Reliable Electrocardiogram-based Seizure Detection using Multi-Modal Electroencephalography-Electrocardiogram Representation Learning with Intra-Triplet Loss

ABSTRACT

As more people are suffering from epilepsy and seizures by the year, ways to cure or detect these sudden seizure attacks are becoming a vital issue. Current methods of medical treatment or seizure detection devices are not practical, though: the current epilepsy treatment is very costly and the most direct way of detecting seizures, electroencephalography–the method of detecting electrical signals from the brain–is also expensive and inconvenient. Thus, I propose to use an alternate method, utilizing a seizure-detection algorithm that utilizes electrocardiography–which detects the electrical signals from the heart–trained by EEG seizure-detection algorithm as EEG is relatively much simpler to detect patterns before sudden seizures from occurring. I trained the algorithms by utilizing previously discovered seizure-detecting convolutional neural networks and by testing three different loss functions to discover the best performing method. In the final analysis, the DenseNet-169 algorithm performed the best with 90.53% accuracy utilizing the inter squared and intra squared loss functions together.

1. Introduction

Seizures, abrupt and often unpredictable disruptions in brian activity, pose a significant challenge in both diagnosis and treatment, affecting millions globally. According to the World Health Organization (WHO), around 50 million people suffer from epilepsy, each experiencing minor to major inconveniences in life such as driving and social restrictions, health and financial struggles faced from medication, and serious injuries that may lead to death due to sudden seizure attacks (WHO 2024). While prescription exists for the patients with epilepsy, more than half of people who take the medication still experience at least one seizure per year, on top of it being costly and reactogenic (CDC 2024).

Currently, there are efforts to develop seizure detection devices, yet they are still very inaccurate or inconvenient, in necessity for further advancements. Fortunately, there exist two signals from the body that allow people to predict a seizure attack: electroencephalography (EEG) and electrocardiography (ECG). EEG is a reliable method that is directly related to seizures as it reads electrical signals from brain activities; precursors of seizure appear explicitly and are simple to detect, though it is excessively expensive and complicated to detect. On the other hand, it is more difficult to notice symptoms of seizure on ECG signals, yet it is portable and practical due to its affordability.

EEG signals are strongly correlated with seizures and contain rich features associated with them. For this reason, numerous studies have focused on analyzing EEG signals for seizure detection. In contrast, the use of ECG for this purpose is less explored due to the difficulty in extracting meaningful features from ECG signals. To address this challenge, this paper proposes a novel ECG-based seizure detection system. To enhance the system's reliability, a multimodal data processing approach is introduced, utilizing both EEG and ECG during the training phase. This representation learning approach improves seizure detection accuracy during the testing phase.

This research is organized into the following chapters: Chapter 2 provides a comprehensive overview of EEG and ECG. Chapter 3 details the proposed approach, and Chapter 4 provides extensive experimental results. Finally, Chapter 5 concludes the paper.

2. Related Work

2.1 Electroencephalography

Electroencephalography (EEG) is a method that reads electrical signals from brain activities by attaching electrodes onto the scalp as shown in figure 1, mainly used to evaluate brain disorders in the medical field. The data collected by using EEG is characterized by certain qualities such as high-density and high-temporal resolution, allowing for an accurate measurement. Since seizures are a type of an abnormality in the brain wave, it can indeed be easily and precisely diagnosed using EEG. However, using this method to prevent sudden seizures in daily life is impractical, as the devices for using EEG are very costly due to its precision and the range of detecting even the slightest noise, and inconvenient especially with its multiple nodes required to be attached to the scalp.

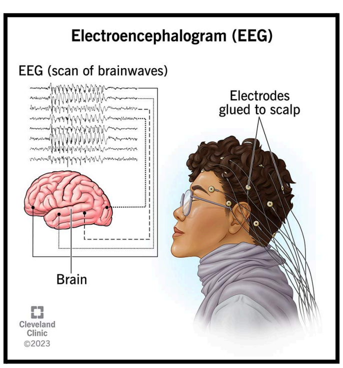

Figure 1. Electroencephalography (Cleveland Clinic 2024)

2.2 Electrocardiogram

Electrocardiogram (ECG) measures the electrical signals in the heart; much like EEG, abnormal activities in the ECG may signify many heart-related conditions. Signals collected from ECG are rather simple and consistent, allowing for an inexpensive and simple device required for measurement. Although ECG may not directly evaluate the brain signals, it has been proven that they are still viable for detecting indications of seizures by examining the activity of the heart. Yet, since data received from ECG is so simple and is not directly related to the brain's electrical activities, further advancements are required to accurately predict the occurrence of sudden seizures.

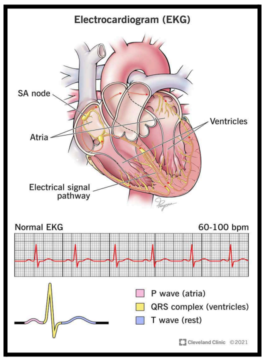

Figure 2. Electrocardiogram (Cleveland Clinic 2024)

3. Proposed Seizure Detection Network

In retrospect, while EEG signals relatively simply identify the precursor for a seizure attack, their real-life application is quixotic. Conversely, although it is a more arduous task to detect seizures through ECG signals, ECG is very accessible and already widely used for different purposes. Therefore by training a convolutional network for ECG with another convolutional network for EEG, we can accurately and cost-efficiently predict seizures.

3.1 Multi-Modal Electroencephalography-Electrocardiogram Representation Learning

Figure 3. Visualization of representation learning for EEG and ECG signals.

This section will discuss the general seizure detection algorithm structure based solely on the inter squared loss function shown in equation 1 and with two other methods shown in equations 2 and 3 combined. The data collected from EEG and ECG is not compatible since EEG is a three dimensional array and ECG is a two dimensional array: EEG is a BNS array (batch size * number of channels * sampling rate), and ECG is a BS (batch size * sampling rate) array. Therefore, through a method called representation learning, the signals collected from both signals will each go through separate convolutional networks and will be projected onto a feature vector. The feature vector represents the data with a complex set of numbers, labeled either with or without seizure, which will be analyzed by machine learning. After creating feature vectors from both signals, the ECG convolutional network will be trained by three separate loss functions and later evaluated to determine which is the most efficient process.

Equation 1: Inter Squared Loss Function

$$\begin{aligned}L_{inter-squared} &= \left\|feat_c^{pos} - feat_e^{pos})\right\|^2 + \left\|feat_c^{neg} - feat_e^{neg})\right\|^2 \\ &+ \max\left(0, \lambda_{inter} - \left\|feat_e^{pos} - feat_c^{neg})\right\|^2\right) \\ &+ \max\left(0, \lambda_{inter} - \left\|feat_c^{pos} - feat_e^{neg})\right\|^2\right)\end{aligned}$$

The feature vectors shown as *feat_c* or *feat_e* each represent the signal evaluated: ECG and EEG, respectively. Additionally, the features labeled positive and negative with a superscript represent the feature vector of the data with seizure and without seizure, and the parameter lambda (λ) is a hyperparameter, or an independent variable that can be altered manually to maximize the efficiency. The inter squared loss function compares four feature vectors, features with positive and negative values from each signal, via a series of L2 functions (a function that squares the difference of two values). The objective is to minimize the difference between feature vectors with the same binary value and maximize the difference between features with opposite binary values of the EEG and ECG model.

Primarily, L2 function is used between the same binary value features for each signal and added together, as the difference between the same binary value feature vectors, the greater the error, and therefore ultimately the loss is greater. On the other hand, L2 function is used between opposite binary value features and subtracted from a hyper parameter, as the difference between the opposite binary value features increase, the ECG model is able to discriminate positive and negative features more easily, and the resulting value goes through the max function with 0 to prevent negative values. This equation will serve as the baseline method as the main purpose of this research is to correlate EEG signals and ECG signals.

Equation 2: Intra Squared Loss Function

$$L_{eeg-intra-squared} = \max\left(0, \lambda_{intra} - \left\|feat_e^{pos} - feat_e^{neg})\right\|^2\right)$$

$$L_{ecg-intra-squared} = \max\left(0, \lambda_{intra} - \left\|feat_c^{pos} - feat_c^{neg})\right\|^2\right)$$

The second equation, intra squared function, compares feature vectors within the same signal, potentially enhancing the individual performances of the convolutional networks. Each subscript and superscript of the features and the parameter λ are identical to equation 1. Unlike the previous loss function, this function simply utilizes the L2 function to calculate the difference between the positive and negative features within the same signal, subtract it from a hyperparameter, and input that value into the max function with 0 again to prevent negative values. This will help the AI model to discriminate two features with opposite binary values as the greater the difference, the loss will decrease.

Equation 3: Intra Triplet Loss Function

$$L_{ecg-intra-triplet} = \max\left(0, \lambda_{intra} + \left\|feat_c^{anchor} - feat_c^{pos})\right\|^2 - \left\|feat_c^{anchor} - feat_c^{neg})\right\|^2\right)$$

$$L_{eeg-intra-triplet} = \max\left(0, \lambda_{intra} + \left\|feat_e^{anchor} - feat_e^{pos})\right\|^2 - \left\|feat_e^{anchor} - feat_e^{neg})\right\|^2\right)$$

Finally, the intra triplet loss function is similar in principle to the intra squared loss function (equation 2), yet a new state of the feature–the anchor state–is introduced, and the terminology deviates from the previous two functions. Now, the features labeled positive are features of the same binary value as the anchor state: if the anchor feature vector is a feature with seizure, the positive feature vector is also a feature with seizure, and the equivalent when the anchor state is a feature without seizure. By the same notion, the feature labeled negative is a feature vector with the opposite binary value to the anchor state feature vector. This function compares features within the same signal by adding the L2 function for the anchor state feature and the same state feature as the anchor state and subtracting the L2 function for the anchor state feature and the opposite state feature from the hyperparameter, therefore when optimized, the difference between same state features will be minimized and different state features will be maximized.

3.2 Seizure Prediction

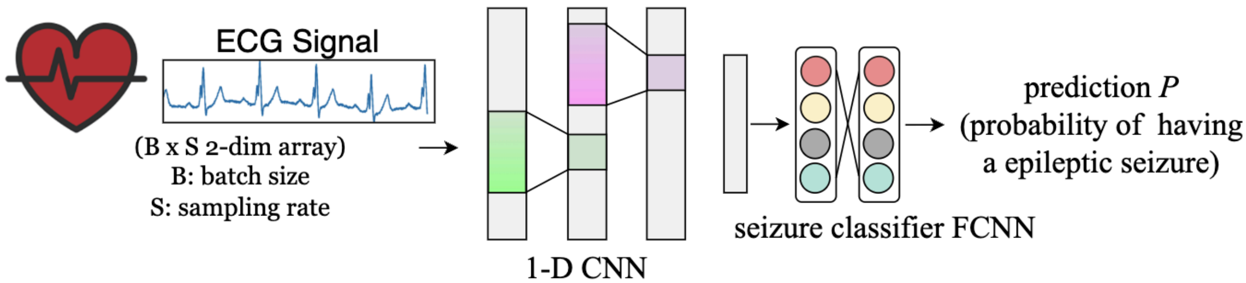

Figure 4. Visualization of transfer learning.

After the representative learning is complete, the ECG convolutional network, trained by the EEG convolutional network, will predict the probability of having epileptic seizure in a process called transfer learning. Later, this model is what I will be using to test the efficiency of this model and the three loss functions by taking in the ECG dataset with and without seizure, outputting the prediction.

Equation 4: Binary Cross Entropy Loss Function

$$L_{binary\_cross\_entropy} = -[y log_e(p) + (1-y) log_e(1-p)]$$

The binary cross entropy function simply takes in the variable y, which is 1 if the data is a signal with seizure and 0 if the data is a signal without seizure. If there is seizure, hence if y value is 1, the function calculates the percentage by taking the log of the prediction p as the second part of the equation cancels out. On the contrary, if there is no seizure, it calculates the percentage by subtracting the probability from 1 and taking the log of that value, and multiplies -1 to the ultimate value, as the first part of the equation cancels out since y is 0. This function will be used to calculate the loss during the transfer learning.

4. Experimental Results and Dataset

4.1 Dataset

The dataset employed to test and train the model is the Seize It1 Dataset (BIOMED Seizure Detection Challenge 2024). This dataset consists of EEG signals collected from 84 participants with 42 of them diagnosed with epilepsy and the other 42 without epilepsy, and out of the 16000 samples collected from the participants, 64.4% of the samples were data without seizure and 35.6% with seizure. When training and testing with this data, a 5-fold cross validation method was used: the dataset was divided into 5 random batches and 80% of the samples were used to train and 20% were used to test, evaluating the sample 5 different times each with different train and test cases. By doing so, the module could accurately measure its efficiency and could maximize the usage of the dataset.

4.2 Experimental Results

Table 1 and figure 5 illustrates the comparison of the performances of the algorithms used to evaluate the data. Accuracy refers to the ratio of accurate predictions to all predictions, recall refers to the ratio of correctly recalled positives to actual positives, precision refers to the ratio of correctly recalled positives to total recalled positives, and the F1-score refers to the harmonic mean of precision and recall. The DenseNet-169 algorithm reported the highest values for all categories with accuracy of 90.5%, recall of 89.5%, precision of 89.3%, and f1-score of 89.4%, and accuracy was generally the highest scoring inference followed by recall and precision by all algorithms. As shown in figure 6, DenseNet-169 correctly predicted 86.2% of data with seizure, incorrectly predicted 13.8% of data without seizure; and correctly predicted 92.7% of control data and incorrectly predicted 7.3% of control data using the intra squared method.

Table 1. Comparison of performance of different convolutional neural networks

	Accuracy	Recall	Precision	F1-Score
VGG-19 (Simonyan et al. 2014)	0.8753	0.8689	0.8672	0.8680
ResNet-18 (He et al. 2016)	0.8807	0.8706	0.8689	0.8697
ConvNext (Liu et al. 2022)	0.8851	0.8760	0.8744	0.8752
HRNet-W30-C (Wang et al. 2020)	0.8944	0.8783	0.8785	0.8784
DenseNet-169 (Huang et al. 2017)	0.9053	0.8945	0.8929	0.8937

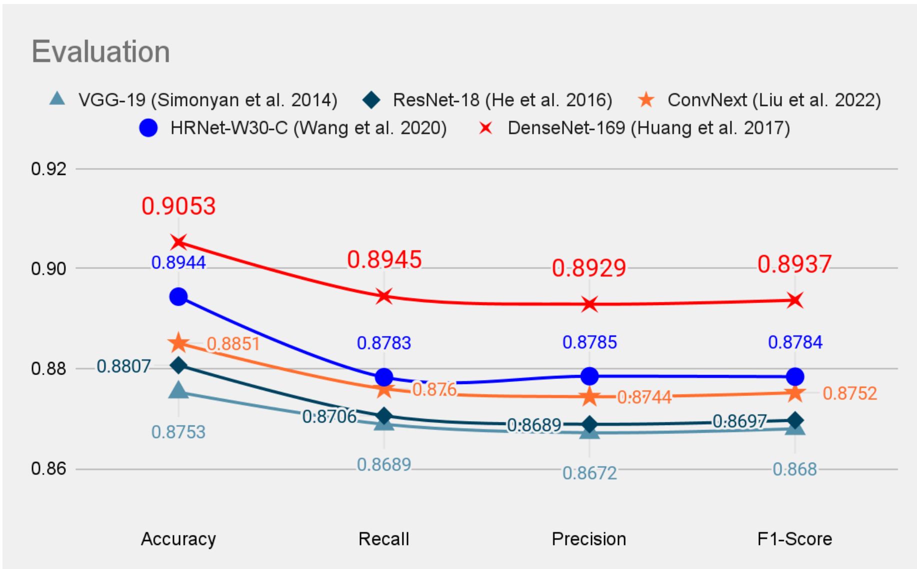

Figure 5. Graph Visualization of Performance of the Seizure Detect Algorithm

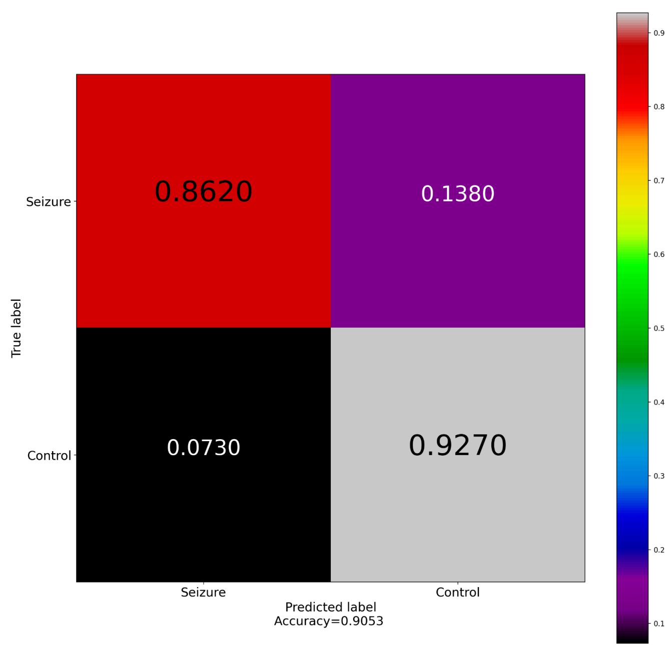

Figure 6. Visualization of Performance of DenseNet-169 Algorithm with Intra Squared Method

Table 2 describes the performance of the three methods proposed earlier: utilizing solely inter squared loss function or incorporating either intra squared loss function or intra triplet loss function. As shown in figure 7, the method of utilizing the intra squared loss function with the inter squared loss function was the best performing method for every algorithm, scoring the highest with 90.53% accuracy with the DenseNet-169 algorithm, followed by the intra triplet method and the baseline method; the intra squared method and the intra triplet method had relatively similar performance compared to the baseline method. Furthermore, each algorithm showed a similar trend for each method, with the DenseNet-169 algorithm performing the best out of all the methods, preceded by HRNet-W30-C, ConvNext, ResNet-18, and VGG-19 algorithm.

Table 2. Comparison of the performances of each methods

	Accuracy (baseline)	Accuracy (triplet)	Accuracy (squared)
VGG-19	0.8217	0.8612	0.8753
ResNet-18	0.8345	0.8635	0.8807
ConvNext	0.8457	0.8698	0.8851
HRNet-W30-C	0.8537	0.8841	0.8944
DenseNet-169	0.8588	0.8957	0.9053

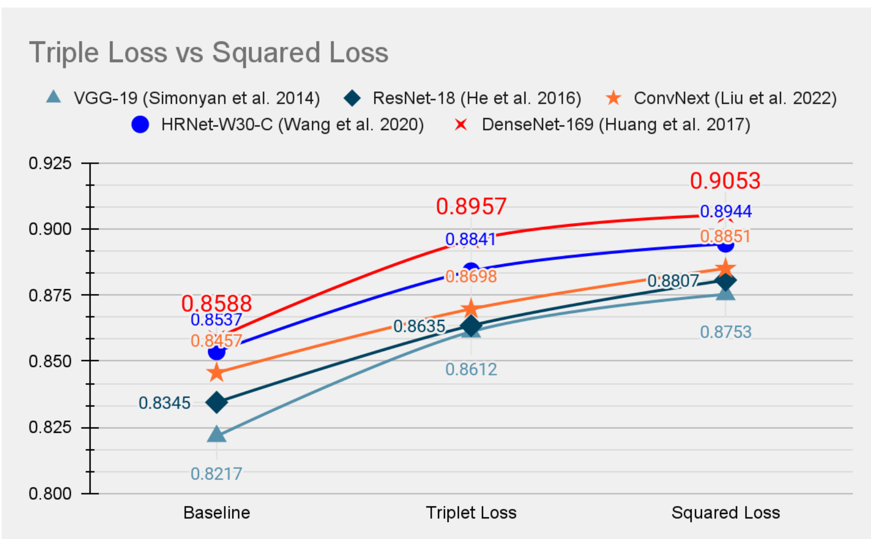

Figure 7. Graph Visualization of Performance of Each methods

5. Conclusion

In this paper, I aimed to merge the benefits of electroencephalography and electrocardiography to detect seizures cost-efficiently, practically, and accurately. I trained a convolutional neural network of ECG with another neural network of EEG to improve the performance of previous seizure-detection algorithms utilizing ECG which finally resulted in 90.53% accuracy utilizing the DenseNet-169 algorithm. Additionally, I tested out three different loss-calculating methods to maximize the performance of the model, which the intra squared loss function utilized with the inter squared loss function resulted in the highest accuracy. I successfully managed to intertwine the different bioelectrical signals to create a model that can efficiently predict a seizure attack, shedding light on the future implications of a more practical seizure detecting device. Henceforward, this system could be applied in real-world circumstances by developing wearable ECG devices with portable embedded computing boards.

References

BIOMED Seizure Detection Challenge. (2024, Aug 14). “Seizure Detection Challenge”: BIOMED Seizure Detection Challenge.
https://biomedepi.github.io/seizure_detection_challenge/dataset/

CDC. (2024, Sep 4). “*Epilepsy Facts and Stats*”: CDC.
https://www.cdc.gov/epilepsy/data-research/facts-stats/index.html

Cleveland Clinic. (2024, Sep 13). “*Electrocardiogram (EKG)*”: Cleveland Clinic.
https://my.clevelandclinic.org/health/diagnostics/16953-electrocardiogram-ekg

Cleveland Clinic. (2024, Sep 13). “*Electroencephalogram (EEG)*”: Cleveland Clinic.
https://my.clevelandclinic.org/health/diagnostics/9656-electroencephalogram-eeg

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
https://doi.org/10.48550/arXiv.1512.03385

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).
https://doi.org/10.48550/arXiv.1608.06993

Liu, Z., Mao, H., Wu, C. Y., Feichtenhofer, C., Darrell, T., & Xie, S. (2022). A convnet for the 2020s. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 11976-11986).

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. https://doi.org/10.48550/arXiv.1409.1556

Wang, J., Sun, K., Cheng, T., Jiang, B., Deng, C., Zhao, Y., ... & Xiao, B. (2020). Deep high-resolution representation learning for visual recognition. IEEE transactions on pattern analysis and machine intelligence, 43(10), 3349-3364. https://doi.org/10.48550/arXiv.1908.07919

WHO. (2024, Feb 7). “*Epilepsy*”: WHO.
https://www.who.int/news-room/fact-sheets/detail/epilepsy