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Epileptic Seizure Detection Using a Neuromorphic-compatible Deep Spiking Neural Network

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Abstract. Monitoring brain activities of Drug-Resistant Epileptic (DRE) patients is crucial for the effective management of the chronic epilepsy. Implementation of machine learning tools for analyzing electrical signals acquired from the cerebral cortex of DRE patients can lead to the detection of a seizure prior to its development. Therefore, the objective of this work was to develop a deep Spiking Neural Network (SNN) for the epileptic seizure detection. The energy and computation-efficient SNNs are well compatible with neuromorphic systems, making them an adequate model for edge-computing devices such as healthcare wearables. In addition, the integration of SNNs with neuromorphic chips enables the secure analysis of sensitive medical data without cloud computations.

Keywords: Epileptic Seizure Detection · Deep Spiking Neural Networks · Bio-neuromorphics · Surrogate Gradient · Precision Medicine · Edge Computing.

1 INTRODUCTION

Epilepsy is a common chronic neurological disorder, affecting millions of people worldwide [1]. High mortality rate of epilepsy—due to its direct and indirect consequences such as accidents, drowning, falling injuries, and sudden unexpected death due to long-term brain damages—necessitates the adequate management and monitoring of the disease for reducing its potential risks. Although the development of antiepileptic drugs have significantly improved the treatment quality of the disease, more than 30% of patients still suffer from a particular type of epilepsy known as Drug-Resistant-Epilepsy (DRE) [1]. In the absence of a curative therapy for DRE, surgical treatment might be the only viable option for reducing the seizure frequency in patients. However, considering the complex mechanism of DRE, achieving radical improvements through surgical

operations, alone, is not feasible [1]. Therefore, tracking the electrical activities of the cerebral cortex, by implanting electrode grids known as intracranial electroencephalography (iEEG) into the skull, provides important information on the treatment progress of DRE; while enabling the accurate prediction of a seizure prior to its development [2]. The availability of long duration iEEG recordings, acquired from DRE patients in clinical settings, has facilitated the adequate statistical analysis for the real-time seizure forecasting, thus transforming the epilepsy care [2,3]. Various Machine Learning (ML) techniques, or more specifically deep learning methods, have been applied in recent studies for predicting seizures in drug-resistant epileptic patients [3,4]. Despite the remarkable performance of the developed Deep Neural Networks (DNNs) for forecasting epileptic seizure, their implementation on the real-world mobile medical devices for point-of-care (PoC) applications is still not practical. This is due to the fact that the astonishing performance of DNNs comes at the cost of immense energy consumption and enormous computational power, thus, requiring cloud computations [3]. On the other hand, complexities associated with cloud communications such as robustness against interference, wide bandwidth requirements, low latency, and data security limit the application of DNN-based methods in sensitive fields like healthcare. On the contrary, hardware-based neuromorphic systems address these limitations by bringing the data-processing from the back-end onto the chip, offering an energy-efficient platform for the real-time analysis of acquired medical data in a secure manner with less time delay [5,6]. However, the conversion of DNN's sophisticate architecture into a rudimentary neuromorphic structure often impairs the accuracy and performance of the network [3]. As an alternative, biologically-plausible Spiking Neural Networks (SNNs) comply better with the specifications of neuromorphic systems considering their incomple network structure [7]. Although, development of deep SNNs for performing complex tasks is still challenging (due to the discrete nature of spikes), recent attempts in using surrogate gradients for the backpropagation calculations have shown promising results for simplifying the algorithmic complexities associated with training these models [7,8]. Therefore, the objective of this work was to develop a neuromorphic-compatible deep SNN for the epileptic seizure detection using a surrogate gradient-based learning algorithm. The implementation of the developed SNN model on IHP's HfO₂-based Resistive Random Access Memory (RRAM) neuromorphic chip will enable the real-time detection of diseases in the future [6]. The inherent stochasticity of CMOS-integrated RRAM devices enables the on-chip learning possibilities using various ML models including SNNs [5]. As a result, advancements in developing neuromorphic-compatible SNNs for medical applications will pave the way towards the better integration of Artificial Intelligence (AI) with PoC medical devices and biosensors [9,10,11]. In addition, the integration of the surrogate gradient model with novel training algorithms such as a few-shot learning, will enable the on-chip training of the SNN-based neuromorphic chips in medical applications with limited data availability [12].

2 METHODS

The open access chronic ambulatory iEEG data, provided for the Kaggle seizure detection-prediction competition (<https://msel.mayo.edu/data.html>), were used in this study for training and evaluating the developed model. The dataset contains information on three classes of seizure (ictal), pre-seizure (preictal), and seizure-free (interictal) signals. The ictal segment of the signal is a representative of the period when a patient experiences a seizure, while the preictal segment represents the 1-hour time window prior to a seizure development. The interictal segment represents any signal period at least 4 hours before or after a seizure has been recorded. The provided data clips for the seizure prediction task were 10-minutes in duration with a sampling frequency of 400 Hz. The iEEG data were collected from canine subjects using surgically implanted electrodes with 15 channels. The similar seizure mechanism between human and dogs, make the acquired data from canine subjects very valuable for clinical applications. On the other hand, the provided data clips for the seizure detection task were 1 second in duration with a sampling frequency of 400 Hz. The iEEG data were collected from human subjects using surgically implanted electrodes with 55 channels. For training our network, 100 iEEG recordings (30–seizure (ictal) and 70–seizure-free (interictal)) of a single patient were split into the training and validation datasets with 70 to 30 percent ratios, respectively. In addition, 41 data points (27–seizure (ictal) and 14–seizure-free (interictal)) were used as the unseen test dataset for the network performance evaluations. Prior to the conversion of iEEG signals into spikes, spectrograms of the recorded data were calculated using the short-time Fourier transform in order to extract the time-frequency representations of the signals in the range of 0–200 Hz with 155 time-steps. The spectrogram transformation was done using the Scipy library of Python on the Jupyter Lab environment. As shown in Fig. 1, a deep spiking neural network with two convolutional hidden layers was developed using the PyTorch library. The conversion of the analog iEEG spectrograms into spikes has been done at the first input layer of the network. The weighted sum of the generated output spikes are the inputs of the following hidden layers. The readout layer with a softmax activation function has two output neurons, representing the seizure and seizure-free categories. The hidden layers are two-dimensional convolutional spiking layers with 32 neurons and a kernel size of 4×3 . It is noteworthy that, the temporal dimension of the convolution in the time-frequency domain is a representative of the propagation delays of the input spikes. Considering the discrete nature of spikes, the surrogate gradient method was used for the backpropagation calculations. For this purpose, a Sigmoid function (with a scale of 8) was used to approximate the derivative of the Heaviside step function. Rectified-Adam optimizer, with a 0.0001 learning rate, and the cross entropy error function were used for training and optimizing the network parameters. Further details of the SNN model are available at the following repository: <https://github.com/Pouya-SZ/DSC0NN>. After modeling the SNN, the pre-processed iEEG data were fed into the network for 20 training epochs with a batch size of 70. Finally, the trained network was used to predict the labels of the unseen test data.

3 RESULTS AND DISCUSSIONS

The developed deep SNN model provided a validation accuracy of 93.3% for the epileptic seizure detection task, after 20 cycles of training. In addition, the network predicted the correct label of the unseen test signals with an accuracy of 97.6%. As illustrated in the confusion matrix of Fig. 2(a), the SNN provided precision and sensitivity values of 100% and 96.3%, respectively, on 41 unseen test data with only one false-negative prediction. The high performance of the developed SNN makes it a reliable model for edge-computing devices capable of real-time detection of seizure episodes. Fig. 2(b) shows an example of such a wearable device which could be used as an epileptic seizure detector in a PoC setting. In such a setup, the iEEG signals acquired from patient’s cerebral cortex can be transmitted by a portable transducer to the healthcare wearable such as a smart watch. The obtained data by the wearable device can be processed locally using a neuromorphic chip, prior to sending to a smartphone-based user interface for patient records.

As presented in Table 1, the introduced deep SNN was able to perform a complex classification task, the epileptic seizure detection, in an accuracy range comparable to the performance of the well-established DNNs. Furthermore, the biologically-inspired structure of SNNs comply better with the hardware-based neuromorphic systems, while requiring less energy and computational power, thus making them an adequate approach for edge-computing applications such as mobile medical devices. As a result, the implementation of the SNN-based ML techniques on the healthcare technologies and medical wearables will revolutionize the PoC medicine in the upcoming years.

Preliminary results of the network performance for the seizure prediction task provided validation and testing accuracies of 87.5% and 93.05% , respectively. However, the repeatability of the results were questionable due to the over-fitting issue experienced during training the network. The over-fitting problem could be due to the small number of data points used for training. Moreover, the prediction task is, without a doubt, a more challenging and complex task compared to the seizure detection, considering the slight differences between two signal categories. Therefore, further investigation on a vast dataset are required

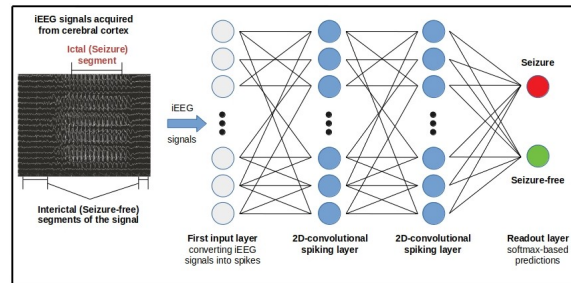


Fig. 1. Architecture of the developed deep SNN for the epileptic seizure detection.

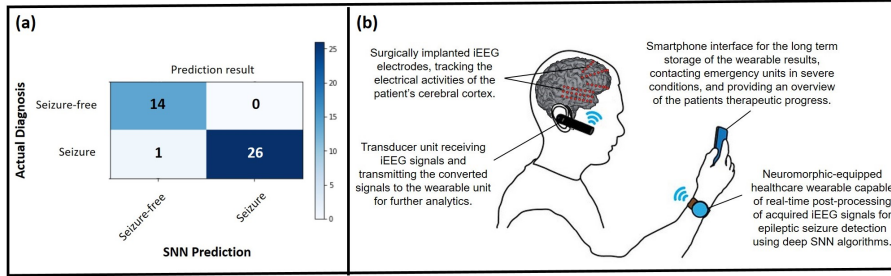


Fig. 2. (a) Confusion matrix for the SNN performance on the unseen test data; (b) Sketch of a PoC healthcare setup for the epileptic seizure detection using a healthcare wearable equipped with neuromorphic chips and a smartphone user interface.

for improving the network performance in the future and to make the results more generalizable and reliable. In addition, taking advantage of the phase information for the spectrogram transformation could possibly improve the network performance.

AI-equipped medical devices will bridge the gap between patients in remote locations and the medical staff by accurate monitoring of patients' health status. Moreover, AI will remarkably improve the management of chronic and degenerative conditions such as epileptic seizure by predicting the critical and emergency conditions. Additionally, collection of further health-related data from patients through edge-computing technologies, such as the one introduced in this work, will facilitate the statistical analysis of medical conditions with better therapeutic outcome for patients. Nonetheless, the trade-off between the mentioned benefits and the risks related to securing sensitive medical data is still a significant concern challenging governments and policy makers today. Therefore, investments for developing precise data safety regulations as well as patient-oriented secure technologies is of great importance. Among these technologies, AI-enabled neuromorphic devices will most likely provide the best platform for patients to take advantage of the AI-based medicine, while having control over their personal data and medical privacy. Therefore, the integration of the presented SNN model, for the epileptic seizure detection, on our previously developed neuromorphic platform is the next goal of this work.

Table 1. Performance of the introduced SNN compared to DNNs.

	Accuracy (%)
SNN	97.6
DNN-classifier [3]	95
Convolutional-DNN [4]	99.6

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