Seizure EEG Signal Classification Using Metric

Learning Based Convolutional Neural Network

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**Abstract.** An epileptic seizure is a neurological condition caused by the abrupt disruption of normal brain activity and poses risks such as paralysis or life-threatening. Early detection is vital because an estimated 70% of individuals with epilepsy can potentially live seizure-free lives if detected early. The electroencephalogram (EEG) is one of the diagnostic tools used for seizure diagnosis. Nevertheless, EEG signals exhibit inherent noise and complexity, exhibiting a substantial degree of similarity between seizure and non-seizure classes, causing a high level of data sparsity. Convolutional neural network (CNN) is inefficient in handling this data sparsity. Therefore, this paper introduces the metric learning training process to improve CNN's ability to organize feature vectors, promoting the clustering of EEG waveforms from the same class. This model is namely the Metric Learning Based Convolutional Neural Network (MLBCNN) where metric learning principles are incorporated into the CNN training process, aiming to shift the emphasis from solely relying on error differences to optimizing the organization of feature vectors in the metric space. It is to cluster feature vectors with high similarity, mitigating the challenges posed by data sparsity and enhancing the CNN's ability to classify EEG data accurately. The performance of the proposed model is evaluated using a publicly available dataset, i.e. Epileptic Seizure Recognition database by the Rochester Institute of Technology. As results, the proposed MLBCNN exhibits superior performance with 97.9% accuracy and a recall rate of 94.4%, surpassing the other machine learning and deep neural networks. The MLBCNN demonstrates considerable promise in terms of reliability, implying its potential as an epilepsy diagnosis tool.

# Introduction

Recent advancements in neuroscience have focused on analyzing brain signals, particularly EEG data, to distinguish between seizure and non-seizure conditions, which is critical for timely medical intervention and patient care [1]. Seizures, characterized by abnormal brain activity, vary widely in presentation and can severely impact health , with early diagnosis enabling 70% of epileptic patients to lead normal lives [2]. However, traditional seizure detection methods face challenges due to human interpretation limitations [3] and a global shortage of neurologists, prompting the exploration of automated approaches like deep neural networks. Despite the potential of CNNs in EEG signal classification, their effectiveness is hindered by the inherent noise, complexity, and sparsity of EEG data, as well as the subtle differences between seizure and non-seizure signals [4]. Researchers are addressing these challenges by adapting CNN architectures and integrating specialized techniques to improve classification accuracy and advance applications in neuroscience and brain-computer interfaces. Hence, this study introduces an improved CNN model, the Metric Learning-based Convolutional Neural Network (MLBCNN), which integrates metric learning into the training process to address the challenge of detecting subtle deviations in EEG signals. Evaluated on the Epileptic Seizure Recognition dataset, the MLBCNN achieves 97.9% accuracy and a 94.4% recall rate, outperforming other machine learning and deep learning models. These results highlight its reliability and potential as a tool for epilepsy diagnosis.

# Related works

While deep learning has advanced EEG-based seizure detection, significant challenges remain unaddressed in current approaches. CNNs and LSTM networks [5,6] have successfully captured temporal patterns, yet they fundamentally struggle with the inherent sparsity and subtle inter-class variations in EEG signals. These architectures typically rely on error minimization objectives that fail to optimize the underlying feature space organization, leading to suboptimal clustering of seizure and non-seizure waveforms. Hybrid CNN-LSTM models [7] and spectrogram-based approaches [8] improve temporal analysis but introduce computational complexity while still lacking explicit mechanisms to handle feature space sparsity.

Recent innovations in transfer learning [9] and ensemble methods like Extra Trees [10] have pushed performance boundaries. Yet, they remain limited by their inability to directly address the core challenge of EEG classification: the high similarity between seizure and non-seizure signals in the feature space. These methods require extensive preprocessing or fail to maintain robustness across diverse patient populations. Particularly concerning is their frequent trade-off between precision and recall, with many models [6,9] reporting either high false positives or missed detections - a critical shortcoming for clinical applications.

Our MLBCNN addresses the mentioned deficiencies using a method that joins metric learning with the CNN architecture. Traditionally, learning features and performing classification are split, but with MLBCNN, optimization focuses on improving the divide between the two classes. The innovation is effective in circumventing the main problems linked to EEG data that previous work has dealt with, and it still works much faster than convolutional or hybrid networks. Unlike spectrogram approaches, our method does not require a great deal of manual effort or heavy hand-processing of the data, and it provides a more reliable result.

# Methodology

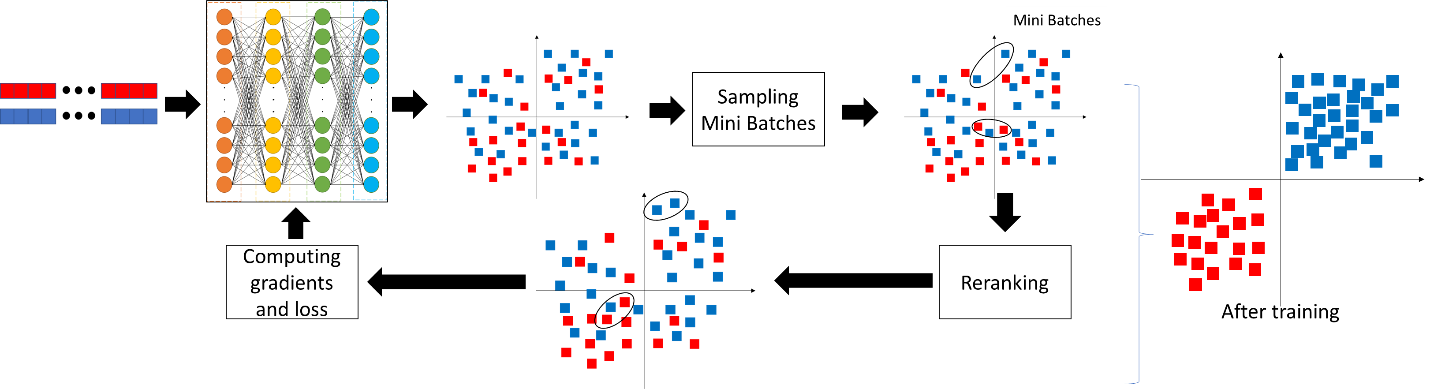
## Datasets

This research utilizes publicly available EEG datasets from the Rochester Institute of Technology, available via the UCI machine learning repository, comprising data from 500 participants [11]. Each participant's EEG data spans 23.6 seconds, divided into 23 groups of 178 samples per second, totaling 11,500 data samples across five categories: eyes open (non-seizure), eyes closed (non-seizure), healthy brain region (non-seizure), tumor region (non-seizure), and seizure activity. Given the low prevalence of seizure data (20%), a sub-sampling technique is applied to balance the dataset, which guarantees a 50% balanced proportion of seizure and healthy classes. The dataset is split into training (70%), testing (15%), and validation (15%) subsets to facilitate model development and evaluation.

## Metric Learning Based Convolutional Neural Network

Analyzing raw EEG signals to identify epileptic seizures is challenging for most conventional approaches [12]. Because EEG measurements are sparse, slight differences in seizure and non-seizure data may not be recognizable when overlapped in the hidden space affected by noise and variations across patients. In addition, regular CNNs successfully lower the classification error by using cross-entropy loss, yet they do not have tools to organize the metric space. They simply treat each feature vector individually rather than as part of a cluster. Because the network does not understand which mutations belong to which classes, it learns ways to separate mutations of different classes only by coincidence.

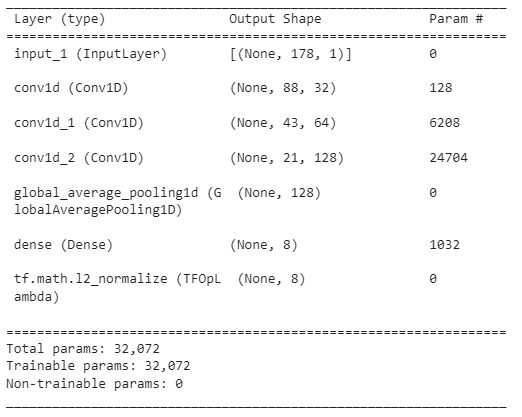
This study introduces a novel approach to training a convolutional neural network (CNN) for analyzing EEG data by incorporating metric learning principles, diverging from traditional error-minimization-based training. Traditional CNN training involves computing errors using a cross-entropy loss function and adjusting network parameters through backpropagation. In contrast, the proposed method focuses on optimizing the arrangement of feature vectors in the metric space to enhance clustering, which is particularly useful given the high similarity between seizure and non-seizure EEG waveforms. Metric learning minimizes distances between similar feature vectors, grouping them together in the metric space, which addresses the challenge of data sparsity and the lack of distinct characteristics in raw EEG data. By shifting the focus from error minimization to organizing feature vectors based on similarity, the enhanced CNN training process improves the network's ability to classify seizure and non-seizure EEG signals effectively. Figure 1 provides an overview of the proposed training process for the modified CNN.



**Figure 1.** Overview of the training process of the proposed MLBCNN

## Convolutional Neural Network (CNN)

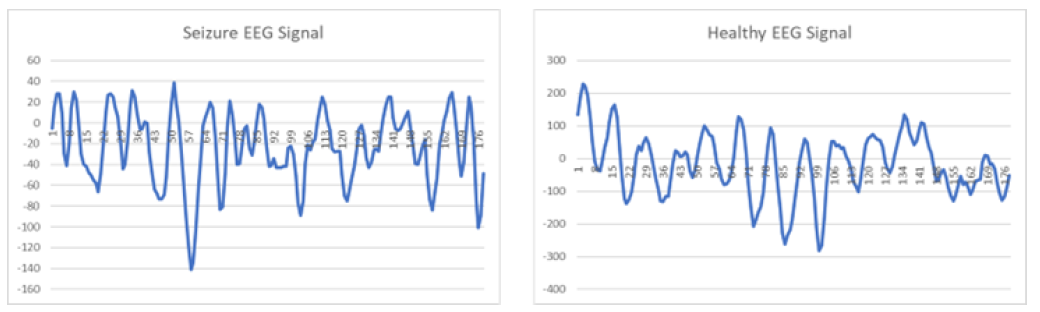
In this study, the primary focus lies on the efficacy of implementing metric learning into the CNN data training process. Thus, a basic CNN architecture is adopted, i.e., a three-layer CNN model is employed to transform raw EEG data into feature embedding vectors. Subsequently, these generated feature vectors serve as data inputs for the metric learning process. By leveraging metric learning principles, the proposed model analyzes the EEG data and produces feature representations that maximize interclass separability, facilitating improved classification of EEG data. Figure 2 depicts the summary of the CNN embedding model.



**Figure 2.** The summary architecture of the CNN embedding model

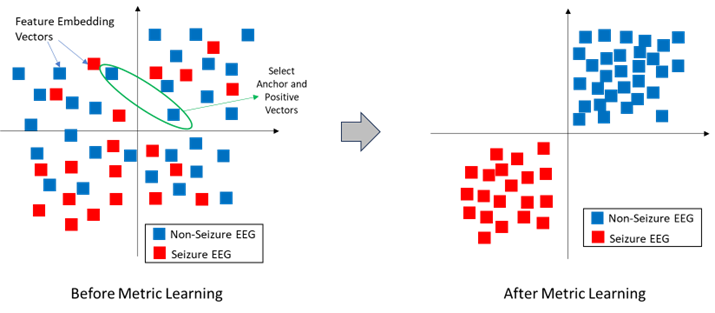
## Metric Learning Training Process

In traditional CNN training, feature embedding vectors derived from EEG waveforms of seizures and non-seizures tend to be sparsely distributed in the metric space due to subtle differences between the two classes. Figure 3 shows the seizure and non-seizure EEG signals.



**Figure 3**. Seizure EEG Signal (left) vs Healthy EEG Signal (right)

Figure 3 shows that the sparsity and dispersion of the signals complicate the classification process. To address this, metric learning is integrated into the training procedure. Metric learning focuses on optimizing distance or similarity metrics to better represent relationships between data points, thereby improving classification accuracy. As illustrated in Figure 4, feature embedding vectors (represented by blue and red squares for non-seizure and seizure signals, respectively) are initially scattered in the metric space. During metric learning, pairs of vectors: a pivot vector (anchor vector) and a target vector (positive vector) from the same class, are selected, and their similarity is calculated using Cosine similarity. Through training, the target vector is adjusted to increase its similarity to the pivot vector, enhancing clustering and classification performance.



**Figure 4.** Metric learning for classifying seizure vs. non-seizure EEG signals

Metric learning starts with the calculation of the angle between a pair of vectors is performed by utilizing cosine similarity [24], as described in Equation (1).

|  |  |
| --- | --- |
|  | (1) |

where is the cosine score of the pivot feature vector and target feature vector ; *j* values are from 1 to 8 as every feature vector consists of the size of 8 that embedded by the CNN. Then, the logit score is computed by utilizing the cosine score as shown in Equation (2).

|  |  |
| --- | --- |
|  | (2) |

where is the logit score. is the temperature coefficient value, which is a hyperparameter and is experimented with a range of values from 0.1 to 1.0 to determine the best temperature coefficient value for the MLBCNN, and the result is compiled in the Results and Discussion section.

Next, the computed logit scores for the two classes are substituted into the SoftMax function for normalization using Equation (3).

|  |  |
| --- | --- |
|  | (3) |

where is the input logit scores for class *i*=1,2. The value n=2 corresponds to the binary classification scenario (seizure and healthy classes). In traditional methods, the logit scores represent the numerical outputs produced by the CNN's final layer for the true class. The logit scores are then utilized together with the SoftMax function for computing the probability of the respective class. Then, the computed SoftMax value is applied to calculate the cross-entropy loss in Equation (4).

|  |  |
| --- | --- |
|  | (4) |

where is the cross-entropy loss, *t* is the labelled value, *i* = 0,1 for healthy and seizure classes. Next, the derivative value is calculated using (5).

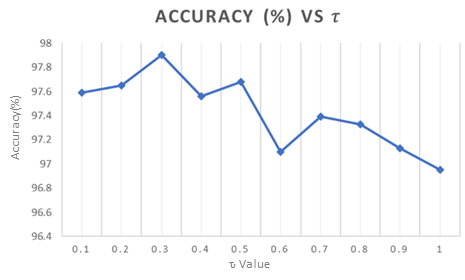
|  |  |
| --- | --- |
|  | (5) |

*∇* is the derivative value, and *o* is the output value. The derivative and loss values are then employed in the backpropagation process, which modifies the weights in the MLBCNN. In this process, Adaptive Moment Estimation (Adam), an optimiser approach with a learning rate of 0.001, is used to accomplish this modification. Following the completion of 30 training cycles, the MLBCNN model's weights are adjusted to optimize the clustering of feature embedding vectors from the same class, while simultaneously ensuring a substantial separation from clusters associated with different classes within the metric space. Therefore, at the end of the training process, it can be observed that vectors from the similar class exhibit a notable degree of similarity based on cosine similarity and are grouped in the metric space. This clustering promotes a clear separation between the two classes through a linear function. Unlike conventional CNNs that treat classes independently, the SoftMax normalization (Equation 3) and temperature scaling (τ) explicitly penalize poor clustering, forcing feature vectors of the same class closer in metric space.

# Results and Discussion

## Setting of Temperature Coefficient Value τ in the MLBCNN

An experimental procedure is carried out to determine the optimal temperature coefficient value τ, one of the crucial hyperparameters of the MLBCNN. In this experiment, a range spanning from 0.1 to 1.0 of this coefficient is evaluated, with an increment of 0.1. Figure 5 visualizes the results plotted based on the accuracy score values of different temperature coefficient values.



**Figure 5.** Plotted chart of accuracy vs temperature coefficient value

The empirical findings exhibit a perceptible performance improvement as the temperature coefficient value increases from 0.1 to 0.3, and the proposed MLBCNN attains the highest classification accuracy at . The temperature coefficient τ critically controls the trade-off between discriminative power and generalization in our metric learning framework. At τ=0.1, overconfident similarity scores exaggerate minor feature differences, causing fragmented clusters and overfitting. Conversely, τ>0.3 over-smooths decision boundaries, diluting clinically meaningful separations. The optimal τ=0.3 balances these effects, preserving gradient strength for discriminative learning while maintaining natural EEG variation scaling, yielding peak accuracy (97.9%). This demonstrates MLBCNN's unique ability to optimize feature space organization where conventional CNNs fail.

## Performance Comparison and Analysis

In this section, we present the empirical results of the experiment, assessing the performance of various models, including the proposed MLBCNN. The performance metrics used include accuracy, recall, precision, and specificity. The results are compiled in Table 1.

**TABLE 1.** Classification Performance of ML and DL Models

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Performance Metrics** | **KNN** | **SVM** | **LR** | **SGD** | **NBC** | **DTC** | **RFC** | **GBC** | **ETC** | **CNN** | **biRNN** | **biLSTM** | **biGRU** | **CNN [6]** | **CNN-LSTM [7]** | **Spec-CNN [8]** | **CNN-BiRNN [9]** | **CNN w/ Autoencoder [10]** | **MLBCNN** |
| **Accuracy**  **(%)** | 85.6 | 96.1 | 70.4 | 63.6 | 95.2 | 90.4 | 95.2 | 94.3 | 96.6 | 89.2 | 91.1 | 92.6 | 91.8 | 95 | 82 | 87 | - | 92.5 | 97.9 |
| **Recall (%)** | 21.7 | 89.9 | 52.2 | 52.2 | 86.5 | 84 | 89.9 | 90.6 | 92.3 | 87.5 | 89.7 | 91.8 | 90.6 | - | - | - | - | - | 94.4 |
| **Precision (%)** | 100 | 88.8 | 31.6 | 25.9 | 87.6 | 69.9 | 84.9 | 80.7 | 87.6 | 82 | 88.2 | 85.1 | 83.2 | - | - | - | 92.88 | - | 95.5 |
| **Specificity (%)** | 100 | 97.3 | 74.5 | 66.2 | 97.2 | 91.8 | 96.4 | 95.1 | 96.9 | 84 | 90.8 | 92 | 86.4 | - | - | - | 93.94 | - | 98.8 |

The MLBCNN uses a simple 3-layer CNN with metric loss, achieving a higher accuracy (97.9%) than complex networks, without overfitting, and stays computationally efficient, unlike CNN-biRNN [9] and CNN-biLSTM [10] hybrids. Instead of discarding important phase data during the time-frequency transformation seen in [8], our method is able to distinguish distinct EEG features in a way that keeps all of the hidden patterns. In addition, while Zhou et al. [9] need preprocessed time-frequency data, MLBCNN can use raw EEG signals without doing feature engineering, allowing it to help more easily in clinical situations where knowledge of preprocessing may not be available. Contributed by its simple architecture, versatile input options, and metric-sensitive learning features, MLBCNN is both a top performer and a useful tool for real seizure detection. From the empirical findings, it can be observed that the proposed MLBCNN scores the best performance overall. It exhibits the highest precision and specificity among the deep neural networks. This implies that the MLBCNN is less prone to generating false positive results, making it the best choice for minimizing such errors in this task. Nonetheless, the MLBCNN has attained the best accuracy of 97.9% and a recall rate of 94.4%. These findings suggest that the MLBCNN can accurately identify the seizure and healthy EEG signals, with a minimal rate of failing to identify positive instances. These characteristics conclude that our proposed MLBCNN is a highly reliable deep neural network for epileptic seizure diagnosis.

# Conclusion

The study proposes an enhanced CNN model for EEG-based seizure detection using the Metric Learning Based Convolutional Neural Network (MLBCNN), a deep neural network. With the incorporation of metric learning principles during the CNN training process, our proposed MLBCNN rectifies the challenges posed by data sparsity inherent in EEG signals. The incorporation of metric learning improves CNN’s ability to organize feature vectors, promoting the clustering of EEG waveforms from the same class. The empirical results demonstrate that the proposed model exhibits the highest accuracy of 97.9% and a recall rate of 94.4%. These findings highlight the reliability of the proposed model in effectively distinguishing the seizure and non-seizure EEG signals, with a minimal occurrence of false negatives. This concludes that our proposed MLBCNN is a highly reliable deep neural network for epileptic seizure diagnosis. These findings hold the potential for improving the quality of life for persons impacted by epilepsy and serve as a noteworthy illustration of the capabilities of artificial intelligence within the healthcare domain.

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