Generalized Tonic-Clonic Seizures Detection Using Deep Learning Techniques

Juan Sebastian Campos Mesa, Evandro Ottoni Teatini Salles, Patrick Marques Ciarelli

***Abstract*— Epilepsy treatment can be significantly enhanced through automated seizure detection from electroencephalography. This study focuses on the detection of generalized tonic-clonic seizures, a critical seizure type associated with risks such as sudden unexpected death in Epilepsy (SUDEP) and postictal pulmonary edema (PPE), by leveraging advanced deep learning models, including Self-Supervised Graph Neural Networks, Long Short-Term Memory networks (LSTM) and CNN. This research aims to improve the precision and reliability of detecting tonic-clonic seizures, as well as applying techniques such as data augmentation and specialized loss functions. These novel approaches demonstrate promising results in enhancing the detection capabilities of EEG-based seizure detection systems.**

***Keywords*— EEG, Epilepsy, Tonic-Clonic Seizure, Deep Learning, Detection.**

I. Introduction

Epilepsy is a disease characterized by the presence of unprovoked or reflex seizures in a person. It can be diagnosed if conditions are met, including recurrent seizures or abnormal findings in the Electroencephalogram (EEG). Epilepsy affects 1-2% of the global population, and it is estimated that around 10% of people will experience a single epileptic seizure during their lifetime [1]. There are several types of seizures according to the primary classification of the International League Against Epilepsy (ILAE), divided into Focal seizure, generalized seizure, unknown onset, and unclassifiable [2].

The frequency of generalized tonic-clonic seizure (GTCS) is considered the most important clinical risk factor for sudden unexpected death in Epilepsy (SUDEP) [3]: the higher the GTCS frequency, the higher the risk of SUDEP. GTCS is associated with Postictal pulmonary edema (PPE) and with traumatic injuries due to falls or jerking movements of the limbs [4].

Due to the need for accurate seizure detectors, several hospital-based research organizations have released public benchmark datasets for seizure detection tasks. This collaborative effort, involving various stakeholders, has led to several attempts to detect seizures and abnormalities using deep neural network models [5]. The complexity and the unbalanced data have been significant challenges, but the research community has been resilient in its pursuit of solutions.

In this paper, we present and compare the performance of three state-of-the-art models under the same experimental setting of binary tonic-clonic detection. Here, the models receive an EEG signal and detect whether the patient is currently having a tonic-clonic or not. We also compare the different loss functions used for EEG purposes, including the dice loss for data imbalance [6].

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II. Methods

A. Database Description

This study uses the public Temple University Hospital EEG Seizure Corpus (TUSZ) v1.5.2, the largest available public EEG seizure database. This database includes 5,612 EEG recordings, of which 3,050 contain annotated seizures from clinical recordings, encompassing eight types of seizures [7]. Our focus is tonic-clonic seizures, which make up only 1% of the seizures in the dataset. The majority of the EEG data were sampled at 250Hz (87%), with the rest sampled at 256Hz (8.3%), 400Hz (3.8%), and 512Hz (1%), including 2,377 seizures from over 200 patients.

The dataset's subjects were 51% female, with ages spanning from under one year to over 90 years old (mean age 51.6, standard deviation 55.9). Each patient had 1.56 sessions on average, although some patients had as many as 37 EEG recordings over eight months [7].

TABLE I
SEIZURE TYPES TUSZ V1.5.2

Seizure Type	Seizure Number	Duration (s)
Focal Non-specific	1836	121139
generalized Non-Specific	583	59717
Complex Partial	367	36321
Absence	99	852
Tonic	62	1204
Tonic-Clonic	**48**	**5548**
Simple Partial	52	2146
Myoclonic	3	1312

B. Preprocessing

The dataset was divided into two groups: one containing tonic-clonic seizures and the other containing background activity combined with other seizure types. 19 EEG channels were used in the standard 10-20 system. The training set was randomly split into training and validation sets with a 85/15 ratio.

Our experiments analyzed EEG clips across train, validation, and test datasets. These sets contained EEG clips related to Generalized Tonic-Clonic Seizures (GTCS), other seizures, and a combined set of background data with seizures, as

shown in Table II. For our tonic-clonic seizure binary detection task, we specifically focused on the subset of EEG clips representing tonic-clonic seizures against background activity and other types of seizures. This targeted approach allowed us to isolate and analyze the distinctive EEG patterns associated with tonic-clonic seizures within a diverse EEG signal context.

TABLE II
DISTRIBUTION OF EEG CLIPS ACROSS TRAIN, VALIDATION, AND TEST.

Data	Train (EEG clips)	Validation (EEG clips)	Test (EEG clips)
GTCS	320	18	103
Other seizures	13466	2420	4580
Backround + seizures	196543	28036	44639
Total	196646	28057	44959

We performed a resampling technique to standardize the EEG signal to a standard frequency of 200 Hz [8]. For detection, we incorporate two groups of signals: a) Tonic-clonic signal and b) Background and the remaining seizure types. We preprocess the EEG signals to extract clips in the frequency domain. EEG clips are generated by sliding a rectangular window of 12 seconds over the EEG signals without overlapping. Each clip is assigned to a label. Specifically, a label equal to 1 is assigned if tonic-clonic seizure is present within the clip and 0 otherwise.

We applied the Fast Fourier Transform (FFT) to each 12-second EEG clip, which corresponds to 2400 samples. Then, the log amplitudes of the non-negative frequency components are generated. The EEG clips are z-normalized for the mean and standard deviation of the training data [8].

C. Models

Our application of three state-of-the-art deep learning models for detecting epileptic seizures has significant practical implications. These models, designed to leverage the latest advancements in neural network architectures, have demonstrated superior performance in accurately identifying and categorizing seizure events in EEG data. By employing these cutting-edge techniques, we aim to enhance the precision and reliability of automated systems for detecting tonic-clonic seizures, thereby improving the quality of life for patients with epilepsy.

1) SELF-SUPERVISED GRAPH NEURAL NETWORK: The spatiotemporal dependencies in EEG signals can be modeled using a framework inspired by the Diffusion Convolutional Recurrent Neural Network (DCRNN), which was initially created for traffic forecasting [9]. DCRNN captures traffic flow dynamics through a diffusion process, a concept that can also be applied to EEG signals. In this context, spatial dependencies among electrodes can be modeled as a diffusion process influenced by neighboring electrodes. This influence is based on functional proximity measured by correlation. The diffusion process is characterized by a bidirectional random walk on a directed graph, leading to a specific diffusion convolution [10].

To capture dynamic brain connectivity, the model defines the connection strength between two nodes based on the absolute value of the normalized cross-correlation between their preprocessed signals. To make the graph more manageable and focused, sparsity is introduced by retaining only the strongest connections: each node keeps edges only with its top-t neighbors. This results in a unique, directed, weighted graph for each EEG clip. For example, with t set to 3, each node in the graph is connected to its three most strongly correlated neighbors [11].

2) Long Short-Term Memory (LSTM): Each data sample undergoes processing via two stacked LSTM networks, which serve as the input for the memory model. The external memory model operates with an initial memory state. An input controller receives the encoded hidden states from the LSTMs, determining relevant information for memory querying, resulting in a query vector. An attention score vector measures the similarity between memory content and the query. The output controller selects which results from the memory stack should be sent to the memory module for the current state. The update controller then modifies the memory state based on the output and transfers it to the next time step. This process incorporates a combination of fixed weights and adaptable components. Finally, the output of the memory model is input into a dense layer with a softmax activation function for seizure type prediction [12].

We maintain consistency by ensuring that the number of Long Short-Term Memory (LSTM) layers and hidden units align with the number of Diffusion Convolutional Gated Recurrent Unit (DCGRU) layers and hidden units in our DCRNN model. This approach ensures a harmonized architecture across both models, facilitating seamless integration and comparison of results between the sequential and memory-based components [13].

3) Convolutional Neural Network (CNN): We use a densely connected inception architecture inspired by [12] for seizure onset detection. This modeling approach combines the most compelling aspects of deep inception46 networks and densely connected net-work47 architectures. Each Inception block, which consists of three convolutional filters with different kernel sizes, is fully connected with other Inception blocks. The model consisted of 8 inception layers followed by two fully connected layers [11].

D. Loss funtions

For the detection of tonic-clonic seizures, we employed all three models with an equal number of layers in the networks. Additionally, we adjusted the loss functions to accommodate the imbalanced nature of the database, considering that only 1% of the EEG clips are labeled as tonic-clonic seizures. To address this, we utilized cross-entropy loss, dice entropy, and focal loss, each tailored to handle class imbalance differently. This modification aimed to emphasize the accurate classification of these minority instances. In order to see if it mitigates the impact of class imbalance and enhances the model's capability to detect tonic-clonic seizures in EEG signals accurately [13].

1) Cross Entropy loss: In addressing the challenge of imbalanced data for tonic-clonic seizure detection, we incorporated cross-entropy loss to enhance the performance of our

models. Cross-entropy loss measures the discrepancy between the predicted probability distribution and the true distribution of classes. It penalizes misclassifications proportionally to the difference between the predicted and true class probabilities, effectively guiding the model towards accurate classification [13]. It can be represented as equation (1):

$$CrossEntropyLoss = -\sum_{j\epsilon\{0,1\}} y_{ij} log p_{ij}. \quad (1)$$

2) Dice Entropy Loss: Dice entropy is a variation of the Dice coefficient, commonly used in image segmentation tasks, and it has been adapted here to handle class imbalance in classification problems. It evaluates the overlap between the predicted and true positive instances, with higher values indicating better performance. The Dice entropy loss function aims to maximize the overlap while minimizing the discrepancy between predicted and true positive instances [6]. It can be expressed as equation (2):

$$DiceEntropyLoss = 1 - \frac{2p_{i1}y_{i1} + \gamma}{p_{i1}^2 + y_{i1}^2 + \gamma}. \quad (2)$$

By incorporating Dice entropy loss, we aim to enhance model performance by effectively addressing data imbalance and prioritizing accurate classification of tonic-clonic seizure instances within EEG signals.

3) Focal Loss: Focal loss is specifically designed to handle class imbalance by down-weighting well-classified examples and emphasizing misclassified instances. This property makes it particularly suitable for tasks where minority classes are crucial. The focal loss function reweights the cross-entropy loss, assigning lower weights to well-classified examples and higher weights to misclassified ones [14]. It can be represented as equation (3):

$$FocalLoss = \alpha_t (1 - p_t)^\gamma log (p_t). \quad (3)$$

E. Data Augmentation

For Data augmentation, we employ the same model as that described in [10]: The raw signals are subject to random scaling, where their amplitudes are adjusted within the range of 0.8 to 1.2. Additionally, the signals undergo random reflection along the mid-line of the scalp.

III. Experimental Results

This research employed DCRNN, LSTM, and CNN models with specific parameters optimized for tonic-clonic seizure detection. The model configuration includes the following key parameters: An input dimension of 100 and an initial learning rate of 0.0001. We use a dual random walk, and the models are structured with three RNN layers, each comprising 64 units and 19 nodes in total. Our training process involves 50 epochs, utilizing a batch size of 40. The optimizer used was Adam, and the algorithm was implemented using PyTorch and run on an RTX 3090 Ti GPU. The raw EEG data was sourced from the designated directory, and training progress was saved accordingly.

In this study, we utilized the Area Under the Receiver Operating Characteristic Curve (AUROC) as the primary evaluation metric for tonic-clonic seizure detection rather than accuracy. The choice of AUROC is particularly pertinent due to detection task [15]. Accuracy, while commonly used, can be misleading in such scenarios because it tends to be dominated by the majority class, potentially masking the model's true performance in detecting rare but critical events like seizures. AUROC, on the other hand, provides a more robust assessment by considering the true positive rate (sensitivity) and false positive rate across different threshold settings, offering a comprehensive view of the model's ability to distinguish between classes [16].

The performance of different models using various loss functions for tonic-clonic seizure detection is summarized in Table III. Each model was evaluated using AUROC to highlight its effectiveness in detecting seizures in the imbalanced dataset.

TABLE III
AUROC Scores for Tonic-Clonic Seizure Detection Models with and without Data Augmentation (wo/DA), trained with three different loss functions Cross Entropy Loss (CE), Dice Entropy Loss (DE) and Focal Loss (FL).

Model		wo/DA AUROC	w/DA AUROC
	DCRNN	0.632 ± 0.124	0.759 ± 0.030
	LSTM	0.598 ± 0.057	**0.778 ± 0.079**
CE Loss	CNN	**0.647 ± 0.085**	0.775 ± 0.107
	DCRNN	**0.675 ± 0.012**	**0.781 ± 0.048**
	LSTM	0.625 ± 0.032	0.764± 0.021
DE Loss	CNN	0.649± 0.114	0.741 ± 0.103
	DCRNN	**0.678 ± 0.014**	0.752 ± 0.095
	LSTM	0.667 ± 0.070	0.734 ± 0.043
FL Loss	CNN	0.642 ± 0.016	**0.753 ± 0.028**

The DCRNN models consistently demonstrated robust performance across all loss functions. Without data augmentation, the AUROC scores ranged from 0.632 ± 0.124 with Cross Entropy Loss to 0.678 ± 0.014 with Focal Loss. The introduction of data augmentation significantly improved these scores, with the Dice Entropy Loss configuration achieving the highest AUROC of 0.781 ± 0.048. This indicates that DCRNN models benefit substantially from specialized loss functions and data augmentation.

While initially showing lower performance than DCRNN models, LSTM models also exhibited notable improvements with data augmentation. Without augmentation, the AUROC scores were lowest with Cross Entropy Loss at 0.598 ± 0.057 and highest with Focal Loss at 0.667 ± 0.070. With data augmentation, the performance of LSTM models improved significantly, achieving the highest AUROC of 0.778 ± 0.079 with Cross Entropy Loss. This suggests that LSTM models are highly responsive to the benefits of data augmentation, even surpassing DCRNN in certain configurations.

CNN models showed competitive performance throughout the study, especially with Dice Entropy Loss. The AUROC scores without data augmentation ranged from 0.642 ± 0.016 with Focal Loss to 0.649 ± 0.114 with Dice Entropy Loss.

Data augmentation led to substantial improvements, with the highest AUROC score of 0.775 ± 0.107 observed with Cross Entropy Loss.

In our evaluation, the CNN model outperformed previous studies [10] with an AUROC of 0.775, while the LSTM model performed similarly with an AUROC of 0.778. However, it should be noted that the DCRNN model, which has demonstrated superior performance in [10] with an AUROC of 0.866, was not explicitly optimized for binary tonic-clonic seizure detection but for general seizure detection. The AUROC values reported in other studies [11] for CNN, LSTM, and DCRNN were 0.749, 0.786, and 0.866, respectively.

IV. Conclusions

Overall, DCRNN models consistently performed well across different loss functions, with Dice entropy loss showing the most significant improvement in AUROC. CNN models also showed strong performance, particularly with Dice entropy loss. LSTM models benefited from Dice Entropy loss. The use of data augmentation significantly enhanced AUROC across all models, highlighting its effectiveness in addressing imbalanced datasets. Using AUROC as the evaluation metric reflected the models' capabilities in detecting tonic-clonic seizures. In the future, we will investigate different methods for using these models in online applications.

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