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Article

ARTIFICIAL INTELLIGENCE FOR EPILEPTIC SEIZURE DETECTION AND PREDICTION: A REVIEW OF EEG-BASED MACHINE LEARNING AND DEEP LEARNING METHOD

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Abstract: Epilepsy is an ongoing neurological condition that results in seizures that are unpredictable and reoccurring due to an imbalance of overexcited neurons in the brain. Despite the fact that electrodes are attached to the scalp, electroencephalography (EEG) is still the most commonly used modality for seizure detection and prediction due to its high temporal resolution. The performance of automated seizure detection and prediction systems have been greatly enhanced by recent developments in artificial intelligence, specifically machine learning (ML) and deep learning (DL). This review gives a detailed overview of the latest advances in EEG based detection and prediction of epileptic seizures. Pre-processing methods for EEG signals are covered, followed by feature extraction algorithms, publicly available EEG datasets, machine learning algorithms, and deep learning architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Transformers. Moreover, this paper emphasizes the issues such as patient-specific variations, imbalanced data, interpretability, computational complexity, and real-time deployment. The cutting edge technologies like wearable technologies, explainable AI, multimodal fusion and seizure prediction are also discussed. Finally, future research directions that seek to enhance generalization, reliability and clinical applicability of seizure prediction systems are discussed in the review..

Keywords: Epilepsy, EEG, Seizure Detection, Seizure Prediction, Deep Learning, Machine Learning, CNN, LSTM, Wearable Technology...

1. INTRODUCTION

Epilepsy is a very common neurological condition, with nearly 50 million people worldwide suffering from it [1]. Defined by periodic seizures due to abnormal electrical activity in the brain [1]. The erratic nature of a seizure can have a profound impact on patients' quality of life and cause injuries, psychological stress, and social isolation. Early detection and prediction of seizures can enable patients to take preventive measures and optimize the treatment [2]. EEG is the main diagnostic tool for epilepsy monitoring since it records electrical brain activity with high temporal resolution [2]. The manual interpretation of EEG by a neurologist was traditionally the most critical step in the diagnosis of seizures and was time consuming and error-prone. Thus, machine learning and deep learning based automated systems for seizure detection and prediction have gained significant importance [2, 3]. The detection of seizures involves recognizing the seizure state (ictal) and the prediction of seizures involves anticipating the seizure state (preictal) before the seizure. The difficulty is greater and the clinical value is greater in prediction as it allows for proactive action [2], [3]. 1.1 Seizure Stages The key to forecasting seizures is to identify small, preictal EEG changes. The usual stages of an epileptic brain state are the interictal (between seizures), preictal (before seizures), ictal (during seizures) and postictal (after seizures) phases [13, 16]. The clinical characteristics of the interictal period are often normal or with occasional epileptiform spikes; the preictal period may last minutes to hours and may include evolving EEG irregularities; the ictal period may show high amplitude rhythmic spikes and waves; and the postictal period includes slowing and suppression of background activity [13, 14]. EEG signatures vary according to stage, with interictal EEG typically displaying a normal background with some occasional spikes or slow waves, while ictal EEG will show progression of high amplitude rhythmic activity. It is variable (2–90 min) as there is no universally accepted gold standard [2], [3], [13]. In this period, biomarkers have been reported, containing spectral power changes, synchronization and coherence, alterations of phase-amplitude coupling (PAC), entropy and complexity changes, emergence of high-frequency oscillations (HFOs) and slow DC changes, as indicators of upcoming seizure activity [13], [16], [17]. For instance, preictal and interictal states can be distinguished with high sensitivity based on patient-specific spectral characteristics in the gamma frequency band [2] and higher rates of HFOs have been correlated to seizure probability [16]. The four phases of epileptic seizure progression are shown in figure 1: interictal, preictal, ictal and postictal. The ictal stage is characterized by abnormal high amplitude discharges, the interictal stage by normal EEG activity between seizures, the preictal stage by subtle EEG changes that occur before onset of a seizure, and the postictal stage by a recovery period where brain activity returns to normal. The knowledge of these stages is crucial in designing effective seizure detection and prediction systems based on EEG.

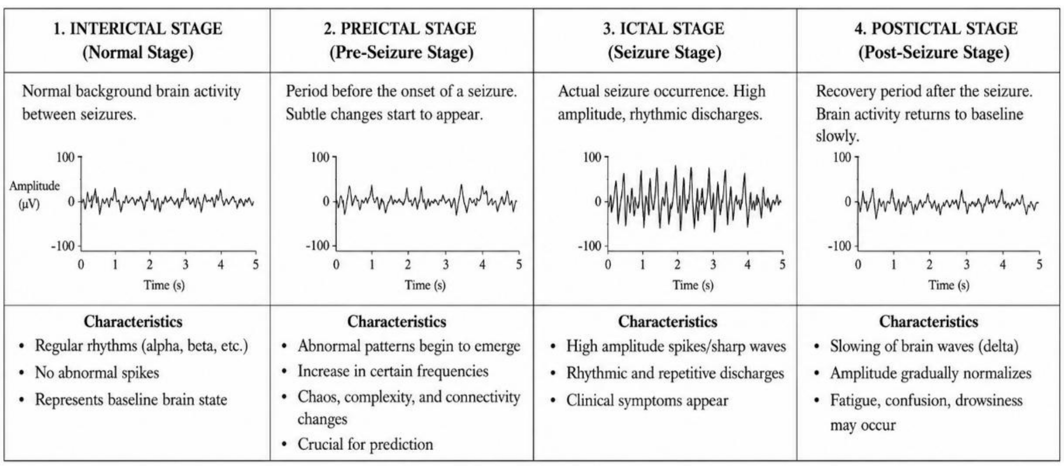


Fig 1: Different Stages of Epilepsy and their characteristics

1.2 EEG Datasets Used in Seizure Research

EEG data is a key component in devising and assessing automatic systems for epileptic seizure detection and prediction. These datasets contain a set of recorded brain signals from patients with epilepsy, which can be used to train, validate, and compare machine learning and deep learning algorithms [13, 21]. EEG datasets are of special interest as they can be made publicly available for the purpose of reproducible research, and various methods can be compared under standardized conditions [11, 13]. These most frequently used datasets include CHB-MIT Scalp EEG Database, Bonn University EEG Dataset, EPILEPSIAE Database, Temple University Hospital (TUH) EEG Corpus and Kaggle American Epilepsy Society (AES) Seizure Prediction Dataset [4]–[8]. The duration of data recordings, number of subjects, electrode configuration, sampling frequency and application vary among the datasets. Some datasets are mainly used for seizure detection, while others are dedicated specifically for seizure prediction studies. The CHB-MIT Scalp EEG Database is the most popular benchmark for seizure detection and prediction studies among the available datasets. It includes long term scalp EEG data from children with intractable epilepsy, as well as a large number of annotated seizures [4]. Bonn University Dataset is commonly used for algorithm development due to its simple signals and clearly distinguishable classes of normal EEG signals and epileptic signals [5]. The EPILEPSIAE Database was specifically created for epilepsy patients that includes long duration clinical recordings to aid seizure prediction research [6]. The Temple University Hospital (TUH) EEG Corpus is one of the largest publicly available clinical EEG databases, which has a wide variety of seizure types and patient populations [7]. More recently, the

Kaggle AES Seizure Prediction Dataset, consisting of intracranial EEG recordings, has become popular for developing advanced deep learning models and seizure forecasting systems [8], [11]. These datasets have greatly propelled research progress and led to the creation of increasingly precise and powerful seizure prediction models [11] – [13]. The most common public EEG datasets used for the epileptic seizure detection and prediction research are given in Table 1. The differences between these datasets include: subject population, signal type, sampling frequency, recording time, and applications. The CHB-MIT and TUH EEG datasets are widely used to study the detection of seizures, while the EPILEPSIAE, AES Kaggle, Freiburg, Mayo Clinic and SWEC-ETHZ are primarily used for studies on the prediction of seizures. Of these, CHB-MIT is the most widely used benchmark dataset, while TUH EEG offers large-scale clinical recordings which are suitable for deep learning. These datasets have paved the way for standardized evaluation, benchmarking and development of high-level machine learning and deep learning models for automated seizure detection and prediction.

Table1: Common EEG Datasets Used in Seizure Research

Ref	**Dataset**	**Year Released**	**Subjects**	**Signal Type**	**Sampling Frequency**	**Application**	**Key Features**
[13]	CHB-MIT Scalp EEG Database	2000	23 pediatric patients	Scalp EEG	256 Hz	Detection & Prediction	Long-term recordings, annotated seizures, most widely used benchmark
[14]	Bonn University EEG Dataset	2001	Healthy and epileptic subjects	Scalp EEG	173.61 Hz	Detection	Five subsets (A–E), simple and balanced dataset
[15]	EPILEPSIAE Database	2012	30 patients	Intracranial & Scalp EEG	256–1024 Hz	Prediction	Long-duration recordings, preictal annotations, designed for seizure forecasting
[16]	TUH EEG Seizure Corpus (TUSZ)	2018	Thousands of patients	Clinical Scalp EEG	Variable (250–400 Hz)	Detection	Largest publicly available seizure dataset, multiple seizure types
[17]	Kaggle AES Seizure Prediction Dataset	2014	Human and canine subjects	Intracranial EEG (iEEG)	400–5000 Hz	Prediction	Created for seizure prediction competition, rich preictal data
[18]	Freiburg EEG Dataset	2003	21 patients	Intracranial EEG	256 Hz	Prediction	Long-term recordings with clearly labeled preictal periods

[19]	Mayo Clinic Seizure Prediction Dataset	2014	Human & canine subjects	Intracranial EEG	400–5000 Hz	Prediction	Used in seizure forecasting competitions
[20]	SWEC-ETHZ Dataset	2019	18 patients	Intracranial EEG	512 Hz	Prediction	Long-term recordings suitable for deep learning models

Table 2: Comparison of Popular Datasets

Feature	**CHB-MIT**	**Bonn**	**EPILEPSIAE**	**TUH EEG**	**AES Kaggle**
Public Availability	Yes	Yes	Restricted	Yes	Yes
Seizure Detection	Excellent	Good	Good	Excellent	Moderate
Seizure Prediction	Good	Limited	Excellent	Moderate	Excellent
Deep Learning Suitability	High	Moderate	High	Very High	Very High
Clinical Realism	High	Low	Very High	Very High	High
Number of Seizures	198+	Limited	Thousands	Thousands	Hundreds

Table 2 shows a comparison of the major EEG datasets employed in seizure detection and prediction studies. The most popular are CHB-MIT and TUH EEG, both for seizure detection, and EPILEPSIAE, AES Kaggle for seizure prediction because of their preictal data. TUH EEG and EPILEPSIAE are highly clinical realistic and suitable for deep learning applications. The whole dataset is a useful benchmark for developing and testing automated seizure detection and prediction systems.

1.3 Dataset Selection Guidelines

Depending on the research goals and needs, researchers choose the EEG data sets they wish to use. The CHB-MIT dataset is one of the most frequently used benchmark datasets for seizure detection and prediction studies, where the long-term scalp EEG recordings have been well annotated for seizure events [4]. Because of its simple structure, balanced classes and easy implementation, the Bonn University dataset is widely used to develop and test their performance of the new machine learning algorithms [5]. The EPILEPSIAE database is frequently used for seizure prediction studies, due to the availability of long duration EEG recordings, and preictal annotations that allow to explore seizure precursors [6]. The Temple University Hospital (TUH) EEG Corpus, the largest publicly available clinical EEG database, has the advantage of being representative of a diverse set of patients, seizure types, and recording conditions for large-scale deep learning applications and patient independent modeling [7]. Along the same lines, the American Epilepsy Society (AES) Kaggle dataset is another popular resource for higher level seizure forecasting research, where there are extensive intracranial EEG recordings and rich preictal data [8] and [11]. The Freiburg EEG data set is also commonly used in seizure prediction studies, such as for examining preictal EEG patterns and implementing early warning systems [10]. With the recent success of deep learning methods, large and clinically realistic datasets have become more important. The most valuable datasets for modern seizure detection and prediction research are considered to be CHB-MIT, TUH EEG and EPILEPSIAE [4], [6], [7]. These datasets allow researchers to create a strong and reliable machine learning and deep learning model that is clinically relevant, with long duration, multiple seizure events and comprehensive annotations, and a diverse patient population. They are also widely referenced in the literature, which has enabled them to be used for benchmarking and comparative assessment and they are therefore valuable tools for developing more powerful automated epilepsy monitoring and seizure forecasting systems [11, 13, 21].

Machine Learning approaches

The most popular methods for automated seizure detection and prediction from EEG signals based on artificial intelligence (AI) are machine learning (ML) and deep learning (DL) [13], [21]. The traditional method of diagnosis of seizures is the visual inspection of EEG recordings by neurologists, which is labor-intensive, time-consuming and subject to subjective interpretation [14]. In order to address these challenges, ML and DL-based models have been proposed that can automatically process EEG signals and detect the patterns associated with seizures with a high level of accuracy [15, 21]. The EEG signals are extremely non-linear, non-stationary and complex, thus making them a good fit for sophisticated computational techniques which can learn the hidden relationships within the information [16].

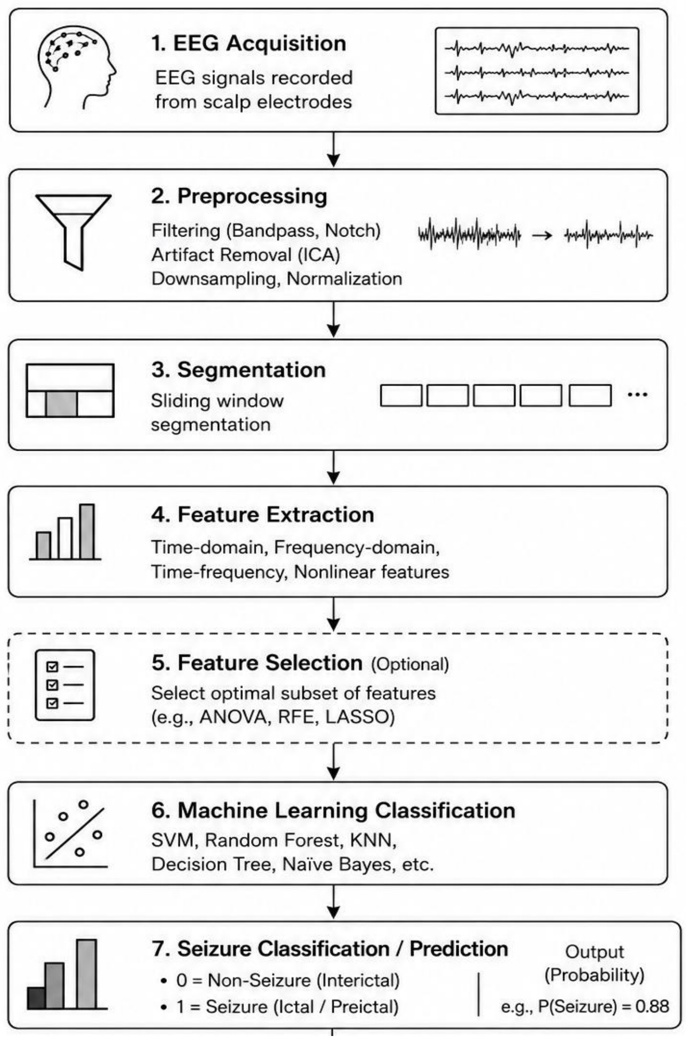


Fig 2: Machine Learning workflow for EEG based Seizure detection and prediction

Typically, machine learning methods are implemented in a three-step process that consists of preprocessing, feature extraction, and classification [17]. The extracted features are then passed to classifiers like Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbour (KNN), Decision tree or Naïve Bayes [17, 18]. While traditional ML methods are able to work well on relatively small datasets and are computationally efficient, they depend heavily on the quality of features manually engineered [15] [21].

In the field of traditional machine learning, Support Vector Machines (SVMs) have proved to be widely applicable in seizure detection: They are able to classify complex EEG patterns in a nonlinear manner in the presence of noise.In the area of traditional machine learning algorithms, Support Vector Machines (SVMs) have been widely applied in seizure detection due to their ability to separate complex EEG patterns using nonlinear kernel functions in the presence of noise [19]. Another popular type of classifiers are the Random Forest classifiers, which are also robust and resistant to over-fitting by using multiple decision trees [20]. The K-Nearest Neighbour methods classify EEG segments according to their similarity with observed examples, Decision Trees give interpretable classification rules that are easily understood by clinicians [17]. These techniques have been shown to perform well, but they are based on features that are carefully designed by experts and do not work well in capturing the more complex relationships between the events that occur in EEG recordings [15] and [21].

The flowchart of conventional machine learning for EEG-based seizure detection and prediction is shown in figure 2. EEG signals are collected, preprocessed, segmented, and converted to meaningful features. The optional feature selection is followed by classification of EEG segments as seizure or non-seizure activity using machine learning classifiers (SVM, Random Forest, KNN) to get the final prediction.

1.5 Deep Learning Approaches

Because of their capacity to automatically learn discriminative features of EEG signals without requiring any manual feature engineering, deep learning has become a very promising method for EEG-based seizure detection and prediction [9, 13, 21]. In general, the EEG signals are pre-processed by filtering, artifact removal and normalization, and then segmented for the fixed length windows. Processed EEG segments are then fed into deep learning models to extract and classify features automatically [13] [21].

Within the different architectures, Convolutional Neural Networks (CNNs) are popular for extracting spatial patterns from EEG data [9, 22] and Long Short-Term Memory (LSTM) networks are especially useful for temporal dependencies in sequential EEG signals [22]. To achieve better performance in seizure detection and prediction, hybrid CNN-LSTM models are used that incorporate both spatial and temporal feature learning [23]. Recently, Graph Neural Networks (GNNs) have been used to model functional connectivity between EEG channels [24] and the Transformer-based models have shown better performance in capturing long-range dependencies through the use of self-attention mechanisms [2]. The results of such models are usually a classification of the EEG activity as either seizure or non-seizure, so as to allow automatic detection and early warning of seizures [9], [13]. Although the accuracy of deep learning models is high, they are data-hungry and computationally demanding, and thus they are the subject of continued research for explainable and patient independent seizure prediction systems [13], [21],[32]. The diagram in Figure 3 shows a typical method of deep learning for EEG-based seizure detection. The initial step in EEG signal preprocessing involves filtering the data, which helps to reduce noise and artifacts.The first step in EEG signal preprocessing is to filter the data to remove noise and artifacts. The processed signals are then inputted into deep learning models like CNNs, LSTMs or hybrid architectures, which automatically extract the features that are relevant to the classification of EEG data. The final output distinguishes between a seizure (ictal) and non-seizure (interictal) state of the EEG segment.

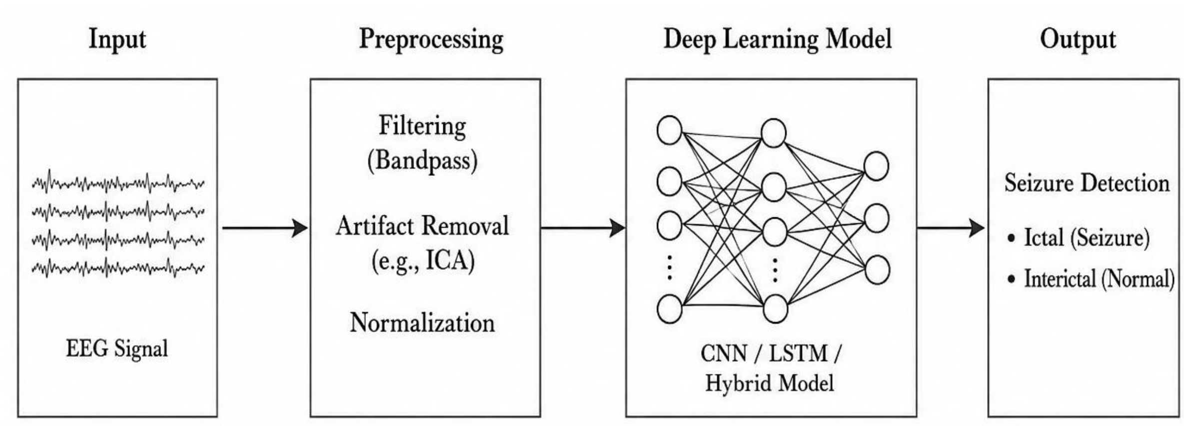


Fig 3: Deep Learning workflow for EEG based Seizure detection and prediction

2. Challenges in EEG-Based Seizure Detection and Prediction

Although significant advances have been made with machine learning and deep learning algorithms, there remain a number of challenges that hinder the reliability, generalizability and clinical use of automated seizure detection and prediction systems. The complexity of EEG signals, patient-to-patient variability of epilepsy and deployment of real time monitoring systems create such challenges [13, 21]. The second aspect of variability concerns the type of pattern the patient exhibits.

2.1 Patient-Specific Variability in EEG Patterns

The highly variable nature of EEG patterns among patients is one of the most important challenges encountered in seizure prediction research. Epilepsy is a very variable neurological condition, and the electrical activity generated during a seizure can vary from person to person. These differences are related to age, type of seizure, location of the seizure, drugs, brain structure and evolution. Therefore, characteristics of EEG that are good for identifying seizures in one patient are not necessarily the same for other patients. Many machine learning and deep learning models are able to perform well when trained and tested on data from a single patient (patient-specific models), but lose accuracy when applied to unseen patients (patient-independent models) [13, 21]. This variability is challenging the development of generalizable systems for seizure prediction that are able to function consistently in a wide range of patient populations [13, 22]. As shown in Figure 4, there are several major challenges with EEG-based seizure prediction systems. However, one important drawback is that the models often fail to generalize well to data from other patients because the data is inter-patient [13], [22]. Another challenge is feature selection, since features that work well for one person, may not work for another [13]. In addition, high-quality prediction models would also require large and diverse datasets from multiple patients [13, 21]. Deep learning models also add the complexity of having to train this model with large amounts of computational resources and time [21] and [23]. The challenges can impact the clinical usefulness of automated seizure prediction systems and are ongoing research concerns [13, 21].

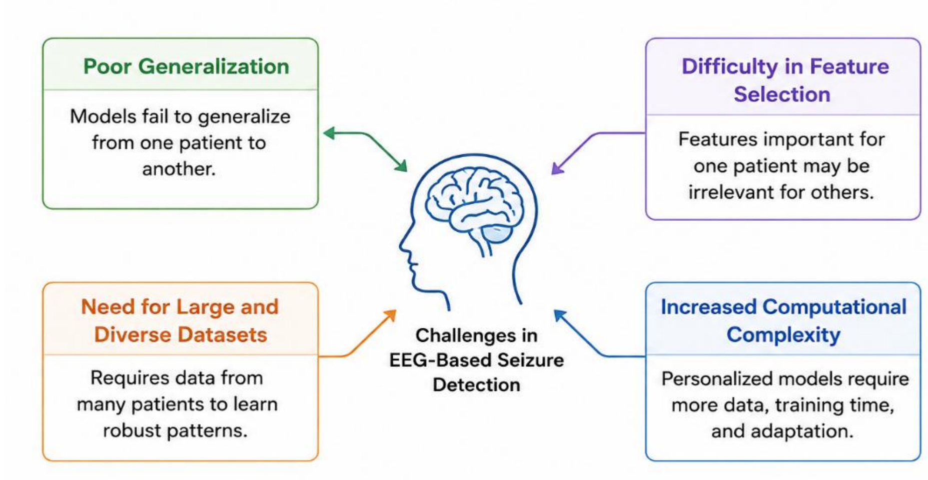


Fig 4: Patient-Specific Variability in EEG Patterns

2.2. Class Imbalance Between Seizure and Non-Seizure Data

The dataset for seizure detection usually consists of numerous samples with normal activity and a relatively small number of samples related to the epileptic seizure process itself. Seizures happen rarely as compared to periods when a person's brain is working normally. It leads to a very imbalanced dataset. Furthermore, the preictal phase, which is utilized by most researchers, constitutes an extremely small portion of the data set since it happens shortly before seizures occur. Consequently, machine learning models may learn the majority class better than the minority, causing seizure detection failures [11], [13], [21].

The approach used by researchers for overcoming the problem of the imbalance includes the utilization of techniques like oversampling, undersampling, creation of synthetic samples (e.g., using SMOTE), utilization of focal loss functions, and cost-sensitive learning. Figure 5 shows class imbalance of EEG samples related to seizures. The number of interictal samples is significantly larger than the number of seizure samples, resulting in imbalanced datasets that may lead to a biased machine learning model [13], [21]. Thus, class imbalance is one of the major problems that has to be addressed.

Figure 5 displays other challenges related to EEG seizure detection and prediction. They include a lack of generalizability across patients, inability to choose robust and independent of patients' specific features, the necessity of having a huge dataset of EEG records, and a higher computational complexity due to the above mentioned requirements. Those challenges might negatively affect performance, reliability, and clinical relevance of machine learning models. Thus, the development of more generalized models is necessary [13], [21], [22], [23]. Class distribution of the CHB-MIT database is presented in table 3 [4].

Figure 6 shows the effect of handling class imbalance on the results of the detection process. The model without handling class imbalance will classify the seizure samples wrong. As shown in Figure 6, the difference between models with and without handling class imbalance is that the seizure samples will be misclassified without handling. Thus, the true positives will be less, and there will be many missed seizures (false negatives).

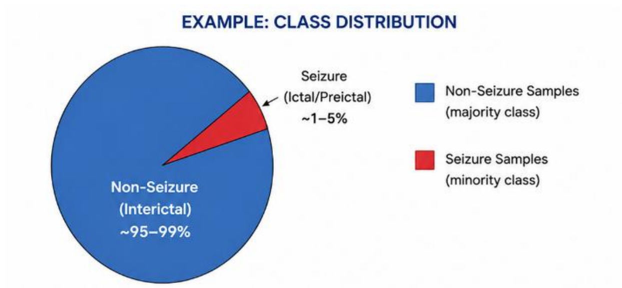


Fig 5: Class imbalance of Dataset

Table 3. CHB-MIT Dataset Statistics

Statistic	**Measurement**
Total EEG Recording Duration	~980 hours
Number of Seizure Events	198
Total Seizure Duration	~1.0 hour
Total Non-Seizure Duration	~979 hours
Seizure-to-Total Data Ratio	~0.1%

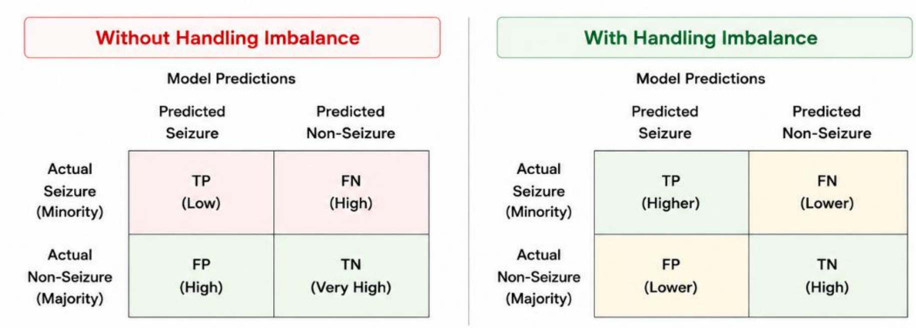


Fig 6: Impact of Class Imbalance

2.3. High False Alarm Rates

Among other difficulties involved in EEG-based seizure prediction, one of the major problems is that of False Alarm Rate (FAR). It can be explained by the fact that the system incorrectly predicts the emergence of seizures, while there is actually no attack during the prediction time window [2], [13],[25]. However, while it is vital to have a high level of sensitivity, the presence of too many false alarms decreases the usefulness of the prediction systems [3], [13].

These false alarms arise from the complexity and nonstationarity of EEG signals, which makes normal brain activity, motion artefacts, stress, tiredness, effects of medicine intake, and external disturbances appear like preictal activity of the brain causing incorrect seizure predictions [13], [17], [21]. Thus, an efficient seizure prediction system needs to find the optimal compromise between its sensitivity and FAR [2], [22].

FAR can be computed according to the following formula:

$$FAR = \frac{NFA}{T} \qquad ----- (1)$$

where:

NFA= Number of false alarms

T= Total monitoring time (hours)

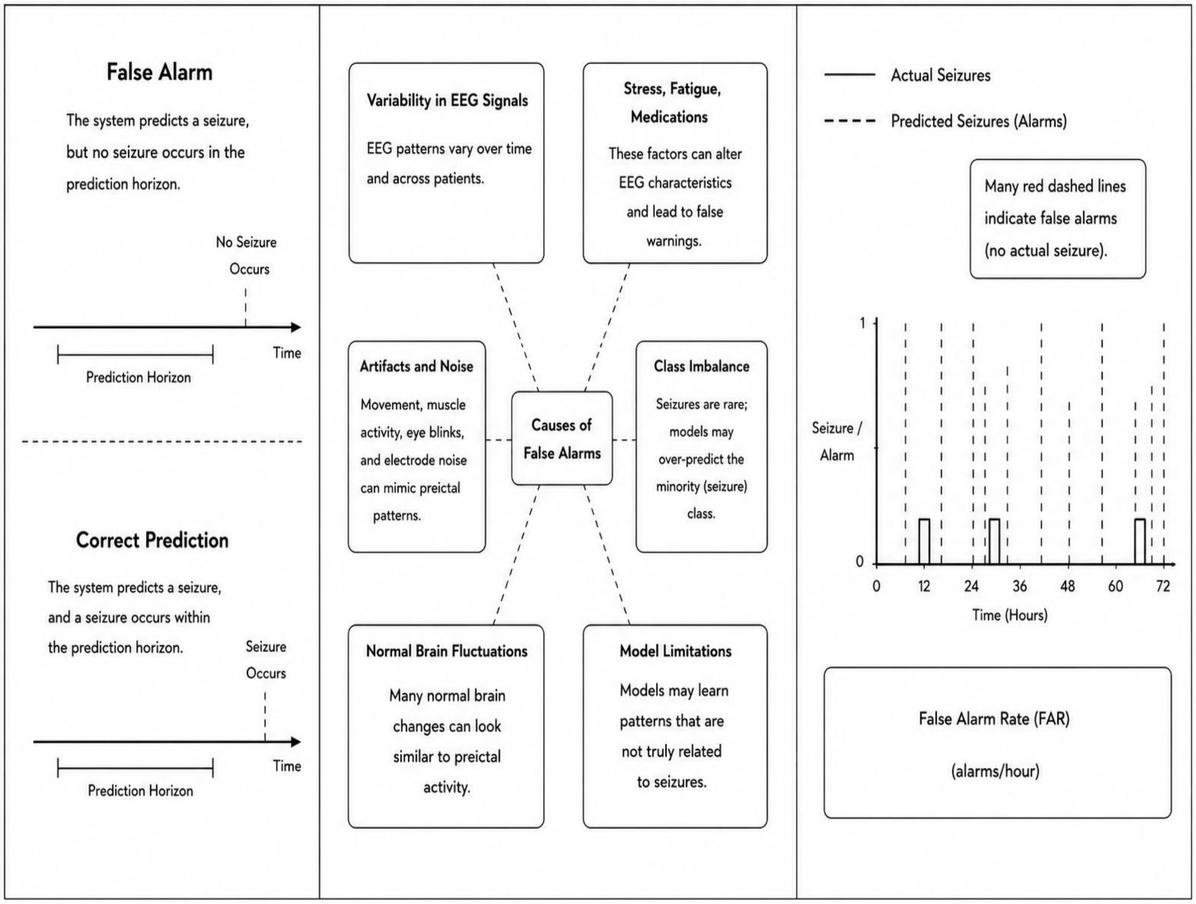
Equation (1) represents a lower FAR indicates better reliability of the prediction system [2], [13].

Researchers commonly evaluate seizure prediction performance using Sensitivity, Specificity, F1-score, False Prediction Rate (FPR), and FAR [2], [3], [22]. Several techniques have been proposed to reduce false alarms, including patient-specific models, ensemble learning, confidence-based thresholds, post-processing methods, and multimodal approaches combining EEG with physiological signals such as ECG and heart-rate variability [13], [21].

Recent deep learning models employ attention mechanisms, temporal consistency constraints, and prediction verification across multiple EEG windows to improve robustness and reduce false alarms [2], [22]. Despite significant advances, minimizing FAR while maintaining high sensitivity remains a key challenge for translating seizure prediction systems into real-world clinical applications [2], [13], [21].

The figure 7. illustrates the relationship between seizure sensitivity and false alarm rate. While increasing sensitivity improves seizure detection performance, it may also increase false alarms. An optimal prediction system should maintain high sensitivity while minimizing false alarms to ensure clinical reliability and patient acceptance [2], [13].

Fig 7: Illustration of a false alarm and a correct seizure prediction in EEG-based seizure forecasting systems



2.4. Computational Complexity for Real-Time Systems

The computational complexity of seizure detection/prediction algorithms based on real-time EEGs occurs due to a number of reasons related to the handling of big data and making fast predictions [13], [21]. First of all, high sampling rate along with many EEG channels results in an increased number of data to process at a constant pace [6], [7], [12]. An increasing number of channels and a high sampling rate make both computation, memory, and processing time much larger [13], [21]. Longer EEG windows of analysis are another reason for the complexity of such models, as they provide better predictive outcomes while at the same time consuming additional resources [2], [22]. Feature engineering is yet another factor that adds computational complexity to real-time EEG algorithms due to complicated mathematics used during its application [15], [16], [17].

The increased complexity is further fueled by the introduction of deep learning algorithms such as CNNs, LSTMs, GNNs, and Transformers, which include many layers and millions of weights [2], [22], [23], [24], [27]. Training and executing such algorithms consumes significant computation, memory, and energy resources [21], [27]. Last but not least, real-time demands enforce the need to provide low latencies in order to deliver predictions in advance of seizures. This means that the computation time per EEG segment is significantly limited [2], [13], [26].

Table 4. Computational Complexity Challenges and Optimization Strategies for Real-Time EEG-Based Systems

Challenge / Factor	Impact on Computational Cost	Complexity / Constraint	Corresponding Optimization Strategy
High Sampling Rate & Many Channels	EEG data size increases with the number of channels and sampling frequency.	O(C * SR)	**Window & Sampling Optimization:** Adaptive window sizing and down-sampling to reduce data volume while preserving relevant information.
Longer Windows for Better Accuracy	Larger temporal windows improve accuracy but increase computation and latency.	O(W)	**Window & Sampling Optimization:** Select optimal window length balancing accuracy and real-time performance.
Feature Engineering	Time-frequency and nonlinear feature extraction are computationally intensive.	O (C* W * F_{ext})	**Efficient Feature Extraction:** Use discriminative low-cost features and incremental/online feature computation.
Deep Learning Models	Increasing layers and parameters leads to higher MAC operations and memory usage.	O (P * L))	**Model Optimization:** Employ lightweight architectures (e.g., MobileNet, Depthwise CNN, GRU), pruning, quantization, and knowledge distillation.
Real-Time Constraint	Strict latency requirements limit model complexity and processing time.	Latency < T_{max}	**Hardware Acceleration and Algorithmic Efficiency:** Utilize GPUs/NPUs/FPGAs, parallel processing, and optimized data structures.
Large Computational Workload	High processing demand can exceed embedded-device capabilities.	System-dependent	**Edge Computing:** Offload computation to edge devices or hybrid cloud-edge frameworks.

Where C= number of EEG channels; SR= sampling rate (Hz); W= window size (samples); F_{ext}= number of extracted features; P= number of trainable model parameters; L= number of network layers; T_{max}= maximum allowable latency.

2.5. Lack of Interpretability in Deep Learning Models

However, despite outstanding results achieved by deep learning algorithms in predicting seizures, these models generally act as black box systems [13], [21]. These algorithms are able to detect relevant patterns automatically but the underlying rationale for the algorithm's decisions is often hard to grasp [21], [22], [23]. At the same time, neurologists and other healthcare practitioners require clear explanation of how a specific system predicts the occurrence of a seizure or classifies an EEG pattern [28], [29]. Lack of interpretability may become a barrier to the adoption of machine learning in medical practice due to lower levels of clinicians' confidence [28], [29]. Therefore, more attention should be paid to XAI approaches like attention mechanisms, saliency maps, SHAP, LRP and others that give the opportunity to shed light on the decision-making process.

In summary, the discussed challenges demonstrate that there is still much work to do before deep learning-based seizure prediction models can be successfully applied to clinical practice. Patient variation is an obstacle to the creation of generalized models, imbalanced datasets cause problems with training; false alarms lead to low user satisfaction; computational costs are rather high; lack of interpretability negatively influences the adoption of AI-based models [13], [21], [26]. Thus, further research is needed in order to develop explainable, efficient, reliable and accurate deep learning algorithms for seizure prediction in various patient groups [2], [13], [21], [26].

3. FUTURE RESEARCH DIRECTIONS

Future research for seizure prediction and detection based on EEG should be geared towards making artificial intelligence systems that are more accurate, easily interpreted, efficient, and clinically reliable [13], [21], [26]. One of these directions includes the collection of more varied and larger EEG datasets, acquired in multiple hospitals and on patients with various conditions [6], [7], [11], [12]. With such datasets, prediction models can predict seizures in patients of any age, of all types of seizure, and in people of any clinical status [6], [7]. The establishment of standardized protocols for collecting and sharing data should allow for easier reproduction and collaboration [6], [7].

The application of XAI methods in future models for predicting epilepsy seizures is another area that researchers are exploring now [28], [29]. Even though deep learning methods provide remarkable results, the way they work remains a black box [13], [21]. Thus, future models must be created with built-in explanation procedures, like attention maps, saliency analysis, SHAP, and LIME, which allow doctors to see why a certain diagnosis is made [28], [29]. The application of explainability tools increases clinicians' trust in AI solutions and thus encourages their adoption [28], [29].

Finally, efficient and lightweight models that work in real time on a patient's device or smartphone are of great interest to researchers [2], [21], [27]. Various approaches to minimizing neural networks, including hardware acceleration, edge computing, model compression, and efficient network architecture can decrease the need for computationally heavy processing while retaining good predictive power [2], [26].

The use of multimodal physiological signals is yet another direction that should be explored. Future systems for predicting seizures based on EEG can include ECG, EOG, heart rate variability measures, motion and accelerometer readings, as well as other physiological data [13], [21]. Additionally, researchers should try combining several physiological data streams to improve the performance of seizure prediction models and make them more resistant to artifacts and noise. Future prediction systems could be built based not only on EEG but also ECG, EOG, HRV, motion, and clinical data [13], [21]. As for EEG signals, it is important to consider using both raw and processed data since they can help increase the prediction performance.

Personalized seizure prediction algorithms are one more aspect that should be considered in future works. Patient specificity is essential as the electrical activity in the brain of patients differs greatly [3], Personalized and adaptive seizure prediction models are also expected to play a significant role in future research. Since EEG patterns vary considerably among individuals, patient-specific models that continuously learn and adapt to changing brain activity may provide more accurate predictions than generalized approaches [3], [13], [26]. Techniques such as transfer learning, federated learning, and continuous learning can help develop adaptive systems that remain effective over long-term monitoring periods [21], [27].

Finally, greater emphasis should be placed on clinical validation and real-world deployment. Large-scale clinical trials are necessary to evaluate the long-term safety, reliability, and effectiveness of seizure prediction systems [26]. Researchers must also address ethical, privacy, security, and regulatory challenges associated with AI-driven healthcare technologies [28], [29]. The ultimate goal is to develop trustworthy seizure prediction systems that can provide early warnings, improve patient safety, enhance quality of life, and support clinical decision-making in everyday healthcare settings [1], [26]. Table 5 presents key interpretability approaches for EEG-based learning models. These methods include visualization techniques, feature importance analysis, interpretable model architectures, EEG domain knowledge integration, and hybrid explainable AI frameworks. Together, they enhance model transparency, facilitate understanding of predictions, and improve the reliability of EEG-based decision-making systems [28], [29],[30],[31].

Table 5: Approaches to improve interpretability

Approach	Examples / Methods	Purpose / Benefit
Visualization Methods	Saliency Maps, Grad-CAM, Attention	Highlight important time points, channels, and frequency bands.
Feature Importance	SHAP, LIME, Permutation Importance	Quantify the contribution of each feature to the prediction.
Interpretable Models	Rule-based Models, Decision Trees, Sparse Models	Use models that are inherently transparent and easy to understand.
EEG-Based Priors	Brain regions, neural rhythms, domain knowledge	Help the model focus on physiologically meaningful patterns.
Hybrid Approaches	Combine deep learning with explainable AI techniques	Balance predictive performance with interpretability.

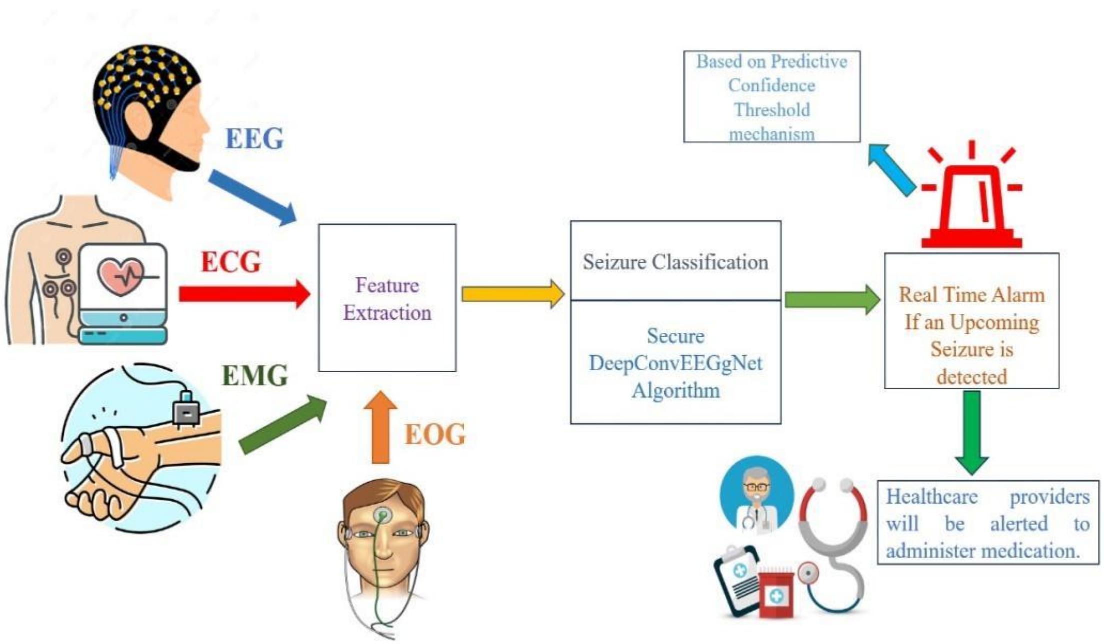


Fig 8. Workflow of the Real-Time Seizure Prediction and Alert System Using Multimodal Physiological Signals and Deep Learning

The following figure 8 depicts a seizure prediction framework that makes use of EEG, ECG, EMG, and EOG signals. Feature extraction is done from the obtained physiological signals, and then the extracted features are fed into the Secure DeepConvEEGNet algorithm to classify the seizures. A threshold value for prediction confidence is set to increase prediction accuracy. Once the Secure DeepConvEEGNet identifies the seizure with enough confidence level, an alert is raised in real-time so that healthcare professionals can intervene accordingly and treat patients effectively. The following table (Table 6.) highlights some of the challenges that EEG-based seizure detection and prediction face, along with solutions to these challenges as proposed by recent studies[33].

Table 6: Challenges and Solutions

Challenges	Proposed Solutions
Patient-specific variability	Personalized learning, transfer learning, federated learning
Class imbalance	SMOTE, GANs, oversampling, focal loss, cost-sensitive learning
High false alarm rates	Multimodal data fusion, ensemble models, adaptive thresholds
Computational complexity	Lightweight models, pruning, quantization, edge computing
Lack of interpretability	XAI techniques, SHAP, LIME, attention mechanisms
Limited EEG datasets	Multicenter databases, transfer learning, data augmentation
EEG noise and artifacts	ICA, wavelet denoising, adaptive filtering
Clinical deployment challenges	Clinical trials, regulatory compliance, ethical frameworks

4. Conclusion

Epilepsy is one of the most common neurological diseases whose effect on the lives of affected patients has necessitated the use of seizure detection and prediction methods. EEG analysis plays an important role in tracking brain activities and has been used in many research works to develop automatic systems for seizure analysis. In recent years, the field of seizure analysis has experienced tremendous growth due to improvements in machine and deep learning algorithms, which have increased the efficacy of pattern recognition from EEG signals. Machine learning methods, including SVMs, random forests, and decision trees, perform efficiently using hand-crafted features, whereas deep learning models such as CNNs, LSTM, GNNs, Transformers, and their combinations outperform other methods using automatically extracted EEG representations.

In this article, the most popular EEG datasets, the main stages of seizures, machine learning, and deep learning techniques, along with recent trends in seizure detection and prediction studies, have been comprehensively discussed. The usage of publicly available databases such as CHB-MIT, Bonn University, EPILEPSIAE, TUH EEG, and AES contributed to the acceleration of research and the standardization of algorithms' performance assessment procedures. Nevertheless, despite great achievements in seizure predictions, a number of limitations persist, including individual variability, imbalance of classes, false alarm rate, computational cost, shortage of data variety, EEG artifacts, and inability to extract any useful information from deep learning algorithms.

Thus, future researches must concentrate on the creation of generalizable, interpretable, and effective models which can function in a real-world clinical environment. The use of Explainable Artificial Intelligence (XAI) methods, multimodal physiological signals, transfer and federated learning, as well as individual-based approaches may contribute greatly to achieving more precise predictions. In addition, the availability of larger multicenter databases, wearable devices, and clinical trials may become the key factors which could make it possible to implement the seizure prediction system in the field of neurology. In conclusion, the invention of an algorithm able to detect seizures accurately and promptly may help to avoid many serious consequences..

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