A Self-Aware Power Management Model for Epileptic Seizure Systems Based on Patient-Specific Daily Seizure Pattern

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***Abstract*—We analyze and compare various hardware-based epileptic seizure systems and discuss the challenges and opportunities for reducing power consumption and increasing the battery lifetime. Furthermore, we propose a power management model that employs patient-specific seizure patterns to manage the power consumption of the overall system. This model determines the patient-specific seizure pattern and switches the system to sleep mode when the likelihood of seizure occurrence is zero or very low. Our analysis shows that our proposed power management model could effectively reduce the power consumption by 49% compared to the complex model while the performance reduction is less than 1%.**

***Index Terms*—Deep learning, energy efficiency, epileptic seizure monitoring, patient-specific daily seizure pattern, self-aware power management model.**

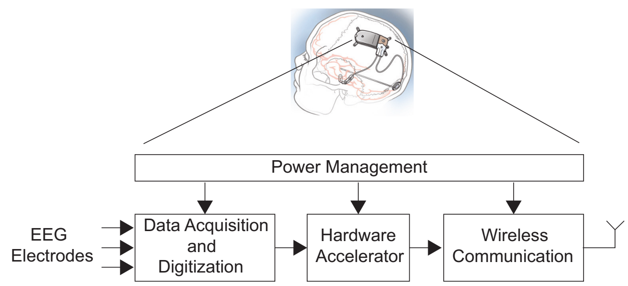

Fig. 1. A battery-powered system for predicting epileptic seizures.

I. Introduction

Epilepsy is a seizure disorder that is usually diagnosed after at least two seizures that are not caused by other medical disorders. Epileptic seizures may be caused by a brain injury or a genetic predisposition, while the reason is usually unclear. According to the World Health Organization (WHO), more than 65 million people worldwide suffer from epilepsy, with 3.4 million people in the United States [1]. Patients who had convulsive movements and loss of consciousness are at a greater risk of Sudden Unexpected Death in Epilepsy (SUDEP), which is a leading cause of death in patients with uncontrolled seizures [2].

Current commercial solutions monitor EEG in real-time to detect the seizure onset. For example, the *Responsive Neurostimulation System* (RNS) is an implantable device that detects the occurrence of certain types of seizures and provides stimulation to reduce the effect of a seizure [3]. Another device, called *Embrace Watch* detects possible convulsive seizures by measuring sympathetic nervous system activity (without using EEG signals), but it fails to detect all convulsive seizures. There is a need not only to detect seizures but also to predict them before they happen so that the patients can take precautions, stop certain activities (such as driving, swimming alone, or climbing ladders), and/or reduce their effects [4].

Deep Learning (DL) methods have become the cornerstone for modern artificial intelligence (AI) applications, especially for healthcare, due to the unprecedented achieved accuracy [5]. DL has been applied in a wide spectrum of healthcare applications, including predicting epileptic seizures [6]. predicting heart attacks [7], finding tumors in MRI images [8], and forecasting COVID-19 cases [9], [10]. Although DL methods can be designed to predict epilepsy with high accuracy [11], the high computational resources and memory bandwidth requirements are the key challenges in implementing DL models in low-power resource-constrained devices.

As illustrated in Figure 1, an automated EEG-based, battery-powered system for epilepsy prediction includes various hardware blocks: electrodes, data acquisition and digitization, hardware accelerator, wireless communication, and power management. Such a system is desired to achieve continuous monitoring and accurate prediction while maintaining low cost and a long battery lifetime [12]. The number of channels is determined by the number of used electrodes. These channels are filtered and digitized by the data acquisition and digitization block, and then processed by the hardware accelerator, which is a custom digital block that implements the DL model. The wireless communication block shares the results with the patient as well as the medical professionals, who can specify the patient-specific patterns and adjust antiseizure drugs accordingly. Finally, the power management module delivers power to all the blocks, ensuring low power consumption and a long battery lifetime.

Digital accelerators can be custom-made for DNNs to provide higher throughput, shorter latency, lower energy, and higher area efficiency [13]. Although digital accelerators provide better performance compared to GPUs, digital systems (including both GPUs and digital accelerators) are fundamentally limited in handling big data efficiently due to the separation of logic and memory (referred to as the Von Neumann bottleneck). Consequently, the system bandwidth is limited by the speed of accessing the data in the memory. Moreover, memory access requires at least 10x higher energy and longer delay compared to the actual computation in DNNs, specifically the multiply-accumulate (MAC) operation [14]. Recent advances in circuit design and memory technologies enable efficient computation through in-memory and near-memory computation, as well as more efficient computation in the analog domain and time domain. Further, it has been shown that computation can be done more efficiently in the analog domain [15] and time domain [16]. These technologies open the door for more innovation in hardware accelerators to achieve low-power and low-cost epilepsy prediction systems.

The use of a wearable accelerometer sensor in seizure detection systems is prevalent because it can detect sudden body movements, such as jerking motions, stumbling movements, and quick body falls, which are common phenomena for most seizure types, such as generalized tonic-clonic seizure (GTCS), tonic-clonic, myoclonic, and hyper motor. Accelerometers utilized in seizure detection systems are precise, three-dimensional, and energy efficient. The majority of accelerometer applications in seizure detection emerge as wearable devices, such as the SmartWatch Inspyre, E4 wristband, Embrace wristband, NightWatch, and a variety of other gadgets created by well-known technology corporations. An accelerometer can be worn in a variety of places on the body, including the wrist, chest, back, and ankle [17]. Channel selection is another approach, which selects only the channels that contain the most important information, thereby lowering the complexity, computation, and power consumption by decreasing the amount of data being processed. In [11], a selection algorithm is implemented to select 10 out of 23 channels on average based on the highest variance entropy product. The results showed that applying such an algorithm decreased 34% of parameters and 50% of training time while maintaining the same accuracy [11]. In [18], an SVM model is tested using 2 to 6 out of 22 channels. The results showed that applying channel selection decreased more than 93% of the computational costs. Channel selection can be an effective technique for reducing computational complexity, but the algorithm itself can be complex.

The power consumption of the hardware accelerator can be reduced by network pruning to remove unimportant connections [19], [20], reducing SRAM voltages based on the level of fault tolerance caused by bit masking, and optimizing the data types [20]. Feature extraction, bit-wise design, and estimation of the activation functions are some other solutions to simplify the design and reduce the design cost.

In this paper, we discuss various systems and hardware accelerators for epilepsy prediction and detection and compare them in terms of performance, size, and power consumption. Besides, According to the patient-specific daily seizure pattern, we propose a model that can switch to low-power mode when the chance of seizure incidence is minimal or zero. This work can help researchers to understand the design challenges for designing an energy-efficient, low-cost, and portable system for epileptic seizure prediction. The remainder of the paper is organized as follows. The prior work on hardware implementation for epilepsy monitoring system are discussed and different hardware structures for epilepsy prediction and detection systems are reviewed in section II. In Section III, we obtained the details of our proposed model. Finally, conclusions are drawn.

II. Prior Work on Hardware Implementations of Epilepsy Monitoring Systems

Table I summarizes the hardware implementations of various epilepsy monitoring systems. As depicted in the table, two commercial solutions are available for epileptic patients; RNS performs detection and requires surgery while Embrace is a non-invasive commercial device. RNS, an FDA-approved therapeutic option, is one of the interventional treatment options for people with refractory and focal epilepsy. The RNS system is the first commercially closed-loop responsive brain stimulation device [21]. RNS is implanted inside the brain to monitor EEG signals, detect seizures, and respond by applying electrical pulses to the patient's brain to reduce the effect of the seizure [3], [22]. Although RNS reduces the seizure frequency and severity, it has a high rate of false detections, raising the question of how much of this effect is attributable to closed-loop suppression of seizure-related ictal activity [23]. In addition, RNS is bulky, has a limited number of channels, and relies on basic hard thresholding with moderate seizure classification accuracy. Because of the power and size limits imposed by implanted devices, complex on-chip classification algorithms cannot be implemented [24].

Wearable sensors, such as the Embrace and Embrace 2 watches developed by MIT, are extremely valuable due to their precision in detecting epilepsy seizures. Embrace watch developed by Empathica is a wrist-worn wearable device that monitors various physiological signals, including heartbeat, temperature, and respiratory rate using EDA (electrodermal activity) sensor. The watch uses machine learning to detect patterns that may be associated with convulsive seizures [25], [26]. The reading is obtained from the watch and transmitted using a Bluetooth connection. The reading is then forwarded to a cloud server and database for storage. This is only possible if an internet connection is present. Users who have been registered to the appropriate user can view the readings of the main user who is wearing the watch via the cloud server and database. When an epileptic seizure occurs, the watch notifies the other users who are registered to the appropriate user. Embrace2 is the second generation with improvements in battery life, weight, and connectivity [27]. Ictal Care365, Neuroon, Ricola, Vigil-Aide, Epi-Care free, and Zephyr are some examples of the possible potential solution for seizure monitoring using biomarker detection systems, which are available in the market [28].

A real-time seizure prediction system is presented in [29] based on an EEG dataset, which has 11 seizures extracted from 4 different focal epilepsy patients and obtained by the University of Texas Health Center using surface implanted electrodes. The system uses a one-class support vector machine (SVM) and is implemented on Zynq-7000 XC7Z045 FPGA which has the requisite FPGA fabric and DSP slices to host the computationally demanding method. Data are converted to Fixed-point to improve utilization of the FPGA fabric and DSP slices. The FPGA implementation consumes about 8 MB of the total 20 MB of block RAM (BRAM). The results showed that the system can predict seizures 3.6 minutes prior to clinical onset with a 3.9 mean false-positive rate (FPR) per hour. A hardware implementation of Bit-Serial Neural Network (BSNN) for epileptic seizure prediction is reported in [30]. The system utilizes a bit-serial data processing unit along with a finite state machine (FSM) to process the one-bit data at a time at each clock cycle to reduce power consumption and reduce area while running at low speed. The system is implemented on an ALTERA Cyclone V FPGA using 3931 ALMs which constitutes about 7% of the Cyclone V A7 capacity. The system achieved an accuracy of 90% when tested on the Bonn dataset [31]. For neural network computing, parallel hardware architecture is typically employed to boost performance. However, in this design, low power and low cost are more important than high performance, so a bit-serial architecture-based data processing unit (DPU) is presented for neural network computing to reduce power and cost. An SRAM is used to store the neural network's weights. For bit-serial processing, the ALU employs a proprietary multiplier. In [32], a deep neural network (DNN), implemented in a Xilinx Zynq-7000 Zybo-7 FPGA, is used to predict seizures. The system is tested on the American Epilepsy Society Seizure Prediction Challenge dataset [33]. The results show that the system predicts seizures with a 74% accuracy, 90% true-positive rate, and power consumption of 1.9 W. In [34], the RusBoosted classifier is applied to classify the data which is suitable for unbalanced data. One channel is used and chosen to reduce power usage and simplify the model. Four blocks from FPGA are used: BRAM, DSP48E, Flip Flop (FF), and Lookup Table with 19%, 52%, 20%, and 62% usage, respectively.

Due to its low power consumption and area requirements, epileptic seizure research has generally focused on ASIC implementation. [35] obtained accuracy higher than 92% at 2.8mW power with total area of 13.47 mm^2. Similarly, [36] and [37] demonstrated on-chip seizure detection with a sensitivity of 95.1% and 83.7% with a total area of $1mm^2$ at 2.73 J and 41.2 nJ per class. However, because these processors are not reprogrammable, ASIC-based wearable devices may face adaption and accuracy loss issues with a more diversified epileptic patient population.

Studies on FPGA-based seizure detection, on the other hand, have revealed partial reconfiguration, high-speed complicated feature extraction, and online training capabilities. [41] obtained 98.4% sensitivity on the Xilinx Zynq-7000 while utilizing 380mW of power at 100 MHz via FFT-based feature extraction. Similarly, [32] obtained 74% accuracy for seizure prediction on the Zynq-7000 with 1909 mW power. [43] extracted 256-point FFT-based features on an FPGA and classified them on-chip at 1.589 mW with a total area of 1409x1402 um^2 for the neural network chip. [45] demonstrated a hybrid approach in which online training is performed

TABLE I
COMPARISON TABLE BETWEEN VARIOUS HARDWARE IMPLEMENTATIONS OF EPILEPSY MONITORING SYSTEMS

Ref	**Goal**	**Implementation**	**Data** (Num of Patient)	**Sensitivity** (%)	**FPR** (h^{-1})	**ML Model**	**Power Consumption (Watt)** & CLK(MHz)
[29]	Prediction	FPGA	sEEG (4) Private data	100	3.9	One-Class SVM	– & 50(MHz)
[30]	Prediction	FPGA	sEEG Bonn	90	–	BSNN	–
[32]	Prediction	FPGA	iEEG UPen	90	–	FC-DNN	1.9 & 25(MHz)
[34]	Prediction	FPGA	sEEG (10) European Epilepsy	77.3	0.04	RusBoosted	–
[38]	Prediction	FPGA	sEEG (8) CHB-MIT	–	–	–	–
[39]	Prediction	FPGA	sEEG (5) CHB-MIT	77.4	–	DL	0.013
[40]	Detection	FPGA	–	–	–	Generic Algorithm	–
[41]	Detection	FPGA	sEEG (24) CHB-MIT	98.4	0.356	SVM	0.38 & 100 (MHz)
[36]	Detection	–	sEEG (24) CHB-MIT	95.1	3.8	Dual LSVM	2.73 uJ/class
[42]	Detection	TSMC 180 nm	iEEG (14) CHB-MIT	95.7	0.02	Dual LSVM	–
[35]	Detection	TSMC 180 nm	iEEG (4) Long-Evans Rats	–	–	Linear Least Square(LLS)	0.028 & 3.125(MHz)
[43]	Detection	FPGA TSMC 180 nm	Data of Mice	–	–	FFNN	0.01589 & 8 (MHz)
[37]	Detection	TSMC 65 nm	iEEG (26)	83.7	–	Boosted Tree	41.2 nJ/class
RNS	Detection	Commercial Device	iEEG	–	–	–	–
Embrace– Embrace 2 [27], [28], [44]	Detection & Prediction	Commercial Device Apple-Android -Smartphone	Non-EEG Non-invasive	–	High-FPR	–	–

on the FPGA and seizure detection is performed on-chip. This system, however, has greater design costs, intermediate data transfer latency, and larger space needs. FPGA's high-performance capabilities come at the expense of increased power consumption and energy requirements. Therefore, designing a feasible and scalable, battery-powered, FPGA-based, seizure detection system is a major task.

III. PROPOSED MODEL BASED ON PATIENT-SPECIFIC SEIZURE PATTERNS

To reduce energy consumption, we propose a new generation of self-aware wearable or implantable systems based on the patient-specific daily seizure pattern. Epileptic seizures have been shown to have biases in distribution over time at various intervals that can be as long as 1 year or as short as 1 h [46]. In another word, the probability of seizure occurrence for each patient can follow a particular daily pattern; For each patient, there are some hours when the risk of having a seizure is high and certain hours when the risk is low or nearly zero. Therefore, we can find a daily seizure pattern for each patient. By analyzing the patient-specific daily seizure pattern, we can manage the power during the day for each patient. Therefore, during times of the day when seizures are not predicted or have a low chance of occurring, the system can switch to a low-power mode.

We determine and utilize the distribution of the number of seizures during the day, which could help to improve epilepsy systems to forecast patient-specific seizures through the addition of 24-hour-cycle information. The distribution of seizures over the 24-hour cycle for 30 patients from the European iEEG Epilepsy Dataset is shown in Figure 2 [47], [48]. The color in each block represents the fraction of seizures that occurred during a certain hour. For example, patient FR_916 had 52 seizures, and thus a block with a value of 0.2 at 2 a.m. depicts that one-fifth of the seizures occurred around 2 a.m. In this graph, dark blue blocks depict no-seizure intervals. Once the patient-specific daily seizure pattern is established, it can be incorporated into the prediction/detection system. The proposed model for power management based on the patient-specific pattern is represented in Figure 3. The patient's data are first read and digitalized. According to the daily seizure pattern for a patient, the power management unit reads the daily pattern and assigns the low-power or high-power mode; low-power mode is given to ratio values greater than 0.025, and high-power mode is given to ratio values greater than 0.025. The key to a patient's daytime power management will be this pattern. Afterward, a simple or complex ML model is employed for the low-power or high-power mode, depending on the assigned mode, respectively.

In this research, we employed the simple and complex detection models in [49], [50] where the classification can be done based on a basic set of features and a more intricate set of features, respectively. Based on the computed threshold in the train section, the two-level classifier in [49] determines whether the simple model is confident to classify the incoming data or the complicated one. Our suggested two-level self-aware classifier, on the other hand, changes from a basic model to a complicated model or vice versa depending on the patient-specific seizure pattern. Making the choice to move between two states in this situation does not need any additional calculations. The influence of threshold (T) on the percentage of time that the system operates in the complex model per day ($P_{Complex}$) and the influence of threshold (T) on the model's performace are shown in Figure 5 and Figure 4. As it can be seen, increasing the threshold from zero to 225 reduces the time of being in the complex model. As a result, the basic model, which has a lower Gmean and power consumption, has a greater impact on system performance. The energy (E) and Gmean for our proposed power-management model are calculated based on the following equations:

$$E = P_{Complex} \times (E_{Complex}) + P_{Simple} \times (E_{Simple}) \quad (1)$$

$$Gmean = \frac{1}{225}(T \times (Gmean_S) + (225 - T) \times (Gmean_C)) \quad (2)$$

Where $P_{Complex}$ and P_{Simple} refer to the percentage of time per day using a complex and a simple model, respectively. $Gmean_C$ and $Gmean_{Simple}$ are the system's performance in the complex and simple models, respectively. T is the threshold which can be between 0 to 225.

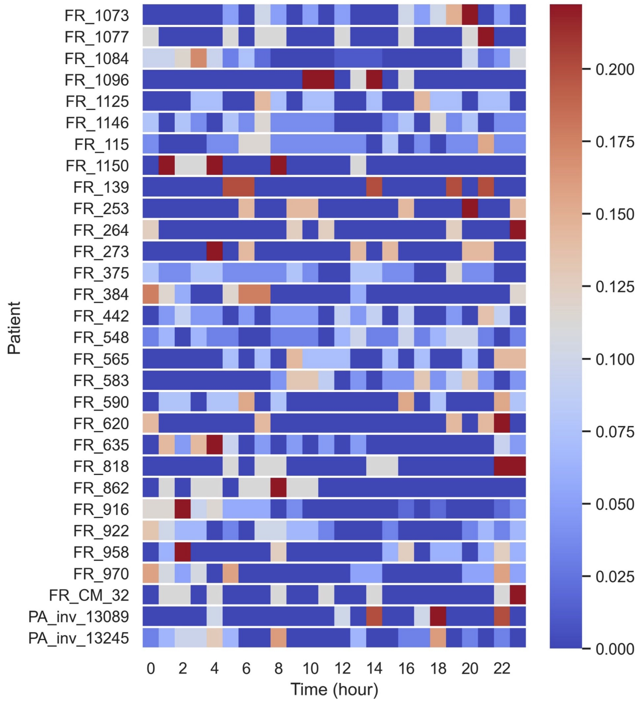

Fig. 2. Distribution seizures over the 24-hour period for the 30 patients.

The average results for 30 patients with $T = 25$ are obtained in Table II. The energy consumption and Gmean for our proposed sef-aware model are calculated and compared with the simple and complex models. As it can be seen, our proposed power-management model could effectively reduce the power consumption by 49% compared to the complex model however the performance reduction is less than 1 %.

The results indicate that our proposed power management model can greatly reduce power consumption for most patients while maintaining the performance.

IV. Conclusion

This paper performed a detailed analysis of the challenges and opportunities for designing low-power epilepsy prediction systems. Designing an efficient epilepsy prediction system requires various levels of software and hardware optimizations, including custom hardware accelerators, machine learning models, channel selection, and statistical analysis of patient-specific EEG data. We proposed a self-aware power-management model to reduce the power consumption for each patient based on the patient-specific pattern. This model is applicable for all types of epilepsy prediction and detection systems. The simulation results indicated that our proposed model can effectively reduce the power consumption by 49 percent compared to the complex model without losing the performance. It is worth to mention that the switch between basic and complicated models is done based on the daily seizure pattern that is unique for each patient and does not require any additional computations.

TABLE II
Estimated results for epilepsy detection based on simple model, complex model, and our proposed model

Model	Low-power mode (Hours per Day)	Gmean (%)	Energy (uJ)
Simple Model	24	75.16	2.832
Complex Model	0	82.53	31.464
This Study	13	81.73	15.955

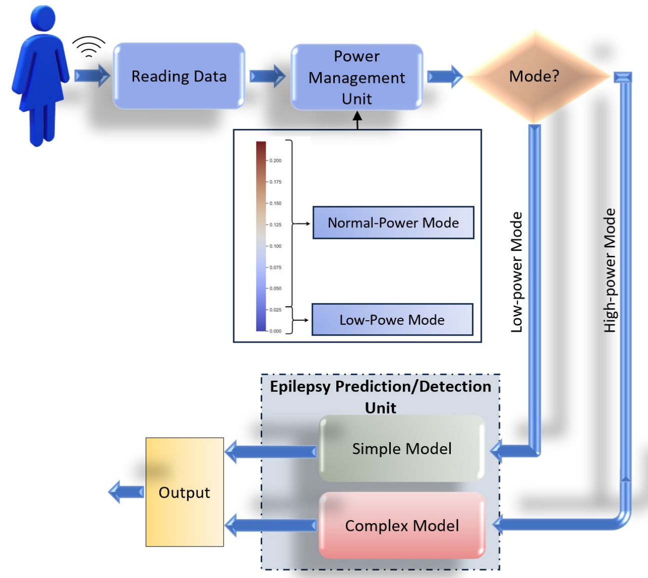

Fig. 3. Block diagram of the proposed self-aware model.

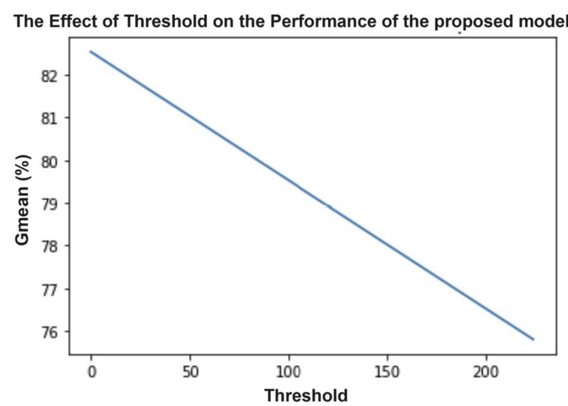

Fig. 4. The effect of threshold on the model's performance.

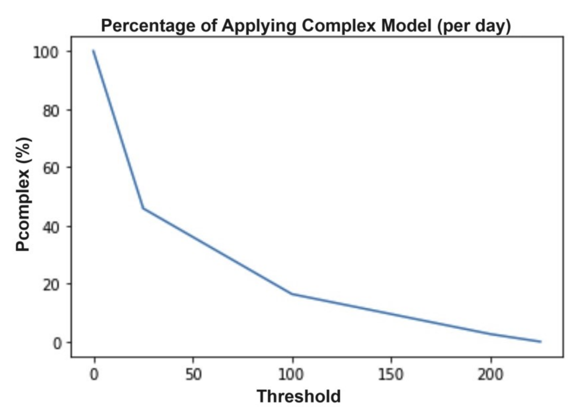

Fig. 5. The effect of threshold on the percentage of time of operating with the complex model per day.

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