# EpilepsyNet: Interpretable Self-Supervised Seizure Detection for Low-Power Wearable Systems

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***Abstract*—Epilepsy is one of the most common neurological disorders that is characterized by recurrent and unpredictable seizures. Wearable systems can be used to detect the onset of a seizure and notify family members and emergency units for rescue. The majority of state-of-the-art studies in the epilepsy domain currently explore modern machine learning techniques, e.g., deep neural networks, to accurately detect epileptic seizures. However, training deep learning networks requires a large amount of data and computing resources, which is a major challenge for resource-constrained wearable systems. In this paper, we propose EpilepsyNet, the first interpretable self-supervised network tailored to resource-constrained devices without using any seizure data in its initial offline training. At runtime, however, once a seizure is detected, it can be incorporated into our self-supervised technique to improve seizure detection performance, without the need to retrain our learning model, hence incurring no energy overheads. Our self-supervised approach can reach a detection performance of 79.2%, which is on par with the state-of-the-art fully-supervised deep neural networks trained on seizure data. At the same time, our proposed approach can be deployed in resource-constrained wearable devices, reaching up to 1.3 days of battery life on a single charge.**

***Index Terms*—epilepsy, real-time seizure detection, self-supervised learning, wearable systems, Internet of Things (IoT).**

## I. Introduction

EPILEPSY is a neurological disorder that affects more than 60 million people worldwide, according to the World Health Organization (WHO) [1]. Despite the advances in anti-epileptic drugs, one-third of the people with epilepsy (PWE) remain suffering from recurrent seizures. Furthermore, epileptic seizures reduce PWE's quality of life and may even lead to sudden unexpected death in epilepsy (SUDEP) [2]. Indeed, PWE have a 2–3 times higher mortality rate compared to the corresponding healthy population [3]. Mobile health monitoring on wearable devices can be used to detect the onset of seizures in real time and alert family members and caregivers for rescue [4], [5].

Modern machine learning techniques, especially deep learning, play a vital role in the state-of-the-art of seizure detection. However, the lack of interpretability still prevents their wide adoption in clinical practice due to clinicians' mistrust [6]. Moreover, deep learning models often need a large amount of data for achieving high prediction performance, which is a major challenge in the case of epilepsy monitoring and seizure detection [6]–[12]. Indeed, many efforts have been paid to use as small amount of data as possible. For instance, Siamese networks with few-shot learning [13], [14], one-shot learning [15], [16], transfer learning [17], and Generative Adversarial Networks (GANs) [18] are used in seizure detection, but still requiring seizure data in the training process. Moreover, anomaly detection techniques [19]–[21] are also used in this concept, which again require seizure data to select the hyperparameters for outlier detection. However, new patients usually do not have any collected and labelled seizure data, a major challenge that has been recognized in the epilepsy domain.

In this paper, we propose EpilepsyNet, the first end-to-end self-supervised network for seizure detection without any need for labelled seizure data for new patients in training. Our proposed network is aimed to be used in wearable and resource-constrained systems, e.g., e-Glass [22] with only two electroencephalogram (EEG) channels or behind-the-ear EEG sensors [23] with eight channels. EpilepsyNet is interpretable in the sense that it is designed to detect seizures by looking into the similarities between the new EEG data and the signature set for non-seizure and seizure signals. The signature set contains representative non-seizure and seizure patterns, which have recently been demonstrated to be highly relevant in epilepsy monitoring [24]. Initially, the network is pretrained offline based on generic non-seizure data and synthetic seizure data (i.e., pretext task in self-supervised learning). Therefore, the signature set originally contains only synthetic seizure and real non-seizure data. At runtime, once a seizure is detected, the new seizure data can be readily incorporated into the signature set stored in the wearable system (i.e., the target/downstream task in self-supervised learning). Thus, this scheme removes the need to retrain the model, hence incurring no energy overhead. Moreover, such a scheme enables incremental improvement of the seizure detection performance by benefiting from the newly-acquired seizure/non-seizure EEG data.

In summary, EpilepsyNet is designed for resource-constrained wearable systems, exploiting the seizure/non-seizure data acquired at runtime to incrementally improve seizure detection performance without the need for online retraining. Our main contributions are summarized below:

1) We propose EpilepsyNet, the first interpretable self-supervised network for seizure detection without any need for real seizure data in training, which has com-

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parable performance with supervised methods.
2) Our self-supervised method has the capacity of exploiting new seizure data at runtime to incrementally improve the seizure detection performance, reaching 79.2% (comparable with 80.8% in the fully-supervised state-of-the-art techniques [25]), without any major energy overheads.
3) We deploy and evaluate our network on the e-Glass wearable system. Our experimental evaluation shows that the battery lifetime of the e-Glass system running EpilepsyNet is 1.3 days, i.e., 31.2 hours on a 225 milliampere-hour (mA·h) battery charge.

## II. EpilepsyNet

### A. Network Overview

Fig. 1 shows the architecture of our proposed EpilepsyNet, which consists of two parts: offline training (Section II-B) and online inference (Section II-C). In the *offline training*, we propose a pretrained *synthesis network* to generate synthetic seizure data based on an autoencoder [20]. Then, we construct the pairs of data and train a Siamese-based *contrastive network* [26] to detect seizures by comparison against non-seizure/seizure patterns in the signature sets. During the *online inference*, we only need to deploy a sub-network of EpilepsyNet, as shown in Fig. 1, on the e-Glass wearable system. We keep the signature sets updated at runtime to incrementally increase the performance of seizure detection without the need to retrain the model, hence incurring no energy overheads.

### B. Offline Training

*1) Synthesis Network:* The synthesis network has two main parts: an encoder and a decoder. We use a 2-layer 1D-CNN as the encoder to extract the latent features and a 2-layer 1D-CNN as the decoder to reconstruct the original data. Here, only the non-seizure data, denoted by $I_{ns}$, is used as input for the training of the synthesis network. Let us denote the reconstructed signal by $\widetilde{I}_{ns}$. Accordingly, the reconstruction loss function $L_{re}$, which makes the synthesis network learn the latent features is defined as:

$$L_{re} = \frac{1}{T}\left\|\widetilde{I}_{ns} - I_{ns}\right\|_1, \tag{1}$$

where $T$ is the length of the input signal. We first train the synthesis network. Then, we use the trained network to generate synthetic seizure data, denoted by $I_{ss}$, by adding Gaussian noise $N \sim (0, 1)$ to the non-seizure data $I_{ns}$. If the reconstruction error exceeds a certain threshold, the reconstructed signal is regarded as synthetic seizure data.

The threshold is determined automatically by calculating the loss between $I_{ns}$ and $\widetilde{I}_{ns}$ and selecting a fixed cutoff at 95% (95th percentile), without the need for any real seizure data.

*2) Contrastive Network:* We consider contrastive learning for seizure detection to avoid the demand for large amounts of data. Specifically, a 3-layer 1D-CNN and a 2-layer fully connected layer are used to measure the relative similarity of the input pairs and a 4-layer 1D-CNN is used to reconstruct these signals from the latent features for both classes. Given that we have $n_{ns}$ non-seizure samples and $n_{ss}$ synthetic seizure samples, we get $n_{ns} \cdot n_{ss} + \binom{n_{ns}}{2} + \binom{n_{ss}}{2}$ pairs. The pairs include three different types of data: $(I_{ns}, I_{ns})$, $(I_{ss}, I_{ss})$ and $(I_{ns}, I_{ss})$. We use all these different pairs to train our contrastive network.

*3) Re2Cons Loss Function:* To train the contrastive network, we propose a new loss function, called $Re2Cons$. This loss function has three parts: $L_1$, $L_2$ and $L_3$ denoting the *reconstruction* loss of non-seizure data, the *reconstruction* loss of synthetic seizure data and the *contrastive* loss, respectively. $L_1$, $L_2$, and $L_3$ are defined as follows:

$$L_1 = \frac{1}{T}\left\|\widetilde{I}_{ns} - I_{ns}\right\|_1, \qquad L_2 = \frac{1}{T}\left\|\widetilde{I}_{ss} - I_{ss}\right\|_1, \tag{2}$$

$$L_3 = \frac{1}{T}((1-Y)\times D^2 + Y \times (\max(0, M-D)^2)), \tag{3}$$

where $Y$ is the label. $Y$ is 1 for $(I_{ns}, I_{ss})$ as a pair and 0 for $(I_{ns}, I_{ns})$, $(I_{ss}, I_{ss})$. $D$ is the Euclidean distance between latent features. Besides, we introduce margin $M$ to maintain the distinguishability of latent features between the non-seizure and synthetic seizure data. The $Re2Cons$ loss includes contrastive and reconstruction losses as shown below:

$$Re2Cons = \lambda_1 L_1 + \lambda_2 L_2 + \lambda_3 L_3, \tag{4}$$

where $\lambda_i$ captures the relative importance of each loss.

### C. Online Inference

In the online inference phase, we only deploy a sub-network of EpilepsyNet on a e-Glass wearable system because the latent feature is the only required output for seizure detection. As shown in Fig. 1, a 3-layer 1D-CNN and a 2-layer fully connected layer are exploited to extract the latent feature and measure the relative similarity. This network is essentially the exact same replica of the contrastive network in Fig. 1, excluding the two decoders. Therefore, this network, denoted by $F(\cdot)$, does not need to be trained online and it uses the corresponding network weights from the trained contrastive network. The network expects two inputs: one is the newly-acquired real-time EEG data at runtime and the other is from the signature sets. In essence, the network measures the distance between the corresponding embeddings of the two inputs. The signature set contains the representative non-seizure and seizure patterns, which provide the references for calculating relative similarity between signatures and real-time EEG data. This demonstrates the interpretability of EpilepsyNet.

We use the 2-way $K$-shot learning strategy, which means that we prepare a non-seizure signature set $S_{ns}$ with $\frac{K}{2}$ non-seizure data/patterns, and a seizure signature set $S_{ss}$ with $\frac{K}{2}$ seizure data/patterns, as shown below:

$$S_{ns} = \left\{I_{ns}^{(1)}, I_{ns}^{(2)}, ..., I_{ns}^{(\frac{K}{2})}\right\}, \quad S_{ss} = \left\{I_{ss}^{(1)}, I_{ss}^{(2)}, ..., I_{ss}^{(\frac{K}{2})}\right\}.$$

For any real-time input $I_i$, the seizure/non-seizure class is determined by selecting the pattern in the signature sets with the highest score of similarity. In other words, the highest score of latent feature similarity is the shortest feature distance $D$ in the latent domain, as formulated below:

$$D_{ns} = \min_{I_{ns}\in S_{ns}} \left\|F(I_i) - F(I_{ns})\right\|_2,$$

$$D_{ss} = \min_{I_{ss}\in S_{ss}} \left\|F(I_i) - F(I_{ss})\right\|_2,$$

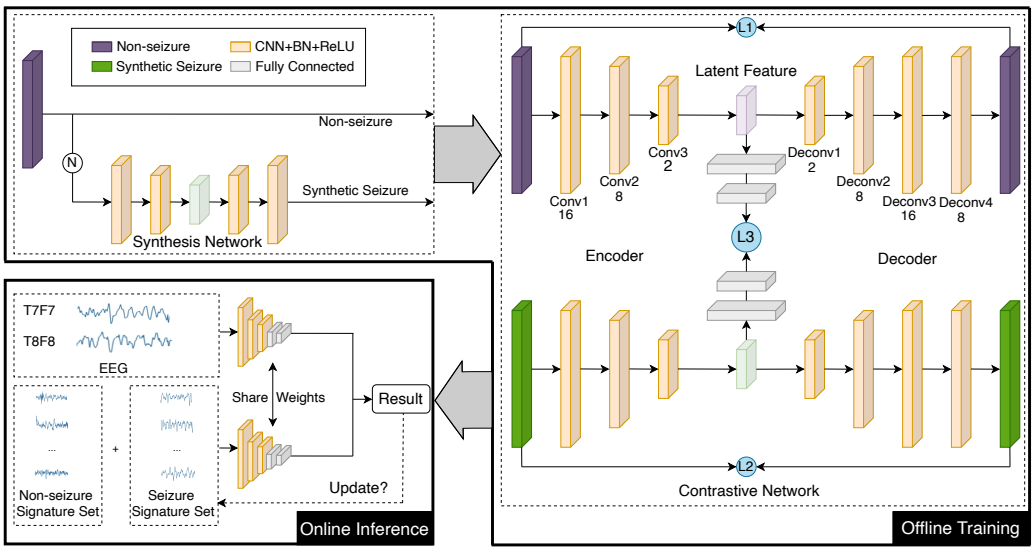


Fig. 1. **EpilepsyNet** contains offline training and online inference. Synthesis Network: only non-seizure data are used and noise is added to generate synthetic seizure data. Contrastive network: it constructs the contrastive pairs with the $Re2Cons$ loss. The yellow blocks are 1D-CNNs with BatchNorm and ReLU activation function and the gray blocks are Fully Connected Layers.

$$I_i = \begin{cases} \text{non} - \text{seizure} & if\ D_{ss} > D_{ns}, \\ \text{seizure} & \text{otherwise.} \end{cases}$$

The update of the signature sets at runtime are computationally efficient. In particular, once a seizure is detected at runtime, the seizure data can be incorporated into the signature sets on the e-Glass wearable system without the need to retrain the model. During the update process, we only need to replace the synthetic seizure data with the detected real seizure data in seizure signature set. We maintain the latent feature of detected real seizures to reduce the number of online inferences in the future. At the same time, we already have the latent feature of the initial signature sets, during the process of the offline contrastive network. Thus, only one inference for each newly-acquired EEG data is conducted during the online inference.

Finally, as more real seizure data are detected at runtime, the seizure signature set is updated accordingly over time and the seizure detection performance will improve. This process also indirectly improves the quality of the seizure signature set. As a result, while the network does not need to be retrained, it can reach a higher contrastive performance over time. In practice, as we will discuss in the next section, only 5 real seizure and 5 non-seizure signatures are sufficient to reach a detection performance comparable with the fully-supervised state-of-the-art techniques [25]. Thus, this capacity of EpilepsyNet for self-evolution enables incremental improvement of seizure detection performance, without incurring any energy overheads.

## III. Experimental Evaluation and Results

### A. Experimental Setup

*1) Dataset:* We evaluate our proposed approach based on the CHB-MIT Scalp EEG Database [27] for both training and inference. Here, we only consider two channels (T7F7 and T8F8) to show the feasibility of running the proposed network on the e-Glass wearable system [22]. Furthermore, we do not consider patients 6, 14, and 16, because they have very short-lasting seizures. For the pre-processing, a bandpass filter with the pass band of 1–30 Hz is applied to the raw EEG signals. Then, we window the filtered signal with the window length of 4 seconds, i.e., 1024 samples with a Z-score standardization.

*2) Implementation Details:* The dataset comprises training sets (70%), validation sets (15%), and testing sets (15%). Furthermore, we set *batchsize* to 16, *learning rate* to $1e^{-3}$, *epochs* to 40 for the synthesis network, and set *batchsize* to 4, *learning rate* to $5e^{-4}$, *epochs* to 50 for the contrastive network with $\lambda_1 = \lambda_2 = \lambda_3 = 1$ and $M = 6.0$. We use the Adam optimizer. EpilepsyNet is implemented in Pytorch and the network is trained on an NVIDIA® V100 Tensor Core.

*3) Evaluation Metrics:* To evaluate the performance of EpilepsyNet, we use three metrics called Sensitivity ($Sens = \frac{TP}{TP+FN}$), Specificity ($Spec = \frac{TN}{TN+FP}$), and Geometric mean ($Gmean = \sqrt{Sens \times Spec}$). The seizure data are regarded as $P$ (Positive) and the non-seizure data are regarded as $N$ (Negative). $TP$ is the number of correctly detected seizure samples. $TN$ is the number of correctly detected non-seizure samples. Furthermore, $FP$ and $FN$ denote the number of false positives and false negatives, respectively.

### B. Experimental Results

*1) Performance:* Here, we evaluate the seizure detection performance of our proposed EpilepsyNet approach and compare the results with the state-of-the-art techniques.

*Basic Inference:* Initially, we only have the synthetic seizure data in the seizure signature set. Therefore, in *EpilepsyNet*, we exclusively use the non-seizure and synthetic seizure data in the training and signature sets. We also consider the case where we train the network using real seizure data, but the network still uses the synthetic seizure signature set and denote it by *EpilepsyNet + Real Seizure*. We perform the experiments four times and report the average results in Table I. The results show that our network, without using any real seizure data, has

TABLE I
QUANTITATIVE COMPARISON OF DIFFERENT EXPERIMENTAL SETUPS.

| Type | Approach | Real Seizure In Training | Real Seizure In Signature Sets | Real Seizure In Evaluation | Re2Cons | Sens(%) | Spec(%) | Gmean(%) |
|---|---|---|---|---|---|---|---|---|
| **Basic** | EpilepsyNet + Real Seizure | ✓ | × | ✓ | ✓ | 63.3 | 89.4 | 73.3 |
| | **EpilepsyNet** | × | × | ✓ | ✓ | **60.7** | **91.5** | **72.2** |
| **Incremental** | iEpilepsyNet + Real Seizure | ✓ | ✓ | ✓ | ✓ | 80.7 | 79.8 | 80.2 |
| | iEpilepsyNet - Re2Cons | × | ✓ | ✓ | × | 76.2 | 77.7 | 76.8 |
| | **iEpilepsyNet** | × | ✓ | ✓ | ✓ | **78.9** | **79.7** | **79.2** |
| **SoA** | Fully-Supervised CNN [25] | ✓ | – | ✓ | – | 71.4 | 91.5 | 80.8 |

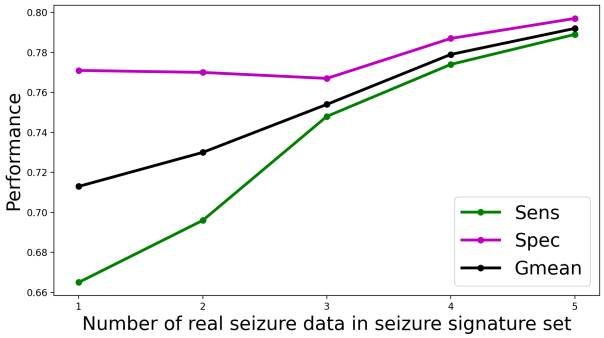


Fig. 2. Performance improvement in incremental inference.

a comparable performance with the case when we use the real seizure data in the training process.

*Incremental Inference:* In the online inference phase, once a seizure is detected, the synthetic seizure data in the seizure signature set will be replaced by the real seizure data incrementally. The incremental replacement of seizure signature data does not require any retraining of the network, hence not requiring any extra energy. Specifically, by increasing the number of real seizures in seizure signature set, all the metrics will be improved incrementally. These results are shown in Fig. 2. As we observe, the *Gmean* increases from 71.3% to 79.2% in the incremental inference when we increase the number of real seizure patterns in the seizure signature set from one seizure to five seizures. Similarly, the *Sens* increases from 66.5% to 78.9% and the *Spec* increases from 77.1% to 79.7%.

Below, we perform several experiments to extensively evaluate our proposed approach:

1) *iEpilepsyNet (incremental EpilepsyNet)*: contrastive learning with the $Re2Cons$ loss function, and with real seizure data used in signature sets and evaluation, but not in the training process. As shown in Table I, the *Gmean* of *iEpilepsyNet* achieves 79.2%. In addition, the *Sens* reaches 78.9% and the *Spec* reaches 79.7%. The results are on par with the fully-supervised state-of-the-art Convolutional Neural Network (CNN) technique in [25] as shown in Table I.
2) *iEpilepsyNet + Real Seizure*: contrastive learning with the $Re2Cons$ loss function, and with real seizure data used in training, signature sets, and evaluation. As shown in Table I, the *Gmean* of *iEpilepsyNet + Real Seizure* achieves comparable 80.2%. The result highlights the fact that using real seizure data in the training process can only marginally (less than 1%) improve the seizure detection performance compared to *iEpilepsyNet*.
3) *iEpilepsyNet - Re2Cons*: contrastive learning without the $Re2Cons$ loss function, and with real seizure data used in signature sets and evaluation, but not in training. As shown in Table I, the *Sens* is 76.2%, the *Spec* is 77.7%, and the *Gmean* is 76.8%. All the evaluation metrics are lower than those of *iEpilepsyNet*, which shows the impact of our proposed $Re2Cons$ loss function.
4) *Fully-supervised CNN [25]*: a fully-supervised CNN-based seizure detection using only 2-channel EEG, corresponding to the e-Glass wearable system. As shown in Table I, the *iEpilepsyNet*, without using any real seizure data for training, achieves a seizure detection performance of 79.2% in terms of *Gmean*, which is comparable with the performance achieved by this fully-supervised state-of-the-art CNN technique, i.e., 80.8%.

*2) Power Consumption:* We deploy our EpilepsyNet in the e-Glass system [18], which includes: (1) a STM32L476RGT6 ARM Cotex-M4 microcontroller, featuring 1 Mbyte of Flash memory and 128 Kbytes of SRAM; (2) an ADS1299 EEG front-end. First, we use the Otii Arc power analyzer and a shunt resistor, i.e., 5 Ohm to measure e-Glass' current consumption in two operating modes: (1) run mode, active while retrieving data and processing; (2) low-power mode, activating the stop 2 mode while idle (only acquiring data). Second, we use the ARM Cortex-M data watchpoint and trace component to determine the inference run time (microcontroller running at 80 MHz). e-Glass board draws an average of 22.45 mA in run mode, which is reduced to 6.40 mA in low-power (always-active ADS1299 circuitry consumes approximately 4.6 mA). Inference lasts only 201.11 ms, a 5% duty cycle (4-second window) leading to a 7.21 mA current consumption on average. When using a 225 mA·h LiPo battery, e-Glass can achieve approximately 31.2 hours of battery lifetime (more than one day).

## IV. CONCLUSIONS

In this paper, we have proposed EpilepsyNet, the first end-to-end self-supervised network that can perform seizure detection for new patients with no need for training the model with their seizure data. EpilepsyNet enables the possibility of long-term ambulatory monitoring on resource-constrained edge devices and wearable systems with a performance on par with the fully-supervised state-of-the-art networks.

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