Multimodal EEG Seizure Prediction Method Based on Deep Learning

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Abstract: Epileptic seizure prediction has become a critical area of research due to its vital role in ensuring patient safety and improving quality of life. Electroencephalography (EEG), as a non-invasive tool with high temporal resolution, is significant in monitoring seizures. However, traditional EEG-based methods are constrained by the complexity of signals and the reliance on manual feature extraction, limiting their accuracy and scalability. The advent of deep learning has introduced automated feature extraction and end-to-end learning, significantly enhancing seizure prediction capabilities. Nonetheless, single-modality EEG approaches often fail to capture the diverse physiological changes associated with seizures. Multimodal methods have emerged to address this limitation. These methods integrate EEG with other physiological signals, such as electrocardiograms (ECG) and electrodermal activity (EDA), offering improved accuracy. This paper provides a systematic review of deep learning-based multimodal seizure prediction methods. It discusses the role of EEG and advances in deep learning, highlights the advantages of multimodal approaches in integrating multiple signals, and examines challenges such as data synchronization, computational efficiency, and practical deployment. The findings demonstrate the transformative potential of multimodal deep learning frameworks in achieving accurate real-time seizure prediction. Through comprehensive analysis, this research provides valuable insights for developing scalable seizure detection systems, thereby advancing both clinical practice and real-world applications.

1 INTRODUCTION

In recent years, EEG has emerged as a critical tool for the monitoring and diagnosis of brain disorders due to its high temporal resolution and ability to directly measure electrical activity in the brain. EEG signals, which are primarily generated by the synchronized activity of cortical neurons, provide valuable insights into brain function, particularly in understanding epileptic seizures (Müller-Putz, 2020). Epileptic seizures result from abnormal, excessive electrical discharges in specific regions of the brain, and EEG is particularly effective in capturing these events. As reported by the World Health Organization (WHO), approximately 50 million individuals globally suffer from epilepsy, making it one of the most common and impactful neurological disorders (Ein Shoka *et al.*, 2023). Despite its importance, traditional seizure detection methods based on manual feature extraction face significant challenges due to the inherent complexity and variability of EEG signals, as well as the reliance on expert knowledge for signal interpretation (Boonyakitanont *et al.*, 2020). Consequently, there has been a growing interest in automating seizure detection and prediction using advanced computational techniques.

The advent of deep learning has significantly advanced EEG signal analysis by automating feature extraction and enabling end-to-end learning from raw data. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), as powerful deep learning models, excel in modeling spatial and temporal dependencies in EEG signals for seizure prediction tasks (Dissanayake *et al.*, 2021). However, single-modality EEG analysis is often limited in capturing the full range of physiological changes that occur during seizures, as they are multifaceted events that may involve other physiological signals, such as ECG, electrodermal activity, and accelerometer data. Recent research has shifted towards multimodal approaches that integrate multiple signal types, thereby enhancing seizure prediction accuracy through complementary information.

This paper presents a comprehensive review of deep learning-based multimodal EEG seizure

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prediction methodologies. It emphasizes the integration of EEG with complementary physiological signals to capture a more comprehensive range of features, thereby enhancing the accuracy of seizure prediction systems. The review examines recent deep learning architectures designed for multimodal signal fusion, critically analyzing their strengths and limitations. Additionally, it explores practical aspects of deploying these systems in real-time applications, focusing on wearable devices for continuous seizure monitoring. The paper also outlines key challenges, such as the need for more scalable models, the importance of high-quality and diverse datasets, and the difficulties inherent in the real-world implementation of multimodal systems.

2 MULTIMODAL EEG SEIZURE PREDICTION METHOD

EEG signals are electrophysiological recordings that reflect the electrical activity of the brain and are widely utilized in epilepsy research and management due to their high temporal resolution and direct representation of brain activity (Boonyakitanont *et al.*, 2020). EEG signal analysis typically involves extracting features from the time domain, frequency domain, and nonlinear features (Daoud and Bayoumi, 2019). Time-domain features are derived from raw or pre-processed EEG signals and capture spike morphology and amplitude variations. Frequency-domain features, obtained through the discrete Fourier transform, provide insights into the power spectral density of specific frequency bands (Boonyakitanont *et al.*, 2020). Nonlinear features combine temporal and spectral information, offering a more comprehensive representation of transient brain activities (Boonyakitanont *et al.*, 2020). These features form the backbone of EEG-based seizure prediction frameworks, enabling models to characterize the complex spatiotemporal dynamics of the brain.

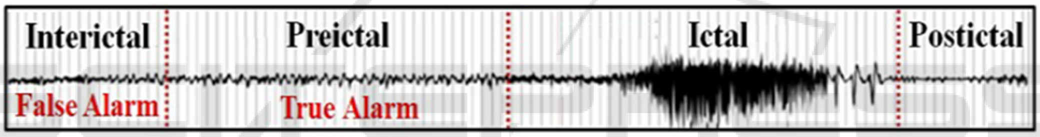

Figure 1: Brain States in a Typical Epileptic EEG Recording (Daoud and Bayoumi, 2019).

Epileptic seizures are associated with distinct changes in brain activity, which can be observed in EEG signals. As shown in Figure 1, EEG signals of epileptic patients are categorized into four major brain states: Preictal, Ictal, Postictal, and Interictal. Among these, the Preictal state, which occurs immediately before seizure onset, is the most critical for seizure prediction (Daoud and Bayoumi, 2019). Early detection of this state allows for timely intervention, significantly improving patient safety and quality of life.

Given the time-consuming nature and low accuracy of manual EEG detection, deep learning-based methods for epilepsy prediction have emerged as a preferred approach. Traditional seizure prediction approaches rely on manually engineered features and machine learning classifiers, such as support vector machines (SVMs) or random forests, which separate feature extraction and classification stages (Daoud and Bayoumi, 2019). However, these methods are limited by their dependence on handcrafted features, often failing to capture the complexity and variability of EEG signals.

Deep learning models overcome these limitations by automating feature extraction and enbling end-to-end learning from raw EEG data. CNNs effectively model spatial patterns, while RNNs capture temporal dependencies, making them particularly suited for EEG analysis (Dissanayake *et al.*, 2021). By integrating time, frequency, and time-frequency features, deep learning models eliminate the need for manual feature engineering, offering more accurate solutions to the inherent challenges of EEG signal variability in seizure prediction. Recent research has expanded beyond EEG-based models to integrate multimodal data, addressing the limitations of single-modality analysis in deep learning approaches. Multimodal approaches involve combining various types of signal data to capture complementary information from different sources. In epilepsy detection and prediction, multimodal methods integrate signals such as EEG, ECG, accelerometers

(ACM), and EDA to comprehensively analyze physiological and behavioral features (Chen *et al.*, 2022). Multimodal methods provide more accurate detection and prediction than unimodal approaches by analyzing multiple physiological systems affected during seizure events (Chen *et al.*, 2022).

The evolution of multimodal approaches in seizure detection and prediction highlights the continuous refinement of methods from static analyses to dynamic, real-time applications and advanced deep learning frameworks. Early work by Memarian et al. established the foundation for integrating multimodal data in epilepsy studies by combining EEG, structural magnetic resonance imaging (MRI), and clinical features to predict surgical outcomes in mesial temporal lobe epilepsy (MTLE) (Memarian *et al.*, 2015). Using traditional machine learning techniques, such as Least Square Support Vector Machines (LS-SVM) and maximum relevance minimum redundancy (mRMR) for feature selection, the study achieved an impressive prediction accuracy of 95% (Memarian *et al.*, 2015). This work demonstrated two key findings: the potential of leveraging complementary data sources and the identification of crucial predictors like ictal EEG onset patterns and gray matter thickness reductions. However, it also highlighted limitations inherent to traditional methods, including a reliance on handcrafted features and offline static analyses, which limit scalability to real-time and dynamic applications (Memarian *et al.*, 2015).

Building on this foundation, Chen et al. extended the application of multimodal methods to wearable and portable technologies, enabling real-time seizure detection and prediction. As illustrated in Figure 2, their framework effectively combined EEG with non-electrophysiological signals including ECG, ACM, and EDA to capture the multisystem physiological changes associated with seizures. The system features a channel-aware module that dynamically selects relevant signal channels, reducing noise and focusing on critical information, while short-time Fourier transform (STFT) is used for feature extraction to convert raw signals into time-frequency representations (Chen et al., 2022). This design automates the process of multimodal signal integration through deep learning. Testing on the CHB-MIT dataset demonstrated that combining EEG and ECG signals achieved over 90% sensitivity, far outperforming unimodal approaches (Chen *et al.*, 2022). This study addressed the practicality of applying multimodal systems in real-world contexts while also highlighting challenges such as signal alignment, computational complexity, and hardware limitations in wearable devices (Chen *et al.*, 2022).

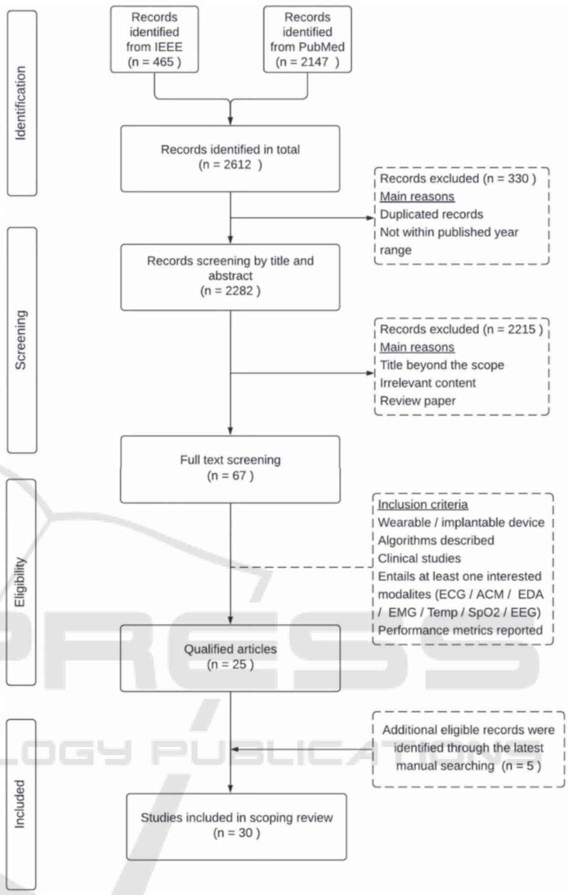

Figure 2: Multimodal Real-Time Seizure Detection Framework Integrating EEG and Peripheral Physiological Signals (Chen et al., 2022).

Recent advances in multimodal methods have been exemplified by Ilias et al., who proposed a state-of-the-art end-to-end deep learning framework to further optimize multimodal seizure detection. Their architecture integrated raw EEG signals and their STFT spectrogram representations through dual feature extraction pathways. The framework consisted of two pathways: a CNN-based pathway for temporal and frequency feature extraction from raw EEG, and a pretrained EfficientNet-B7 pathway for spectrogram image analysis (Ilias and Psarras, 2023). A Gated Multimodal Unit was introduced to dynamically assign weights to each modality, suppressing irrelevant information and enhancing fusion. This novel framework eliminated the need for handcrafted features and achieved an accuracy of 97% on the University of Bonn EEG dataset, surpassing previous methods. By demonstrating the effectiveness of multimodal end-to-end solutions, this study marked a significant milestone in seizure prediction research, particularly in overcoming information redundancy and improving detection robustness.

Expanding on the use of multimodal signals for real-time seizure prediction, Saeizadeh et al. proposed a progressive prediction framework combining EEG and ECG signals. The system, as illustrated in Figure 3, employs a 1D-CNN architecture for feature extraction followed by logistic regression techniques to achieve optimal signal fusion. Unlike prior studies focusing solely on real-time detection, this framework introduces progressive prediction, providing seizure warnings at 15-minute intervals, with up to 1-hour anticipation (Hosseini *et al.*, 2020). This approach addresses challenges in real-time multimodal integration by optimizing computational efficiency and leveraging a low-power body area network. Additionally, their combiner model mitigates data imbalance issues by weighting predictions from individual modalities dynamically (Hosseini *et al.*, 2020). This work demonstrates the feasibility of integrating multimodal deep learning frameworks into wearable devices while highlighting key challenges in real-world deployment.

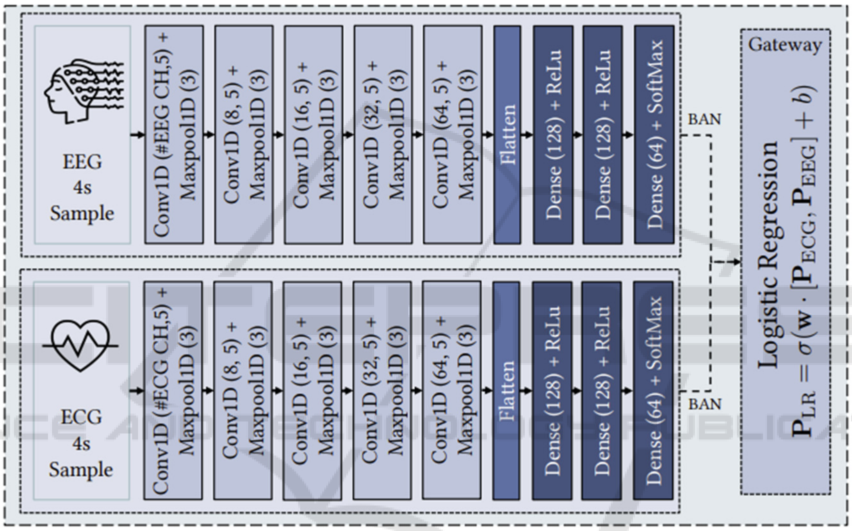

Figure 3: Deep Learning Model and Prediction System Structure (Hosseini et al., 2020).

In addition to advancements in dynamic detection, multimodal approaches have also been explored in more complex medical imaging contexts, as demonstrated by (Hosseini et al., 2020). To analyze functional connectivity within epileptic networks and localize seizure foci, their study integrated EEG data with resting-state functional MRI (rs-fMRI) (Saeizadeh *et al.*, 2024). By leveraging CNNs for EEG feature extraction and Long Short-Term Memory networks (LSTMs) for integrating spatial and temporal features, the framework provided a solution for combining high temporal resolution from EEG and spatial information from rs-fMRI (Saeizadeh *et al.*, 2024). Furthermore, the integration of an edge computing framework allowed for reduced latency and enhanced real-time capabilities. Tested on clinical datasets, this approach achieved high accuracy (98%) and sensitivity (96%) in predicting seizures and localizing epileptogenic zones (Saeizadeh *et al.*, 2024). While the study focused more on the clinical application of multimodal systems for brain network analysis, it highlighted the scalability of multimodal methods in addressing both diagnostic and predictive challenges in epilepsy research.

Multimodal seizure prediction has evolved significantly, progressing from static analysis to real-time and wearable applications by integrating diverse signals and optimizing deep learning frameworks. However, several limitations and challenges remain. The synchronization and alignment of multimodal data, particularly with signals of varying temporal and spatial resolutions, pose significant difficulties (Chen *et al.*, 2022) (Saeizadeh *et al.*, 2024). Real-time processing requires substantial computational resources, which can hinder the scalability of such systems, especially in low-power wearable devices (Chen *et al.*, 2022) (Hosseini *et al.*, 2020). Additionally, data imbalance and the scarcity of high-quality, labeled multimodal datasets complicate model training and generalization (Hosseini *et al.*, 2020). Despite their powerful capabilities, deep learning models face limited clinical acceptance due to their lack of interpretability (Hosseini *et al.*, 2020) (Saeizadeh *et al.*, 2024).

Furthermore, the transition from research to clinical application demands user-friendly systems that integrate seamlessly into medical workflows while addressing patient compliance and ethical concerns (Chen *et al.*, 2022) (Saeizadeh *et al.*, 2024). Overcoming these limitations represents a critical step toward realizing the full potential of deep learning-based multimodal seizure prediction systems in clinical applications.

3 CONCLUSION

In conclusion, the integration of deep learning with multimodal data has made significant advancements in epileptic seizure prediction, improving both the accuracy and real-time detection capabilities. By combining EEG with physiological signals like ECG, ACM, and EDA, recent approaches have successfully automated feature extraction, eliminating the need for manual engineering. This progress has led to more comprehensive systems capable of capturing complex physiological interactions and offering enhanced prediction accuracy.

The transition from conventional, static analysis to dynamic, real-time applications signifies a substantial shift in the deployment of seizure prediction systems. This transition directly improves patient care through wearable technologies, enabling continuous monitoring and rapid interventions. These systems are becoming increasingly practical and accessible. The real-time insights they provide markedly enhance patient safety through early detection, a critical component of effective seizure management.

However, challenges persist, including the alignment of multimodal data, the efficiency of real-time processing, and the necessity for high-quality labelled datasets. Future research directions should focus on three key areas: improving data alignment, reducing model complexity, and enhancing system scalability for wearable devices. Additionally, the interpretability of deep learning models must be addressed to facilitate clinical adoption. The continued evolution of multimodal approaches and deep learning techniques points toward the development of more personalised, efficient, and reliable seizure prediction systems. These advancements will revolutionize epilepsy management through proactive interventions and personalized care strategies.

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