



# A Review of Epileptic Seizure Prediction Using EEG, ECG, PPG and EMG Signals

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**Abstract.** Epilepsy is a neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain. Predicting seizures before their onset can significantly improve patient safety and enable timely medical intervention. Recent advancements in wearable biosensors and artificial intelligence have enabled continuous monitoring of physiological signals in real-world environments. This paper presents a survey of epileptic seizure prediction approaches based on physiological signals including electroencephalography (EEG), electrocardiography (ECG), photoplethysmography (PPG), and electromyography (EMG). The study summarizes commonly used public datasets such as CHB-MIT, Bonn EEG, and the Temple University EEG corpus that are widely used to develop and evaluate prediction algorithms. Furthermore, traditional machine learning approaches as well as recent deep learning architectures for biomedical signal analysis are reviewed. The review also highlights recent progress in wearable monitoring systems and multimodal signal fusion strategies. Finally, major research challenges including limited datasets, signal noise, patient variability, and large number of false alerts are analyzed, and future research directions such as multimodal sensing, personalized prediction models, wearable AI systems, and explainable artificial intelligence are outlined.

**Keywords:** Epileptic Seizure Prediction, EEG, ECG, PPG, EMG, Wearable Healthcare, Deep Learning

## I. Introduction

Epilepsy is a neurological disorder characterized by recurrent seizures resulting from abnormal electrical activity in the brain. The condition affects millions of individuals worldwide and can significantly impact daily activities, personal safety, and overall quality of life. Since seizures often occur unexpectedly, patients are at increased risk of injury and psychological stress. Therefore, the development of reliable techniques for early seizure detection and prediction has become an important research focus in biomedical engineering and healthcare technology [1], [2].



Advancements in wearable sensing devices and artificial intelligence (AI) have enabled continuous monitoring of physiological signals and automated seizure analysis. Modern wearable systems can record multiple biosignals including electroencephalography (EEG), electrocardiography (ECG), photoplethysmography (PPG), and electromyography (EMG). These signals reflect neurological, cardiovascular, and muscular responses that may change before or during seizure episodes. By integrating AI-driven analysis with wearable sensors, researchers are developing intelligent monitoring platforms capable of detecting and predicting seizures in real-world environments [3].

Among the available biosignals, EEG is the most widely studied for seizure prediction because it directly captures electrical activity produced by neurons in the brain. Early research primarily relied on signal processing and statistical methods to identify spatial and temporal EEG patterns associated with seizure onset [4]. With the rapid development of machine learning and deep learning techniques, advanced computational models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures have been applied to analyze EEG recordings and detect preictal patterns that may precede seizures [5], [6]. Some studies also demonstrate that combining traditional machine learning approaches with deep learning models can further improve seizure detection performance [7].

Apart from EEG signals, seizures can also influence cardiovascular and muscular activity due to changes in the autonomic nervous system. ECG signals and heart rate variability (HRV) are commonly analyzed to study cardiac responses during seizure events. Wearable ECG monitoring systems combined with machine learning algorithms have shown promising capability in detecting seizure-related abnormalities in ambulatory environments [8], [9]. Similarly, PPG signals can capture variations in peripheral blood flow, while surface electromyography (sEMG) can detect muscle contractions associated with motor seizures such as generalized tonic-clonic seizures [10], [11].

More recently, multimodal monitoring approaches that combine multiple physiological signals have gained increasing attention. By integrating signals such as EEG, ECG, PPG, and EMG, multimodal systems can capture complementary physiological information and potentially improve prediction reliability. Several wearable monitoring platforms have demonstrated the feasibility of detecting seizures using multimodal physiological data collected from portable devices [12], [13]. Despite these advancements, challenges including signal noise, variability among patients, and data quality issues continue to limit the performance of real-world seizure monitoring systems [14]. Additionally, non-EEG monitoring techniques have been explored to enhance continuous patient monitoring and reduce the risk of sudden unexpected death in epilepsy (SUDEP) [15].

This paper presents a comprehensive review of epileptic seizure detection and prediction methods based on physiological biosignals. The study discusses commonly used biosignals, publicly available datasets, and machine learning and deep learning ap-



proaches for seizure prediction. Furthermore, re-cent developments in wearable monitoring technologies are highlighted, along with key research challenges and potential future directions for improving seizure prediction systems.

## II. Physiological Signals Used for Seizure Prediction

Seizure prediction systems rely on physiological signals that reflect neurological and autonomic changes associated with epileptic events. Advances in biomedical sensing technologies have enabled continuous monitoring of biosignals such as electroencephalography (EEG), electrocardiography (ECG), photoplethysmography (PPG), and electromyography (EMG). These signals provide complementary information about brain activity, cardiovascular responses, vascular dynamics, and muscular activity during seizures.

### 1. Electroencephalography (EEG)

Electroencephalography (EEG) is the most widely used signal for epileptic seizure detection and prediction because it directly records electrical activity generated by neurons in the brain. EEG signals often exhibit distinctive patterns such as spikes, sharp waves, and rhythmic discharges that may appear before seizure onset. Early studies applied signal processing and statistical methods to identify spatial and temporal correlations in EEG recordings that indicate potential seizure precursors [4].

Recent developments in artificial intelligence have introduced advanced computational techniques for EEG analysis. Deep learning models such as convolutional neural networks (CNNs), graph neural networks (GNNs), and transformer-based architectures can learn complex spatial and temporal relationships from multi-channel EEG signals [5], [6]. These models reduce the need for handcrafted feature extraction and have shown improved performance in seizure prediction tasks. Hybrid approaches that combine traditional machine learning with deep learning have also demonstrated promising results when applied to EEG datasets [7].

### 2. Electrocardiography (ECG)

Electrocardiography (ECG) records the electrical activity of the heart and provides insights into cardiovascular function. Epileptic seizures can affect the autonomic nervous system, leading to changes in heart rate and heart rate variability (HRV). These physiological responses can therefore serve as useful indicators for seizure detection and prediction.

Recent studies have investigated wearable ECG monitoring systems combined with machine learning techniques to analyze HRV patterns and detect seizure-related anomalies. Machine learning-based anomaly detection applied to ECG signals has shown promising capability in identifying abnormal cardiovascular patterns associated with seizure onset [8]. Additionally, wearable ECG datasets have demonstrated the feasibility of seizure detection in real-world ambulatory environments [9].



### **3. Photoplethysmography (PPG)**

Photoplethysmography (PPG) is a non-invasive optical technique used to measure variations in peripheral blood volume. Due to its low cost and compact design, PPG sensors are widely integrated into wearable devices such as smartwatches and fitness trackers. PPG signals provide indirect information about cardiovascular activity and autonomic nervous system responses.

During seizure episodes, changes in heart rate and blood circulation may occur and can be detected through PPG recordings. Several studies have reported noticeable cardiovascular variations in PPG signals during seizures, indicating that this signal can provide useful complementary information for seizure monitoring systems [10].

### **4. Electromyography (EMG)**

Electromyography (EMG) measures electrical activity produced by skeletal muscles and is particularly useful for detecting motor seizures such as generalized tonic-clonic seizures. Surface EMG (sEMG) sensors capture muscle contractions that occur during seizure episodes and can provide valuable information about seizure characteristics.

Previous studies have shown that sEMG monitoring can effectively detect convulsive seizures by analyzing characteristic muscle activation patterns during seizure events [11]. As a result, EMG is often used as a complementary signal in multimodal seizure monitoring systems.

### **5. Multimodal Signal Integration**

Although individual physiological signals can provide useful information, relying on a single modality may limit prediction accuracy. Multimodal approaches that combine signals such as EEG, ECG, PPG, and EMG can improve system performance by capturing complementary physiological responses associated with seizures.

Recent wearable monitoring systems integrate multiple sensors to collect multimodal physiological data and apply machine learning algorithms for seizure detection and prediction [12], [13]. These approaches can improve reliability and reduce false detections. However, challenges such as signal noise, sensor reliability, and variability in data quality must be addressed to ensure accurate analysis of physiological signals in wearable environments [14].

## **III. Publicly Available Datasets for Seizure Prediction**

The development of reliable seizure detection and prediction algorithms depends on the availability of large annotated datasets containing physiological recordings from patients with epilepsy. Publicly accessible datasets play a significant role in training artificial intelligence and deep learning models and enable researchers to perform fair and consistent comparisons between different prediction methods.

One of the most commonly used resources in seizure prediction studies is the CHB-MIT EEG dataset. This dataset consists of long-term scalp EEG signals collected from



pediatric patients diagnosed with epilepsy. It includes multi-channel EEG signals recorded over extended monitoring sessions along with detailed annotations of seizure events. Due to its availability and well-labeled recordings, the CHB-MIT dataset is now a widely used benchmark for developing and evaluating seizure detection and prediction algorithms.

Another commonly used dataset is the Bonn EEG dataset, which contains pre-segmented EEG signals representing different brain states including healthy, interictal, and seizure activity. Although the recordings are shorter compared to long-term datasets, the Bonn dataset is frequently used for evaluating classification models due to its clear separation of physiological conditions.

The Temple University Hospital (TUH) EEG corpus is among the largest publicly available EEG datasets used in epilepsy research. It contains a large collection of clinical EEG recordings obtained from numerous patients and includes detailed annotations of seizure events. Due to its large size, diversity, and clinical relevance, the TUH EEG corpus is commonly used for training and evaluating advanced artificial intelligence and deep learning models for seizure identification and prediction.

Furthermore, besides EEG-based datasets, recent research has introduced datasets that include wearable physiological signals such as ECG and PPG. These datasets enable the investigation of cardiovascular and peripheral physiological responses associated with seizure activity. For instance, wearable ECG datasets have been utilized to analyze heart rate variability patterns linked to seizure events and to evaluate machine learning models designed for real-world seizure monitoring applications [9]. The availability of such datasets supports the development of multimodal seizure detection systems that integrate neural and cardiovascular signals.

Table I summarizes several commonly used datasets for epileptic seizure research.

#### **IV. Machine Learning Approaches for Seizure**

##### **Prediction**

Machine learning (ML) techniques are widely used for automated epileptic seizure detection and prediction. Traditional ML-based systems typically analyze physiological signals such as EEG, ECG, and PPG through preprocessing, feature extraction, and classification stages. These methods aim to identify patterns that differentiate normal brain activity from preictal or ictal states associated with seizures.

Common ML algorithms used for seizure prediction include Support Vector Machines (SVM), Decision Trees, Random



Table I: Common Public Datasets Used For Epileptic Seizure Research

Dataset	Signal	Key Characteristics
CHB-MIT EEG [7]	EEG	Long-term scalp EEG recordings from pediatric epilepsy patients
Bonn EEG [7]	EEG	Pre-segmented EEG signals representing different brain states
TUH EEG Corpus [7]	EEG	Large clinical EEG dataset with annotated seizure events
SeizeIT2 Dataset [9]	ECG	Wearable ECG recordings for seizure monitoring
Wearable Multimodal Dataset [12]	ECG + PPG	Multimodal physiological signals from wearable devices
Clinical sEMG Recordings [11]	EMG	Surface EMG recordings collected in clinical seizure monitoring studies

Forests, and K-Nearest Neighbor (KNN). These models generally rely on handcrafted features extracted from biomedical signals, such as statistical measures, spectral features, entropy-based metrics, and nonlinear dynamics. Early studies showed that features derived from EEG recordings can capture spatiotemporal patterns associated with seizure onset [4].

Machine learning methods have also been applied to cardiovascular signals. ECG recordings and heart rate variability (HRV) have been analyzed to detect seizure-related changes in autonomic nervous system activity. For example, wearable ECG monitoring systems using HRV-based anomaly detection algorithms have demonstrated promising results in identifying seizure events in real-world environments [8], [9].

Furthermore, ML models have been applied to multimodal physiological data collected from wearable sensors. By combining signals such as EEG, ECG, and PPG, these systems can capture complementary physiological responses associated with seizure activity. Multimodal monitoring frameworks have shown improved performance compared with single-signal approaches [12], [13].

Despite their effectiveness, traditional ML approaches require careful feature engineering and domain expertise. Model performance can also be affected by signal noise, data imbalance, and variability between patients. Ensuring high-quality physiological recordings is therefore essential for reliable seizure prediction systems [14].

Due to these limitations, recent research increasingly focuses on deep learning approaches that can automatically learn discriminative features from raw physiological signals, improving the ability to capture complex temporal and spatial patterns in biomedical data.



## V. Deep Learning Approaches for Seizure Prediction

Deep learning (DL) techniques have significantly improved epileptic seizure detection and prediction in recent years. Unlike traditional machine learning methods that rely on hand-crafted features, deep learning models can automatically learn hierarchical representations directly from raw physiological signals. This ability allows DL algorithms to capture complex temporal and spatial patterns present in biomedical data such as EEG, ECG, and PPG.

Convolutional Neural Networks (CNNs) are widely used in seizure detection because they can effectively learn spatial features from time-series signals or transformed representations such as spectrograms. CNN-based models can automatically extract discriminative patterns from multi-channel EEG recordings and have demonstrated promising results in identifying seizure-related abnormalities. Some studies also report improved performance when combining traditional machine learning techniques with deep learning models in EEG analysis [7].

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are commonly applied to sequential biomedical signals. These models are designed to capture temporal dependencies in time-series data, making them suitable for seizure prediction where physiological changes occur before seizure onset. Hybrid CNN–LSTM architectures have been proposed to simultaneously learn spatial and temporal characteristics of EEG signals.

Recent research has explored advanced architectures such as transformer-based models and graph neural networks. Transformer models use self-attention mechanisms to capture long-range dependencies across multi-channel EEG signals [5]. Similarly, graph neural networks combined with LSTM models have been proposed to represent spatial relationships among EEG electrodes and improve seizure prediction performance [6]. Deep learning approaches have also been applied to multimodal physiological data collected from wearable devices. By integrating signals such as EEG, ECG, and PPG, these models can capture complementary physiological information related to seizure activity. Such multimodal frameworks show promising potential for real-time wearable seizure monitoring systems [12], [13].

Despite their advantages, deep learning models require large annotated datasets for training and may be affected by noise and artifacts present in wearable physiological recordings. Therefore, ensuring high-quality data and effective preprocessing techniques remains important for reliable seizure prediction systems [14]. Nevertheless, ongoing research on lightweight neural networks, multimodal data fusion, and wearable AI continues to improve real-time seizure monitoring capabilities.

## VI. Comparison of Existing Methods

A variety of approaches have been proposed for epileptic seizure detection and prediction using physiological signals such as EEG, ECG, PPG, and EMG. These methods differ in several aspects, including the type of physiological signals used, the applied

artificial intelligence or deep neural learning techniques, the datasets utilized for evaluation, and the overall system performance.

Traditional machine learning approaches typically involve a sequence of signal preprocessing, handcrafted feature ex-

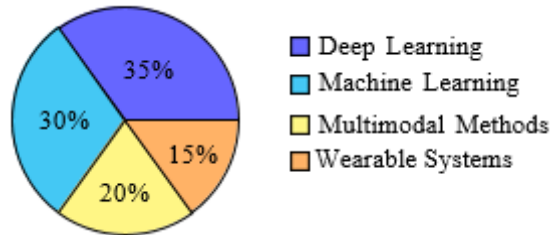


Fig. 1. Distribution of commonly used approaches in epileptic seizure prediction research.

Table 2: Distribution Of Studies Using Different Physiological Signals

Signal Type	Number of Studies
EEG	8
ECG	3
PPG	2
EMG	2
Multimodal	4

traction, and classification. Commonly used classifiers include Support Vector Machines (SVM), Decision Trees, and Random Forests. These methods are generally computationally efficient and offer a certain level of interpretability. However, their performance often depends heavily on the quality of manually designed features and domain-specific expertise [4], [8].

In contrast, deep learning approaches aim to automatically learn discriminative features directly from raw physiological signals. Architectures such as convolutional neural network models (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), and transformer-based models have demonstrated strong capability in capturing complex spatial and temporal dependencies in biomedical data [5]–[7]. These models reduce the reliance on manual feature engineering and have shown improved performance in many seizure detection studies.

More recently, researchers have also explored multimodal monitoring systems that combine multiple physiological signals, including EEG, ECG, and PPG. By integrating information from different biosignals, these systems can capture complementary physiological responses associated with seizure activity and potentially improve prediction reliability in real-world environments [12], [13]. Nevertheless, several challenges remain, such as signal noise, variability among patients, and reliability issues in wearable sensors, which can affect the practical deployment of such systems [14].



## VII. Research Challenges and Research Gaps

Despite significant progress in epilepsy seizure detection and prediction, several challenges still limit the development of reliable monitoring systems. One major issue is the limited availability of large-scale annotated datasets, which affects the generalization capability of machine learning models [4]. In addition, epileptic seizures vary significantly across patients, making patient-independent prediction models difficult to develop [6].

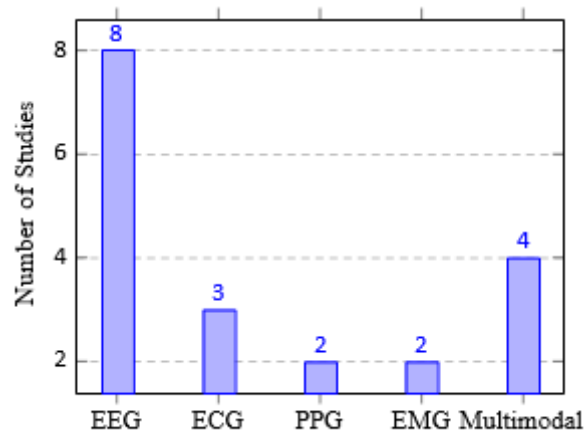


Fig. 2. Distribution of research studies using different physiological signals for epileptic seizure prediction.

Table 3: Reported Accuracy of Different Seizure Detection Methods

Method	Accuracy (%)
EEG Spatiotemporal	80
HRV-ML	85.7
PPG Analysis	88
Wearable ML	90
Multimodal ML	91.5
Transformer EEG	92
EMG Detection	93
MLDL EEG	93
GCN-LSTM	94

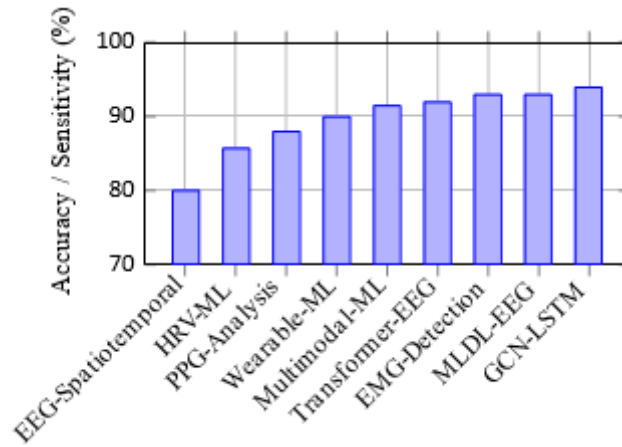


Fig. 3. Performance comparison of different seizure detection approaches reported in the reviewed literature.

Signal noise and motion artifacts also affect physiological recordings collected from wearable devices, reducing the accuracy of detection algorithms [14]. Another challenge is the high false alarm rate observed in many systems, which can reduce user trust in real-world applications. Furthermore, multimodal systems that combine EEG, ECG, and PPG signals introduce challenges related to data synchronization and computational complexity [12], [13]. Addressing these issues requires improved datasets, robust preprocessing techniques

Table 4: Year-Wise Trend of Seizure Prediction Research

Year	Number of Publications
2012	1
2016	1
2017	1
2018	1
2019	2
2020	1
2021	1
2022	3
2024	2
2025	2

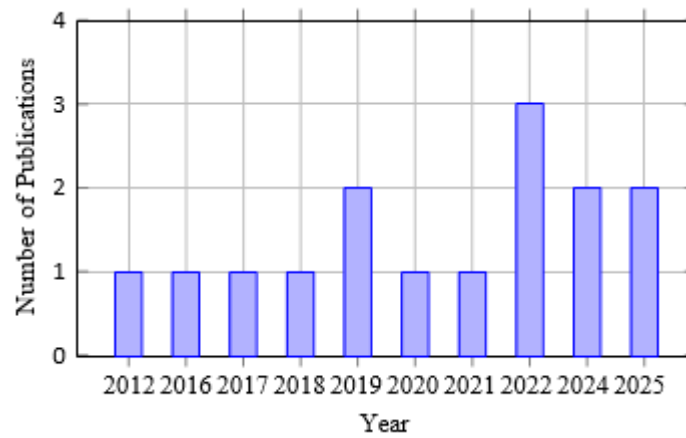


Fig 4: Year-wise trend of research in seizure detection and prediction based on the selected literature.

Table 5: Accuracy Comparison Of ML And DL Models

Method	Accuracy (%)
SVM	85
Random Forest	87
CNN	92
LSTM	91
Transformer	94

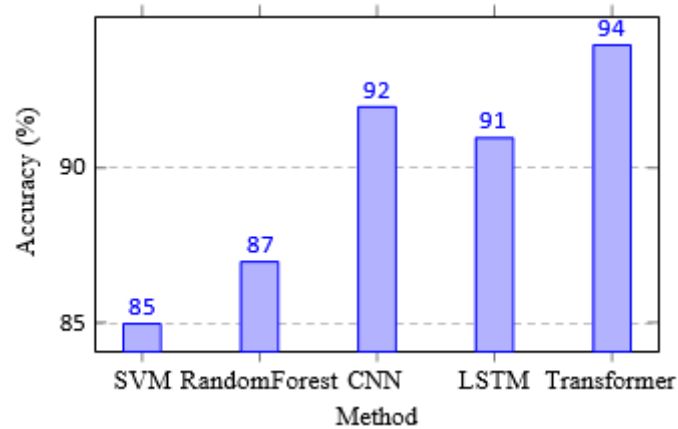


Fig. 5. Performance comparison of machine learning and deep learning models for epileptic seizure prediction.

and more generalized predictive models. Table VI presents a

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Table 6: Quantitative Comparison Of Seizure Detection Approaches

Method	Signal Type	Reported Accuracy (%)
SVM	EEG	85
Random Forest	EEG	87
CNN	EEG	92
LSTM	EEG	91
Transformer	EEG	94
Multimodal ML	EEG+ECG+PPG	91.5

quantitative comparison of commonly used machine learning and deep learning methods reported in recent seizure prediction studies.

### Future Research Directions

Despite recent advances in epileptic seizure detection and prediction, several research directions remain for improving system reliability and clinical applicability. One important direction is the development of multimodal systems that integrate signals such as EEG, ECG, PPG, and EMG to capture complementary physiological responses and improve prediction accuracy [12], [13].

Wearable and real-time monitoring technologies also offer promising opportunities for continuous patient monitoring and early seizure warning systems [8], [9]. In addition, personalized prediction models that adapt to patient-specific seizure patterns may further enhance prediction performance.

Future work should also focus on lightweight deep learning models for edge devices and the use of explainable artificial intelligence (XAI) techniques to improve the interpretability and clinical acceptance of seizure prediction systems.

## VIII. Conclusion

Epileptic seizure prediction has become an important research area in biomedical engineering and healthcare technology. Early detection of seizures can improve patient safety and support timely medical intervention. This review summarized recent developments in seizure detection and prediction using physiological signals such as EEG, ECG, PPG, and EMG.

The paper discussed commonly used biosignals, public datasets, and computational approaches including machine learning and deep learning techniques. While traditional machine learning methods rely on handcrafted feature extraction, modern deep learning models can automatically learn complex patterns from physiological data. In addition, wearable biosensors and multimodal monitoring technologies have enabled continuous and real-time seizure monitoring.

Despite these advancements, challenges such as limited annotated datasets, signal noise, patient variability, and high false alarm rates remain. Future research should focus on multimodal data fusion, personalized prediction models, and lightweight wearable AI systems to develop reliable and practical seizure prediction solutions.



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