG dataset	Accuracy = 86.25%, Recall = 84.5%, Precision = 100%, F1-score = 91.6%, MCC = 0.616
[32]	STFT, GoogleNet CNN	The computational efficiency of the model allows for minimal delay in real-time seizure detection.	It is unable to identify seizures marked by amplitude depression	CHB-MIT dataset	Accuracy = 97.74%, Sensitivity = 98.90%, FP rate = 1.94%, Delay = 9.85s
[33]	PS, BiLSTM, AM	Signal rhythm decomposition and post-processing operations are unnecessary for the model.	Due to fewer seizure segments and more noise-affected scalp EEG recordings, some patients have sensitivity levels below 80%.	TUH CHB-MIT, dataset	Sensitivity = 91.05%, Specificity = 98.63%, Accuracy = 94.84%.
[34]	SE-TCN-BiGRU	The model significantly reduces the false detection rate	Significant differences in ictal EEG patterns among patients may cause performance decline in cross-patient scenarios.	CHB-MIT dataset	Accuracy = 96.28%, Specificity = 96.05%, Sensitivity = 94.6%, F1-score = 91.16%, MCC = 88.92%, Time = 5.33s
[35]	EMD, CNN, PSD	The models are not overfitting	The model exhibits high computational complexity	Unknown dataset	Accuracy = 100%, Sensitivity = 100%, Specificity = 100%

III. RESULT AND DISCUSSION

The performance evaluation of the existing DL techniques presented in Table 1 illustrates the overall prediction and classification of seizure detection.

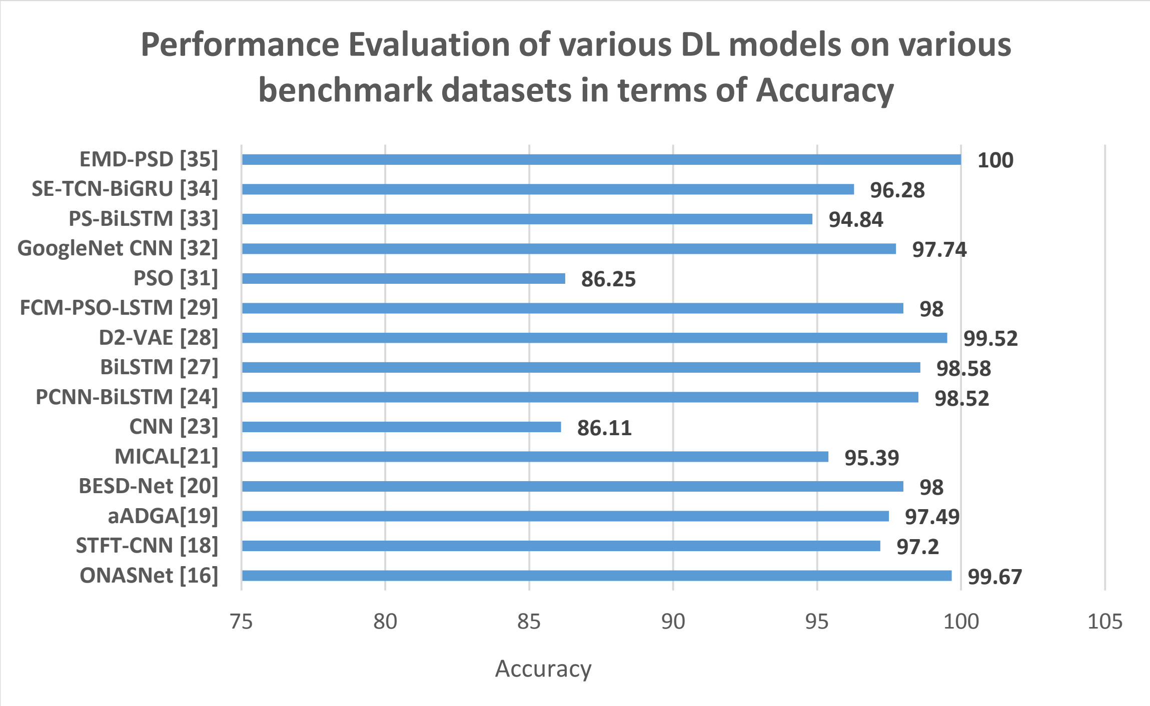

Figure. 2 Comparison of accuracy of different DL models on various datasets

Using a variety of datasets, Figure 2 compares the accuracy of seizure detection models. It is evident that the model from [35] outperformed the others, demonstrating superior effectiveness in predicting epileptic seizures. In contrast, the models from [23] and [31] performed the worst, likely due to their computational complexity, which negatively impacted their overall performance.

IV. CONCLUSION

Epilepsy is a severe neurological disorder that requires timely and accurate detection to prevent recurrent seizures and improve patient outcomes. Early diagnosis is critical to managing the condition effectively. Recently, DL techniques have been extensively utilized for epilepsy detection by analysing EEG signals. In this survey, various DL approaches are evaluated for their effectiveness in predicting epilepsy, outlining their advantages, limitations and performance metrics. The challenges identified in existing models guide researchers to develop more efficient frameworks for epilepsy diagnosis and management, supporting clinical decision-making and accurate outcome prediction. Future research will focus on advanced DL models capable of processing diverse EEG datasets and identifying subtle epilepsy patterns to enhance treatment strategies.

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