SeizNet: An AI-enabled Implantable Sensor Network System for Seizure Prediction

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Abstract—**In this paper, we introduce SeizNet, a closed-loop system for predicting epileptic seizures through the use of Deep Learning (DL) method and implantable sensor networks. While pharmacological treatment is effective for some epilepsy patients (with ∼65M people affected worldwide), one out of three suffer from drug-resistant epilepsy. To alleviate the impact of seizure, predictive systems have been developed that can notify such patients of an impending seizure, allowing them to take precautionary measures. SeizNet leverages DL techniques and combines data from multiple recordings, specifically intracranial electroencephalogram (iEEG) and electrocardiogram (ECG) sensors, that can significantly improve the specificity of seizure prediction while preserving very high levels of sensitivity. SeizNet DL algorithms are designed for efficient real-time execution at the edge, minimizing data privacy concerns, data transmission overhead, and power inefficiencies associated with cloud-based solutions. Our results indicate that SeizNet outperforms traditional single-modality and non-personalized prediction systems in all metrics, achieving up to 99% accuracy in predicting seizure, offering a promising new avenue in refractory epilepsy treatment.**

I. Introduction

Epilepsy is a common neurological disorder disease with around 65M people diagnosed worldwide and a risk of premature death three times higher than that of the general population [1]. Although most patients diagnosed with epilepsy respond well to pharmaceutical drugs to treat epilepsy, approximately one-third of them suffer from drug resistant epilepsy [2]. Therefore, there is a need for alternative epilepsy treatments that goes beyond the pharmaceutical care. Recently, studies has been devoted to predicting seizure onsets well ahead of time in order to notify patients in advance to prevent detrimental accidents with their precautionary actions. [3]–[5].

One of the main challenges in data-driven seizure prediction techniques arises due to the infrequency of seizures in patient recordings, making these methods prone to biases. Prior research has addressed this issue through under-sampling the non-seizure periods. However, any misjudgment can potentially lead to excessive false positives, i.e., falsely alerting the patients of an upcoming seizure that never happens. Furthermore, among many works that use DL techniques to predict seizures, almost all rely on using a single biological time-series signal such as electroencephalogram (EEG), iEEG, or ECG, with the majority using EEG or iEEG [6]–[8]. While these single modality prediction techniques have shown to be effective, there is untapped potential in possibly using a combination of different modalities to create prediction with less variance [9].

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In this work we propose an end-to-end framework for multimodal seizure prediction using iEEG and ECG, utilizing a sensor network to enhance seizure prediction accuracy at the edge. We utilize an ultrasonic intra-body communication system to facilitate safe, secure and low-power communication between the sensors. We design DL structures using both forms of sensor recordings, as well as an effective way for combining the classifications results driven from each sensor's DL model classifying pre-seizure (*preictal*) from non-seizure (*interictal*) periods. Our framework can achieve the utmost accuracy in seizure prediction, surpassing 99% in both sensitivity and specificity. We further employ a focal loss function to address the imbalances in DL dataset, and showcase the potential of using only ECG signals as a non-invasive and easily accessible input for seizure prediction with unprecedented accuracy (up to 94% sensitivity and 99% specificity).

In Sec. II we outline the ultrasonic sensor network model; Sec. III explains the dataset; Sec. IV presents the proposed combined sensors seizure prediction method; Sec. V shows the experimental results; and, Sec. VI concludes the paper.

II. Sensor Network

At its core, our proposed system, SeizNet, consists of three wearable or implantable nodes: (i) the iEEG classifier; (ii) the ECG classifier (both use a DL model to process the sensor data); and (iii) the gateway, that receives and combines the DL classification results from the two classifiers to make decisions as explained in Sec. IV. The nodes in wireless sensor network use an ultrasonic communication platform [10] (see Fig. 1).

Based on the result of the prediction, either an alerting signal can be sent to the patient, or a stimulation command can be sent to a Deep Brain Stimulator (DBS) system to responsively stimulate targeted areas in the brain and alleviate the effect or prevent a seizure onset from happening [11]. This ensures timely intervention and appropriate medical attention.

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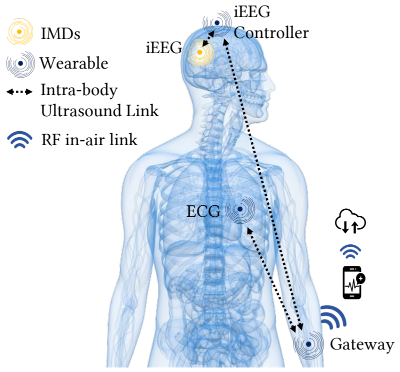

Fig. 1. System architecture; Gateway receives the classification results from the iEEG and ECG nodes that execute DL algorithms.

Physical Layer. Short-range and long-range through-tissue ultrasonic communication channel are considered to transmit and receive data between the implanted and wearable nodes that executes iEEG and ECG data classifications and the wearable gateway. The short-range (few mm) ultrasonic link allows for focused propagation with lower transmission power that saves energy on the implant. This is a critical aspect for the implant, since its charging operations are more complicated than the wearable nodes, and the energy buffer size has to be small to be easily implanted [12]. Besides the ultrasonic communication transceiver, the gateway uses traditional RF-based communications, such as Bluetooth or Wi-Fi, to exchange data with an Internet enabled device [10].

Medium Access Control (MAC) Layer. The following *application messages* (not including control frames) are exchanged between the sensor nodes and the gateway: (i) classification results from iEEG classifier to iEEG controller; (ii) classification results from over-the-skin nodes (iEEG controller and ECG sensors) to the gateway; (iii) stimulation settings from the gateway back to the iEEG controller (in case of using a closed-loop DBS system); and (iv) alert messages from the gateway to an internet-connected devices. An impulse based transmission, i.e., a pulse position modulation (PPM), with a superimposed spreading code is used as explained in [13].

The outcomes of the DL models are encoded into B_{app} bits (application bits) and transmitted every t_{app} seconds. Consequently, the minimum required bit rate R_{app} for each node is calculated as $R_{app} = B_{app}/t_{app}$ in bits per second (bit/s). Considering the existence of four nodes (ECG, iEEG, gateway, and DBS), the total bit rate R_{total} equals to $4 \times R_{app}$. The time resolution of the system is $4s$, implying $t_{app} = 4s$ for all nodes. Unlike prior works such as [13], we can adopt a simplified centralized MAC mechanism. This centralized MAC protocol is chosen due to the system's inherent characteristics: a fixed number of nodes and a gateway. Initially, the gateway coordinates other nodes by dispatching a control message encompassing the spreading code and time-hopping frame sequence assigned to each sensor node.

The employed spreading code and time-hopping frame sequence enable multiple nodes to effectively share the channel, enabling simultaneous communication. This obviates the necessity for control messages to synchronize and mutually exclude nodes, a challenging task in ultrasonic communications due to extended and unpredictable propagation delays. As described in [13], the MAC protocol can proficiently support all four nodes, achieving an average throughput of $25kbit/s$ with a close to 0.005 packet drop rate. Consequently, each node is allocated $R_{app} = \frac{R_{total}}{N_{nodes}} = 5kbit/s$. Given that we transmit binary classification results and operate within a time resolution of $4s$, this bandwidth allocation is more than adequate for the system's requirements.

III. Dataset

We utilize a robust dataset generated under the EPILEPSIAE project [14], an EU endeavor, featuring EEG, iEEG and ECG data from 275 focal epilepsy patients. Recorded between 2009 and 2012 at three reputable European Centers, the dataset is known for continuous long-term recordings with an average duration of 165 hours, and and an average of 9.8 seizures per patient. Ultimately, we used 27 patients that have both ECG and iEEG together. The number and placement of the leads for iEEG are different among the patients; however, all of them have single channel ECG recorded from their chests. It is worth noting that the iEEG signal can be captured with commercial DBS systems and used in our proposed solution.

Our objective is to predict seizures an hour in advance of the seizure onset. This is achieved by classifying/differentiating between the pre-seizure and the non-seizure data samples. As seen in Table 1, the vast majority of the data is non-seizure iEEG data, amounting to 1.8 billion seconds of data (note that every four seconds of the recording corresponds to one sample in our database). In our analysis, we observed that the mean ratio of pre-seizure to non-seizure states was about 0.0826, with a variance of 0.0039. These statistics highlight the imbalance in the dataset, emphasizing the rarity the pre-seizure states compared to non-seizure states.

The data is stored in a postgreSQL database with a relational structure, containing tables for raw iEEG and ECG data, time references, and a treasure trove of metadata. The metadata encompasses elements such as electrode positions, seizure annotations, medication dosages, patient history, and imaging data, while also containing raw electrode data in binary files.

Seizure State	ECG	EEG	iEEG
Non-Seizure	32,016,786	465,407,245	1,805,183,428
Pre-Seizure	2,500,364	28,659,972	160,301,747

Table 1. Distribution of data sample size for different seizure states

IV. Combined DL-Based Seizure Prediction

Pre-Processing. For simplicity and power consumption, high-end pre-processing has been avoided for both ECG and iEEG. However, the performance of the model has been investigated which was showing that the use of pre-processing including notch-filter for power-line noise and band pass filter does not help improving the results significantly.

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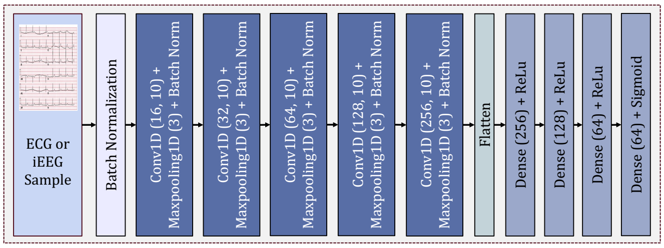

Fig. 2. Deep Learning Model Structure.

A. Deep Learning Model

Our proposed DL model for seizure prediction based on ECG/iEEG recordings consists of multiple stages (Fig. 2). Initially, the raw ECG/iEEG samples undergo batch normalization to enhance their suitability for subsequent processing. These normalized samples then pass through a series of five 1-dimensional Convolutional Neural Network (CNN) blocks each accompanying by a Max-pooling layer, in order to extract latent features with maximum information content. The utilization of 1-D Convolutional layers enables the model to effectively capture crucial features from each sample. The resulting features are flattened and subsequently fed into four dense layers for binary classification. The three intermediate layers employ the ReLu, while the final layer utilizes the Sigmoid activation function. We optimized this model to strike a balance between computational efficiency and accuracy.

In our extensive study, we observe that CNN models are better capable of capturing spatial patterns within iEEG and ECG signals, extracting nuance features, hence identifying intricate seizure-related patterns more effectively. The CNN architecture shown in Fig. 2 remains consistent across all patients; however, individualized training occurs for each patient. This process results in the creation of a distinct trained model specific to each patient. We allocate 80% of the dataset for training, 10% for validation, and 10% for testing purposes.

B. Focal Loss Function

Training neural networks for biomedical tasks can be challenging, primarily due to the uneven and inconsistent distribution of labels. This issue persists in the EPILEPSIAE dataset [14], as demonstrated by the fact that the pre-seizure to non-seizure period sample ratio for patients ranges from 0.020 to 0.233. In order to achieve optimal training results, it is crucial to address the class imbalance and leverage all the valuable information contained within the data. To tackle this problem, we employ a novel loss function called Focal loss function [15], which specifically addresses the issue of class imbalance better than balanced cross entropy (BCE) loss function. The focal loss function can be defined as:

$$FL(p_t) = \begin{cases} -\alpha(1-p)^\gamma \log p, & y=1 \\ -(1-\alpha)p^\gamma \log 1-p, & \textit{otherwise} \end{cases} \tag{1}$$

where, $p \in [0,1]$ represents the model's estimated probability for each class and y is the actual label of the class. We consider $y=1$ for pre-seizure periods and $y=0$ for non-seizures.

There are two knobs to tune the loss function: α which can be used similar to imbalanced BCE loss function, that puts predefined weight on different classes' loss; and γ which helps to improve the behavior of the cross entropy by assigning a lower loss to the misclassified samples. Through exhaustive search, we identified that setting $\alpha = 0.2$ and $\gamma = 2$ yields the optimal performance across all patients.

This weighting strategy ensures that the model does not favor non-seizure instances, effectively combating the bias and improving the overall classification performance.

C. Time and Channel Voting

To ensure optimal performance and mitigate the risk of false detection based on a single faulty sample, a majority voting strategy is employed for both channels and time in our proposed approach. For ECG signals, which consist of a single channel, time voting is performed by buffering the decisions of the last 15 samples (60 second of the recording) and determining the final decision based on the majority vote. In the case of iEEG signals, multiple channels are available, decisions are collected based on buffering both channel and time buffering.

V. Experimental Results

A. Performance Metrics

We employ several performance metrics to analyze the SeizNet performance. These metrics include sensitivity, specificity, and accuracy, providing insights into the model's ability to detect pre-seizure periods, non-seizure periods, and overall performance, respectively, as follows:

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP + FN}}\ , \quad \text{specificity} = \frac{\text{TN}}{\text{TN + FP}} \tag{2}$$

$$\text{accuracy} = \frac{\text{TN + TP}}{\text{TN + TP + FP + FN}} \tag{3}$$

In addition, we calculate the false positive rate per hour as:

$$\text{FPR}(h^{-1}) = \frac{\text{FP}}{\text{TN + FP}} \times \frac{3600}{4} \tag{4}$$

B. ECG-based perdicter with new Focal Loss Function

Fig 3 shows the improvement in Area Under the Curve (AUC) using SeizNet with the proposed focal loss function (Sec. IV-B) and utilizing ECG signal, compared to the iEEG-based predictor using the DL network structure in AiEEG [5], showing an average 17% increase (from 81% to 98%).

As it can be seen in figure 4, thank to the new DL structure, the SeizNet network is able to reach up to 99% accuracy in predicting seizure by only using the non-invasive ECG signal, exceeding the performance of the stat-of-the-art [5]. Note, that all the seizure prediction are performed up to one hour in advance of a seizure onset. Leveraging the accessibility of ECG signals and their compatibility with smartwatches, this method offers a convenient and practical solution for seizure prediction. However, it is worth noting that the model experiences a relatively high false positive per hour (FPH) (up to 4.13 FPH). Repetitive false alarms may result in ignoring the true positives, or unneeded stimulation in a closed-loop system with DBS.Addressing this false positive issue will be

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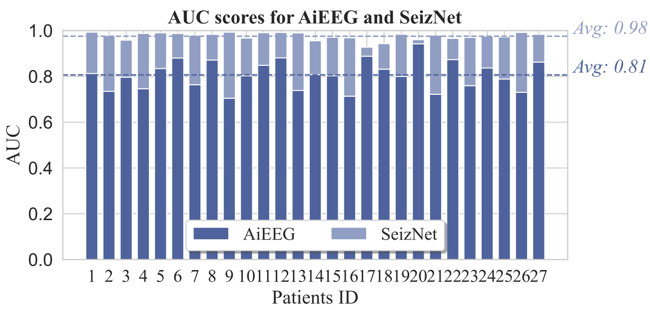

Fig. 3. SeizNet AUC improvements using the new loss function, compared to the baseline model (AiEEG).

an essential focus for further refinement and improvement of ECG predictors.

C. ECG, iEEG, and Combined Seizure Predictors

The iEEG-based predictor utilizes multiple channels and adopts time and channel voting for making the final decision (for details on the voting mechanism we refer the readers to [5]). As a result, it demonstrates superior performance in avoiding false predictions (achieving accuracy of 99.9%) compared to the ECG predictor, thanks to its diverse dataset.

As it can be seen in Fig. 4, the results of both the ECG and iEEG predictors individually are $> 99.9\%$ for all metrics thanks to the new focal loss function and the voting mechanism. However, by aggregating the ECG and iEEG classification results, SeizNet can maintain high accuracy while ensuring minimal false positive rate (as low as 0.23 FPH thanks to the high sensitivity and specificity). In previous studies, such as [16], the most notable performance reached approximately 99% of sensitivity within a 60-minute pre-ictal time window. Although our results appear comparable, it's important to note that our proposed model, stands out due to its high specificity (very low FPH) and low computational cost (low weight CNN model, without need for additional feature extraction), making it a more practical and feasible method for implementation on resource-restricted medical devices.

VI. Conclusion

In this paper we introduced SeizNet, an AI-enabled sensor network system for seizure prediction, based on DL models and advanced data curation techniques. The SeizNet architecture incorporates iEEG and ECG classifiers, connected to a gateway for real-time decision-making. We leveraged a large-scale dataset from the EPILEPSIAE project, and addressed class imbalance challenges through a focal loss function in the proposed DL model. The proposed sensor network, comprising implantable and wearable nodes, can form a closed-loop system for effective monitoring, prediction and intervention (as needed) of seizure occurrence. Experimental results show the system's high sensitivity, specificity, and accuracy (>99%) in predicting pre-seizure periods.

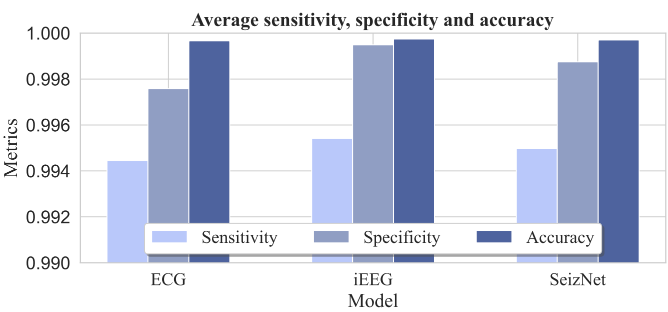

Fig. 4. Average Sensitivity, Specificity, and Accuracy among all the patients with ECG, iEEG, and combined model on test dataset.

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