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Real-Time Epilepsy Seizure Detection: Leveraging Machine Learning for Electroencephalography Signal Classification

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ABSTRACT

A seizure is a burst of electrical activity in the brain that can lead to a range of complications. Seizures occur when the normal communication between brain cells is disrupted which leads to abnormal electrical activity. The unpredictable nature of seizures makes daily life challenging for those affected. Because seizures can occur without warning, individuals often face significant anxiety and fear about when and where a seizure might happen. This unpredictability can limit their participation in everyday activities, such as driving, attending social events, or even going to work or school. To address this problem, I proposed an EEG-based seizure detection system utilizing machine learning techniques. EEG captures the brain's electrical activity through electrodes placed on the scalp which provides real-time data on neuronal patterns. By analyzing this data, the system can identify specific electrical signatures associated with seizure activity. To enhance the accuracy of the system, I introduced a triplet loss function that leverages improved feature representation. Extensive experimental results clearly demonstrate that the proposed approach increased accuracy by 5.28%. Additionally, the proposed approach was evaluated with four state-of-the-art convolutional neural networks which achieved an accuracy of 80.2% on a public dataset.

Introduction

A seizure is a burst of electrical activity in the brain, that causes changes in levels in several areas such as consciousness, behavior, feelings, etc. According to WHO, the duration of seizures can vary widely depending on the type of seizure and the individual. If the seizure spans more than five minutes, it is considered a medical emergency. Seizures have many causes, the most common one is epilepsy. Other causes include after-stroke head injuries, infection of the brain such as meningitis and encephalitis, severe illness, such as coronavirus, low blood sodium, lack of sleep, painkillers, anti-depressants, head trauma, and illegal or legal drug usage are some other causes. Seizures lead to a series of complications, that are not only dangerous to one but also to others. If one falls during a seizure, this can lead to an injury in the head, or bones. Another danger can be car accidents, the loss of awareness from a seizure while driving can cause car accidents, which can severely affect others. Swimming or bathing during a seizure can cause drowning. A seizure during pregnancy can cause danger to both the baby and the parent, and anti-seizure medications increase the risk of birth defects. People with seizures have a likelihood of depression, and anxiety, which can be a side effect of anti-seizure medicine.

To improve the quality of life for patients who are suffering from seizures, technologies that can detect incoming seizures are necessary. These technologies will be able to prevent extreme consequences of seizures, which can extend to harming not only the patient but the ones around them as well. There have been a few studies regarding detecting incoming seizures. Wei et al. proposed a Convolutional Neural Network, that was able to prove the feasibility of the usage of EEG to detect seizures (Wei et al. 2018). Thuwajit et al, later proposed a multiscale Convolutional Neural Network, to increase the accuracy of the detections (Thuwajit et al. 2021). Albaqami et al, proposed a seizure-type classification, after further studies (Albaqami et al. 2023). However, all previous methods are sensitive to EEG noise which makes their results inaccurate when they were applied to real-world scenarios.

To address these issues, this paper proposes a triplet loss function to identify robust representations of seizure-related features. The proposed seizure detection system consists of two modules: representation learning and transfer learning. The representation learning module employs the triplet loss function to minimize and maximize the feature distance based on EEG sample pairs. The transfer learning module builds on this by continuing the training process from pre-trained weights to determine whether an individual is experiencing a seizure.

The remaining chapters of this paper are organized as follows: Chapter 2 provides essential background knowledge to better understand the proposed approach. Chapters 3 and 4 detail the implementation of the triplet loss function and present the experimental results. Finally, Chapter 5 summarizes the findings and limitations of the study.

Electroencephalogram and Epilepsy Seizure

Electroencephalogram

An EEG (Electroencephalogram) is a test that detects brain waves, or the brain's electrical activity for abnormalities. During the test, 21 electrodes are pasted onto the scalp, on metal disks with wires connected. These electrodes detect electrical charges that result from the activity of brain cells, and these later appear as a graph on the computer screen. The use of EEG can be used to warn patients of a coming seizure, which significantly will decrease the risk of seizure-related consequences. As shown in Figure 1, seizures can be detected from EEG signals using a machine model, as these signals exhibits distinc patterns.

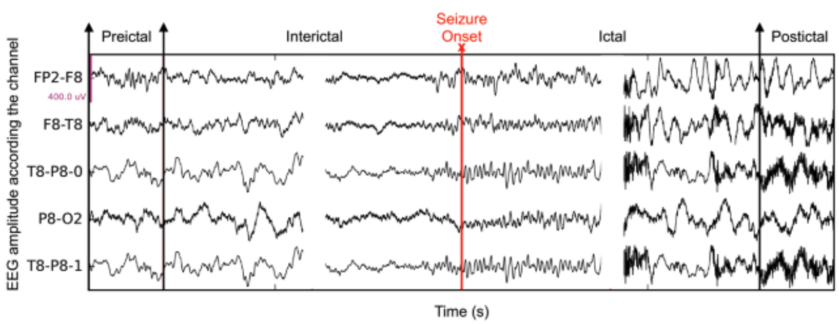


Figure 1. Seizure Patterns In EEG(Jemal et al. 2021)

There are various types of seizures, such as epileptic seizure, which occurs when nerve cells in the cerebral cortex go through hyperexcitability. Partial seizure begins in one part of the brain but spreads to the entire brain due to hyperexcitability of nerve cells. Seizures can also lead to a series of complications, affecting not only one but also others. If one falls during a seizure, then this can lead to an injury in the head, or cause fractions in the bones.

Seizures during driving can lead to car accidents, also affecting others. Drowning can result from a seizure while swimming or bathing. If one is alerted 15-20minutes before a seizure starts, all these complications can be avoided, and certainly, individuals and others around them will be safe.

Epilepsy Seizure

Epilepsy Seizures can be divided into two different types of seizures, partial and generalized. Partial seizures begin in a part of the cerebrum but don't spread out through the cerebrum, which allows one to maintain consciousness. Some seizures can show jerking a part of the body, heart pounding, feeling dizzy and sweaty, and other mental symptoms. Generalized Seizures, cause the patient to lose consciousness, and the patient will have difficulty in breathing. After this, stiffness will persist for some time, and this can cause many different movements, such as trembling limbs, tongue biting, and even trouble urinating or defecating. After this, the patient will go in a deep sleep, which may result in memory loss for some time.

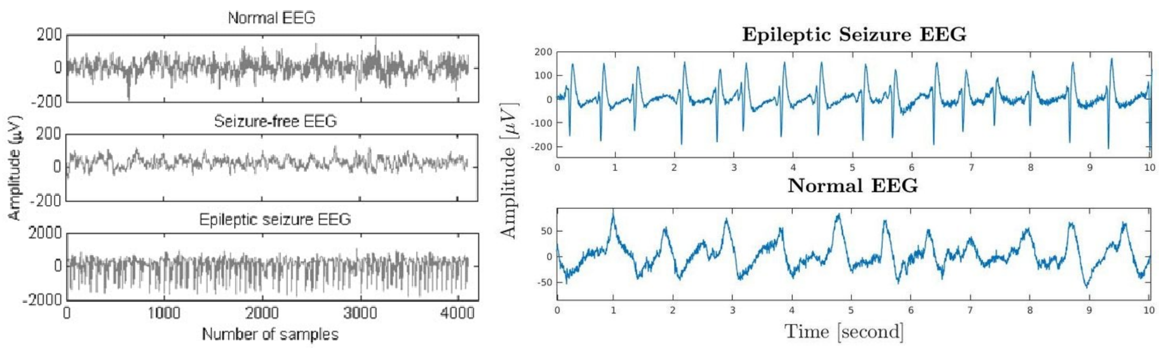


Figure 2. Seizure-free EEG and Epileptic seizure EEG signals (Ebrahimpour et al. 2012)

As seen in Figure 2, the difference between an epileptic seizure EEG, and a seizure-free EEG is very clear. The seizure-free EEG consists of small, minor fluctuations, while the one with epileptic seizures consists of major fluctuations, that happen frequently. To use EEG to benefit the patient's daily life, the development of an accurate automated seizure detection system is vital. In this research, I proposed a machine learning-based seizure detection system that can tell when a seizure is approaching clearly and will alert the patient 10-15 minutes before, to prevent extreme consequences. Detailed explanations of the proposed system will be elaborated in Chapter 3.

Proposed Method

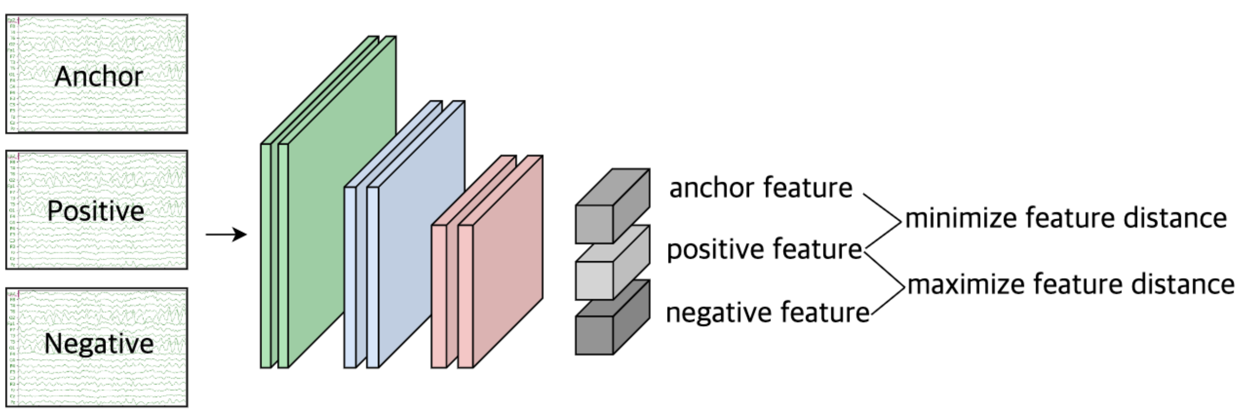


Figure 3. The architecture of the proposed triplet loss training network

Figure 3 illustrates the proposed representation learning module. The convolutional neural network processes a triplet pair of input EEG signals to generate their corresponding features. Each triplet consists of an anchor, a positive sample, and a negative sample. The anchor and positive samples share the same label, while the anchor and negative samples have different labels. For example, if the label of the anchor sample is "seizure occurred," then the positive sample will also be labeled "seizure," while the negative sample will be labeled "normal."

For each sample, the convolutional network processes the input and generates feature representations. The features of the anchor and positive samples should be mathematically similar since they share the same label. In contrast, the features of the anchor and negative samples should be dissimilar due to their different labels. To incorporate this concept into the training procedure, I proposed a triplet loss function that utilizes the feature distances between the anchor-positive pairs and the anchor-negative pairs. To implement this, each feature distance is computed using the distance function, as shown in Equation 1.

Equation 1: Distance function

$$d_{(a,p)} = \|\varphi(e^a) - \varphi(e^p)\|^2$$
$$d_{(a,n)} = \|\varphi(e^a) - \varphi(e^n)\|^2$$

Here, *d(i, j)* represents the features distance between the feature vectors. φ denotes the convolutional neural network that processes the EEG samples as input and generates the corresponding feature representations. The feature distance between similar feature maps, such as the anchor and positive samples, should be minimized, while the distance between dissimilar feature maps, such as the anchor and negative samples, should be maximized. To capture this, a triplet loss function is employed, as explained in Equation 2.

Equation 2: Triplet loss function

$$L_{triplet} = \max\,(0, \alpha + d_{(a,p)} - d_{(a,n)})$$

The loss function compares two values and identifies the maximum value between 0 and the disparity of the two feature distances. The variable $\boldsymbol{\alpha}$ denotes the minimum margin that the two distances should maintain to minimize the loss value, and it is typically set to a positive value. In this research, I set $\boldsymbol{\alpha}$ to 1.

For example, if the feature distance between the anchor and positive samples is equal to the feature distance between the anchor and negative sample, the loss will equal $\boldsymbol{\alpha}$. To minimize the loss value to zero, the disparity between the two feature distances must be less than $\boldsymbol{\alpha}$.

Equation 3: Triplet loss function

$$L_{triplet} = \max\,(0, \alpha + \|\varphi(e^a) - \varphi(e^p)\|^2 - \|\varphi(e^a) - \varphi(e^n)\|^2)$$

Equation 3 presents an alternative form of Equation 2 by substituting the feature distance with Equation 1. The proposed network learns to extract more robust features using the triplet loss function. Once representation learning is complete, this pre-trained network is utilized to train the EEG detection network, which refers to transfer learning.

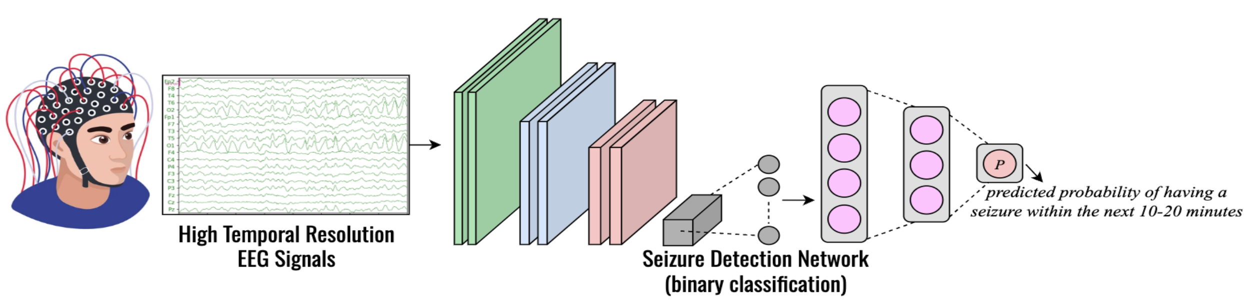


Figure 4. Architecture of the proposed seizure detection network

Figure 4 illustrates the architecture of the proposed seizure detection network. The network takes a single EEG sample and extracts features. It is important to note that the weights of the network are derived from the previous module. The extracted features are then fed into the seizure detection network, which consists of two fully connected layers. The final output, $\boldsymbol{P}$, represents the probability of the input individual experiencing a seizure. To train the seizure detection network, I used the binary cross entropy loss function often used in many binary classification tasks. The binary cross entropy loss function is explained in Equation 4.

Equation 4: Binary cross entropy loss function

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

In equation 4, p and y denote the predicted probability of having a seizure and its corresponding ground truth, respectively. The first term of the function computes the loss value for the positive case when $\boldsymbol{y}$ is 1 which makes the second term zero. Conversely, the second term computes the loss value for the negative case when $\boldsymbol{y}$ is 0.

Experimental Results

Dataset

To train and evaluate the proposed seizure detection network, I utilized the CHB-MIT Scalp EEG Database dataset (Goldberger et al. 2010) which was collected from the Children's Hospital Boston. 23 patients around the age group of 10-22 (5 males,a ge 3-22; and 17 males, age 1.5-19) were tested for 969 hours, where their scalp EEG was recorded. In the dataset, 173 seizure cases were included, as shown in Figure 5.

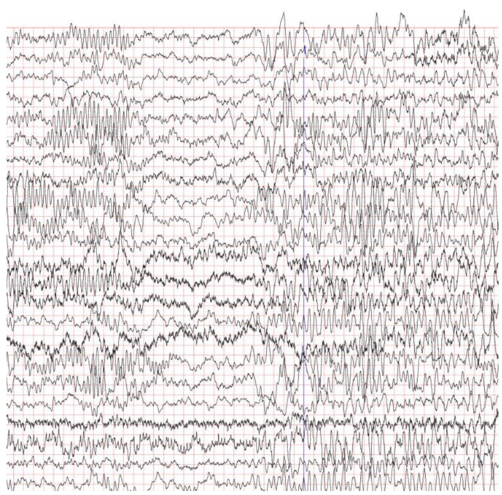


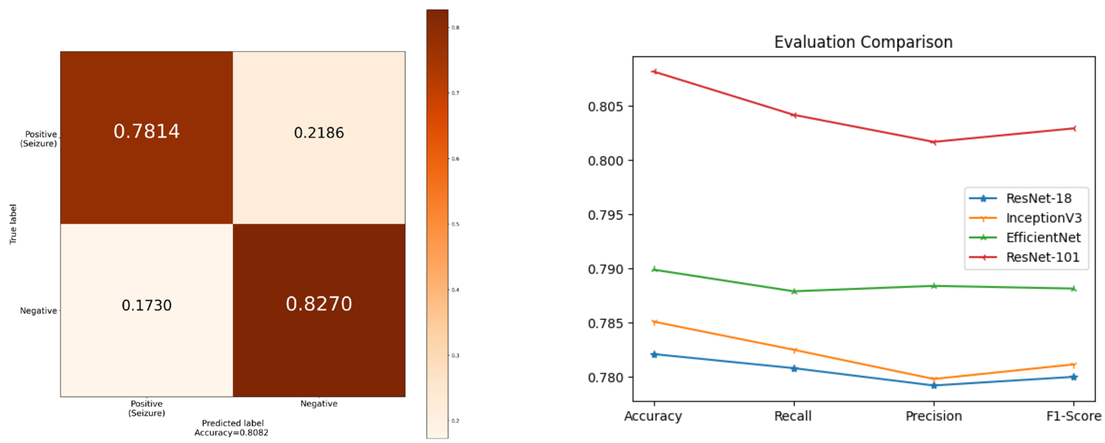
Figure 5. Example sample of CHB-MIT Scalp EEG dataset (Goldberger et al. 2010)

Evaluation Result

To assess the performance of the proposed system, I measured four evaluation metrics: accuracy, recall, precision, and F1 score. Accuracy calculates the proportion of correct predictions made by the model out of all total predictions. Precision measures the accuracy of positive predictions, dividing the number of true positive predictions by the total number of positive predictions which includes both true positives and false positives. Recall calculates the number of true positives out of the actual positives in the dataset. The F1 score is the harmonic mean of precision and recall which provides a balanced measure of the two metrics.

Table 1. Seizure detection performance comparison

	Accuracy	**Recall**	**Precision**	**F1-Score**
ResNet-18 (He et al. 2016)	0.7821	0.7808	0.7792	0.7800
InceptionV3 (Szegedy et al. 2015)	0.7851	0.7825	0.7798	0.7811
EfficientNet (Tan et al. 2019)	0.7899	0.7879	0.7884	0.7881
ResNet-101 (He et al. 2016)	0.8082	0.8042	0.8017	0.8029



(a) (b)

Figure 6. (a)**:** Confusion matrix of ResNet-101 result and (b): performance comparison (line graph)

Table 1 and Figure 6 summarize the evaluation results of the proposed method. I trained the proposed triplet loss function using four state-of-the-art convolutional neural network architectures that have demonstrated comparable performance in various classification tasks. Among these architectures, ResNet-101 achieved the highest accuracy at 80.8%. In contrast, ResNet-18, the shallowest model, achieved the lowest accuracy at 78.2%, which is still a comparable result.

Figure 6(a) presents the evaluation of the confusion matrix. The true positive rate is 78.1%, the true negative rate is 82.7%, the false positive rate is 21.8%, and the false negative rate is 17.3%. The left diagonal components of the matrix (true positives and true negatives) show a high ratio compared to the right diagonal components (false positives and false negatives). This result demonstrates the robustness of the proposed method. Figure 6(b) displays a line graph comparing the evaluation metrics which shows that ResNet-101 achieves the highest performance among the tested architectures.

Table 2: Ablation study result

	Accuracy (with triplet loss)	**Accuracy (baseline: without triplet loss)**

ResNet-18	0.7821	0.7348
InceptionV3	0.7851	0.7411
EfficientNet	0.7899	0.7427
ResNet-101	0.8082	0.7554

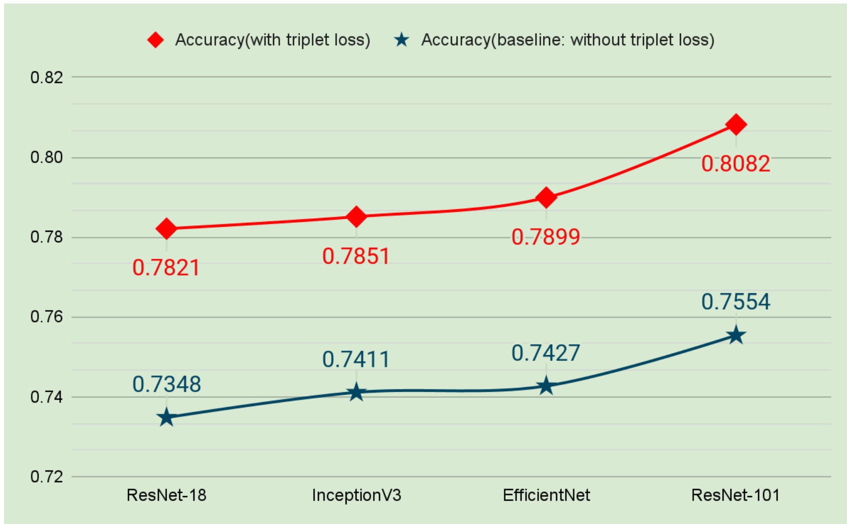


Figure 7. Ablation study results

Additionally, I conducted an ablation study to investigate the effectiveness of the proposed triplet loss function. This study aimed to evaluate the impact of the triplet loss function on the model's ability to detect seizures. Two identical models were tested in different experimental setups: one model was trained using the triplet loss for the seizure detection network, while the other was trained without the triplet loss.

After training, the evaluation results of two models were compared. As shown in Figure 7 and Table 2, the model trained with the triplet loss achieved higher accuracy across all state-of-the-art convolutioanl neural network rchitectures. Notably, ResNet-101, which has the greatest depth among the comparison models, achieved the most significant improvement with an accuracy increase of 5.28%.

Conclusion

In this research, I proposed a method for detecting epilepsy seizures using EEG data and machine learning technology. To enhance the accuracy of the trained model, I utilized a triplet loss function that encourages the network to learn more robust feature representations. The proposed approach was evaluated using four state-of-the-art convolutional neural networks. The results demonstrate an accuracy of 80.2% on the public seizure dataset (CHB-MIT EEG). Additionally, an ablation study clearly showed that the proposed approach improved accuracy across all comparison architectures with an increase of 5.28%. In the future, I plan to implement the system on an embedded board which aims to develop a real-time solution for monitoring seizures in epilepsy patients using the analyzed EEG data.

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