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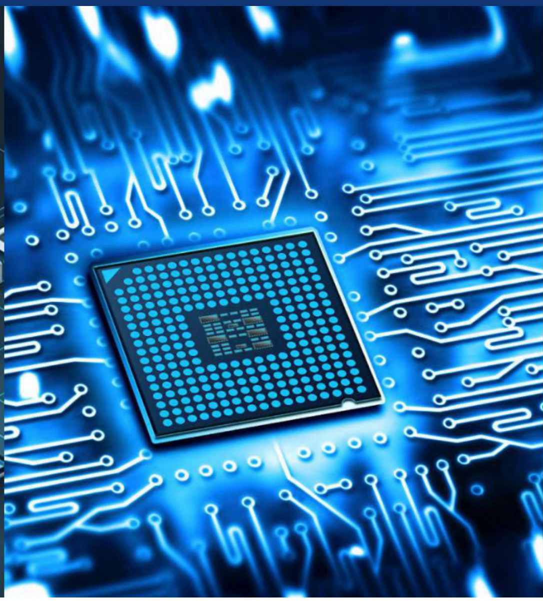


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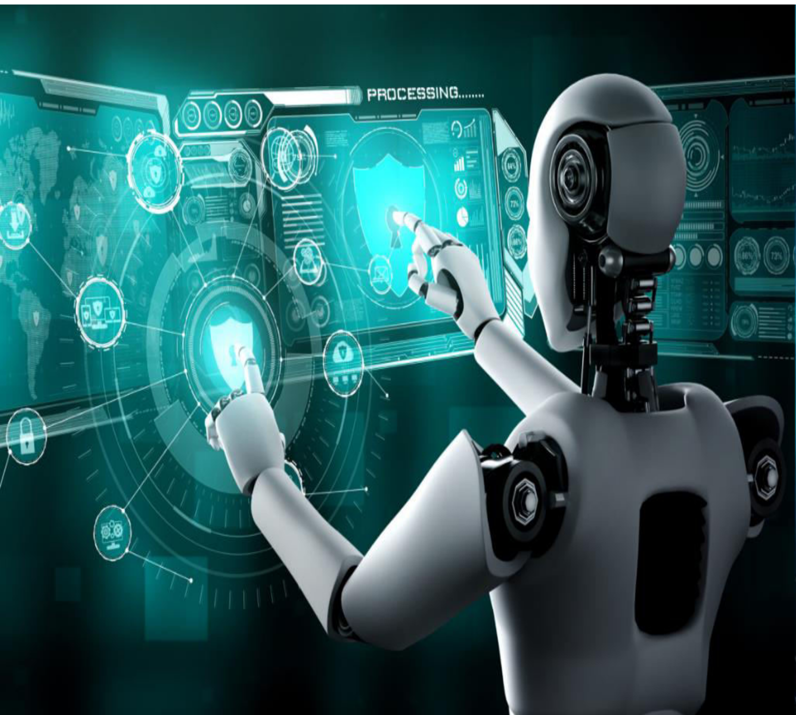

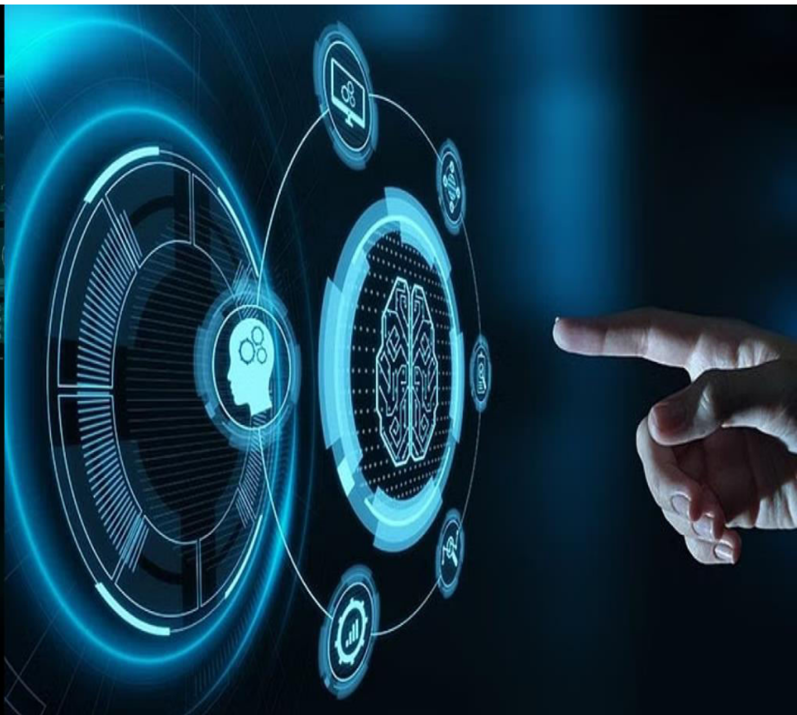

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A Survey on Epileptic Seizure Detection Using Deep Learning

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ABSTRACT: Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain. Electroencephalography (EEG) is widely used for epilepsy diagnosis because of its high temporal resolution and ability to capture neural activity in real time. However, manual inspection of long-duration EEG recordings is time-consuming and prone to human error. Automated seizure detection has therefore become an important research area in biomedical signal processing and artificial intelligence. Recent advances in deep learning enable models to automatically learn discriminative patterns from EEG signals without extensive handcrafted feature engineering. Architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, hybrid CNN–LSTM models, attention mechanisms, and transformer-based approaches have demonstrated promising results in recent studies. This survey reviews recent deep learning approaches for EEG-based epileptic seizure detection published between 2022 and 2025, analyses commonly used datasets and evaluation metrics, and highlights research limitations such as partial dataset utilization and accuracy-centric evaluation. Finally, potential research directions are discussed for developing reliable and clinically deployable seizure detection systems.

KEYWORDS: Epileptic Seizure Detection; EEG; Deep Learning; CNN; LSTM; Attention Mechanism; Ensemble Methods

I. INTRODUCTION

Epilepsy is one of the most common neurological disorders worldwide and affects more than 50 million individuals. It is characterized by recurrent seizures resulting from abnormal neuronal discharges in the brain. Early and accurate detection of epileptic seizures is essential for effective diagnosis, treatment planning, and long-term monitoring.

Electroencephalography (EEG) is widely used to record electrical activity in the brain and detect seizure patterns because of its high temporal resolution. However, EEG recordings collected in clinical environments often span several hours or days, making manual analysis by neurologists extremely time-consuming. In addition, visual inspection of EEG signals may lead to inconsistent interpretation due to human error and observer variability.

To address these challenges, automated seizure detection systems have been widely explored using machine learning and deep learning techniques [1, 2]. Early research relied on handcrafted feature extraction combined with traditional classifiers such as Support Vector Machines and Decision Trees. Although these methods achieved moderate success, their performance strongly depended on domain knowledge and carefully engineered features.

Recent advances in deep learning have significantly improved EEG signal analysis. Deep neural networks can automatically learn hierarchical representations from raw EEG signals and therefore eliminate the need for extensive feature engineering. Consequently, architectures such as CNNs, RNNs, LSTMs, and hybrid CNN–LSTM models have become dominant techniques for epileptic seizure detection.

This survey reviews recent deep learning approaches for EEG-based seizure detection, analyses commonly used datasets, discusses performance evaluation metrics, and identifies research gaps and limitations in current studies.

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II. COMMONLY USED EEG DATASETS

The performance of automated seizure detection systems strongly depends on the EEG datasets used for training and evaluation. Publicly available datasets allow researchers to benchmark different algorithms and compare model performance under standardized conditions.

Bonn EEG Dataset: The Bonn EEG dataset is one of the earliest publicly available datasets for epilepsy research. It contains single-channel EEG recordings divided into five subsets representing healthy and epileptic conditions. Each subset consists of 100 EEG segments with a duration of 23.6 seconds. Due to its controlled experimental setup and clear separation between seizure and non-seizure signals, this dataset is widely used for evaluating machine learning algorithms. However, it lacks the complexity and variability present in real clinical EEG recordings.

CHB-MIT EEG Dataset: The CHB-MIT dataset is one of the most widely used datasets for epileptic seizure detection research. It contains multi-channel EEG recordings collected from paediatric patients with intractable seizures. The dataset includes 23 subjects with continuous EEG recordings ranging from several hours to multiple days. Each recording contains multiple EEG channels sampled at 256 Hz. The dataset supports both patient-specific and cross-patient evaluation, making it highly valuable for validating deep learning models.

TUH EEG Seizure Corpus: The Temple University Hospital (TUH) EEG seizure corpus is one of the largest publicly available EEG datasets for seizure detection research. It contains thousands of EEG recordings collected in clinical environments. Compared to other datasets, TUH EEG includes more diverse seizure types and patient conditions. As a result, it is commonly used to evaluate the generalization capability of deep learning models in real-world clinical scenarios.

III. TRADITIONAL AND MACHINE LEARNING BASED APPROACHES

Early epileptic seizure detection research relied on classical signal processing techniques combined with traditional machine learning classifiers. These approaches focus on extracting meaningful features from EEG signals before classification.

3.1 Traditional Signal Processing Based Approaches

Traditional seizure detection systems typically involve multiple stages including signal preprocessing, feature extraction, and classification. Common preprocessing techniques include filtering, artifact removal, and normalization of EEG signals. Feature extraction methods such as Fourier Transform, Wavelet Transform, entropy-based features, and statistical measures are used to characterize EEG signals in time and frequency domains.

These handcrafted features are designed to capture changes in brain activity during seizure events. Although such approaches are computationally efficient and interpretable, their performance strongly depends on expert knowledge and carefully designed features. In addition, seizure patterns vary significantly across patients, which limits the generalization capability of rule-based detection systems.

3.2 Machine Learning Based Approaches

Machine learning techniques improved seizure detection performance by replacing rule-based decision systems with statistical classifiers. In these approaches, extracted EEG features are used to train classifiers such as Support Vector Machines (SVM), k-Nearest Neighbours (KNN), Decision Trees, Random Forests, and ensemble learning models [1, 3, 4].

For example, the EasyEnsemble framework proposed by Kumar et al. [1] addresses class imbalance in EEG datasets by combining multiple classifiers trained on balanced subsets of data. Similarly, SVM-based seizure detection models have been widely used due to their strong generalization ability.

Despite these improvements, machine learning approaches still depend heavily on feature engineering and may fail to capture complex temporal patterns in EEG signals. This limitation motivated the development of deep learning-based seizure detection models.

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IV. DEEP LEARNING BASED APPROACHES

Deep learning techniques have significantly advanced EEG-based seizure detection by enabling automatic feature extraction from raw EEG signals. Unlike traditional machine learning approaches, deep neural networks can learn hierarchical representations of EEG signals without relying on handcrafted features.

4.1 CNN Based Approaches

Convolutional Neural Networks (CNNs) are widely used in EEG analysis because they can automatically learn spatial patterns from input signals. In seizure detection tasks, one-dimensional CNN architectures process EEG time-series data to identify characteristic seizure patterns. Alhussein et al. [5] proposed a deep 1D-CNN architecture that achieved high detection accuracy on the CHB-MIT dataset. CNN models are computationally efficient and suitable for real-time applications; however, they mainly capture local temporal patterns and may struggle to model long-term dependencies in EEG sequences.

4.2 RNN and LSTM Based Approaches

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are designed to process sequential data and capture temporal dependencies. These models are particularly suitable for EEG signals because seizure patterns often evolve over time. Furui et al. [6] applied RNN-based architectures to capture temporal relationships in EEG signals, while Palanisamy et al. [7] demonstrated the effectiveness of LSTM networks for early seizure detection.

4.3 Hybrid CNN–LSTM Approaches

Hybrid CNN–LSTM architectures combine the strengths of convolutional and recurrent networks. In these models, CNN layers extract spatial features from EEG signals, while LSTM layers capture long-term temporal dependencies. Abdelhameed et al. [2] demonstrated that such hybrid architectures outperform standalone CNN or LSTM models for seizure detection.

4.4 Attention-Based and Transformer Models

Attention mechanisms improve model performance by allowing neural networks to focus on the most relevant EEG segments during classification. Tang et al. [8] proposed a Bi-LSTM model with an attention mechanism that achieved improved detection accuracy. More recently, transformer based architectures such as Vision Transformers have been explored for EEG signal analysis [9]. Although these models achieve high accuracy, they often require large training datasets and substantial computational resources.

4.5 Three-Dimensional CNN Approaches

Three-dimensional CNN architectures capture spatial, temporal, and frequency characteristics of EEG signals simultaneously. Khan et al. [10] proposed an attention-enhanced 3D-CNN model that achieved state-of-the-art seizure detection performance. However, these models require significant computational power, which may limit their deployment in real-time clinical systems.

V. PERFORMANCE EVALUATION METRICS

Performance evaluation commonly includes accuracy, sensitivity, specificity, precision, recall, F1score, and AUC. Balanced metrics are important because EEG datasets are often imbalanced.

Sensitivity measures the ability of a model to correctly detect seizure events, while specificity evaluates the capability to correctly identify non-seizure EEG segments. Precision and recall provide additional insight into the reliability of seizure predictions, and the F1-score combines both metrics into a single performance indicator. The Area Under the Receiver Operating Characteristic Curve (AUC) is also widely used to evaluate the overall discrimination capability of seizure detection models across different classification thresholds.

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VI. COMPARATIVE ANALYSIS

Table 1: Comparison of Existing EEG-Based Seizure Detection Methods

Reference	Year	Method	Dataset	Accuracy (%)
[1]	2022	EasyEnsemble	CHB-MIT	94.6
[2]	2023	CNN-RNN-LSTM	CHB-MIT	96.8
[3]	2024	SVM	Bonn	92.4
[5]	2024	1D-CNN	CHB-MIT	97.1
[4]	2024	Ensemble Learning	Bonn	95.9
[6]	2024	RNN	CHB-MIT	96.2
[7]	2024	LSTM	CHB-MIT	98.0
[8]	2024	Bi-LSTM + Attention	CHB-MIT	99.1
[9]	2024	Vision Transformer	CHB-MIT	98.4
[11]	2025	1D-CNN	Clinical EEG	95.1
[12]	2025	CNN-LSTM	CHB-MIT	96.9
[10]	2025	3D-CNN + Attention	TUH EEG	99.8

VII. LIMITATIONS OF EXISTING APPROACHES

Despite significant progress in EEG-based epileptic seizure detection, several limitations remain in current research. One major issue is that many studies train and evaluate their models using only a portion of the CHB-MIT dataset. Partial dataset utilization may lead to optimistic performance results and limits the ability of models to generalize across different patients.

Another limitation is the heavy reliance on accuracy as the primary evaluation metric. EEG datasets are typically highly imbalanced, where non-seizure segments significantly outnumber seizure events. In such cases, accuracy alone does not provide a reliable measure of model performance. Metrics such as precision, recall, F1-score, and AUC are necessary to evaluate the true effectiveness of seizure detection systems.

In addition, many high-performing deep learning models such as transformer-based architectures and 3D-CNN networks require large computational resources and extensive training data. This makes their deployment challenging in real-time clinical environments.

Finally, variations in preprocessing techniques, data segmentation methods, and evaluation protocols make direct comparison between different studies difficult. These challenges highlight the need for standardized evaluation frameworks and computationally efficient models that can achieve reliable seizure detection in practical healthcare systems.

VIII. FUTURE WORK

Future research should focus on lightweight and generalized seizure detection models capable of cross-patient evaluation and real-time deployment. Developing computationally efficient deep learning architectures that can operate on long EEG recordings without excessive resource requirements remains an important research direction.

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In addition, future studies should emphasize the use of larger and more diverse EEG datasets to improve model generalization across different patients and seizure types. Integrating explainable artificial intelligence techniques may also help clinicians better understand model decisions and increase the reliability of automated seizure detection systems in practical healthcare applications.

IX. CONCLUSION

This survey reviewed recent deep learning approaches for EEG-based epileptic seizure detection and highlighted current research challenges related to dataset utilization, evaluation metrics, and deployment in clinical environments. The analysis of widely used datasets such as Bonn, CHBMIT, and TUH EEG emphasizes the importance of dataset diversity and realistic evaluation. Furthermore, the study of different methodologies indicates that hybrid and attention-based deep learning models provide improved detection performance compared to traditional approaches.

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