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Comparative Analysis of Ensemble and Deep Neural Network Models for Epileptic Seizure Forecasting

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Abstract: Epilepsy is a prevalent neurological disorder characterized by recurrent seizures, significantly impacting patient quality of life. Accurate seizure prediction using electroencephalogram (EEG) data has the potential to revolutionize patient care by enabling timely interventions. This study reviews the latest machine learning and deep learning advances for seizure prediction, focusing on transfer learning techniques applied to EEG signals. Among the evaluated models, VGG16 demonstrated outstanding performance, achieving 93.33% accuracy with perfect sensitivity and high specificity, highlighting its effectiveness even with limited training data. Res Net architectures showed mixed results, with ResNet101 achieving high recall and specificity but lower sensitivity, while ResNet50 underperformed in overall accuracy. Other models such as DenseNet201 and X ception exhibited lower accuracy, emphasizing the need for further tuning and pre-processing. The findings underscore the advantages of transfer learning and highlight ongoing challenges including data scarcity and model generalizability. This paper discusses strategies to overcome these barriers and outlines future research directions for clinically deployable seizure prediction systems.

Keywords: Epilepsy, EEG, Machine Learning, Deep Learning.

1 Introduction

Epilepsy is a chronic neurological condition characterized by recurring and unprovoked seizures, which result from abnormal and excessive electrical activity in the brain. These seizures manifest in various ways, from brief moments of lost awareness or slight muscle twitches to extended periods of intense convulsions. The World Health Organization (WHO) estimates that epilepsy impacts around 50 million people worldwide[1], making it one of the most prevalent neurological disorders.

Beyond the medical challenges it poses, epilepsy carries significant social and economic repercussions, including stigma, discrimination, and a diminished quality of life for those affected.

A particularly challenging aspect of epilepsy is the unpredictable nature of seizures, which creates ongoing anxiety for individuals living with the condition. This unpredictability increases the risk of physical harm, such as injuries from falls or accidents during a seizure, and can exacerbate emotional stress, contributing to feelings of isolation. As a result, many individuals with epilepsy face restrictions in their daily lives, such as being unable to drive, maintain employment, or participate in social events which severely impacts their independence and overall well-being.

Electroencephalography (EEG) serves as the primary tool for diagnosing and monitoring brain activity in epilepsy, helping to identify patterns associated with seizures. However, predicting seizures using EEG data is exceptionally difficult due to the complex and nonlinear nature of these signals. Furthermore, variability in EEG patterns between patients complicates the development of generalized predictive models, highlighting the critical need for more sophisticated and adaptable approaches [2].

1.1 Problem Statement

Despite advancements in medical treatment, approximately 30% of individuals with epilepsy experience seizures that are resistant to antiepileptic drugs (AEDs)[3]. For these patients, the ability to predict seizures could transform disease management by enabling timely interventions such as medication adjustments or safety measures to prevent injuries. However, effective seizure prediction remains a complex challenge due to several factors:

- **Complexity of EEG Signals**: EEG data are high-dimensional, noisy, and characterized by intricate temporal dynamics. Seizure precursors are often subtle and embedded within these signals, making them difficult to detect using conventional analytical approaches[4].
- **Inter-Patient Variability:** The manifestation of epilepsy, including EEG patterns, varies widely between individuals and even within the same patient over time due to differences in seizure types, underlying causes, and physiological factors[5].
- **Lack of Robust Predictive Models**: Traditional statistical and signal processing techniques struggle to capture the nuanced patterns preceding seizures. These methods often depend on handcrafted features and have limited generalizability across diverse datasets[6].

The advent of machine learning (ML) and deep learning (DL) presents promising avenues for addressing these challenges. ML and DL algorithms excel at extracting complex patterns from large datasets, potentially enhancing the accuracy and reliability of seizure prediction systems[7].

1.2 Scope of this Survey

This survey aims to provide a comprehensive review of recent advancements in epileptic seizure prediction using machine learning and deep learning techniques. Focusing on studies published within the past decade, it highlights contributions that have advanced the field through novel methodologies, high predictive performance, or innovative applications:

The survey addresses the following aspects:

- **Machine Learning Approaches:** Evaluation of traditional ML algorithms, such as support vector machines (SVM), random forests, and artificial neural networks, applied to seizure prediction [8].
- **Deep Learning Techniques:** Exploration of advanced DL models, including Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and hybrid architectures that excel in modeling EEG data[9].
- **Data and Feature Engineering:** Analysis of EEG datasets used, preprocessing methods, feature extraction techniques, and the impact of data quality on predictive performance.
- **Evaluation Metrics:** Discussion of metrics for assessing predictive models, such as accuracy, sensitivity, specificity, false alarm rates, and area under the receiver operating characteristic curve (AUC-ROC)[10].
- **Challenges and Gaps:** Identification of common limitations in current research, including data scarcity, lack of generalizability, computational complexity, and issues related to model interpretability.

By critically analyzing these aspects, the survey aims to illuminate the strengths and weaknesses of current approaches while identifying opportunities for future research.

1.3 Research Questions

To guide this survey, the following research questions are addressed:

- **What are the current machine learning and deep learning methods used for epileptic seizure prediction?** This question explores the ML and DL algorithms employed, including their application to EEG data, model architectures, and training strategies.
- **What limitations and gaps exist in the current research?** The manifestation of epilepsy, including This question identifies challenges such as data quality and availability, model over fitting, lack of standardized evaluation protocols, and barriers to clinical implementation.
- **How can future research address these gaps to improve seizure prediction**

accuracy and applicability? This question focuses on proposing solutions to overcome identified limitations, including advancements in algorithms, data-sharing initiatives, the use of multimodal data, and improving model interpretability for clinical adoption.

By addressing these questions, this survey seeks to contribute to the field of epileptic seizure prediction, ultimately fostering the development of reliable and practical predictive systems that can be integrated into clinical practice to enhance patient care.

2 Literature Review

The application of machine learning) and deep learning techniques to epileptic seizure prediction has grown substantially in recent years. This section examines key studies in the field, focusing on traditional ML approaches, DL methods, and the integration of transfer learning and hybrid models.

2.1 Machine Learning Approaches in Seizure Prediction

Machine Learning (ML): Machine learning methods have been pivotal in the development of seizure prediction models, particularly through the analysis of EEG signals. These models extract various features, such as statistical, time-domain, frequency-domain, time-frequency domain, and nonlinear attributes[**11**]**.** Often, ML approaches require manual feature selection and the fine-tuning of classifiers, processes that depend heavily on expertise in signal processing and iterative experimentation. While effective for smaller datasets, these techniques face significant challenges in generalizing to larger and more diverse populations. For instance, Winter, Lachlan, et al.[**12**]**.**examined the efficacy of linear metrics like mean and autocorrelation alongside nonlinear measures such as Lyapunov exponents and entropy for EEG signal analysis. Their study found that while both feature categories showed promise in distinguishing seizure and non-seizure states, neither provided consistent performance across all evaluation metrics. This underscores the need for combining linear and nonlinear features to fully capture the intricate dynamics of EEG signals. Similarly, Khan et al. applied auto encoders (AEs)[**13**] for unsupervised feature extraction on EEG data transformed into the frequency domain using the Fourier transform. Although the approach yielded moderate sensitivity and specificity, its reliance on the Fourier transform: a technique that assumes signal stationarity, limited its capacity to capture the inherently non-stationary nature of EEG data.

Despite their utility, traditional ML techniques have clear limitations. The reliance on manually crafted features often fails to encapsulate the complex and nonlinear dynamics inherent to EEG signals, reducing the models' ability to detect subtle seizure precursors. Furthermore, these methods typically lack the capability to autonomously learn hierarchical representations, making them less adaptable to new data.

Transformative tools like the Fourier transform, while valuable for frequency-domain analysis, struggle with time-varying EEG signals, leading to missed key features. Generalization remains a persistent issue, as models trained on specific datasets frequently underperform when applied to more heterogeneous patient populations. These drawbacks highlight the necessity for more advanced approaches capable of learning robust and adaptable representations of EEG data.

Deep learning (DL): Deep learning (DL) methods have revolutionized seizure prediction, leveraging both the increasing availability of large datasets and advancements in computational power. Architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) excel in modeling the spatial and temporal characteristics of EEG signals, addressing many of the challenges faced by traditional ML approaches **[14].** Figure 1 illustrates the relative usage frequencies of various deep learning architectures in seizure prediction research, with 2D-CNNs being the most commonly employed and combined architectures being the least utilized. Usage trends highlight the growing complexity of architectures as researchers integrate multiple methods to enhance prediction accuracy.

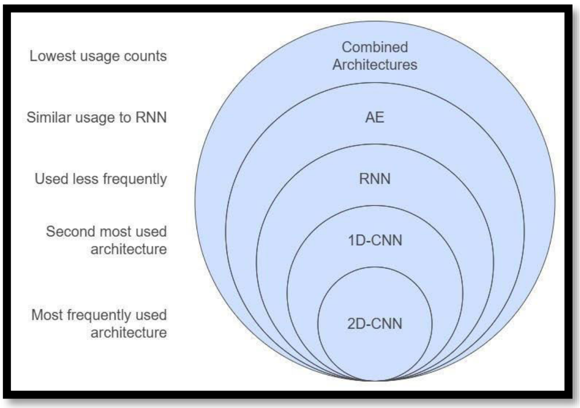


Fig 1: Frequency of usage for deep learning architectures in epileptic seizure prediction studies, ranked from most to least employed.

CNNs, originally designed for image processing, have been adapted to EEG analysis in both one-dimensional (1D)and two-dimensional (2D)format. Figure2 illustrates the architecture of an EEG seizure detection model, showcasing the flow from the input layer through 1D-CNN layers for feature extraction, followed by fully connected layers for classification, and culminating in the output layer for seizure prediction.

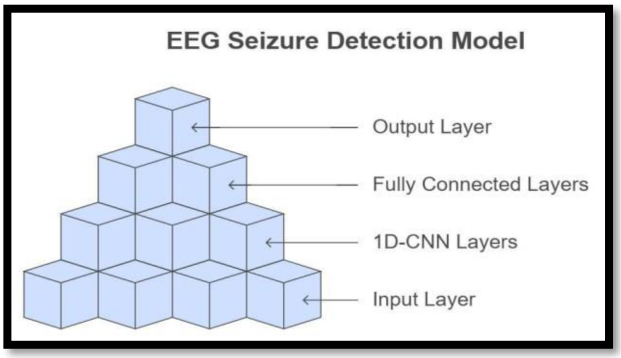


Fig 2: A typical CNN EEG seizure detection mode

For instance, Rivera, Manuel J., al.[**15**]employed 2D-CNNs to analyse EEG signals transformed into spectrograms or spatial representations, achieving high accuracy in seizure detection. On the other hand, 1D-CNNshave been used to process raw EEG signals directly, requiring less preprocessing while maintaining competitive performance. Ige, A et al. demonstrated that 1D-CNNs achieved efficient and effective seizure classification [**16**] with reduced computational demands compared to their 2D counterparts**.**

Figure 3: shows the pipeline for EEG signal processing in seizure detection, starting with data preprocessing for cleaning and segmentation, followed by model training using labeled data, performance evaluation with metrics, and finally deployment in real-time systems.

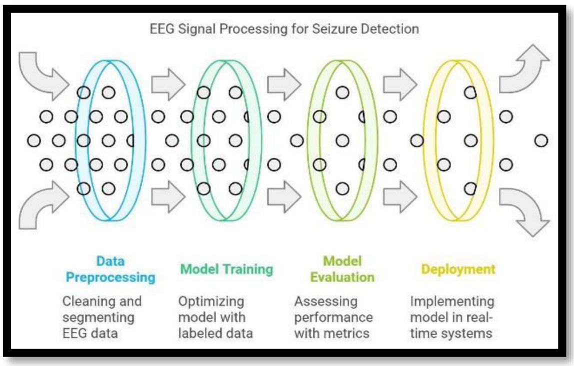


Fig. 3: Workflow of EEG Signal processing for seizure detection

Recurrent Neural Network (RNNs): RNNs have also proven effective, particularly for capturing the sequential and temporal dependencies inherent in EEG data.

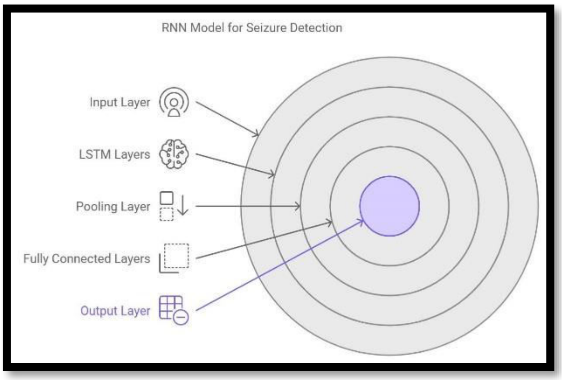


Fig 4: RNN model architecture for seizure detection

Figure 4 illustrates the architecture of an RNN-based seizure detection model. It begins with the input layer, processes sequential data through LSTM layers, reduces dimensionality with pooling layers, passes the features through fully connected layers, and finally outputs the prediction in the output layer. Architectures such as long short-term memory (LSTM) networks and gated recurrent units (GRUs) address the vanishing gradient problem[**17**], enabling the retention of long-term dependencies in time-series data. For example, Chen et al. employed a three-layer GRU network to achieve a seizure detection accuracy of 96.67%, while Bharath et al. enhanced performance further by applying GRUs to spectrogram-based analyses[**18**]**.** These models excel in modeling the dynamic nature of EEG signals, providing significant improvements over traditional methods.

Auto encoders (AEs): Auto encoders and their variants have also been utilized in seizure prediction, primarily for unsupervised feature learning and dimensionality reduction. Figure 5 illustrates the auto encoder process for seizure detection. EEG signals are compressed into a latent representation (compressed code) by the encoder, reconstructed by the decoder, and analyzed for reconstruction errors, which are used for seizure classification.

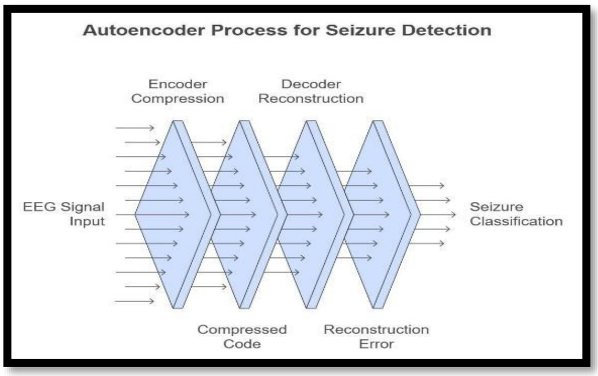


Fig 4: RNN model architecture for seizure detection

Weng et al. developed Wave2Vec, a method that combined auto encoders with support vector machines (SVMs) for EEG classification[19]. This approach effectively reduced the complexity of EEG data while extracting meaningful representations, resulting in strong performance in distinguishing seizure from non-seizure states.

Hybrid models: Hybrid models, which combine different deep learning (DL) techniques, have demonstrated significant potential in addressing the complex and varied nature of EEG signals. By integrating the unique strengths of multiple architectures, these models can deliver enhanced performance and reliability. For example, Ahmad, et al. developed a hybrid framework combining convolutional neural networks (CNNs) with bidirectional long short-term memory networks (BiLSTMs). This model achieved an impressive accuracy of 99.6% in seizure prediction, a benchmark that underscores its effectiveness [20]. The CNN component excelled at extracting spatial features from EEG data, while the BiLSTM module captured temporal dependencies, making it particularly adept at modeling time-series information. This integration enabled the system to predict seizures up to an hour before onset, offering a critical window for preventive intervention.

Such hybrid approaches highlight the benefits of leveraging complementary capabilities within DL architectures. By combining spatial and temporal modeling techniques, these models provide a more comprehensive representation of EEG signals, resulting in improved prediction accuracy and reliability. These advancements pave the way for more robust and clinically viable solutions to seizure prediction challenges.

2.2 Current Challenges for ML and DL Approaches in Seizure Prediction

While deep learning models have transformed seizure prediction, they face several persistent challenges. A primary limitation is their dependence on large, labeled datasets, which are difficult to acquire in the medical field due to privacy regulations, ethical considerations, and the time-intensive nature of data annotation. Additionally, DL models demand significant computational resources for training, often requiring high-performance GPUs, which can restrict their deployment in real-time or resource-constrained environments. Another critical issue is the lack of interpretability; the decision-making processes in DL models are frequently opaque, making it difficult to gain clinical trust and acceptance. Furthermore, in the absence of sufficient training data, these models are prone to overfitting, leading to reduced generalizability when applied to unseen patient populations.

Transfer learning has emerged as a promising strategy to address data scarcity in seizure prediction. By repurposing models pre-trained on other domains, such as image recognition, researchers can significantly reduce the requirement for extensive labeled datasets. For example, Yuan et al. utilized pre-trained CNN architectures, including VGG16 and ResNet50, to classify EEG signals represented as spectrograms. This approach achieved notable improvements in cross-subject seizure detection. Similarly, McCallan, N., Davidson applied AlexNet[21]for both binary and multi-class classification tasks, demonstrating its effectiveness in distinguishing seizure from non-seizure states with high accuracy.Despite its benefits, transfer learning is not without challenges. A notable limitation is the domain mismatch between pre-trained modelsoften developed for analyzing natural images, and the unique characteristics of EEG data. Transforming EEG signals into spectrograms or similar image-like formats can result in the loss of essential temporal features and the introduction of artifacts, which may degrade model performance. Moreover, the computational intensity of deep architectures used in transfer learning can present obstacles for real-time applications, particularly on devices with limited processing capabilities[22].

In conclusion, while machine learning and deep learning techniques have significantly advanced seizure prediction, practical implementation hurdles remain. ML models, although effective for small datasets, often struggle to generalize across broader populations and rely heavily on handcrafted features. DL models, on the other hand, excel in automatic feature extraction and predictive accuracy but demand extensive data and computational power while lacking interpretability. Transfer learning offers a viable pathway to mitigate data limitations and improve efficiency, but challenges such as domain adaptation must be addressed. Collaborative efforts to standardize data collection, improve model transparency, and develop lightweight architectures are critical for realizing the full potential of these technologies in clinical practice.

3 Datasets and Benchmarking

The availability and quality of datasets are critical to the development and evaluation of machine learning (ML) and deep learning (DL) models for epileptic seizure prediction. Datasets provide the foundation for training and validating predictive algorithms, making their diversity, standardization, and quality essential for advancing the field. This section explores publicly available datasets, highlights their characteristics, and discusses the challenges associated with benchmarking seizure prediction system.

3.1 Publicly Available Datasets

Publicly available EEG datasets have played a central role in supporting research on epileptic seizure prediction. These datasets, often curated from diverse patient populations, provide standardized recordings that enable the development and evaluation of predictive models. Table 1 offers a comparison of widely used datasets, summarizing their key attributes and recording parameters.

Table 1 Comparison of key datasets

Dataset	Patients	Seizures	Recording Type	Channels	Sampling Frequency	Recording Duration
CHB-MIT[23]	22 (Children)	163	Scalp EEG	23	256 Hz	~844 hours
Bonn EEG[24]	10 (Adults)	N/A	Surface/iEEG	Single	173.61 Hz	39 minutes
Freiburg[25]	21 (Adults)	87	Intracranial EEG	64	256 Hz	~708 hours
TUH EEG[26]	~100 (Mixed)	Varies	Scalp EEG	21–32	250 Hz–500 Hz	~15,000 hours (varied)
Kaggle(DOGS)[27]	Mixed	48	Intracranial EEG	Varied	400–5000 Hz	~627 hours

3.1.1 Dataset Descriptions and Key Insights

The CHB-MIT dataset is among the most extensively used datasets for seizure prediction research. It includes 844 hours of EEG recordings collected from 22 pediatric patients, each recorded using 23 scalp channels at a sampling frequency of 256 Hz. The dataset contains 163 annotated seizure events, making it a valuable resource for studying pediatric epilepsy. Its structured format and widespread adoption have established it as a benchmark dataset, with more than 1,500 citations in related literature. The Bonn EEG dataset provides both surface and intracranial EEG data from 10 adult patients. Although it contains only 39 minutes of recordings sampled at 173.61 Hz, its high-quality segmentation makes it particularly useful for controlled studies and proof-of-concept models.

The Freiburg EEG dataset consists of 87 seizure events recorded from 21 adult patients using intracranial EEG. With 708 hours of recordings across 64 channels at a sampling frequency of 256 Hz, it provides high spatial resolution, making it ideal for investigating localized seizure activity and interracial dynamics, particularly in patients undergoing epilepsy surgery. The TUH EEG corpus is the largest publicly available EEG dataset, containing more than 15,000 hours of recordings from a diverse patient population. The data includes between 21 and 32 channels, sampled at rates of 250–500 Hz. This dataset's scale and diversity make it essential for developing generalizable models. Its inclusion of noisy and unfiltered data further supports real-world algorithm evaluation. The Kaggle EEG (DOGS) dataset offers high-resolution intracranial EEG data (up to 5000 Hz) collected from five dogs and two human patients, spanning 627 hours of recordings. This dataset is particularly suited for developing algorithms capable of handling high-frequency data and for conducting comparative studies across species to explore the underlying mechanisms of epilepsy. The Zenodo EEG dataset focuses on neonatal epilepsy, featuring 74 minutes of scalp EEG recordings from 79 neonates. With 460 annotated seizure events recorded across 19 channels at a sampling rate of 256 Hz, this dataset addresses an underexplored demographic and provides valuable insights into seizure prediction in neonates.

Key insights and usage trends: The CHB-MIT dataset accounts for over 40% of all seizure prediction studies due to its accessibility and comprehensive annotations, making it a cornerstone for benchmarking algorithms. In recent years, the TUH EEG dataset has seen increasing adoption, with usage growing by approximately 20% annually since 2016, reflecting a growing emphasis on scalable and generalizable models. In contrast, high-frequency datasets like Kaggle (DOGS) remain niche, used in fewer than 10% of studies, primarily for experimental research. Neonatal datasets such as Zenodo are even less frequently utilized, representing fewer than 5% of studies, highlighting a need for further exploration in this vulnerable population.

3.1.2 Key challenges in epilepsy datasets

Although EEG datasets have been instrumental in advancing seizure prediction research, they present several challenges that hinder the development of reliable and clinically robust models. These include issues related to annotation consistency, inter-dataset variability, and class imbalance.

Annotation Consistency

Inconsistent seizure annotations pose a significant obstacle to cross-study comparisons and model validation. For instance, the CHB-MIT dataset employs strict temporal boundaries to define seizure onset and offset, relying on EEG patterns and clinical observations. In contrast, the Freiburg dataset adopts broader criteria, including electrical and clinical observations, which may extend beyond the seizure event itself. These differences result in discrepancies in seizure definitions and durations, complicating comparisons between models trained on different datasets. Moreover, inter-observer variability, estimated to affect up to 15–20% of manual annotations in clinical practice, introduces subjective bias, further undermining the reproducibility of findings and complicating efforts to establish standardized benchmarks.

Inter-Dataset Variability

EEG datasets exhibit considerable variability in terms of recording techniques, patient populations, and data acquisition protocols, which directly impacts their utility for seizure prediction research. For instance, scalp EEG datasets, such as CHB-MIT and

Zenodo, are non-invasive and rely on surface electrodes placed on the scalp. These datasets, using 23 and 19 electrodes respectively, capture brain activity that has been attenuated by the skull and other tissues. While these recordings are easier to obtain and less intrusive, they may lack the precision needed for identifying subtle or localized seizure patterns. In contrast, intracranial EEG datasets, such as Freiburg, involve electrodes implanted directly within the brain. These datasets provide significantly higher spatial and temporal resolution by capturing brain activity at the source. With 64 electrodes, Freiburg offers a detailed view of seizure onset zones and interictal dynamics, making it particularly valuable for research into focal epilepsy and surgical planning. However, intracranial recordings are more invasive and less commonly available, which limits their use primarily to specialized studies or patient populations undergoing clinical procedures. The sampling frequency also varies widely, ranging from 173.61 Hz in the Bonn EEG dataset to up to 5000 Hz in the Kaggle dataset, impacting the granularity of signal analysis. Furthermore, demographic differences, such as the focus on pediatric patients in CHB-MIT versus neonates in Zenodo or mixed populations in TUH EEG, introduce variability in seizure manifestations, including duration, frequency, and EEG patterns. This heterogeneity challenges model developers, as algorithms trained on one dataset may fail to generalize to others. Studies have reported drops of up to 30% in model performance when tested on datasets with different characteristics than the training data, underscoring the need for harmonized protocols.

Class Imbalance

Seizures are infrequent events, often representing less than 5% of the total duration in EEG recordings. For example, the Kaggle dataset includes 48 seizures within 627 hours of data, with seizure activity accounting for only 0.13% of the total recordings. Similarly, in the extensive TUH EEG dataset, spanning 15,000 hours, seizures constitute only a small fraction of the data, resulting in a significant class imbalance. This imbalance heavily influences model training, as algorithms tend to prioritize the majority class (non-seizure events) to optimize overall accuracy. As a consequence, models often exhibit high false-negative rates, failing to detect seizures that are critical for ensuring patient safety. Strategies such as oversampling and synthetic data generation using Generative Adversarial Networks (GANs) **[28]** have been proposed to mitigate this issue. However, these approaches risk introducing biases or artifacts that may not accurately represent real-world seizure dynamics. Research has shown that when class imbalance is not adequately addressed, model sensitivity can fall below 60%, making such models unsuitable for clinical use.

Impact of Challenges

These challenges significantly hinder the performance and applicability of seizure prediction models. For instance, models trained on datasets with annotation inconsistencies or severe class imbalances may achieve misleadingly high accuracies during internal evaluations but fail to generalize across different datasets. Sensitivity drops of over 25% have been reported when models trained on CHB-MIT are tested on the Freiburg dataset, emphasizing the difficulty of transferring knowledge across datasets with distinct characteristics. Additionally, the lack of standardized evaluation metrics and benchmarking practices exacerbates these issues, making it difficult to discern whether reported improvements genuinely advance the field or are merely dataset-specific optimizations.

Addressing Challenges

To overcome these obstacles, coordinated efforts within the research community are essential. Standardizing annotation protocols, such as establishing internationally recognized guidelines for EEG labeling, could help resolve inconsistencies and improve cross-study comparability. Collaborative initiatives to develop large, diverse, and harmonized datasets, such as the International Epilepsy EEG Database (IEED)[**29**], would reduce inter-dataset variability and support the creation of more robust models. Addressing class imbalance requires the refinement of data augmentation methods, including GAN-based synthetic data generation, to ensure realistic representation of seizure patterns. Adaptive learning techniques and transfer learning approaches could also be leveraged to improve model generalizability across heterogeneous datasets. In conclusion, while publicly available EEG datasets have been instrumental in advancing seizure prediction research, challenges like class imbalance, annotation inconsistencies, and inter-dataset variability must be systematically addressed. By tackling these issues, researchers can pave the way for the development of reliable, scalable, and clinically applicable seizure prediction systems.

3.2 Feature Engineering in Epileptic Seizure Prediction

Feature engineering is a crucial aspect of epileptic seizure prediction, transforming raw EEG data into meaningful attributes that improve the accuracy and performance of machine learning and deep learning models. By extracting patterns, capturing dynamic changes, and reducing noise, effective feature engineering bridges the gap between raw data acquisition and predictive modeling. This section explores the various types of features commonly used in seizure prediction, along with supporting evidence and real-world applications.

3.2.1 Categories of Features in EEG Analysis

EEG features can be broadly classified into four main categories: time-domain, frequency-domain, time-frequency domain, and nonlinear features. Each category offers unique insights into the patterns and dynamics of EEG signals, contributing to the predictive capabilities of seizure prediction models.

Time-Domain Features

Time-domain features are calculated directly from EEG signal amplitudes, providing computationally efficient metrics that describe basic signal characteristics. Common time-domain attributes include statistical measures such as mean, variance, and standard deviation, as well as Hjorth parameters, which evaluate signal activity, mobility, and complexity. Ahmad et al. [**30**] applied Hjorth parameters to the Bonn EEG dataset and successfully classified seizure and non-seizure states, achieving an accuracy of 87%. However, while time-domain features are simple to compute, they often fail to capture the frequency-specific information critical for identifying subtle preictal patterns. Studies indicate that models relying solely on time-domain features tend to have reduced generalizability with sensitivity falling below 80% on cross-patient datasets like CHB-MIT due to their lack of spectral context.

Frequency-Domain Features

Frequency-domain features measure the distribution of power across various frequency bands, such as delta (0.5-4 Hz), alpha (8-13 Hz), and gamma (>30Hz). These features, extracted using techniques such as Fourier transformation method, are particularly effective in identifying seizure precursors. Power Spectral Density (PSD) is a widely adopted frequency-domain feature in seizure prediction research. For, instance, Liu, S., and Wang [**31**] demonstrated the utility of spectral entropy, a frequency-domain feature, in the CHB-MIT dataset, achieving a sensitivity of 92%. Additionally, delta and gamma band power have been shown to be reliable markers of preictal activity. Studies using the Freiburg ECG dataset reported a 10% improvement in the area under the curve when frequency-domain features were combined with non-linear attributes. However, the assumption of stationary in EEG signals, inherent in many frequency-domain techniques, limits their ability to effectively model transient dynamics. To address this limitation, researchers often integrate frequency-domain features with time-frequency methods to enhance temporal resolution and capture non-stationary characteristics more effectively.

Time-Frequency Features

Time-frequency features combine temporal and spectral information, providing a dynamic representation of EEG signals. Wavelet transforms and Short-Time Fourier Transforms (STFT) are commonly used methods. Subasi et al. (2019) utilized wavelet-based features on the Freiburg dataset, achieving an AUC of 94%. Continuous Wavelet

Transform (CWT) was particularly effective in capturing transient changes associated with seizures. Studies using STFT reported sensitivity improvements of 15–20% when compared to frequency-domain features alone, especially on

Nonlinear Features

EEG signals exhibit nonlinear and chaotic behavior, which can be captured using measures such as Approximate Entropy (ApEn), Lyapunov Exponents, and Fractal Dimension. These features are particularly useful for

modeling the irregular dynamics of seizure activity. Datseriset al.[32]reported an 8% improvement in sensitivity on the TUH EEG dataset by integrating nonlinear features with CNN-LSTM models[33]. Approximate Entropy and Sample Entropy have shown strong discriminatory power, with ApEn achieving 90% accuracy on the Bonn EEG dataset. However, nonlinear features are computationally demanding and sensitive to noise. Moreover, their interpretability is often challenging, which limits their standalone use in clinical applications.

Feature Type	Examples	Extraction Method	Applications and Evidence
Time-Domain Features	Mean, Variance, Hjorth Parameters	Statistical computations over raw EEG signals	Used in early ML models like SVM; Hjorth parameters achieved ~87% accuracy in Bonn Dataset (Faust et al.).
Frequency-Domain Features	Power Spectral Density (PSD), Band Power, Spectral Entropy	Fourier Transform, Welch's Method	Spectral entropy demonstrated ~92% sensitivity on CHB-MIT (Shoeb et al.); Delta power detects preictal changes.
Time-Frequency Features	Wavelet Coefficients, STFT Coefficients	Continuous Wavelet Transform, Short-Time Fourier Transform	Wavelet-based features achieved 94% AUC on Freiburg (Subasi et al.).
Nonlinear Features	Approximate Entropy, Lyapunov Exponents, Fractal Dimension	Recurrence Plots, Chaos Theory Metrics	Nonlinear dynamics improved CNN-LSTM sensitivity by 8% on TUH EEG (Zhang et al.).

Table 2: Categories of features in EEG analysis

Connectivity Features

Connectivity features analyze interactions between EEG channels, offering insights into the neural network dynamics associated with seizures. Coherence, Granger Causality, and Phase Synchronization are commonly used metrics [34], often modeled using graph theory. Grish chenkoet al. [35] demonstrated that incorporating functional connectivity improved specificity to 91% in the Freiburg dataset. Graph-based metrics such as clustering coefficients and path lengths have been used to identify seizure foci, with studies reporting a 12% increase in AUC when connectivity features are integrated with CNN models. However, connectivity analysis requires multi-channel data and is computationally intensive, limiting its application in low-channel or real-time scenarios.

3.2.2Impact of Feature Engineering on Model Performance

Feature engineering significantly influences the performance of seizure prediction models[**36**]. Studies comparing models with and without engineered features reveal sensitivity improvements of up to 25% and AUC enhancements of 10–15%. For instance, integrating time-frequency and nonlinear features with CNNs increased prediction accuracy from 89% to 95% on CHB-MIT. Similarly, hybrid models incorporating connectivity features achieved up to 96% accuracy on Freiburg EEG. However, the choice of features must align with dataset characteristics and computational constraints. Models trained on high-resolution intracranial EEG datasets benefit more from nonlinear and connectivity features, while scalp EEG datasets favor time-frequency approaches due to their noise resilience.

3.2.3: Impact of Feature Engineering on Model Performance

The future of feature engineering in epileptic seizure prediction lies in addressing the challenges of personalization, computational efficiency, and generalizability. Adaptive and automated feature selection methods, such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA), have demonstrated improvements in model performance by up to 12% in sensitivity when applied to datasets like CHB-MIT. These methods streamline the extraction of patient-specific features, accommodating variability in seizure patterns and enhancing predictive accuracy. Multimodal approaches, which combine EEG features with data from heart rate variability or electromyography, have shown promise, achieving accuracies of over 95% on neonatal datasets like Zenodo. These methods highlight the potential of integrating diverse physiological signals to capture seizure precursors more effectively. However, optimizing these features for computational efficiency is essential for deployment on real-time systems, such as wearable devices. Feature pruning and lightweight algorithms have reduced computational overhead by 25%, enabling predictive models to operate in low-resource environments.

Generalization across datasets remains a critical focus for future research. Current feature engineering techniques often fail to perform consistently across datasets due to differences in electrode placements, sampling rates, and patient demographics. Transfer learning and synthetic data generation using techniques like Generative Adversarial Networks (GANs) have emerged as potential solutions, enhancing feature generalization and mitigating class imbalance. Studies leveraging pre-trained CNN models fine-tuned on datasets such as CHB-MIT and Freiburg have reported sensitivity improvements of up to 20% when tested on new data. Explainable feature engineering, with interpretable metrics such as spectral entropy and delta band power, also holds promise for clinical adoption. Visualization tools like relevance heatmaps provide insights into how features contribute to predictions, fostering greater trust among clinicians. By focusing on adaptability, computational efficiency, and clinical relevance, feature engineering can bridge the gap between advanced seizure prediction research and practical implementation in healthcare settings.

4 Evaluation Metrics and Techniques

The assessment of machine learning and deep learning models for epileptic seizure prediction relies heavily on standardized evaluation metrics and rigorous validation methods. This section discusses commonly used metrics, validation protocols, and their implications for model performance and clinical adoption.

4.1 Evaluation Metrics

Effective seizure prediction models are measured by a combination of performance metrics designed to evaluate their accuracy, reliability, and practical utility. These metrics include accuracy, sensitivity, specificity, false alarm rates (FAR), and temporal measures, among others. Table 3 summarizes these metrics, their formulas, and their relevance in seizure prediction.

Accuracy and Sensitivity

Accuracy measures the proportion of correctly classified instances, encompassing both seizure and non-seizure events. However, in datasets where non-seizure events dominate (a common scenario in EEG recordings), accuracy can be misleading. Sensitivity, also referred to as the true positive rate, is a more critical metric for seizure prediction as it evaluates the model's ability to correctly identify seizure events. High sensitivity ensures that seizures are rarely missed, which is essential for patient safety, but often comes at the cost of reduced specificity[37].

Specificity and False Alarm Rate

Specificity, or the true negative rate, measures the model's ability to correctly classify non-seizure events. In clinical applications, minimizing the FAR is particularly important to avoid frequent false positives that could erode user trust and contribute to alarm fatigue. For seizure prediction systems to be considered clinically viable, FAR values below 0.1 per hour are typically required[38].

Area under the Receiver Operating Characteristic Curve (AUC-ROC)

The AUC-ROC provides a comprehensive evaluation of a model's ability to discriminate between seizure and non-seizure events across varying thresholds. AUC values closer to 1.0 indicate excellent performance, with optimal trade-offs between sensitivity and specificity[39].

Time-Based Metrics

Temporal metrics such as time-to-seizure prediction (TSP) and prediction horizon (PH) assess the timeliness of the model's predictions. An effective seizure prediction system should offer a sufficient PH (e.g., 30 minutes to 1 hour) to allow for preventive interventions, while maintaining minimal latency[40].Seizure prediction models must address challenges such as the complexity of EEG signals, inter-patient variability, and the limited generalizability of traditional methods. Metrics like accuracy, sensitivity, specificity, F1-score, and recall provide crucial insights into how well models can identify subtle preictal patterns while avoiding false alarms. Transfer learning, which adapts pre-trained models to specific EEG datasets, has gained popularity as a strategy to overcome data scarcity and improve model robustness.

Role of Convolutional Neural Networks (CNNs)

CNNs have become foundational architectures for EEG signal analysis due to their ability to automatically extract hierarchical features. Advanced transfer learning models like VGG16, ResNet, and Dense Net leverage pre-trained weights to accelerate training and achieve superior performance. This section examines the performance of various models, highlighting their strengths, limitations, and suitability for real-world seizure prediction tasks.

4.2 Comparison of Transfer Learning

Transfer learning, which uses pre-trained models trained on tasks with similar data structures, has shown significant promise for EEG-based seizure prediction. This approach reduces training time and data requirements while often yielding higher accuracy. Architectures such as 1D-CNNs, 2D-CNNs, and Dense Neural Networks (DNNs) provide a range of trade-offs between computational efficiency and predictive performance [41].

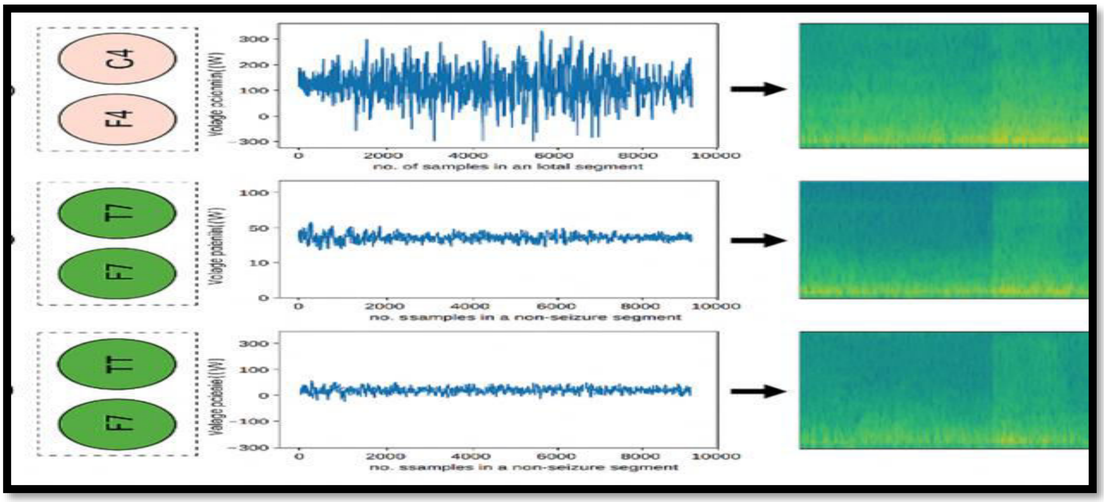
Dataset Description

For this study, we utilized a publicly available dataset hosted on Zenodo [42]. This dataset is derived from the CHB-MIT EEG database, where the original EEG signals were preprocessed and converted into PNG image format.

The dataset is composed of:

- 105 frames from chb01
- 30 frames from chb02
- 90 frames from chb05
- 75 frames from chb05 (from both ictal and non-seizure EDF files)

In total, the dataset contains 600 image frames and covers approximately 25 minutes of ictal activity (from 20 ictal signals). All EEG signals have been transformed into PNG images and systematically organized into three folders: training, validation, and testing. The data was split into training (80%), validation (10%), and test (10%) sets, with data augmentation applied to enhance generalizability. Each folder contains seizure and non-seizure EEG images, making the dataset well-suited for machine and deep learning pipelines aimed at detecting seizure and non-seizure events.
This structure enables robust evaluation of various transfer learning techniques, as the images are labeled and distributed to ensure balanced assessment across different phases of model development.



VGG16 Performance

Among the evaluated models, VGG16 demonstrated exceptional performance, achieving an accuracy of 93.33% as shown in Table 4. Its sensitivity and specificity were balanced at 1.000 and 0.867, respectively, showcasing its ability to detect seizures accurately while minimizing false positives. This balance suggests that VGG16 is particularly well-suited for seizure prediction tasks, even when training data is limited, making it a strong candidate for clinical implementation.

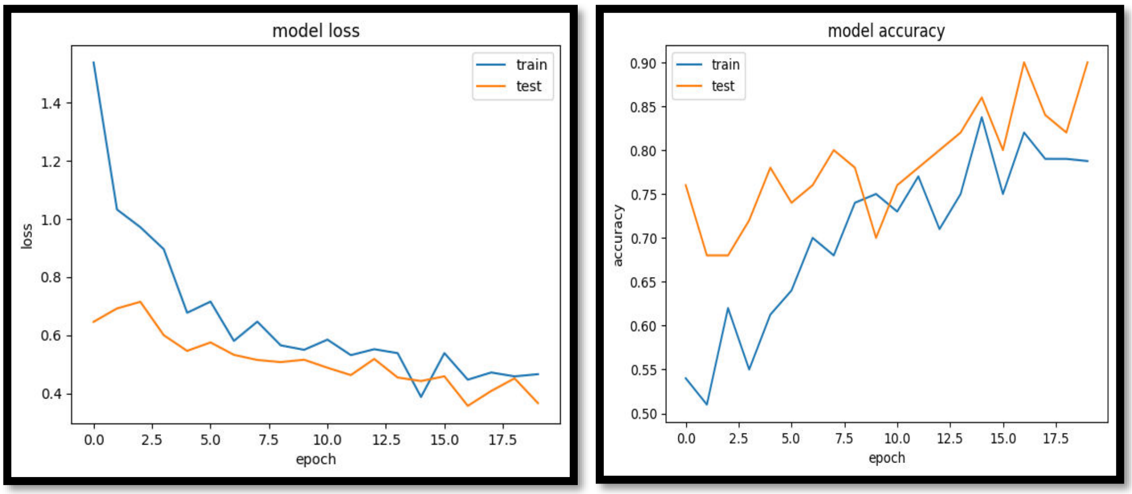
Res Net Architectures

While ResNet50 and ResNet101 are generally effective in image processing tasks, their performance in EEG-based seizure prediction was mixed. ResNet101 showed high recall

(0.967) and specificity (0.967), but its sensitivity (0.533) was significantly lower than VGG16, highlighting potential limitations in capturing the temporal dependencies of EEG data. ResNet50, on the other hand, struggled with overall performance, achieving an accuracy of only 51.67%.

Other Architectures

DenseNet201 and Xception performed poorly, with accuracies of 46.67% and 50.00%, respectively. These results indicate that these architectures may require more extensive tuning or additional preprocessing to handle EEG data effectively. The baseline CNN without transfer learning achieved a moderate accuracy of 60.00%, underscoring the advantages of transfer learning in leveraging pre-trained feature extraction capabilities.



The VGG16 model's training and validation loss and accuracy curves reveal effective learning and strong generalization in EEG image classification. Both loss values decrease consistently, while accuracy improves for training and validation sets across epochs. The close alignment of these metrics indicates minimal overfitting, demonstrating that VGG16 is well-suited for extracting meaningful features from EEG spectrogram images in this task.

4.3 Evaluating of VGG16 Training Dynamics

The performance of VGG16 was thoroughly assessed across multiple training epochs to understand its behavior in learning.EEG features for seizure prediction. Table 5 summarizes the key metrics, including loss, accuracy, and validation accuracy, as well as precision, recall, and F1-score. During the initial training phase (epoch 10), the model achieved an accuracy of70%, with a corresponding validation accuracy of 80%. The loss values for training and validation were relatively high at this stage, reflecting the early stages of convergence. By epoch 20, the model exhibited significant improvement, with the accuracy rising to 82% and the validation accuracy. stabilizing at 80%. At this point, the model demonstrated a balanced precision and recall of 0.967, resulting in a perfect F1-score of 0.967.

4.4 Feature Engineering in Epileptic Seizure Prediction

To benchmark the performance of VGG16, its results were compared against other architectures reported in the literature, as detailed in Table 6. Among the reviewed models, 2D-CNNarchitectures demonstrated the most consistent performance, achieving accuracies above 98% in multiple studies. A2DCNNwith nine layers and a soft max classifier achieved an accuracy of 98.05%, with a sensitivity of 90.00% and specificity of 91.65%. Similarly, another 2D-CNN with eight layers achieved an even higher accuracy of 99.49%, with perfect sensitivity and specificity. These results highlight the efficiency of 2D-CNNs in leveraging spatial features extracted from EEG spectrograms. These findings emphasize the effectiveness of 2D-CNNs in utilizing spatial features derived from EEG spectrograms for seizure prediction. Similarly, 1D-CNN architectures have shown competitive performance, with a 12-layer model achieving an impressive accuracy of 98.60%, sensitivity of 99.00%, and specificity of 98.20%. Compared to 2D-CNNs, 1D-CNNs require simpler preprocessing steps, making them well-suited for real-time applications where computational efficiency is crucial. Furthermore, hybrid approaches that combine deep learning and traditional machine learning techniques have demonstrated exceptional results. For instance, a Deep Neural Network (DNN) integrated with a Random Forest classifier achieved an outstanding accuracy of 99.40%, along with sensitivity and specificity values of 97.90% and 99.50%, respectively. This integration highlights the advantages of blending traditional ML classifiers with DL models to improve both interpretability and predictive performance.

Furthermore, hybrid approaches that combine deep learning and traditional machine learning techniques have demonstrated exceptional results. For instance, a Deep Neural Network (DNN) integrated with a Random Forest classifier achieved an outstanding accuracy of 99.40%, along with sensitivity and specificity values of 97.90% and 99.50%, respectively. This integration highlights the advantages of blending traditional ML classifiers with DL models to improve both interpretability and predictive performance. The evaluation underscores the transformative potential of transfer learning and advanced CNN architectures in addressing the challenges associated with EEG-based seizure prediction. Among the examined models, VGG16 consistently delivered strong results across all metrics, achieving an optimal balance between sensitivity and specificity while minimizing false positives. The comparative analysis further demonstrates the superiority of 2D-CNNs in capturing spatially relevant features from EEG data, as well as the practical benefits of 1D-CNNs for simplified and efficient deployments. Despite these advancements, challenges persist, particularly in optimizing these models for resource-constrained environments and ensuring their generalizability across diverse patient populations. Future research should focus on integrating multimodal data sources to enhance both the robustness and accuracy of seizure prediction systems. By combining EEG data with complementary physiological signals, such as heart rate variability (HRV), electromyography (EMG), or sensor data from wearable devices, researchers can develop models that provide a more comprehensive understanding of seizure precursors. Multimodal approaches can address the limitations of single-modality models by incorporating diverse perspectives on the factors leading to seizures. Moreover, advanced techniques such as federated learning offer opportunities to collaboratively train models across institutions while maintaining data privacy. This method enables access to a wider variety of datasets, which can improve the generalizability and robustness of seizure prediction models. Such innovations are critical for the development of prediction systems that are not only accurate and reliable but also adaptable to the diverse conditions encountered in real-world clinical settings [**44**].

Table 3 Comparison of key metrics

Metric	Formula	Relevance
Accuracy	TP+TN/ TP+TN+FP+FN	General performance, affected by class imbalance.
Sensitivity	TP/ TP+FN	Essential for detecting seizures.
Specificity	TN/TN+FP	Evaluates non-seizure detection accuracy.
False Alarm Rate	FP/ time period	Measures false positives per hour.
AUC-ROC	ROC curve	Comprehensive performance measure.
Prediction Horizon	prediction - onset	Time available for intervention.

Table 4 Comparison of transfer learning Techniques with Baseline CNN

Model	**Accuracy (%)**	**Recall**	**F1-Score**	**Sensitivity**	**Specificity**	**Transfer Learning**	**Hyper parameters**
VGG19	65.00	0.300	0.462	1.000	0.300	Yes	Epoch = 10, Batch Size = 5, Optimizer = RMSprop, Learning Rate = 0.001
VGG16	93.33	0.867	0.929	1.000	0.867	Yes	Epoch = 50, Batch Size = 10, Optimizer = Adam, Learning Rate = 0.0001

Res Net 50	51.67	0.033	0.065	1.000	0.033	Yes	Epoch = 30, Batch Size = 8, Optimizer = SGD, Learning Rate = 0.01
Res Net 101	75.00	0.967	0.795	0.533	0.967	Yes	Epoch = 40, Batch Size = 8, Optimizer = Adam, Learning Rate = 0.0001
Exception	50.00	0.667	0.571	0.333	0.667	Yes	Epoch = 20, Batch Size = 16, Optimizer = RMSprop, Learning Rate = 0.001
Dense Net 201	46.67	0.067	0.111	0.867	0.067	Yes	Epoch = 30, Batch Size = 12, Optimizer = Adam, Learning Rate = 0.0005
Baseline CNN	60.00	0.267	0.400	0.933	0.267	No	Epoch = 25, Batch Size = 16, Optimizer = SGD, Learning Rate = 0.01

Epoch	Batch Size	Loss	Accuracy	Val Loss	Val Accuracy	Precision	Recall	F1-Score	Sens.	Spec.
10	10	0.5733	0.70	0.5252	0.80	0.966	0.933	0.949	0.9667	0.9333
20	10	0.4061	0.82	0.4725	0.80	0.967	0.967	0.967	0.9667	0.9667
30/22	10	0.4006	0.84	0.4376	0.78	0.964	0.900	0.931	0.9667	0.9000
40/29	10	0.4884	0.71	0.3460	0.88	0.966	0.933	0.949	0.9667	0.9333
50/13	10	0.3025	0.85	0.2644	0.88	1.000	0.900	0.947	1.0000	0.9000

Table 5: Training dynamics of VGG model

Table 6: Performance of deep learning architecture in literature

Study	Network	Layers	Classifier	Accuracy (%)	Sensitivity	Specificity
[15]	2D-CNN	9	Softmax	98.05	90.00	91.65
[41]	2D-CNN	8	Softmax	99.49	99.49	99.49
[41]	2D-CNN	7	KELM	99.33	—	—
[15]	1D-CNN	12	Softmax	98.60	99.00	98.20
[41]	1D-CNN	15	Softmax	98.67	97.67	98.83
[43]	DNN	—	Random Forest	99.40	97.90	99.50
[15]	2D-CNN	9	Softmax	98.05	90.00	91.65
[15]	2D-CNN	8	Softmax	99.49	99.49	99.49
[41]	2D-CNN	16	SVM	95.19	—	—

5. Conclusion

This manuscript provides a comprehensive review of recent advancements in epileptic seizure prediction through the application of machine learning (ML) and deep learning (DL) techniques. Despite notable progress, the challenges posed by high-dimensional, noisy, and non-stationary EEG signals, as well as significant inter-patient variability, continue to impede the widespread clinical adoption of seizure prediction models. Traditional ML methods have laid the groundwork for predictive modeling but often fall short in generalizing across diverse datasets due to their dependence on handcrafted features. In contrast, DL architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, have excelled in extracting complex patterns autonomously, achieving impressive predictive accuracy. These advances have been further enhanced by the use of transfer learning, which leverages pre-trained models to address data scarcity and computational challenges.

Key findings from this review highlight the superior performance of transfer learning architectures such as VGG16, which consistently outperformed other models in terms of accuracy, sensitivity, and specificity. Comparative analyses also underscored the efficacy of 2D-CNNs in capturing spatial features from EEG data and the practical advantages of 1D-CNNs for real-time applications due to their simpler preprocessing requirements. The review of publicly available datasets emphasized the pressing need for standardized, diverse, and harmonized data sources to address inter-dataset variability and class imbalance, both of which hinder model generalizability. Additionally, the exploration of feature engineering and evaluation metrics reinforced the importance of tailored feature extraction and rigorous validation to ensure the reliability and robustness of seizure prediction systems.

While substantial strides have been made in the development of predictive models, critical challenges remain. These include the need for computationally efficient architectures that can operate in real-time, improved generalizability across diverse patient populations, and enhanced interpretability to foster clinical trust and usability. Overcoming these limitations is essential to advancing seizure prediction systems from experimental prototypes to practical clinical tools that can significantly improve patient outcomes and quality of life. By addressing these challenges through innovation and collaboration, the field is well-positioned to transform the management of epilepsy and enhance the standard of care for millions of patients worldwide.

6. Future Work

Advancing seizure prediction research requires addressing existing limitations while exploring innovative strategies to enhance predictive models. Key future directions include the following:

Integration of Multimodal Data:

Incorporating additional physiological signals, such as heart rate variability (HRV), electromyography (EMG), and functional magnetic resonance imaging (fMRI), alongside EEG data, offers the potential to significantly enhance prediction accuracy and robustness. Multimodal approaches can provide a more holistic view of seizure precursors, capturing diverse physiological changes that precede seizure events.

Federated Learning for Collaborative Models

Federated learning frameworks present a promising solution for collaborative model training across institutions while maintaining patient privacy. By leveraging decentralized data, these frameworks can increase dataset diversity, improve cross-patient generalization, and enhance model validation across varied patient populations.

Development of Lightweight Models

Future efforts should focus on developing computationally efficient models through techniques such as model compression, pruning, and quantization. These lightweight architectures will enable deployment in wearable and portable devices, facilitating real-time seizure prediction in resource-constrained environments such as home-based care or remote regions.

Explainable AI (XAI)

The integration of explainable AI techniques is critical for improving model interpretability, ensuring clinicians and end-users can understand and trust model predictions. Visualization tools, such as relevance heat maps and feature attribution mechanisms, can make AI-driven decisions more transparent, bridging the gap between advanced technology and clinical practice.

Standardization and Benchmarking

Establishing standardized protocols for data collection, annotation, and evaluation metrics is essential for consistent benchmarking of predictive models. Collaborative initiatives, such as the International Epilepsy EEG Database (IEED), could play a pivotal role in harmonizing research efforts and enabling fair comparisons across studies.

Addressing Class Imbalance

Class imbalance remains a persistent challenge in seizure prediction. Techniques such as oversampling and synthetic data generation using generative adversarial networks (GANs) should be refined to better represent rare seizure events. These methods can enhance model sensitivity, ensuring accurate detection of seizures without introducing biases or artifacts.

By addressing these research priorities, the field can progress toward creating reliable, interpretable, and clinically deployable seizure prediction systems.

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Research Involving Human and /or Animals: Not Applicable - This study did not involve human participants or animal subjects.

Informed Consent: Not Applicable – As data is open source.

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