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

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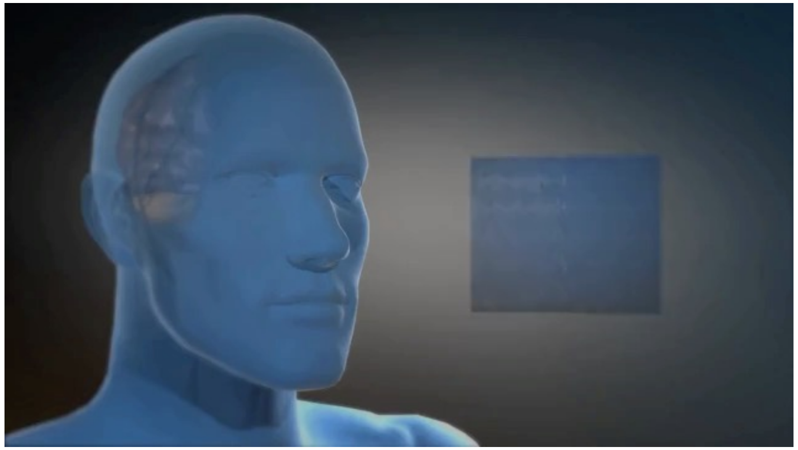
Introduction and Background of Epilepsy

Epilepsy

Epilepsy, as one of the most common neurological disorders, is characterized by **recurrent and unpredictable seizures**. An epileptic seizure is the clinical manifestation of an abnormal and purposeless electrical discharge in the brain cells called neurons.



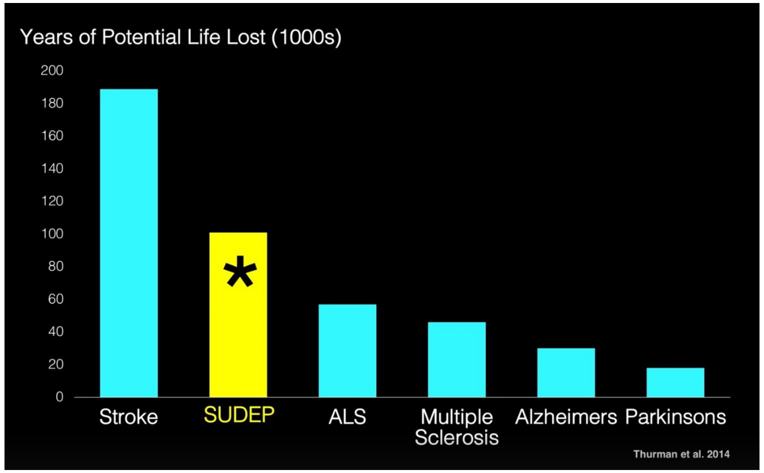
Source: https://gfycat.com/ornatehastykentrosaurus-amyloid-beta-neuroscience-microglia

Epilepsy affects around 65 million people worldwide.

[1] World Health Organization. Epilepsy: a public health imperative[M]. World Health Organization, 2019.

Sudden Unexpected Death in Epilepsy (SUDEP)

People with epilepsy (PWE) have a 2-3 times **higher mortality rate** compared to the corresponding healthy population, mainly because of seizure-caused accidents and Sudden Unexpected Death in Epilepsy (**SUDEP**).



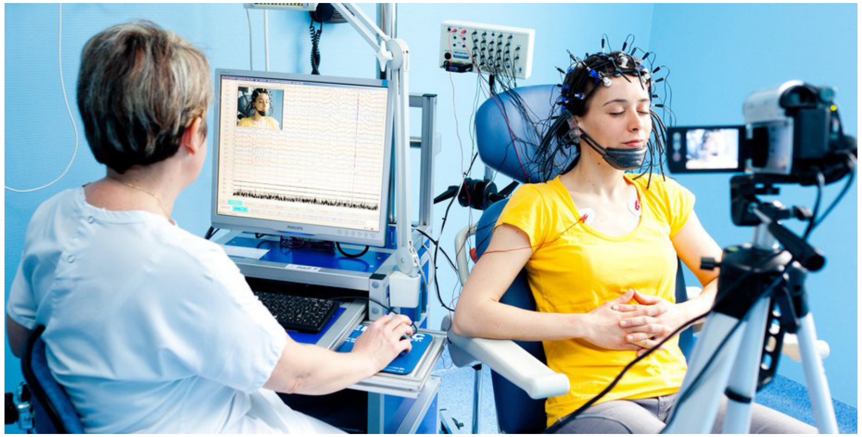
Source: https://www.ted.com/talks/rosalind_picard_an_ai_smartwatch_that_detects_seizures

Epilepsy is the second neurological cause of years of potential life lost mainly due to seizure-caused accidents and SUDEP.

[2] Thurman et al.. Sudden unexpected death in epilepsy: assessing the public health burden[J]. Epilepsia, 2014.

Gold Standard

Video-EEG recording is the gold standard of epilepsy monitoring but has **several limitations** for monitoring outside the hospital environment. Patients need to stay in the hospital for a long time to collect seizure data.



Source: https://www.baraniscans.com/

Wearable Technology: e-Glass

Automated EEG-based seizure detection on wearable devices (e-Glass) provides the possibility of **real-time patient monitoring** in ambulatory settings. However, wearable devices have stringent **resource constraints**, including limited memory storage, computing power, and battery lifetime.

[22] Sopic D, et al. e-glass: A wearable system for real-time detection of epileptic seizures[C]. ISCAS, 2018.

Problem and Challenge

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.

Current Methods	Source
Few-shot Learning*	[13]
One-shot Learning*	[15]
Transfer Learning*	[17]
Generative Adversarial Networks (GANs) *	[18]
Anomaly Detection*	[21]

***Still require seizure data**

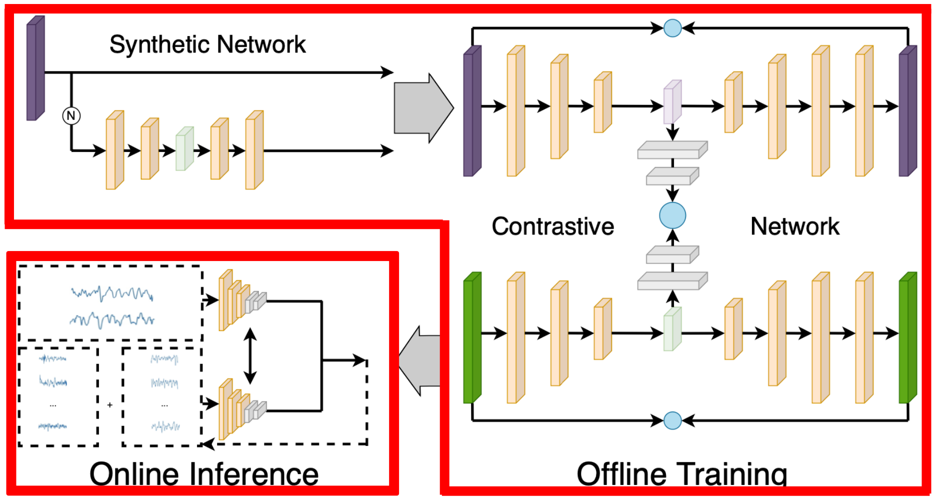
New patients usually do not have any collected and labelled seizure data, a major challenge that has been recognized.

[13,15,17,18,21] in our paper.

Proposed Interpretable Self-Supervised Seizure Detection for Low-Power Wearable Systems

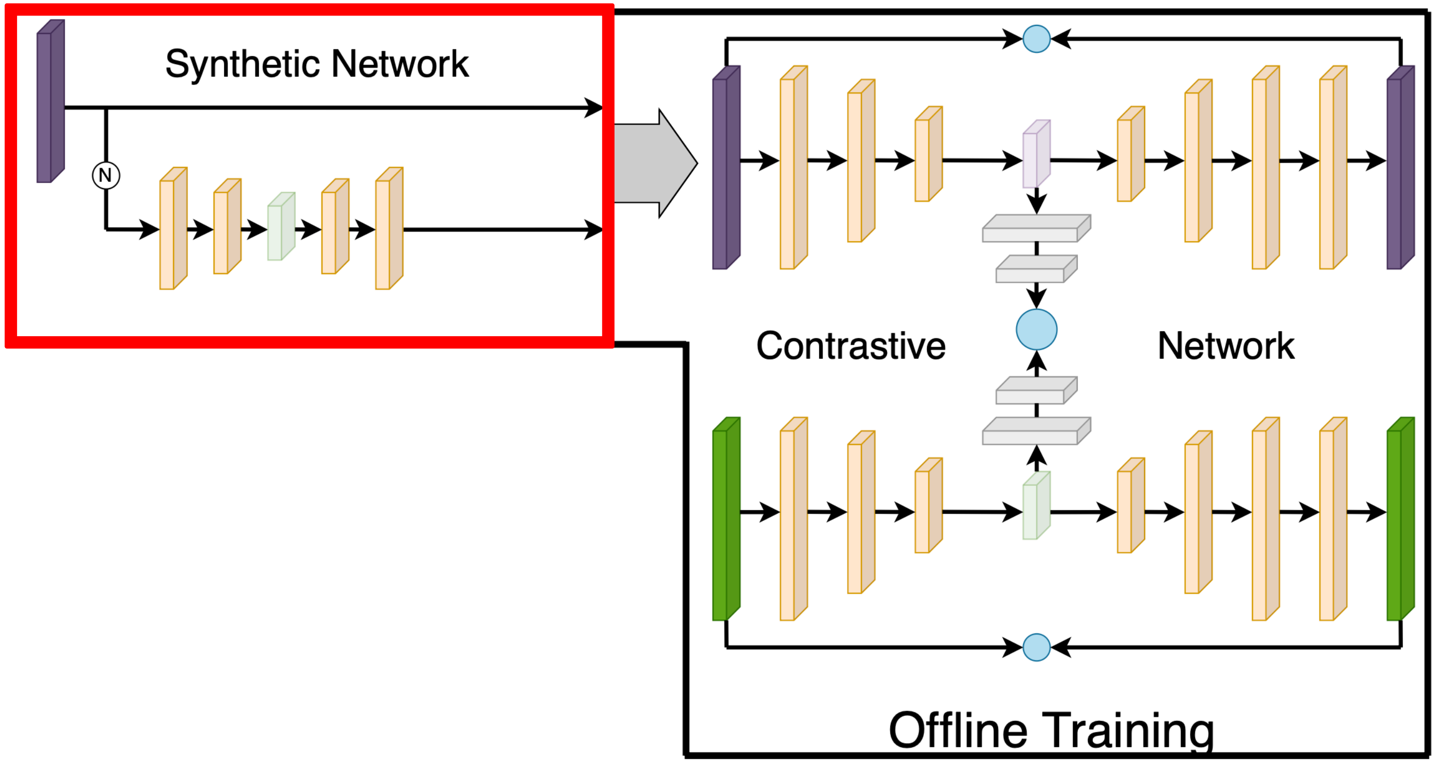
EpilepsyNet

We propose EpilepsyNet for resource-constrained wearable systems, the first interpretable self-supervised network for seizure detection **without any need for labeled seizure data** for new patients in training.



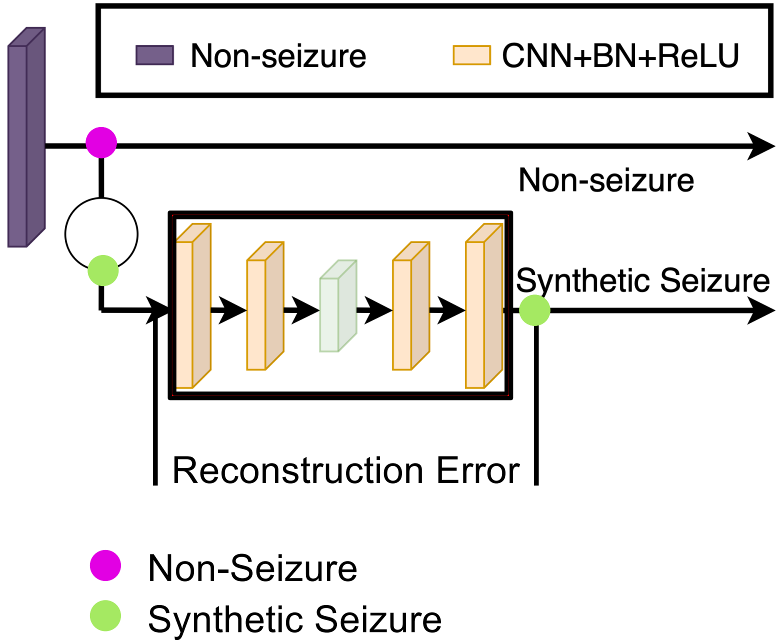
Offline Training + Online Inference

Offline Training: Synthetic Network

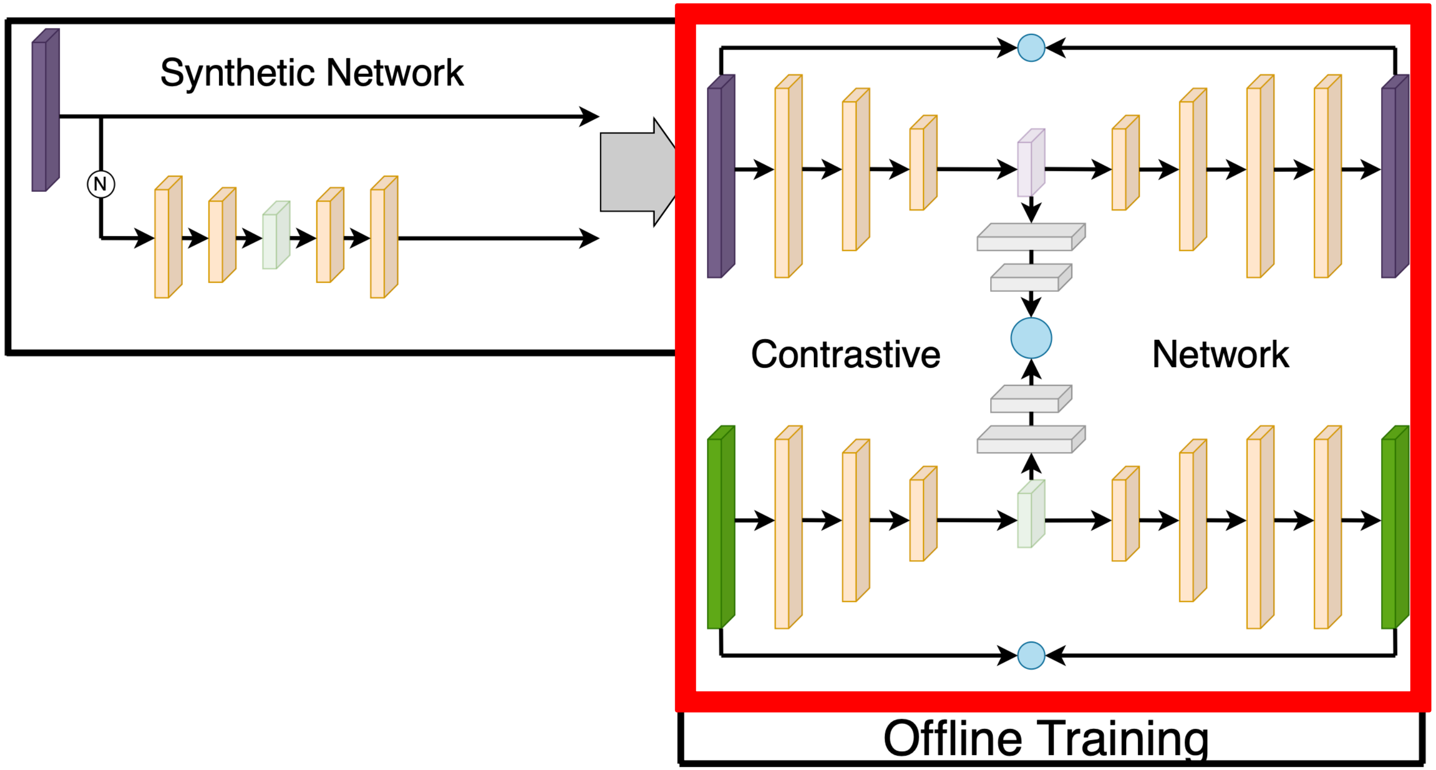


Offline Training: Synthetic Network

The synthesis network is based on an autoencoder. By adding Gaussian noise to non-seizure data, **the synthetic seizure data are available** if the reconstruction error exceeds a certain threshold.



Offline Training: Contrastive Network



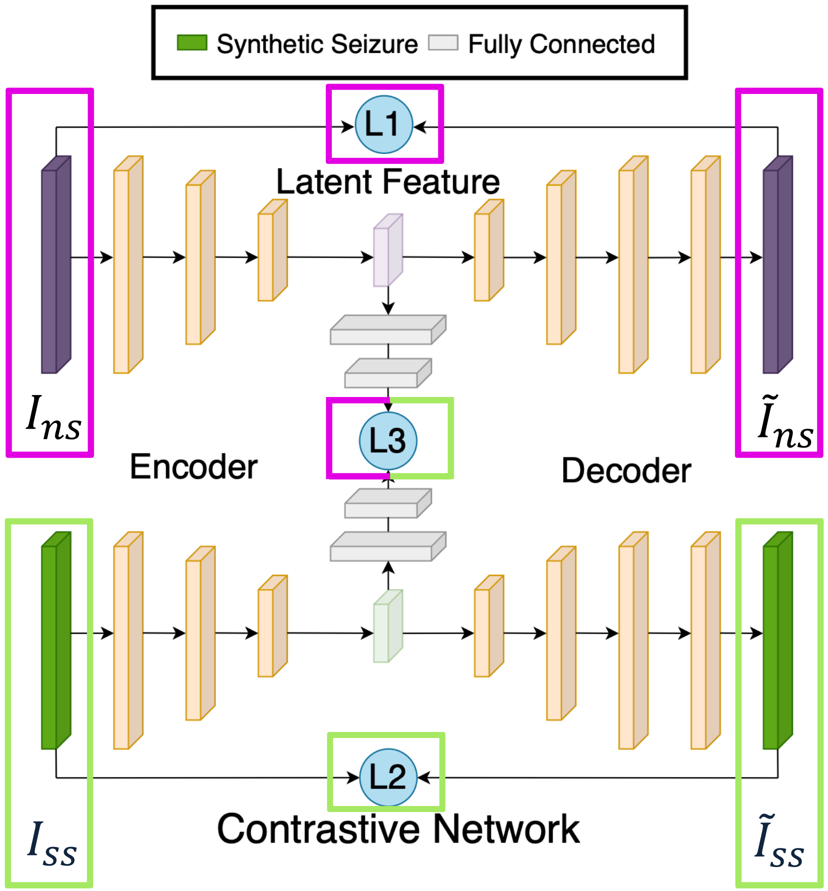
Offline Training: Contrastive Network

We construct two kinds of pairs:
same class and **different class**
to train the contrastive network.

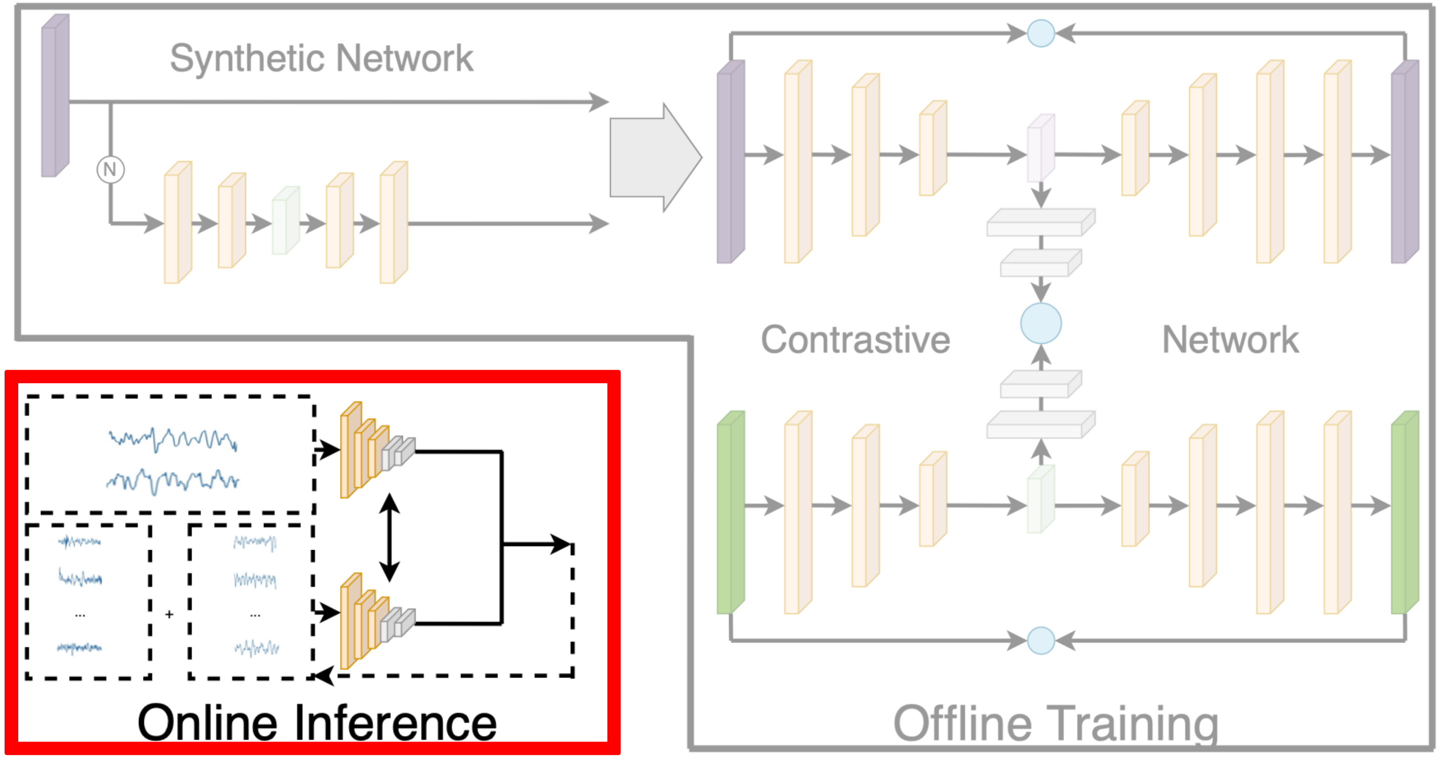
$$Loss = L_1 + L_2 + L_3$$

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

$$L_1 = \frac{1}{T}\|\tilde{I}_{ns} - I_{ns}\|_1$$

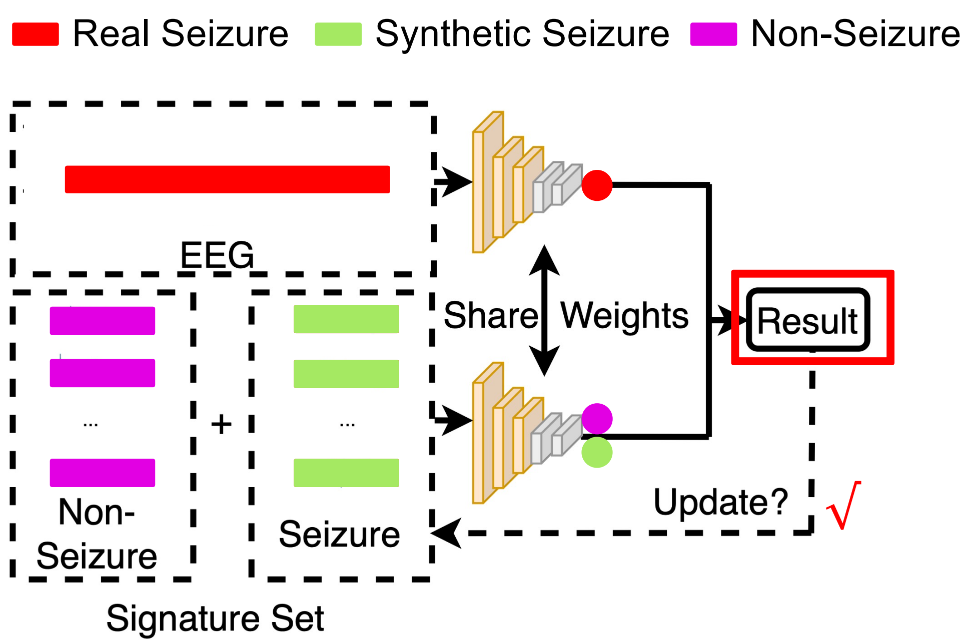


Online Inference



Online Inference: Incremental Improvement

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.



Experimental Results

CHB-MIT Scalp EEG Database

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 and a Z-score standardization.

$$\text{Sensitivity}\left(\text{Sens} = \frac{\text{TP}}{\text{TP}+\text{FN}}\right), \quad \text{Specificity}\left(\text{Spec} = \frac{\text{TN}}{\text{TN}+\text{FP}}\right), \quad \text{Geometric mean}\left(\text{Gmean} = \sqrt{\text{Sens}\times\text{Spec}}\right).$$

[27] Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, MIT, 2009.

Quantitative Comparison

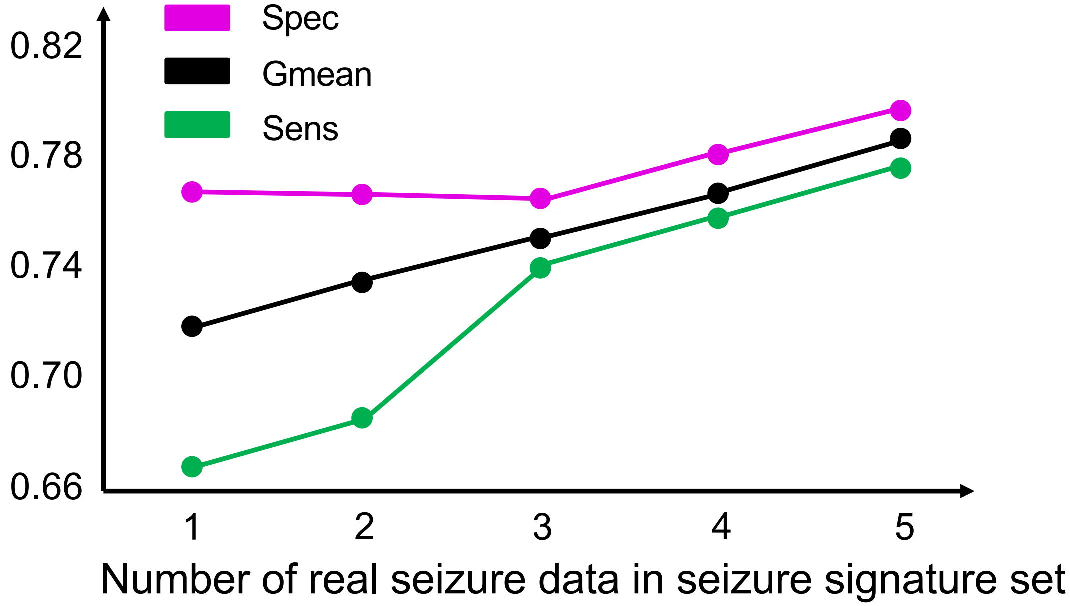
Type	Approach	Real Seizure In Training	Real Seizure In Signature Sets	Real Seizure In Evaluation	Re2Cons	Sens(%)	Spec(%)	Gmean(%)
Basic	EpilepsyNet + Real Seizure	✓	×	✓	✓	63.3	89.4	73.3
	EpilepsyNet	×	×	✓	✓	**60.7**	**91.5**	**72.2**
Incremental	iEpilepsyNet + Real Seizure	✓	✓	✓	✓	80.7	79.8	80.2
	iEpilepsyNet - 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

Our network, without using any real seizure data in training, has a comparable performance with the case having real seizure data.

[25] Gómez C, et al. Automatic seizure detection based on imaged-EEG signals through fully convolutional networks[J]. Scientific reports, 2020.

Incremental Improvement

The Gmean increases in the **incremental inference** when we increase the number of real seizure patterns in the seizure signature set from one seizure to five seizures.



The incremental replacement of seizure signature data does not require any retraining , hence not requiring any extra energy.

Power Consumption

Run mode: active in processing data and model inference on e-Glass;
Low-power mode: activating the stop 2 mode while idle (only acquiring data).

Mode	Duty Cycle	Current
Active	5.02%	22.45mA
Low-power	94.98%	6.40mA
Battery life (225 mA·h)	100%	31.2 hours

Our approach can be deployed in resource-constrained wearable devices, reaching up to 1.3 days of battery life on a single charge.

[22] Sopic D, et al. e-glass: A wearable system for real-time detection of epileptic seizures[C]. ISCAS, 2018.

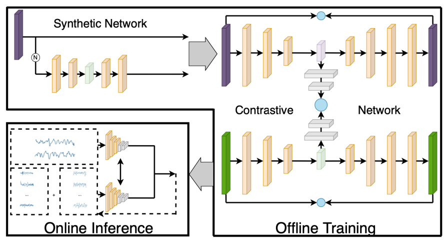
Conclusion

Problem & Challenge

New patients
without seizure data.

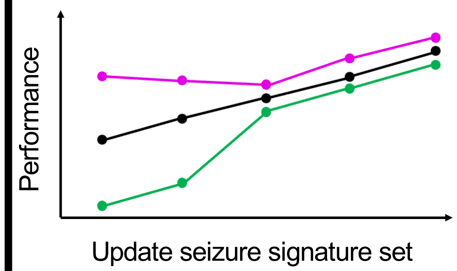
Approach

EpilepsyNet for e-Glass:
the first self-supervised
network for epilepsy.



Performance

Comparable with
supervised SOTA.




Questions?
Thank you!
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