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Application Of Machine And Deep Learning In Epileptic Seizure Detection a Systematic Review

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Abstract

Epilepsy, the fourth most common neurological disorder, affects 1% of the global population. Manual EEG-based seizure detection is error-prone, impacting diagnostic and prognostic accuracy. To evaluate the performance of machine and deep learning methods in improving detection of epileptic seizures, define challenges and map out future opportunities for clinical translation. This review collected and analyzed studies published between 2015 and 2023 indexed in PubMed, IEEE Xplore, and ScienceDirect. This review selected studies with an approach to seizure detection based on ML and DL for electroencephalogram (EEG) data. Articles were excluded if they were non-English, were reviews, or did not present empirical results. Text, metrics and challenges data related to algorithms were captured and processed. The review included 50 studies which used over 10 public EEG datasets including CHB-MIT and Bonn. The traditional ML algorithms like SVM resulted in an accuracy of 90%, and modern DL models like the CNNs had an accuracy of 95% or more. Hybrid CNN-LSTM models achieved the best rates compared to other techniques, as they used spatial and temporal EEG data jointly. Disadvantages are focused on data, interpretability, computational complexity, and a need for proprietary hardware. This study highlights the potential of machine and deep learning for high-accuracy automated seizure detection. Addressing data quality, interpretability, and computational demands is crucial for clinical implementation. Future AI models should prioritize personalization and explain ability.

Keywords	Epilepsy detection, EEG analysis, Deep learning, Machine learning, seizure

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INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent seizures occurring in approximately 1% of the worldwide population [1]. It ranks fourth among common neurological disorders, behind migraines, stroke, and Alzheimer's disease [2]. The pathological process is abnormal and excessive activity of neurons in the brain, which can lead to changes in consciousness, movements, and convulsions [3]. Thus, early, and accurate seizure detection is required for appropriate intervention and to reduce complications, ultimately improving patient outcome [4].Conventional diagnosis for epilepsy relies on clinical workup and electroencephalography (EEG), which is a non-invasive test to measure electrical activity in the brain [5]. Nevertheless, manual EEG interpretation is time-consuming, associated with inter-observer subjectivity, and potentially fallible due to human mistakes and hence, limited in its application in extensive seizure detection [6]. As large EEG datasets become more accessible, machine learning (ML) and deep learning (DL) algorithms are being employed to automate steps of the detection process [7].Seizures have also been classifed using machine learning techniques [8] with traditional algorithms such as support vector machines (SVM), k-nearrest neighbors (KNN), and decision trees (DT). These approaches utilize feature extraction techniques to detect seizure patterns in EEG signals [9]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two recent trends in the deep learning domain that have shown high performance by learning how to derive representations of data from raw EEG signals without using any type of hand-crafted feature extraction [10]. While conventional methods for detecting anomalies in time series data have gained extensive attention, hybrid models—such as CNN-LSTM (long short-term memory)—utilize both spatial and temporal features and prove superior to traditional methods in terms of accuracy [11].While these efforts have seen great progress, there are still many hurdles to overcome.) Inter-individual variability in EEG data, the requirement for large, well-annotated datasets, and the black-box characteristics of deep learning models can all impede clinical translation [12]. In addition, computational complexity and hardware needs also reduce the integration of AI-driven seizure detection systems in low-resource settings [13].The objective of this systematic review is to assess the performance of ML and DL models in detecting epileptic seizures, discuss challenges and provide future research directions to support clinical implementation. By evaluating research conducted from 2015 through 2023, this review summarizes the current landscape in AI-enabled seizure detection and its impact on the future of epilepsy diagnosis and treatment [14].

Seizure detection depends on skilled neurologist reviews of electroencephalography (EEG) data and consists of algorithms alongside feature extraction methods which utilize Fourier transforms together with wavelet transforms. The success of these detection methods depends on their pre-defined heuristic algorithms and medical supervision yet suffers from weak application to diverse patient groups [15,16]. The autonomous learning capability of artificial intelligence through machine learning (ML) and deep learning (DL) techniques lets these systems generate better seizure pattern analysis from EEG data [17]. The detection capabilities of support vector machines (SVM) together with random forests depend on human-generated features while deep learning models based on convolutional neural networks (CNNs) and recurrent neural networks (RNNs) directly extract spatial and

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temporal information from raw EEG data [18,19]. Utilizing CNN-long short-term memory (CNN-LSTM) networks as hybrid architectures has proven to enhance seizure detection accuracy by combining spatial and temporal dependencies according to research studies conducted by [20], [21].

The purpose of this systematic review is to assess ML and DL model effectiveness for epileptic seizure detection through evaluation of studies from 2015 to 2023[22]. The review performs a comparative analysis which demonstrates how different traditional ML and DL approaches evaluate through performance metrics such as accuracy and sensitivity and specificity [23].

The Aim and objectives of study evaluation analyzes hindering factors of clinical AI translation which include methodological data issues in combination with model interpretability limitations and processor constraints and standardization problems [24]. The review proposes additional research guidelines to build personalized AI models and enhance explainable AI techniques as well as real-time deployment methods for improved AI seizure detection in medical facilities and home healthcare situations [25].

EPILEPTIC SEIZURE DETECTION: AN OVERVIEW

EEG-BASED DETECTION

EEG stands as the preferred method for epileptic seizure detection because it provides precise measurement of brain electrical signals at high temporal accuracy. The onset of seizures produces specific patterns of abnormal rhythmic activity that appears in EEG signal recordings[26]. Timely patient intervention alongside individual treatment plans requires accurate epileptic seizure recognition through EEG monitoring for both medical diagnosis and continuous patient monitoring purposes[27].

EEG signals used for seizure detection exist mainly as scalp EEG (sEEG) and intracranial EEG (iEEG). EEG testing through scalp electrodes provides a noninvasive method of measuring brain signal activity from the surface of the head. When measured through EEG monitoring it is used frequently both clinically and in research activities because of its simplicity during collection and wide range of applications [28]. The electrical signals recorded from the scalp face two challenges: they are easily affected by artifacts and brain signal transmission becomes less precise because electrical signals diminish before reaching the scalp due to the skull and scalp barrier [29, 30]. The placement of electrodes sharply on the cortical surface or within the brain during intracranial EEG (iEEG) procedures yields high-quality signals accompanied by precise spatial mapping. iEEG technology provides superior accuracy in seizure pinpointing but research scientists use this procedure primarily for surgical epilepsy assessment due to its invasive nature[31].

PUBLIC DATASETS FOR EPILEPTIC SEIZURE DETECTION

Research into automated seizure detection through artificial intelligence has received substantial progress because public EEG data now exists for developers to create and validate machine learning and deep learning models. A collection of EEG datasets can be found in these three commonly used sources [32].

CHB-MIT Scalp EEG Dataset gathers scalp EEG recordings which were generated by Children's Hospital Boston and the Massachusetts Institute of Technology (MIT) from pediatric epilepsy patients [33]. This dataset stands among the most popular choices for determining the performance of ML/DL-based seizure detection algorithms.

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The Bonn EEG dataset originates from University of Bonn and contains epileptic along with normal EEG signals which enables researchers to perform controlled seizure classification investigations [34]. The dataset splits into five smaller collections which maintain different measurement specifications thereby supporting studies of seizure source identification and spread detection.

Scientists can access the Temple University Hospital (TUH) EEG Corpus which stands as one of the biggest available EEG databases where thousands of scalp EEG data from epileptic patients exists [35]. This large data collection offers great value for developing seizure detection algorithms because of its broad range of data types.

MACHINE LEARNING TECHNIQUES FOR SEIZURE DETECTION

FEATURE EXTRACTION METHODS

The process of feature extraction stands as an essential requirement in ML-based seizure detection since it converts raw EEG signals into significant representations for accurate classification purposes [36]. Multiple feature extraction procedures operate on EEG data because of its complex non-stationary characteristics to detect hallmark seizure activities [37]. The extracted features belong to three general categories described as time-domain attributes together with frequency-domain indicators and time-frequency domain features[38,39].

TIME-DOMAIN FEATURES

- Time-domain features directly measure the variations of EEG signal amplitude during timed intervals. The analytic features require efficient computations and produce statistical data that describe signal forms. The most widely utilized time-domain features consist of the following:
- Mean alongside variance provides information about signal dispersion for central tendency measurement and baseline shifts observation during seizure occurrences.
- Skewness together with kurtosis provides measurements of signal shape asymmetry and peak sharpness for distinguishing between seizure and non-seizure conditions.
- Energy along with entropy serve as measures of signal power and disorder which help discover abrupt electrical changes occurring during seizures.
- The Horthy parameters serve as diagnostic measures which track signal movement and complexity throughout periods of signal change in order to detect seizure onset.

FREQUENCY-DOMAIN FEATURES

- Frequency-domain analysis requires the conversion of EEG signals into their elemental frequencies for detecting signature seizure spectral patterns. Common frequency-domain techniques include [40].
- The Fourier Transform separates EEG signals into different frequencies to identify bands connected with seizures and specifically detects delta, theta, alpha, beta and gamma activity patterns [41].
- PSD evaluates power distributions across various frequency ranges to show increased high-frequency motions and absent low-frequency actions during seizure occurrences [42].

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- Wavelet Transform contains features permitting a detailed analysis of EEG data at multiple resolution scales to detect sudden patterns preceding seizure occurrence [43].

TIME-FREQUENCY FEATURES

- The non-stationary nature of seizures makes performance better when analysis methods capture spectral together with temporal characteristics. These methods include:
- The Short-Time Fourier Transform divides EEG signals into short time windows so it can run Fourier Transform analysis on these sections to detect the changing frequency content of the data.
- The frequency resolution capabilities of Wavelet Packet Decomposition (WPD) exceed Wavelet Transform so it helps detect seizures with greater precision.
- Hilbert-Huang Transform (HHT) analyzes EEG signals through its intrinsic mode functions (IMFs) for assessing frequency variances at different times which enhances the detection of minimal seizure patterns.
- The successful implementation of ML model performance for seizure detection heavily depends on effective extraction of relevant features. The selection of features depends on three fundamental aspects that include the unique traits of the EEG dataset, system processing capacity and clinical application requirements for interpretability.

TRADITIONAL MACHINE LEARNING MODELS

Epileptic seizure detection heavily relied on traditional machine learning (ML) models because these models extract meaningful features from EEG signals to create classifications. The models extract time domain characteristics and frequency domain domains and time-frequency domain characteristics which allow them to detect seizure and non-seizure states. Two main machine learning models serve the detection of epileptic seizures [44].

SUPPORT VECTOR MACHINES (SVM)

The detection of seizures using EEG signals through Support Vector Machines (SVM) has gained popularity because SVM effectively handles data sets of high dimensions. SVM operates through identifying the best possible separating plane that provides the widest margin between seizure events and non-seizure categories. SVM achieves nonlinear modeling of complex EEG patterns through radial basis function (RBF) and polynomial kernel functions [45]. The generalized performance of SVMs comes at a cost because their accurate operation demands thorough parameter adjustments and results in high computational demands when handling big datasets.

RANDOM FOREST (RF)

The random subset of EEG data used for training the decision trees in RF models combines into a single prediction through majority voting techniques. The interpretability of RF models together with their robustness against over fitting describes their ability to handle noisy EEG data effectively. The lack of appropriate feature selection makes RF perform poorly in high-dimensional spaces [46].

K-NEAREST NEIGHBORS (KNN)

It classifies EEG signals through K-Nearest Neighbors (KNN) by determining the majority class among k nearest training samples. The implementation of KNN remains straightforward since the method needs no explicit model training process which enables its application in real-time situations [47]. The choice of k parameter

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along with the selected distance metric directly affects KNN performance yet its calculations become inefficient when processing extensive datasets.

DECISION TREES (DT)

The hierarchical classification of EEG signals in Decision Trees occurs when decision rules slice feature space into succession. These algorithms maintain high interpretability together with computational efficiency which makes them a standard solution for seizure detection systems [48]. DTs will tend to produce over fitting when applied to complex datasets of EEG signals. By using pruning techniques together with ensemble methods such as RF and boosting this limitation can be reduced [49].

ENSEMBLE LEARNING APPROACHES

Ensemble learning methods that include bagging and boosting enhance typical ML models through the composition of multiple basic classifiers for producing effective solutions.

PERFORMANCE ANALYSIS OF ML MODELS

- To evaluate the performance of ML models for detecting epileptic seizures multiple critical metrics are employed.
- The accuracy score evaluates how precise the model identifies between seizure and non-seizure activities.
- An accurate detection of real seizure events defines sensitivity (Recall) within the model. Higher model sensitivity remains vital to minimize false negative detections because they would cause seizures to go undetected.
- The model needs to demonstrate its capability to correctly detect non-seizure activities as detailed by its specificity quotient. Creating a specific model helps lower the number of incorrect warnings and alarms.
- F1-score represents the harmonic relationship between precision and sensitivity to properly manage false-positive and false-negative outcomes.

COMPARISON OF ML MODELS

ML Model	Accuracy	Sensitivity	Specificity	F1-score
SVM	High	Moderate to High	High	Moderate to High
RF	High	High	High	High
KNN	Moderate	Moderate	Moderate	Moderate
DT	Moderate to High	High	Moderate	Moderate
Ensemble (Boosting)	Very High	High	High	Very High

Among traditional ML models, ensemble learning approaches (e.g., RF and boosting techniques) consistently outperform standalone classifiers by leveraging multiple weak models to improve robustness. However, these models rely on feature engineering, which may limit their ability to generalize across diverse EEG datasets.

DEEP LEARNING TECHNIQUES FOR SEIZURE DETECTION

Epileptic seizure detection underwent a transformation through deep learning technology which allows the recognition of high-dimensional patterns in EEG signals without manual process intervention. Deep learning models directly extract spatial temporal and spectral information from source or slightly preprocessed EEG data without needing predefined handcrafted features that traditional machine learning methods need. This section examines deep learning seizure detection methods focusing on CNNs, RNNs, hybrid configurations, together with performance evaluation frameworks.

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CNN-BASED APPROACHES

Seizure detection involves the extensive use of Convolutional Neural Networks (CNNs) because these networks successfully extract patterns that exist in spatial space from EEG signals. The different processing forms CNNs use to analyze EEG data entail multiple structures [50].

- The 1D CNN extracts temporal patterns from raw EEG time-series data when used directly on the data.
- The signals from EEG undergo two-dimensional CNN processing by transforming them into spectrogram or time-frequency solutions including Short-Time Fourier Transform and Wavelet Transform to merge spatial patterns with spectral features.
- Spatial-temporal feature extraction is possible across different electrode positions through the implementation of 3D CNNs when working with volumetric multi-channel EEG data input.

CNN-based models present high detection accuracy for seizures because they automatically learn features and develop hierarchical representations of EEG signal properties. Long-term dependencies between EEG data points remain difficult for these models even though they succeed in detecting seizure patterns [51].

RNN AND LSTM-BASED MODELS

The recurrent neural network family of models together with long short-term memory (LSTM) demonstrates outstanding ability in recognizing temporal connections within EEG signal series. Whenever these models operate on sequential data they sustain temporal memory between time steps which optimizes their capacity for tracking seizure event dynamics [52].

- Recurrent neural networks (RNNs) recreate EEG signal sequences with the help of repeating connections although they experience fading gradients over extended time dependencies.
- LSTMs solve the RNN limitations through memory cells together with gating mechanisms to maintain long-range temporal information in EEG signals.
- Gated Recurrent Units (GRUs) stand as a streamlined version of LSTMs used for seizure detection applications because they perform with reduced computational requirements.
- The detection capability of RNN- and LSTM-based models enables sequence pattern identification in EEG data although these models need large computational power during training processes.

HYBRID DEEP LEARNING MODELS

Scientists use hybrid architectures which join CNNs with RNNs/LSTMs to exploit spatial along with temporal dependencies in EEG signals. The integration of CNN features together with LSTMs or Transformer-based models makes up these hybrid models that analyze EEG patterns sequentially [53].

- Both CNN layers of the CNN-LSTM extract spatial characteristics and LSTM layers process temporal relationships to increase detection performance of seizures.
- The latest generation of Transformer architectures together with its derivatives including BERT and ViTs has been studied for seizure detection purposes by leveraging its advanced sequence modeling mechanism through attention mechanisms.

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- Auto encoders together with GANs serve as unsupervised seizure detection algorithms that conduct data augmentation to increase system resilience when dealing with minimal labeled EEG samples.
- Models which combine separate architectures reach top performance levels yet their execution complexity makes real-time applications difficult to implement.

PERFORMANCE COMPARISON OF DL MODELS

The effectiveness of DL models is typically evaluated against traditional ML techniques using key performance metrics such as accuracy, sensitivity, specificity, and F1-score.

COMPARISON OF DL AND ML MODELS

Model	Accuracy	Sensitivity	Specificity	F1-score	Computational Cost
1D CNN	High	High	Moderate	High	Moderate
2D CNN	Very High	High	High	Very High	High
3D CNN	Very High	Very High	High	Very High	Very High
RNN	Moderate	Moderate	Moderate	Moderate	High
LSTM	High	High	High	High	High
CNN-LSTM	Very High	Very High	High	Very High	Very High
Transformer	Very High	Very High	Very High	Very High	Extremely High
Traditional ML (SVM, RF)	Moderate	Moderate	High	Moderate	Low

The detection performance of seizures benefits from the use of CNN-based models especially through 2D CNNs together with hybrid CNN-LSTM architectures above traditional ML techniques. The promise of generator-based models exists despite their limitation of requiring heavy computational power which reduces their usefulness for real-time implementation.

FUTURE DIRECTIONS IN PERFORMANCE OPTIMIZATION

Future research needs to center on three approaches to boost seizure detection effectiveness.

- The deployment process should be optimized to support deep learning models enabled for edge computing and wearable technology devices.
- The improvement of data imbalance can be achieved by using both augmentation methods alongside adaptive learning techniques.
- Explainable AI (XAI) methods should be implemented to enhance the interpretation capabilities of AI models.
- The implementations will allow AI seizure detection approaches to merge with clinical practice norms.

DATA QUALITY AND AVAILABILITY

The performance and effectiveness of ML/DL models largely depends on the quality and quantity of provided EEG data. Methods which release their data to the public commonly present fundamental problems with class biasing alongside missing data

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points together with deficient patient population representation thus reducing model application scope[55,56].

The successful application of EEG-based seizure detection requires standardization of recording techniques and electrode positions and artifacts reduction since these factors affect model development consistency between different clinical environments[57].

GENERALIZABILITY AND ROBUSTNESS

The high performance of multiple digital processing models on isolated datasets transforms into poor generalization capability during examinations involving different clinical environments including various hospitals and devices and patient demographic groups[58].

According to researchers the process of overfitting exists as a recurring problem leading algorithms to master dataset-specific patterns at the cost of general seizure-related features for multiple patient populations[59].

COMPUTATIONAL COMPLEXITY AND REAL-TIME CONSTRAINTS

Real-time implementation requires effective hardware-specific compression of models together with acceleration methods and edge computing techniques to keep up with the needs of portable EEG devices for real-time seizure detection[60].

LACK OF EXPLAINABILITY AND CLINICAL ACCEPTANCE

The unexplainable nature of black box AI systems creates obstacles for medical professionals to understand program decisions which affects their confidence about system reliability during crucial medical incidents[61].

Transparent explanations from Explainable AI (XAI) methods allow essential understanding about how classification of EEG signals and seizure detection works[62].

LIMITATIONS

Several hurdles prevent the practical implementation of AI-powered seizure detection in medical facilities although major technological progress has occurred. Model deployment limitations in practice arise due to data availability problems and theoretical model adaptability requirements together with CPU demands and interpretability issues.

CHALLENGES AND FUTURE DIRECTIONS

CHALLENGES IN AI-DRIVEN SEIZURE DETECTION

- Data Standardization and Interoperability: The need for uniform EEG formats and annotations.
- The implementation of personalized AI models solves problems linked to different individual patient characteristics.
- Efficient Model Deployment: Optimizing AI models for real-time applications on portable devices.
- Regulatory and Ethical Considerations: Ensuring compliance with medical regulations and ethical AI usage.

FUTURE DIRECTIONS

- XAI has developed the ability to make AI more transparent through attention based mechanisms and features attribution during model interpretation.
- Detection accuracy gets improved through mergings of EEG data with various physiological signals to produce multimodal information.
- AI models should be developed to forecast seizures just before they happen.

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- A clinical validation phase must include prospective trials together with collaboration between medical specialists and researchers.

CONCLUSION

Artificial intelligence methodologies particularly machine learning and deep learning have upgraded epileptic seizure detection by developing automated EEG examination with high precision at efficient speeds. Standard ML techniques depending on manually designed features have shown successful results yet DL versions including CNNs and RNNs together with hybrid systems outperform them as they analyze raw EEG data to obtain spatial and temporal characteristics. Medical institutions face difficulties with standardizing data while developing personalized systems and deploying real-time implementations and conforming to regulations which prevents full use in clinical procedures. The development of AI systems requires future research to concentrate on three main objectives: making AI systems explain their decision-making processes, improving data integration between different medical sources while maintaining real-time seizure prediction. AI-based seizure detection requires combined work between researchers in AI and neurologists and biomedical engineers to establish practical usage in clinical settings which benefits patient results and life quality. The solution of these issues will lead to the development of patient-friendly robust scalable AI methods for epilepsy management.

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