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# Performance Analysis of Deep-Learning and Explainable AI Techniques for Detecting and Predicting Epileptic Seizures

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**Abstract**— Epilepsy is one of the most common neurological diseases globally. Notably, people in low to middle-income nations could not get proper epilepsy treatment due to the cost and availability of medical infrastructure. The risk of sudden unpredicted death in Epilepsy is considerably high. Medical statistics reveal that people with Epilepsy die more prematurely than those without the disease. Early and accurately diagnosing diseases in the medical field is challenging due to the complex disease patterns and the need for time-sensitive medical responses to the patients. Even though numerous machine learning and advanced deep learning techniques have been employed for the seizure stages classification and prediction, understanding the causes behind the decision is difficult, termed a black box problem. Hence, doctors and patients are confronted with the black box decision-making to initiate the appropriate treatment and understand the disease patterns respectively. Owing to the scarcity of epileptic Electroencephalography (EEG) data, training the deep learning model with diversified epilepsy knowledge is still critical. Explainable Artificial intelligence has become a potential solution to provide the explanation and result interpretation of the learning models. By applying the explainable AI, there is a higher possibility of examining the features that influence the decision-making that either the patient recorded from epileptic or non-epileptic EEG signals. This paper reviews the various deep learning and Explainable AI techniques used for detecting and predicting epileptic seizures using EEG data. It provides a comparative analysis of the different techniques based on their performance.

**Keywords**-Electroencephalography(EEG); Epileptic Seizures; Deep-Learning; Explainable AI.

## I. INTRODUCTION

Epilepsy, a persistent neurological condition marked by recurring and unforeseeable seizures, affects millions of people worldwide, imposing substantial physical, emotional, and economic burdens on individuals and society [1]. These seizures arise from atypical electrical activity within the brain and can manifest in a range of forms, from subtle sensory alterations to convulsive episodes. In the medical field, epilepsy disease diagnosis heavily relies on examining Electroencephalography (EEG) signals, which are critical for understanding the dynamic, pathological complex patterns occurring in the brain during seizures [2]. Many risks associated with epileptic seizures related to sudden unexpected death are a major concern [3]. Manually determining the location of seizures from the EEG signals with the aid of the users' experience is difficult and time-consuming. The automated detection system has become the potential solution for assisting doctors and patients in the perspective of early diagnosis [4] [5]. Epileptic seizure detection and prediction significantly impact timely and provide accurate insights regarding the epileptic behaviors on the patients' EEG samples for the epilepsy diagnosis. To overcome the limitations in the existing EEG signal processing methods in Epilepsy, recent epilepsy diagnostic approaches have focused on employing Machine Learning (ML) and Deep Learning (DL) models. Deep learning-assisted EEG signal analysis plays a substantial role in various research application directions, including Epilepsy, depression, schizophrenia, movement disorder, memory, and sleep [6][7]. Due to the large-scale data and deep learning, black-box models have successfully tackled the constraints in real-world and mission-critical applications [8].

In recent years, interpretable and explainable decision-making mechanisms in AI-based systems have steadily gained prominence as they foster transparency and instill confidence among diverse end-users and medical experts. The embrace of deep models largely hinges on the comprehensibility of underlying processes, intensified with an escalating sophistication of machine learning approaches and models [9]. The relentless advancement of machine learning models has led to heightened complexity, rendering it increasingly challenging to comprehend their decision-making processes. The opacity of "black box" models poses significant obstacles when applied in the critical domain of medical practice, where sensitivity is paramount, especially in epilepsy detection [10]. To overcome this constraint, the burgeoning field of Explainable Artificial Intelligence (XAI) has emerged, which is one of the pioneering methodologies to elucidate and interpret deep learning algorithms. Integrating XAI-based epileptic seizure detection enforces reduced medical risks and reliable and scalable healthcare solutions [11]. Embracing the power of XAI methods empowers the creation of interpretable ML models for disease comorbidity prediction, bestowing heightened transparency upon machine learning practices. By employing these interpretable ML models, healthcare professionals forecast disease patterns and gain insights into the underlying reasons driving increased risk predictions.

In consequence, such emerging transparency is pivotal for fostering the seamless adoption of ML in the medical field. By applying machine learning along with explainable AI techniques to analyze the cognitive aspects of patients' health behaviors, there emerges a transformative opportunity to provide tailored and exceptionally efficient healthcare to individuals managing multiple health conditions. This approach augments treatment precision and ultimately amplifies health outcomes, achieving a higher level of personalized care [12]. Although the black-box nature of DL remains a lingering conundrum in epilepsy detection and prediction research, the currently available automated decision-making models are inadequate for an accurate and early diagnosis of Epilepsy due to the lack of comprehension in medical reporting.

## II. RELATED WORK

This section reviews several epilepsy detection and prediction research with the predominant focus on the hybrid EEG feature extraction, Deep Learning, and explainable AI model.

### *A. Spatial and Temporal Features based Epileptic Seizure Detection and Prediction*

The robust deep Convolutional Neural Network (CNN) model [13] detects epileptic seizures using an open-access EEG epilepsy dataset. A comprehensive evaluation encompasses cross-patient and within-patient EEG recordings, showcasing the system's exceptional performance compared to machine learning and deep learning techniques regarding accuracy and sensitivity. To overcome the limitations of small public EEG seizure datasets, implement a cropped training strategy that optimizes training efficiency on limited data. Furthermore, novel visualization techniques facilitate the creation of accurate brain maps, allowing in-depth study and localization of EEG seizures. The spatial distribution of CNN in different frequency bands is effectively revealed through visualization, offering valuable insights for enhanced understanding and diagnosis. According to [14], the research proposes a novel intelligent EEG identification system for automated seizure detection using a channel-embedding spectral-temporal squeeze-and-excitation network (CEstSENet). The group convolution squeezes and excitation (gcSE) unit, a version of the SE block, is presented to investigate spectral-temporal embedding unified. To avoid overfitting concerns caused by the inadequacy of seizure events, a hybrid training goal containing a maximum mean discrepancy-based information maximizing loss is adopted. In [15], an intelligent detection approach for epileptic EEGs unified a multi-level spectral-temporal feature learning framework proposed to detect seizure onsets automatically. In the temporal domain, discriminative features are recovered using a combination of Principal Component Analysis, Common Spatial Pattern (PCA-CSP), and Multivariate Multiscale Sample Entropy (MMSE). Finally, for epileptic EEG identification, a set of Support Vector Machine (SVM) Classifiers are employed in conjunction with a decision fusion module for the intelligent recognition of epileptic EEGs. In [16], an innovative spatio-temporal-spectral hierarchical graph convolutional network with an active preictal interval learning scheme (STS-HGCN-AL) framework was introduced to revolutionize seizure prediction. Two novel graph convolutions were proposed to enhance the prediction of preictal EEG transitions: the residual graph convolution (resGCN) and rhythm attention (rhythmAtt) units.

Furthermore, a semi-supervised active learning strategy was studied to deduce the ideal pre-ictal state specific to each patient interval that significantly bolsters the robustness of the seizure predictor furthering its potential for clinical applicability and real-world impact. By skilfully combining inputs from different domains and employing channel attention mechanisms, the framework adaptively learns representations of EEG signals to substantially improve the utilization of temporal, spectral, and spatial information for superior predictive capabilities. According to [17], a Spatio-Temporal Channel Attention Residual Network (STCARN) was proposed and enhanced with the extended series Mean Amplitude Spectrum (MAS) of EEG signals. The extended series MAS feature representation smartly integrates temporal significance from multiple MAS sources and spatial significance from EEG channels, proficiently capturing brain activities. The STCARN incorporates a powerful fusion of residual convolutional structure, channel attention mechanism, and recurrent network structure, enabling robust spatiotemporal information extraction from extended series MASs. In [18], employed the

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Multivariate Variational Mode Decomposition (MVMD) approach and developed the dispersion index (DI) as a novel brain network weight calculation method to extract features from single-channel temporal brain networks and multi-channel spatial brain networks for seizure detection. Identifying temporal and spatial networks is promising, and DI may be used to determine correlation. The research work [19] proposes an end-to-end epilepsy seizure prediction method based on Multi-Layer Perceptron (MLPs). The method comprises two crucial blocks such as denoising-weighted and MLPs blocks. A learnable denoising matrix effectively mitigates undesired artifacts. A redundancy reduction is achieved through a dedicated reduction layer. An average pooling layer and a Fully Connected (FC) layer distinguish between pre-ictal and inter-ictal brain states for prediction. The method exhibits promising results in EEG-based epilepsy seizure prediction, validated through experiments on the CHB-MIT and Kaggle databases.

*B. Detecting and predicting Epileptic Seizures using deep-leaning*

The various deep-learning algorithms are used to classify the seizure states in the literature.

*1) Artificial Neural Network (ANN)*

The research work [20] introduced an automated technique for detecting epileptic seizures in which they employed an Artificial Neural Network (ANN) in conjunction with the Wavelet Transform (WT) for signal decomposition. [21] introduced an innovative approach for distinguishing between epileptic patients and individuals without the condition, employing a combination of Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN). Initially, noisy data were filtered out, followed by subjecting the data to DWT for feature extraction. The utilization of DWT was employed to capture crucial attributes from the EEG data. The data enriched with features was then directed through a Feed-forward Artificial Neural Network (FFANN) for subsequent analysis and classification.

*2) Convolutional Neural Network (CNN)*

A 13-layer Deep Convolutional Neural Network (DCNN) was introduced [22] with the primary objective of efficient seizure detection. Notably, this method does not necessitate feature selection and extraction steps. However, a noteworthy limitation of this approach is its demand for substantial datasets due to its reliance on deep learning techniques. One of the researchers [23] introduced a method for detecting epileptic seizures using a Convolutional Neural Network (CNN), wherein manual feature extraction was circumvented. In the study outlined by [24], a novel method was introduced for seizure detection using an attention-based CNN-BiRNN architecture. The construction of this model follows a 3-step procedure: the first step involves a multi-scale convolutional model, succeeded by an attention-based model in the second step, and the third step is implemented through a multi-stream recurrent bidirectional algorithm. Notably, this model demonstrates the ability to handle EEG signals with missing or varying channels. The researchers [25] introduced a combined approach for seizure detection, utilizing a fusion of spectrogram and 1D CNN techniques to achieve enhanced and efficient outcomes. However, it's important to note that this model's accuracy is compromised. In the realm of ES onset and offset detection, the research work [26] presented a Convolutional Neural Network-based model that takes EEG signals as input. This approach employs a factorized filter to capture distinct Spatio-temporal patterns. Notably, this model effectively identifies both the onset and offset phases of seizures. According to [27], an innovative deep learning framework, channel attention dual-input convolutional neural network (CADCNN), was introduced, tailored for EEG-based seizure prediction tasks. CADCNN elegantly leverages prior knowledge to enhance the model's capability to capture spectral information, a unique feature rarely explored in previous works. In the study referenced as [28], training of the model was orchestrated by uniting multi-scale convolution with a spatial-temporal feature extraction module. The model showcased its capacity for generalization by assimilating features across various convolutional scales. In a bid to enhance its applicability to un-encountered patient data, a leave-one-out cross-validation (LOOCV) approach was employed as outlined in [28, 29].

*3) Recurrent Neural Network (RNN)*

The researchers [30] introduced a method for epilepsy detection utilizing a deep Recurrent Neural Network (DRNN). The authors also introduced a mapping technique to enhance signal processing efficiency. This mapping technique facilitates the acquisition of Spatio-temporal features from raw EEG signals. In [31] a combined model for seizure prediction involving Bidirectional Long Short-Term Memory (Bi-LSTM) and Deep Convolutional Auto encoder (DCAE) was introduced. The authors conducted a comparison of Bi-LSTM and DCAE against four other approaches, with the conclusion that Bi-LSTM and DCAE demonstrated superior performance. The Bi-LSTM component focuses on extracting temporal information from raw EEG data, while the DCAE component learns spatial data. By leveraging transfer learning, the study explored semi-supervised learning strategies based on DCAE, leading to reduced training times. The authors affirmed the model's suitability for real-time applications. However, a significant concern arises due to the necessity of accumulating the entire data sequence before initiating predictions, posing challenges for real-time implementation.

### *C. Explainable AI-based Epileptic Seizure Detection and Prediction*

In research work [32], a sequential segment of EEG data was used and comprised information on ten successive EEG sub-windows. By utilizing the data as a series of 10 sub-windows, an ideal deep sequence learning architecture generates the label with the aid of attention on the CNN, BiLSTM, and fully connected neural networks. The relevance is calculated by applying the model weights in an activation value of the receptive fields at a certain layer. The learned weight models aided in understanding the significance of selected attributes and demonstrated that they represent cross-patient data and open the way to future studies for seizure analysis. In [33], inpatient and outpatient administrative health claims data were used for epilepsy patients. To predict the time-dependent risk of prevalent comorbidities in epilepsy patients, the work in [33] presented a specialized multimodal neural network architecture (Deep personalized LOngitudinal convolutional RIsk model—DeepLORI). DeepLORI-based forecasts can be interpreted on an individual patient basis. A game theoretic method is proposed to uncover key characteristics in DeepLORI models, showing that model predictions are explainable considering current illness information. DeepLORI discovered the homogeneous disease progression based on the comorbidity risk profile, thereby providing options for designing more personalized therapeutics in the future.

The focus of [34] is to propose a digitalized epileptic seizure detection method that will be more accurate, efficient, and time-consuming. It primarily examines and analyses the Decision Tree Algorithm, Random Forest Algorithm, K-Nearest Neighbour Classifier, Gradient Boosting Classifier, Gaussian Nave Bayes, and other methods. The clinical procedure of deciphering EEG data and identifying electrical activity for the expert is neither straightforward nor efficient. Furthermore, it will also focus on the future development of minimizing difficult situations, with the outcomes interpreted using XAI. Many viable strategies for epilepsy diagnosis using EEG data and machine learning have been suggested in this research [35], and it provided an explainable AI technique for epilepsy diagnosis that uses Shapley Explanations (SHAP) - a unified framework built from game theory to explain the output aspects of the model. In epilepsy diagnosis, the explanations provided by Shapley values are effective for feature explanation for a model's output. The feature explanation technique demystifies black-box algorithms that may be used to comprehend model predictions even when incorrect. In [36], a model for categorizing epilepsy subgroups in magnetic resonance imaging (MRI) is suggested and employs a Quantum Machine Learning (QML) approach to assess classification performance, which is more efficient than typical deep learning classification. To predict the epilepsy class, a Quantum Convolutional Neural Network (QCCN) was used. QML can handle big, biased datasets while taking up less time and space. A Layer-wise Relevance Propagation (LRP) was utilized to describe the prediction process to make the suggested model more trustworthy and dependable. In addition, it also demonstrates how LRP can refute the quantum machine learning model for feature assessment in MRI data.

The groundbreaking study [37] presents stereo electroencephalography (SEEG-Net), a highly sensitive and practical model for detecting SEEG pathological activity in real-world clinical DRE scenarios. SEEG-Net incorporates an innovative Multiscale CNN (MSCNN) that significantly expands the model's receptive field in local and global characteristics. To further enhance performance, a novel Focal Domain Generalization loss (FDG-loss) function was introduced, which effectively prioritizes target samples and promotes learning of domain consistency features. Additionally, it outlines a comprehensive SEEG processing and database construction flow, meticulously designed to align seamlessly with real-world clinical scenarios. The research work [38] introduces XAI4EEG, an innovative application-aware approach that combines deep learning with explainability for detecting seizures in EEG time series. The proposed method utilizes SHAP values from two SHAP explainers in the EEG data spectral, spatial, and temporal dimensions. It incorporates a hybrid seizure detection system comprising EEG data preparation and two DL models (1D-CNN and 3D-CNN). Furthermore, the evaluation scenario is designed to replicate clinical diagnosis conditions, considering time pressure, and adopting a human-grounded evaluation principle for rigorous assessment.

## III. METHODOLOGY

The generalized process for interpretable epileptic seizure detection and prediction is described as follows:

Step 1: Data Pre-processing and Feature Extraction

Input: Raw EEG data recorded during epileptic events and non-seizure periods.

1. Apply noise reduction and data cleaning to remove artifacts and noise from the EEG signals.
2. Perform spectral analysis on EEG data to extract spectral features using methods like Fast Fourier Transform (FFT) or Wavelet Transform.
3. Apply the Discrete Wavelet Transform (DWT) to capture spatiotemporal features by decomposing EEG signals into different scales and sub-bands.

Step 2: Temporal Feature Learning

1. Construct temporal sequences from the EEG data by creating time windows or segments.
2. Feed the temporal sequences into a recurrent neural network (RNN) architecture.

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3. Train the RNN to capture temporal dependencies and patterns in the EEG data, learning the temporal features associated with epileptic behaviors.

Step 3: Spatial Relationship Learning
1. Utilize the spatial layout of EEG channels to capture the relationships between different brain regions.
2. Employ techniques like Convolutional Neural Networks (CNNs) to analyze the spatial relationships among EEG channels, thereby extracting spatial features.

Step 4: Multi-Level Spectral Analysis
1. Combine the spatiotemporal features learned from the temporal and spatial models.
2. Apply multi-level spectral analysis to the combined features, dissecting them into different sub-bands representing different frequencies.

Step 5: Transfer Learning for Diversified Patterns
1. Use transfer learning techniques to Utilize pre-trained knowledge from related tasks or datasets.
2. Fine-tune the model using the combined features to adapt to diversified epileptic EEG patterns.

Step 6: Epilepsy Detection and Prediction
1. Train the model on the combined spatiotemporal and spectral features to perform epilepsy detection and prediction.
2. Utilize binary classification for seizure detection, and temporal modeling for predicting the timing of seizures.

Step 7: Explainability Mechanisms
1. Generate visualizations or explanations that showcase the spatiotemporal and spectral characteristics the model relies on for its predictions.

Step 8: Model Evaluation and Validation
1. Evaluate the model's performance using metrics like accuracy, precision, recall or sensitivity and specificity,
2. Validate the model's predictions and explanations with real-world clinical data and insights from medical experts.

The process of interpretable epileptic seizure detection and prediction is described in Figure 1.

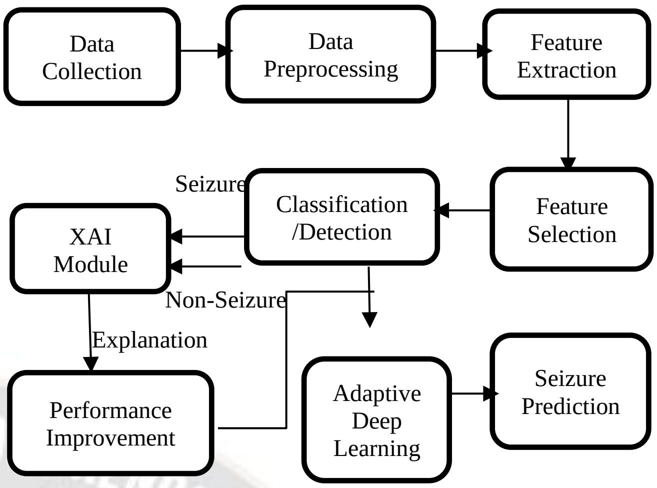


Figure 1. Process Outline for Epileptic Seizure Detection and Prediction Using Explainable AI

The process of detecting and predicting epileptic seizures is divided into six phases and described in detail as follows.

*A. Data Collection*

The commonly used datasets for the research on detection and prediction of epileptic seizures are as follows:

*1) CHB-MIT Scalp EEG Database:* The CHB-MIT dataset, accessible via PhysioNet, is a multichannel scalp EEG (sEEG) collection obtained from the collaboration between Children’s Hospital Boston and the Massachusetts Institute of Technology (CHB-MIT) [39]. The dataset encompasses 977 hours of sEEG recordings utilizing 23 bipolar channels, though certain recordings include 24 or 26 channels. These channels adhere to the International 10–20 electrode positioning system and possess a sampling frequency of 256 Hz. The dataset was gathered from 23 pediatric patients, encompassing 5 males aged between 3 and 22 years, 17 females aged between 1.5 and 19 years, and one anonymous patient. Each patient's data comprises between 9 and 42 EEG recordings, stored in EDF file format, with a duration of 1 hour per recording. However, certain recordings extend up to 4 hours.

*2) Bonn EEG Seizure Dataset:* The Bonn dataset, curated by the University of Bonn [40], comprises five distinct sets of EEG recordings. The first two sets (A and B) originate from individuals without medical conditions, while the remaining three sets (C, D, and E) are derived from patients preparing for brain surgery. Sets A and B capture EEG data from healthy subjects with their eyes open (set A) and closed (set B), each showcasing different states. Sets C and D, on the other hand, encompass EEG recordings during the interictal state from distinct brain regions: the hippocampal region (set C) and an epileptogenic zone (set D). Meanwhile, set E solely contains EEG recordings from the ictal state.

Each set is composed of 100 single-channel EEG recordings, each lasting 23.6 seconds. These recordings are stored in a

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textual file format. Prior to analysis, all segments undergo preprocessing via a band-pass filter featuring a frequency range of 0.53 Hz to 40 Hz. As mentioned in [40], the initial recording setup utilized 128 channels; however, comprehensive information regarding patients and channels is notably absent from the dataset.

### *B. Data Pre-processing*

Preprocessing is a crucial step in data analysis including the analysis of EEG data for tasks like epilepsy detection and prediction. The goal of preprocessing is to prepare the raw EEG data for further analysis by cleaning, enhancing, and transforming it. Following are the general methods used for Data Pre-processing.

- Noise Removal: Apply filters to remove noise and artifacts from the EEG signal. A common filter is the notch filter to eliminate power line interference.
- Baseline Correction: Adjust the EEG data to have a consistent baseline, often by subtracting the mean of the signal.
- Segmentation: Divide the continuous EEG signal into shorter segments (epochs) for analysis. This helps to focus on specific time periods.
- Artifact Rejection: Detect and remove segments with excessive artifacts, such as muscle activity or electrode artifacts, using techniques like thresholding or independent component analysis (ICA).
- Resampling: If needed, resample the data to a consistent frequency to ensure uniformity in analysis.

In the creation of automated systems using Deep Learning models and EEG signals, the preprocessing consists of a three-step process: eliminating noise, normalizing the data, and preparing the signal for utilization in Deep Learning network applications, as described in [41],[42].

### *C. Feature Extraction*

Feature extraction is the major process. The following are the different commonly used methods for EEG characterization. It includes the time domain, frequency domain, and time-frequency domain. The time-domain features describe various statistical and mathematical characteristics of the EEG signal within a specific time interval. The frequency-domain features are extracted from the transformed representation of EEG signals in the frequency domain. These features provide insights into the frequency content and distribution of energy within different frequency bands. In the context of epilepsy detection and prediction using EEG data, frequency domain features are crucial for capturing specific frequency patterns associated with seizures and other brain activities. Time-frequency domain features capture the dynamic changes in EEG signals by examining their characteristics simultaneously in both the time and frequency domains. These features are crucial for capturing transient events and frequency patterns that can be indicative of seizures or other brain activities. The relevant features of the time domain, frequency domain, and time-frequency domain are described in TABL I.

TABLE I. FEATURE EXTRACTION METHODS

| Type | Feature Extraction Methods | |
|---|---|---|
| | ***Relevant features*** | ***Description*** |
| Time-Domain | Mean | The average value of EEG amplitudes within a given time window. |
| | Variance | A measure of the dispersion or spread of EEG values around the mean. |
| | Skewness | Measures the asymmetry of the EEG distribution around the mean |
| | Kurtosis | Measures the "tailedness" or “peakedness” of the EEG distribution. |
| | Zero Crossing Rate | Counts the number of times the EEG signal crosses the zero-amplitude line within the time window. |
| | Hjorth Parameters | • Activity: A measure of signal magnitude variability within the time interval.<br>• Mobility: Quantifies how quickly the signal changes in amplitude.<br>• Complexity: Reflects the waveform complexity, involving both the rate of change and the number of zero crossings |
| | Mean Absolute Value (MAV) | Calculates the average absolute value of EEG amplitudes within the time window. It's a measure of signal intensity. |
| | Line Length | Measure of signal complexity within a given time interval. It quantifies the cumulative length of the waveform's path |
| | Energy | Represents the magnitude of signal activity within a time window |
| | Power | Represents the average energy per unit of time |
| | Shannon Entropy | Quantifies the uncertainty or disorder in the signal distribution. It measures the average amount of information needed to describe the signal's amplitude distribution. |
| | Sample Entropy | Measure of signal complexity and irregularity. It calculates the likelihood of similar patterns occurring within a signal, considering different pattern lengths. |
| Frequency-Domain | Power Spectral Density (PSD) | Quantifies the distribution of signal power across different frequency components. |
| | Relative Power in Frequency Bands | Calculate the ratio of power within specific frequency bands to the total power. |
| | Spectral Entropy | Measures the complexity of the distribution of power in different frequency bands. |

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| | | |
|---|---|---|
| | Peak Frequency and Power | Identify the frequency at which the highest power occurs (peak frequency) and the corresponding power value. |
| | Mean Frequency | The weighted average frequency of the power spectrum |
| Time-Frequency Domain | Power Spectral Density (PSD) | Quantifies the distribution of signal power across different frequency components |
| | Relative Power in Frequency Bands | Calculate the ratio of power within specific frequency bands to the total power |
| | Spectral Entropy | Measures the complexity of the distribution of power in different frequency bands. |
| | Peak Frequency and Power | Identify the frequency at which the highest power occurs (peak frequency) and the corresponding power value |
| | Mean Frequency | The weighted average frequency of the power spectrum. |

### *D. Feature Selection*

After the feature extraction, selecting the key features is crucial for distinguishing EEG signals into epileptic or non-epileptic seizure states. The feature selection methods for epilepsy detection and prediction can be categorized into three main categories based on their approach and underlying principles.

*1) Filter Methods:* Filter methods assess the importance of features without any reliance on a specific machine learning model. They rely on statistical measures to rank and select features based on their characteristics and their relationship with the target variable. Some of the methods that fall under this category include:

a) *Mutual Information-Based Feature Selection:* Mutual information measures the amount of information shared between a feature and the target variable. Features with higher mutual information are likely to be more relevant. This approach can be used to rank and select the top-k features [43].

b) *Correlation-Based Feature Selection (CFS):* CFS assesses the correlation between features and the target variable while considering the correlation between features themselves [44]. It helps identify features that are most predictive of epileptic activity.

*2) Wrapper Methods:* Wrapper methods select features by employing a specific machine learning model as part of the evaluation process. They rely on the model's performance (e.g., accuracy) as a criterion for feature selection. These methods are computationally more intensive as they involve repeatedly training and evaluating models with different feature subsets [45]. Some of the methods that fall under this category include:

a) *Recursive Feature Elimination (RFE) with Cross-Validation:* RFE is a wrapper method that iteratively removes the least important features from the dataset while training and evaluating the model's performance using cross-validation. This method is suitable for selecting features that contribute the most to the model's performance [46].

b) *Genetic Algorithm-Based Feature Selection:* Genetic algorithms optimize feature subsets by mimicking the process of natural selection. This approach can help find an optimal combination of features that leads to improved model performance [47].

c) *Sequential Feature Selection (SFS) with Machine Learning Models:* SFS involves building models iteratively by adding one feature at a time based on their contribution to the model's performance. Machine learning algorithms like Support Vector Machines or Random Forests can be used to evaluate feature subsets.

*3) Embedded Methods*: Embedded methods incorporate feature selection within the process of training a machine learning model. They often utilize regularization techniques to penalize less important features and automatically select relevant ones [45]. Some of the methods mentioned earlier that fall under this category include:

a) *L1 Regularization (Lasso):* L1 regularization can be applied to linear models for epilepsy detection and prediction. It shrinks some coefficients to zero, effectively performing feature selection and retaining only the most relevant features.

b) *Random Forest Feature Importance:* Random Forests are well-suited for feature selection due to their ability to assess the significance of each feature in the model. The feature importance scores provided by the Random Forest algorithm can guide in selecting the most relevant features [48].

### *E. Classification*

Deep learning methods have displayed encouraging outcomes in the identification and forecasting of seizures using EEG data, owing to their capacity to autonomously acquire intricate patterns and representations from unprocessed data. Following are some popular deep-learning classification techniques used for these tasks:

*1) Convolutional Neural Networks (CNNs):*
Convolutional Neural Networks (CNNs) are widely embraced as a prominent deep learning classifier for the prediction and diagnosis of medical conditions [49]. Both 1D-CNN and 2D-CNN demonstrate the ability to diagnose epileptic seizures.

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*a) 2D CNNs:* EEG data can be treated as 2D images, with time as one dimension and EEG channels as the other. 2D CNNs can learn spatial patterns and relationships between channels. The research studies [50], and [51] used 2D CNN for epileptic seizure diagnosis.

*b) 1D CNNs:* These networks are designed specifically for sequential data like EEG signals. They can capture local patterns and are computationally efficient. The researchers [52], and [53] used 1D CNN for epileptic seizure diagnosis.

*2) Recurrent Neural Networks (RNNs):*

Recurrent Neural Networks (RNNs) are a neural network category specifically crafted for handling sequential data. They incorporate loops within the network architecture to enable information persistence over time, making them suitable for tasks such as natural language processing, speech recognition, and time series analysis. RNNs have internal memory states that allow them to capture dependencies in sequential data, making them valuable for modeling temporal relationships. Within learning techniques based on Recurrent Neural Networks (RNNs), both the Long Short-Term Memory (LSTM) model and the Gated Recurrent Unit (GRU) are frequently used components.

*a) Long Short-Term Memory (LSTM) Networks:* LSTMs are well-suited for modeling sequential data with long-range dependencies. They can capture temporal patterns in EEG signals.

*b) Gated Recurrent Unit (GRU) Networks:* Like LSTMs, GRUs are used for sequence modeling and can be more computationally efficient.

Numerous literature sources employ RNN and LSTM networks for the purpose of seizure detection [54],[55].

*3) Hybrid Models:*

Combining CNNs and RNNs in a hybrid architecture allows the model to capture both spatial and temporal patterns in EEG data. For example, a CNN can be used for feature extraction, followed by an LSTM for sequence modeling. Some studies available in the literature based on hybrid models are [56], and [57].

*4) Transformer-Based Models:*

Transformer models, originally designed for natural language processing, have shown promise in handling sequential data. EEG data can be treated as a time series, and transformer models can capture temporal dependencies and long-range interactions. A recent research study using a Transformer-Based model is [58].

*5) Attention Mechanisms:*

Incorporating attention mechanisms, such as self-attention, into neural networks can allow the model to focus on specific segments of the EEG data that are most relevant for seizure detection or prediction [59].

*6) Deep Learning Autoencoders:*

Autoencoders can be used for unsupervised feature learning and dimensionality reduction [60]. Variational Autoencoders (VAEs) and Denoising Auto encoders (DAEs) have been applied to EEG data for feature extraction.

*7) Transfer Learning:*

Pre-trained deep learning models, especially those trained on large datasets, can be fine-tuned for seizure detection or prediction tasks using transfer learning techniques [61].

### *F. Explainability Mechanism*

Traditional ML and DL models exhibit a higher classification accuracy when implemented for disease detection tasks. However, these techniques lack explainability. Implementing Explainable AI can address this problem and provide better performance in terms of accuracy, transparency, explainability, and interpretability. Hence, Explainable AI is widely used in various medical applications. Explaining the decisions made by machine learning models for the detection and prediction of epileptic seizures is essential for gaining trust in these systems and for facilitating their clinical adoption. Explainability methods aim to provide insights into why a model made a particular prediction or decision. The following are some common explainability methods that can be used for seizure detection and prediction.

*1) Feature Importance Analysis:*

For traditional machine learning models, feature importance scores can be analyzed to understand which EEG signal features contributed the most to the model's decision. Techniques like Permutation Feature Importance or Gini Importance can be used.

*2) LIME (Local Interpretable Model-Agnostic Explanations):*

LIME is a model-agnostic method that creates locally faithful explanations by perturbing the input data and observing how the model's prediction changes. It fits a simple interpretable model (e.g., linear regression) to the perturbed data to explain the model's behavior for a specific instance.

*3) SHAP (SHapley Additive exPlanations):*

SHAP values provide a unified measure of feature importance by considering the contributions of each feature to every possible prediction. They can be used to explain predictions at both the global and local levels. Research studies available in the literature for epileptic seizure diagnosis are [35][37]

*4) Grad-CAM (Gradient-weighted Class Activation Mapping):*

Grad-CAM is commonly used for image-based models but can be adapted to CNN-based EEG models. It highlights regions of the input (EEG signals) that are most relevant to the model's decision, providing a visual explanation [37].

*5) Attention Mechanisms:*

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If the model uses attention mechanisms, the attention weights can be visualized to understand which parts of the EEG signals the model focuses on when making a prediction.

*6) Partial Dependence Plots (PDPs) and Individual Conditional Expectation (ICE) Plots:*

PDPs show how a feature's value affects the model's prediction while keeping other features constant. ICE plots provide similar insights but for individual instances. These plots are useful for understanding feature interactions.

*7) Rule-Based Explanations:*

Generate interpretable rules or decision trees that mimic the behavior of the complex model for specific instances. These rules can be easily understood by clinicians.

## IV. PERFORMANCE METRICS

In the confusion matrix for the task of epilepsy detection and prediction, the True Positive (TP) denotes the number of correctly detected seizure samples as the positive samples, True Negative (TN) refers the number of correctly rejected samples in the seizure class, False Positive (FP) denotes the number of false alarms, and False Negative (FN) refers the number of missed samples in the seizure category.

To evaluate the performance of epilepsy detection and prediction, the widely used popular metrics are discussed as follows.

*1) Accuracy:* Accuracy is a straightforward metric that measures the proportion of correctly classified instances (seizures and non-seizures) out of the total number of instances in the dataset.

It provides a general overview of the model's performance but can be misleading when the dataset is imbalanced.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

*2) Precision:* Precision measures the proportion of correctly predicted positives out of all instances predicted as positive by the model. It quantifies the model's ability to minimize false alarms or false positives, which is vital in scenarios where misclassifying non-seizure events such as seizures can lead to unnecessary interventions, anxiety for patients, or resource wastage.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

*3) Recall or Sensitivity:* Sensitivity measures the ability of the model to correctly detect positive patterns when they occur. It indicates the proportion of true positives out of all actual seizures.

$$\text{Recall or Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

*4) Specificity:* Specificity measures the ability of the model to correctly identify negative events. It indicates the proportion of true negatives out of all actual negative patterns from the dataset.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

## V. PERFORMANCE ANALYSIS

This section presents the performance analysis of various deep-learning techniques and Explainable AI techniques used for Epileptic Seizure detection and prediction. TABLE II presents the performance analysis of deep-learning techniques for Epileptic Seizure detection and prediction.

TABLE II. PERFORMANCE ANALYSIS OF DEEP-LEARNING TECHNIQUES FOR DETECTION AND PREDICTION OF EPILEPTIC SEIZURES

| ***Publication*** | ***Research Problem and Application*** | ***Proposed Approach*** | ***Dataset*** | ***Performance*** | | |
|---|---|---|---|---|---|---|
| | | | | ***Accuracy %*** | ***Sensitivity %*** | ***Specificity %*** |
| 2015 [21] | Identifying epileptic patient | FFANN and DWT | Bonn EEG Seizure Dataset | 93.23 | 93.87 | 90.07 |
| 2016 [30] | Epileptic Seizure Detection | Deep RNN | CHB-MIT Scalp EEG Database | Not Mentioned | 100 | (False Detection 0.08) 92 |
| 2017 [22] | Epileptic Seizure Detection | Deep-CNN | Bonn EEG Seizure Dataset | 88.67 | 95 | 90 |
| 2018 [23] | Epileptic Seizure Detection | Convolutional Neural Network (CNN) | CHB-MIT Scalp EEG Database, Freiburg | 95.6 | 94.2 | 96.9 |
| 2019 [24] | Epileptic Seizure Detection | CNN-BiRNN | CHB-MIT Scalp EEG Database | Not Mentioned | 93 | 94 |
| 2019 [31] | Early Prediction of Epileptic Seizure | Bidirectional Long Short-Term Memory (Bi-LSTM) and Deep | CHB-MIT Scalp EEG Database | 99.6 | 99.72 | 99.60 |

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| *Publication* | *Research Problem and Application* | *Proposed Approach* | *Dataset* | *Performance* | | |
|---|---|---|---|---|---|---|
| | | | | *Accuracy %* | *Sensitivity %* | *Specificity %* |
| | | Convolutional Autoencoder (DCAE) | | | | |
| 2020 [25] | A novel approach for Seizure detection | 1D CNN and Spectrogram | CHB-MIT Scalp EEG Database | 77.57 | 79.54 | 75.59 |
| 2020 [26] | Onset and offset detection of Epileptic Seizure | CNN | CHB-MIT Scalp EEG Database | Over 90% | Not Mentioned | Not Mentioned |
| 2021 [27] | Prediction of Epileptic Seizure | Channel attention dual-input convolutional neural network (CADCNN) | CHB-MIT Scalp EEG Database | Not Mentioned | 97.1 | 95.6 |
| 2022 [28] | EEG Seizure detection | CNN | CHB-MIT Scalp EEG Database, TUSZ, Bonn | 96.17 | 56.83 | 96.97 |
| 2023 [62] | Prediction of Epileptic Seizure | 3D-2D Hybrid CNN | CHB-MIT Scalp EEG Database | 98.43 | 98.58 | 98.86 |

Figure 2,3 and 4 show the performance analysis of different Deep Learning techniques for epileptic seizure detection and prediction in terms of Accuracy, Sensitivity and Specificity respectively.

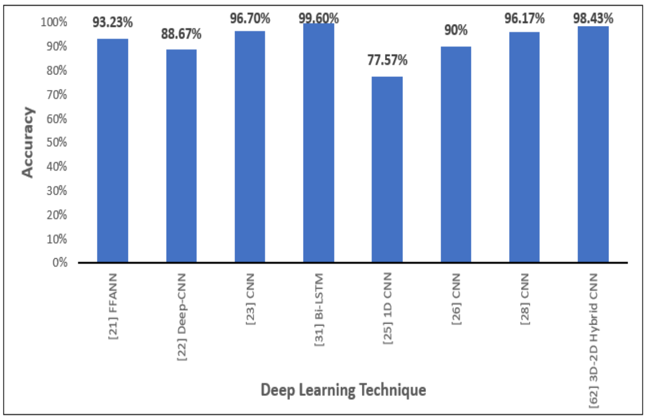


Figure 2. Performance Analysis of Deep Learning Techniques for Epileptic Seizure Detection and Prediction in terms of Accuracy

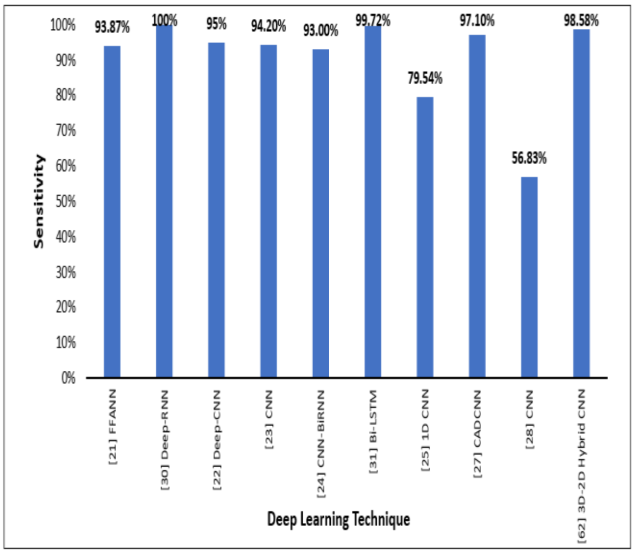


Figure 3. Performance Analysis of Deep Learning Techniques for Epileptic Seizure Detection and Prediction in terms of Sensitivity

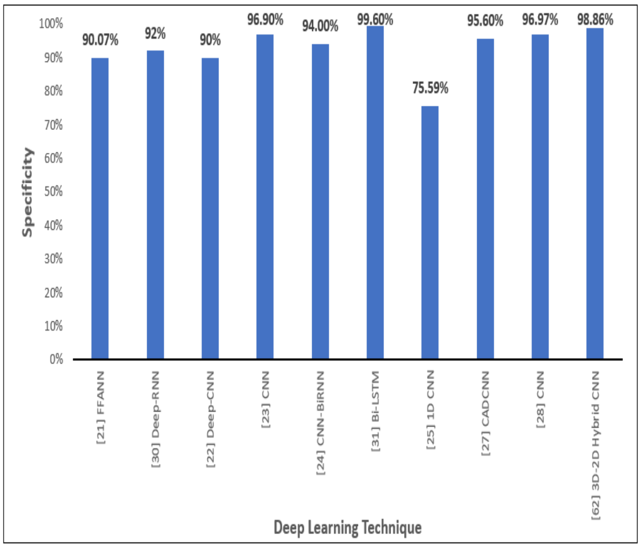


Figure 4. Performance Analysis of Deep Learning Techniques for Epileptic Seizure Detection and Prediction in terms of Specificity

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From the analysis of different deep-learning techniques considered in the study, it was observed that H. Daoud et al. [31] used a Bi-LSTM approach and achieved an accuracy of 99.60%. The highest Sensitivity score of 100% is achieved by L. Vidyaratne et al. [30] using the Deep-RNN approach. The highest Specificity of 98.86% is achieved by Qi N. et al. [62] using 3D-2D Hybrid CNN.

TABLE III presents the performance analysis of different deep-learning approaches that incorporated Explainable AI techniques for Epileptic Seizure detection and prediction.

TABLE III. PERFORMANCEERFORMANCE ANALYSIS OF DEEP-LEARNING APPROACHES THAT INCORPORATED EXPLAINABLE AI TECHNIQUES FOR EPILEPTIC SEIZURE DETECTION AND PREDICTION

| ***Publication*** | ***Research Problem and Application*** | ***Proposed Approach*** | ***Dataset*** | ***Performance*** | ***Explainable AI Technique Used*** |
|---|---|---|---|---|---|
| 2019 [13] | Detection of Epileptic Seizure | convolutional neural networks (CNN) | EEG epilepsy dataset collected at the Boston Children's Hospital. | Overall Accuracy of 99.65% | Visualization Explainability, feature relevance at different frequency bands |
| 2020 [32] | Interpretable EEG seizure detection | convolutional neural network (CNN), (BiLstm) | MIT-BIH data subset | Accuracy of 97.03%, Sensitivity of 97.65%, Specificity of 96.58%, precision of 95.40% | Posthoc, input-based explainability driver |
| 2021 [33] | Predicting Epilepsy Comorbidities | Deep personalized LOngitudinal convolutional RIsk Model (DeepLORI) | independent data from around 97,000 patients | 71% for overweight, obesity to 77% for stroke and ischemic attacks | SHAP and DeepLORI-based Explainable model, reliable prediction |
| 2022 [35] | Epileptic seizure detection | Different ML algorithms | Bonn EEG Seizure Dataset | - | SHAP |
| 2022 [37] | Detection of drug resistance epilepsy | Convolutional neural networks (CNN) | public benchmark multicentre SEEG dataset and a private clinical SEEG dataset | Accuracy of 93.85%, TPR of 87.61%, FPR of 6.24%, TNR of 95.09% | Interpretation of model learning process using Grad-CAM++ |
| 2023 [38] | Detection of Epileptic Seizure | Hybrid Deep Learning | A total of 79 neonates were admitted to the Neonatal Intensive Care Unit (NICU) at Helsinki University Hospital between 2010 and 2014 | Accuracy of 98.89% | Two SHAP explainers |

## VI. RESEARCH GAPS AND FINDINGS

- The lack of investigation of the state transitions among various epileptic EEG states misleads the accurate diagnosis of the epileptic seizure due to the collaborative pattern changes.
- Discriminating only binary epilepsy classes is inadequate among the variation of epilepsy behaviors in the multiple epilepsy states for the accurate localization of the epileptic seizure.
- Early detection and prediction of epileptic seizures from the generalized time-series EEG signal analysis are challenging.
- Automated epilepsy diagnosis model often encounters reliability constraints due to the lack of non-interactive human feedback during the model training.
- The lack of explanation regarding the deep EEG patterns to patients and doctors enforces the delayed diagnosis and risk-level analysis.
- Modeling the explanation using a single modality provides inadequate knowledge to understand epilepsy behaviors for an early and accurate diagnosis.

## VII. CONCLUSION

This research paper explored into the comprehensive analysis of the performance of deep-learning and Explainable AI techniques in the acute domain of detecting and predicting epileptic seizures. The paper reviews the recent Deep-Learning and Explainable AI techniques and suggests that Deep Recurrent Neural Networks (Deep-RNN) and Hybrid models exhibit superior performance for epileptic seizure detection and prediction. Explainable AI techniques such as SHAP and Grad-CAM are widely used and integrated with Deep-Learning methods. Our findings underscore the immense potential of deep learning as a powerful tool for improving the accuracy of seizure detection and prediction systems. Furthermore, the integration of Explainable AI methodologies adds an extra layer of transparency, addressing the crucial need for clinical understanding and decision support. It is important to acknowledge that the field is continually evolving, and several research avenues remain unexplored. Further investigations are warranted to enhance model robustness, optimize real-time performance, and address ethical and privacy concerns.

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