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Neuromorphic Computing-Based Real-Time EEG Epileptic Seizure Detection Using Spiking Neural Networks

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Abstract

Epilepsy is a long-term neurological condition marked by recurring seizures that affect a large population across the globe. Detecting seizures in real time is particularly challenging because electroencephalogram (EEG) signals exhibit highly dynamic, non-linear, and patient-specific behavior. Conventional machine learning and deep learning approaches, although effective in certain scenarios, often demand significant computational resources and power, which limits their applicability in continuous monitoring systems.

This study proposes a framework based on neuromorphic computing to overcome these challenges, enabling real-time detection of epileptic seizures through the use of spiking neural networks (SNNs). The proposed approach adopts an event-driven processing mechanism inspired by biological neural systems, allowing efficient handling of temporal EEG data. A spike encoding method is utilized to transform continuous EEG signals into distinct spike sequences, allowing them to be compatible with neuromorphic systems.

The proposed system is designed to enhance detection performance while reducing latency and energy consumption. By combining temporal signal representation with low-power computation, the framework offers a promising approach for applications in real-time healthcare. This study demonstrates how neuromorphic computing can contribute to the development of next-generation intelligent monitoring systems for neurological disorders.

Keywords: Neuromorphic Computing, Epilepsy, Epileptic Seizure Detection, Spiking Neural Networks (SNN), Electroencephalogram (EEG), Real-Time Monitoring, Brain-Inspired Computing, Low-Power Systems, Signal Processing, Healthcare AI.

I. Introduction

Neurological disorders are a significant global health issue, greatly contributing to disability and a diminished quality of life. Among these conditions, epilepsy is one of the most commonly observed disorders, characterized by sudden and recurrent disturbances in brain activity [2], [16]. Timely and precise identification of epileptic seizures is crucial for successful treatment and ongoing patient observation.

Electroencephalogram (EEG) signals are widely used to study brain activity and identify seizure patterns. However, analyzing EEG data is inherently challenging due to its non-linear, noisy, and highly variable nature across individuals. Traditional seizure detection methods rely either on manual interpretation or conventional machine learning techniques, both of which can be time- consuming and require significant computational resources.[3], [6].

Recent progress in artificial intelligence has resulted in the use of deep learning models, including convolutional and recurrent neural networks, for EEG analysis [5], [7]. While these methods improve detection accuracy, they typically require high computational power and are not well-suited for real-time or energy-constrained environments.

Neuromorphic computing has emerged as an alternative paradigm that mimics the operational principles of the human brain. In this context, spiking neural networks enable event-driven computation and efficient temporal data processing [8], [20]. These characteristics make them particularly suitable for handling time-dependent signals such as EEG.

Despite these advantages, the application of neuromorphic techniques in real-time seizure detection remains limited. Many existing approaches still struggle with latency, energy efficiency, and adaptability in dynamic environments [9], [10]. This encourages the creation of a scalable and efficient framework for real-time detection of epileptic seizures.

II. Problem Statement

Most existing epilepsy detection systems are built upon conventional machine learning or deep learning techniques, which often involve high computational complexity and energy consumption. Such requirements make them unsuitable for real-time and continuous monitoring applications, especially in portable or wearable devices.

In addition, many current approaches focus primarily on detecting seizures after they occur rather than enabling early-stage prediction. The inherent variability and complexity of EEG signals further reduce model robustness and generalization. These challenges emphasize the importance of a more efficient and flexible method that can process real-time EEG data with lower computational demands.

III. Research Contributions

The key contributions of this work are outlined below:

- A neuromorphic computing-based framework is developed for real-time epileptic seizure detection.
- An effective spike encoding mechanism is introduced to transform continuous EEG signals into spike-based representations.
- A spiking neural network architecture is designed to capture temporal dynamics in EEG data.
- The proposed system allows for quick processing, making it appropriate for real-time applications.
- The framework is optimized for energy efficiency, supporting deployment in wearable healthcare devices.
- A comparative analysis highlights the advantages of the proposed approach over conventional methods.

IV. Literature Review

Recent advancements in epileptic seizure detection have been largely driven by the application of machine learning and deep learning techniques to EEG signal analysis. Early approaches primarily depended on handcrafted feature extraction methods combined with classifiers such as support vector machines and k-nearest neighbors [3], [4]. Although these techniques provided reasonable performance, their effectiveness was often limited by feature quality and generalization capability. With the rapid growth of deep learning, models such as convolutional neural networks and recurrent neural networks have significantly improved seizure detection accuracy by learning complex representations from EEG data [5], [6], [7]. Furthermore, transformer-based and attention-driven models have enhanced the ability to capture long-range dependencies in EEG signals [13], [14].

In addition to performance improvements, research has increasingly focused on explainable and hybrid AI models to improve interpretability and robustness in clinical applications [12], [19]. Several review studies emphasize that, despite high accuracy, many deep learning approaches remain computationally expensive and unsuitable for real-time deployment [2], [20].

Neuromorphic computing has recently gained attention as an efficient alternative for processing time-dependent signals. Spiking neural networks, inspired by biological neurons, utilize event-driven computation and temporal encoding, making them suitable for EEG-based seizure detection [8], [22], [23].

However, the practical application of neuromorphic approaches in real-time environments is still limited. Challenges such as variability in EEG signals and lack of adaptive mechanisms continue to affect performance. These gaps highlight the need for an efficient and scalable neuromorphic framework.

V. Research Methodology

The proposed study introduces a neuromorphic computing-based framework designed for real-time epileptic seizure detection using electroencephalogram (EEG) signals. The methodology focuses on efficiently processing time-dependent brain signals through biologically inspired computational principles. Unlike conventional approaches that rely on continuous numerical computation, the proposed system adopts an event-driven processing mechanism to enhance efficiency and reduce computational overhead.

Initially, raw EEG signals are acquired and prepared for analysis. Since EEG data often contains noise and unwanted artifacts caused by external interference and physiological movements, an appropriate preprocessing stage is essential. This stage ensures that the input signals are clean, stable, and suitable for further processing.

Following preprocessing, the continuous EEG signals are transformed into discrete spike sequences using spike encoding techniques. This transformation plays a crucial role in enabling compatibility with neuromorphic systems, where information is represented in the form of spikes rather than continuous values. Both rate-based and temporal encoding strategies can be employed to capture meaningful characteristics of the EEG signals.

Once the spike representation is obtained, the encoded data is processed using a spiking neural network (SNN) architecture. The spiking neural networks enable efficient temporal processing [8], [20]. The network operates in an event-driven manner, where neurons generate outputs only when specific conditions are met. This significantly reduces redundant computations and improves overall efficiency. The architecture is designed to capture temporal dependencies within EEG signals, allowing effective identification of seizure- related patterns.

The entire framework is structured to support continuous and real-time signal processing. By combining preprocessing, spike encoding, and neuromorphic computation, the system enables efficient detection of epileptic seizures with reduced latency and power consumption. This makes the proposed methodology particularly suitable for real-time healthcare applications and wearable monitoring systems.

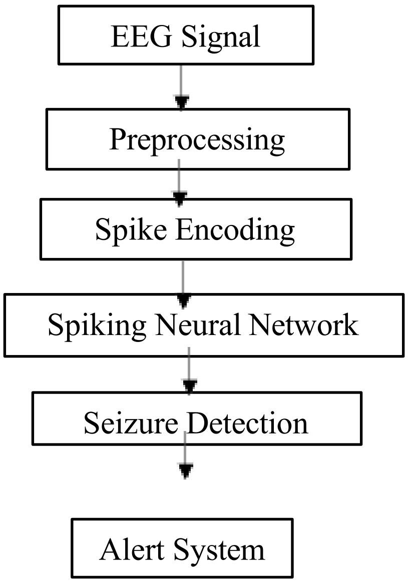

Figure 1. Proposed Neuromorphic Framework for Real-Time Epileptic Seizure Detection

The suggested framework outlines the complete processing pipeline for detecting epileptic seizures using EEG. It includes key stages such as signal acquisition, preprocessing,
spike encoding, and classification using a spiking neural network. The system is designed to enable real-time detection with improved efficiency and reduced computational complexity.

a) EEG Signal Acquisition and Dataset Handling

The EEG data used in this study is obtained from publicly available benchmark datasets, such as the University of Bonn EEG dataset. These datasets contain recordings representing both normal and epileptic brain activity under different conditions. Each EEG signal is treated as a time-series sequence that reflects dynamic neural behavior over time.

To ensure uniformity in processing, the signals are divided into fixed-length segments. This segmentation helps in capturing both short-term variations and long-term temporal dependencies associated with seizure activity. It also improves computational efficiency and supports effective model training.

b) Signal Preprocessing and Noise Reduction

EEG signals are highly sensitive to noise and artifacts caused by factors such as eye movements, muscle activity, and environmental disturbances. Therefore, a preprocessing stage is necessary to enhance signal quality before further analysis.

In this work, band-pass filtering is applied to retain relevant Frequency components, generally between 0.5 Hz and 40 Hz, play a key role in detecting seizures. Additionally, normalization techniques are used to scale the signal amplitude, ensuring consistent input for the model. These preprocessing steps improve the reliability and robustness of the system, as EEG signal processing techniques enhance data quality [22].

c) Spike Encoding Mechanism

A key component of the suggested framework involves transforming continuous EEG signals into spike-based representations. This is achieved using spike encoding techniques that transform analog signals into discrete spike trains.

Rate coding and temporal coding are frequently employed techniques in this context. In rate coding, information is conveyed by the number of spikes, while in temporal coding, the exact timing of the spikes holds the information. This encoding process enables the system to mimic biological neural communication and facilitates efficient processing within neuromorphic architectures.

d) Spiking Neural Network Architecture

The EEG signals, which are encoded with spikes, are analyzed through a multi-layer spiking neural network. The typical architecture includes input, hidden, and output layers made up of spiking neurons. These neurons are represented with biologically inspired models, such as the Leaky Integrate-and-Fire (LIF) model. The network operates based on an event-driven mechanism, where neurons emit spikes only when their internal state exceeds a predefined threshold. This reduces unnecessary computations compared to traditional neural networks. The model learns to identify temporal patterns associated with seizure activity by adjusting synaptic connections, enabling accurate classification of EEG signals into seizure and non-seizure categories.

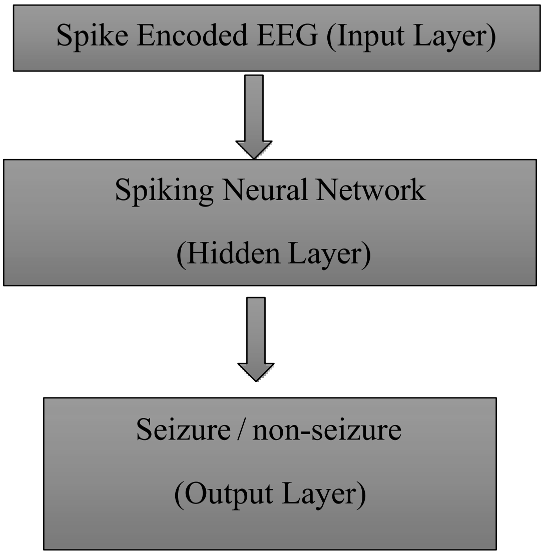

Figure 2. Spiking Neural Network Architecture for EEG-based Epileptic Seizure Detection

The figure depicts the architecture of the spiking neural network used for seizure detection. The network consists of input, hidden, and output layers, where neurons communicate through spike-based signals. This architecture effectively captures temporal patterns in EEG data, enabling accurate and efficient classification of seizure and non-seizure states.

e) Real-Time Processing and Seizure Detection

A main objective of the proposed system is to facilitate real-time detection of seizures. The framework constantly analyzes incoming EEG signals, enabling the instant detection of abnormal patterns. Due to the event-driven nature of spiking neural networks, only relevant signal changes trigger computation, which minimizes delay and improves response time. This capability makes the system suitable for time-sensitive healthcare applications. Once a seizure pattern is detected, an alert signal is generated, which can be integrated with monitoring systems or wearable devices.

f) System Integration and Output

The final stage of the framework involves producing an output that indicates the presence or absence of a seizure. The system performs binary classification based on the learned patterns from EEG data.

The overall design focuses on being lightweight and energy-efficient, making it ideal for use in portable and wearable medical devices. Moreover, the framework can be expanded to enable personalized monitoring by adjusting to individual patient EEG patterns.

VI. Results and Discussion

The proposed neuromorphic framework is analyzed with respect to its ability to efficiently process EEG signals and support real-time seizure detection. Unlike conventional approaches that rely heavily on continuous numerical computation, the presented system adopts an event-driven mechanism, which reduces computational overhead and improves responsiveness.

One of the key challenges in EEG-based seizure detection is handling the complex and time-dependent nature of brain signals. Traditional machine learning models often depend on manually extracted features, which may not capture subtle temporal variations effectively. Deep learning models improve performance by learning features automatically, but they require significant computational resources. Such models typically require high computational resources [9], [10]. In contrast, the proposed spiking neural network processes temporal information inherently through spike-based dynamics, allowing more efficient representation of EEG patterns.

Another important advantage of the proposed approach lies in its computational efficiency. Since neurons in the network are activated only when relevant spike events occur, unnecessary processing is avoided. This reduces latency and makes the system suitable for real-time applications. Additionally, the asynchronous nature of neuromorphic processing eliminates the need for continuous clock-driven operations, further enhancing efficiency. The framework also demonstrates strong potential for real-time seizure detection. By continuously analyzing incoming EEG signals, the system can identify abnormal patterns as they occur. Similar real-time EEG processing systems have been explored in prior studies [11], [21]. This capability is especially useful in healthcare scenarios where timely alerts are essential for patient safety. The integration of an alert mechanism further supports practical deployment in monitoring systems. Energy efficiency is another notable strength of the proposed method. Traditional deep learning models often consume high power due to dense computations, whereas the event-driven behavior of spiking neural networks minimizes energy usage. This makes the system more suitable for wearable and portable devices that require long-term operation with limited power resources.

Overall, the proposed framework provides a balanced solution by combining efficient temporal processing, reduced computational complexity, and real-time responsiveness. While experimental validation can further strengthen the findings, the current analysis clearly indicates the advantages of neuromorphic computing for epileptic seizure detection.

These findings underscore the real-world viability of the suggested framework for future real-time seizure detection systems.

VII. Conclusion

This research introduced a framework based on neuromorphic computing for real-time detection of epileptic seizures using EEG signals. The suggested method aims to address the shortcomings of traditional machine learning and deep learning techniques. Particularly in terms of computational complexity, latency, and energy consumption.

By utilizing spiking neural networks, the system introduces an event-driven processing mechanism that aligns more closely with biological neural behavior. This enables efficient handling of temporal EEG data while reducing unnecessary computations. The incorporation of spike encoding techniques further enhances the ability of the system to represent and analyze dynamic brain signals.

An important contribution of this work is its emphasis on real-time processing. The framework is designed to continuously monitor EEG signals and detect seizure activity with minimal delay. Such capability is highly valuable in practical healthcare applications, where timely intervention plays a critical role in improving patient outcomes.

In addition, the energy-efficient nature of the proposed system makes it suitable for deployment in wearable and portable devices. This opens up possibilities for continuous monitoring solutions that are both reliable and sustainable.

Overall, the study demonstrates that neuromorphic computing offers a promising direction for developing next-generation seizure detection systems. By combining efficiency, adaptability, and real-time performance, the proposed framework provides a strong foundation for future research and practical implementation.

VIII. Future Scope

Although the proposed framework shows promising potential, several opportunities exist for further improvement and practical implementation. One important direction is the deployment of the model on dedicated neuromorphic hardware platforms. Evaluating the system on such hardware can provide better insights into real-world performance, scalability, and energy efficiency.

Another possible improvement could be the incorporation of multimodal data. Combining EEG signals with other physiological signals, such as ECG or EMG, may improve detection accuracy and provide a more comprehensive understanding of patient conditions.

Personalized modeling is also an important area for future research. Since EEG patterns vary significantly between individuals, incorporating adaptive learning mechanisms can help improve system performance for patient-specific data. Techniques such as online learning and adaptive synaptic updates can be explored in this context.

Further research can also focus on improving training methods for spiking neural networks. Developing efficient learning algorithms that combine traditional optimization techniques with biologically inspired mechanisms may enhance model performance.

Finally, large-scale validation using real-world clinical data is essential for practical deployment. Collaborations with healthcare institutions and access to diverse datasets will help evaluate the reliability and effectiveness of the proposed system in real-time scenarios.

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