UDC 004
SCOPUS CODE 1701
https://doi.org/10.36073/1512-0996-2025-2-127-132

Interpretation and Characterization of Seizure Detection In Epilepsy with Deep Learning Processing

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Abstract. Electroencephalography (EEG) plays a major role in detecting seizure and epilepsy. However, scanning and interpretation of EEG have been limited to the area of experts and professionals. The aim of this study is to suggest the possible method of EEG interpretation characterized by the deep learning process to reduce labor intensive work for professionals and enhance accurate and automated diagnosis. 54 patients scalp EEG data of CHP-MIT (Children's Hospital and MIT university in Boston) and MCG (Mediclub Hospital in Georgia) EEG dataset were used with 20 channels. CNN based Convolutional Neural Networks was conducted in ResNet and Efficientnet for EEG signal was conducted to classify and characterize seizure detection with increasing relative scores such as specificity, sensitivity, and accuracy.

Keywords: CNN; Deep learning; Epilepsy.

Introduction

Seizure is the most dangerous symptom of epilepsy which causes a loss of consciousness and violent muscle contractions. Approximately, more than 1% of the population in the world. More than 50 million individuals have been suffered and living under the condition, among them, approximately 30% of patients were suffer from intractable epilepsy which is hard to control with convulsant medication. (Fisher et al, 2005). Many experiments and researches have been studied to detect it to overcome it and EEG signals are considered the most reliable biomarkers for epilepsy diagnosis, enabling specialists to analyze abnormal synchronous firing of cortical neurons that is characteristic of seizures(Hazarika, 1997). In 2020, Zhang et al used CHP-MIT scalp EEG dataset to transform raw EEG to visualize image with SFTF spectrogram to improve accuracy which could be used with deep learning to detect and predict chronic seizure prediction.

Convolutional Neural Network (CNN) is the most used deep learning algorithm to find pattern of identifying image recognition (Fig 1). CNN consists of convolution layers which extract characterized image and of pooling layers which maximize each selected filtered image by convolution layers. Connected processing with all those generated images, it is characterized scores or images that can be classified in certain output.

Withing many of CNN based model, Res Net and Efficient net are used for this EEG classification. ResNet is one of the algorithms developed by Microsoft which add convolutional layers based structure (He et al, 2016). Res Net provides residual blocks for smooth processing of the gradient which prevent gradient vanishing of the data processing. Efficient net is one of the effective model for scaling among depth, width, and resolution to improve model performance with balance (Tan et al, 2019). Cross Patient Specific Method(CPSM) learning process was used for this study which can be scanned all the patient data with only one patient seizure data. 3 channels (F7-T3, T4-T6, T3-T5) were chosen to multi-channel data experiment through ResNet-18 and Efficient Net learning process were used.

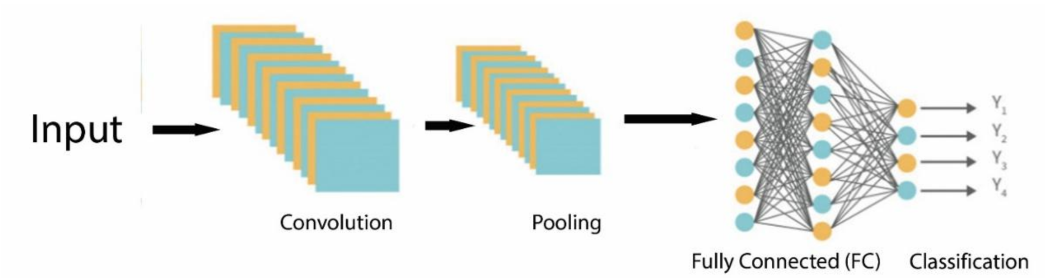

Fig 1. Simple CNN structure

Main Part

Although each patient had variations in electrode placement, the most common scalp EEG placement method described by Rojas (2018) (Fig 2) was followed in this study. The experiment was conducted using 20 commonly available channels among the many channels and 3 channels were selected which had highly contrasts between Ictal and Inter-ictal stages.

Two sets of scalp EEG data used in this study collected at CHB-MIT (Children's Hospital and MIT university in Boston) in 24 patients and Mediclub Hospital in Georgia(MCG) data scalp EEG in 30 pediatric patients(table 1). Composed recorded signal with sampling rate was 256Hz and 196, 20 common channels were used for electrodes among 72.

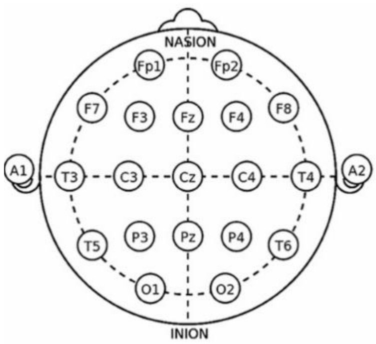

Fig 2. Scalp EEG channel locations in this study

ISSN 1512-0996
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Table 1.

EEG dataset information with channels

Dataset	CHB-MIT	MHG
EEG type	Scalp EEG	Scalp EEG
Number of Patients	24	30
Number of channels	20 among 72 channels	20 among 40 channels
Selected channels	3	3
Number of seizures	245	192
Sampling rate	256	240

3 channels selected to conduct machine learning training and STFT(Short time Fourier Transform) spectrogram was used to convert raw EEG to visualize EEG signal as images. The power value of the corresponding frequency band at a specific time is calculated with the original signal input. In order words, correlated with time and signal frequency, the power value can be identified by STFT.

Selected 3 channels were used to multiple channel data training with ResNet-18 and EfficientNet model. Brief diagram of processing to detect seizure when selected channels are input as multiple channel model.

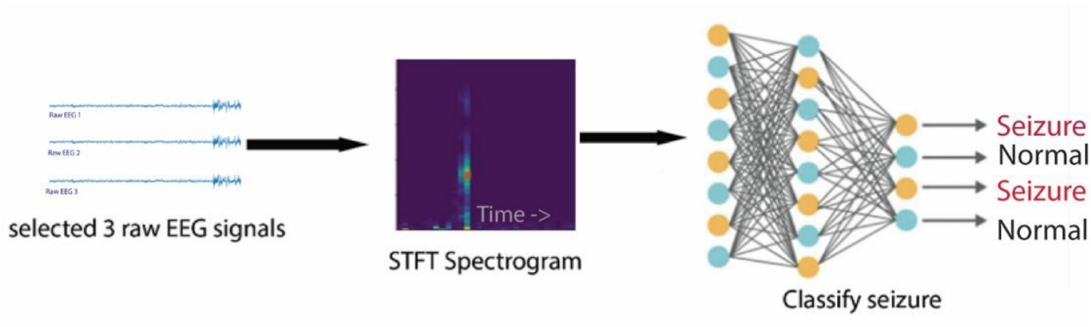

Fig 3. Diagram of multiple channel model processing

Conclusion

CPSM method was used as a generalization model and train and validation model consisted of 80% and 20% of train and validation, respectively. Hyperparameters values are; 64 batch size, cosine annealing learning rate, categorical cross entropy loss function, adam optimizer, 20 Epoch.

Table 3.

ResNet score of sensitivity, specificity, and accuracy in multiple channels.
Averages were 76.28 in specificity, 76.69 in sensitivity, and 76.95 in accuracy respectively

Channel		Specificity	Sensitivity	Accuracy	Channel	Specificity	Sensitivity	Accuracy
1		65.3	75.3	75.1	11	81.9	79.3	81.0
2		83.5	81.2	82.3	12	78.3	75.2	77.1
3		80.2	68.4	73.5	13	77.1	75.2	76.1
4		78.3	79.2	78.2	14	72.2	75.2	73.0
5		82.6	79.1	82.9	15	80.1	75.3	77.2
6		66.8	70.9	70.1	16	66.1	75.8	73.8
7		70.1	78.3	77.3	17	76.9	78.9	77.2
8		78.1	80.1	79.2	18	70.7	79.2	75.3
9		76.9	76.2	77.5	19	81.1	81.7	80.9
10		78.3	75.1	76.2	20	81.1	74.2	75.1

Table 4.

EfficientNet score of sensitivity, specificity, and accuracy in multiple channels.
Averages were 89.64 in specificity, 87.75 in sensitivity, and 87.99 in accuracy respectively

Channel	Specificity	Sensitivity	Accuracy	Channel	Specificity	Sensitivity	Accuracy
1	85.3	85.2	87.6	11	92.2	86.8	81
2	93.5	92.4	94	12	88.2	88.7	87.5
3	80.2	89.1	88.7	13	91.2	85.1	86.9
4	90.1	79.5	92.1	14	90.9	88.3	83
5	95.2	96.7	97.1	15	89.1	85.7	91.2
6	86.8	87.1	80.1	16	88.1	85.8	85.3
7	92	83.3	84.1	17	90.1	88.9	85.4
8	92.1	84.1	89.1	18	89.7	89	87.1
9	91.1	86.1	87.5	19	88.9	98.1	97.2
10	91.9	85.1	86.1	20	86.3	90.1	88.2

ISSN 1512-0996
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The result of EfficientNet are shown in Table 4. Specificity improved in 10.36, sensitivity increased in 11.06, and accuracy increased in 11.01in comparison of ResNet-18 model. Reliable results were scaled up by EfficientNet which is similar result in Mingxing Tan and Quoc V, 2020. Though it was short window size with 10 sec model, this model showed that it is able to applied to initial scanning of seizure in raw EEG signal data with the averages reliable average score; 89.64 in specificity, 87.75 in sensitivity, and 87.99 in accuracy. Further research and experiments are considered to various models in near future for predicting seizure based on this study process.

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UDC 004
SCOPUS CODE 1701
https://doi.org/10.36073/1512-0996-2025-2-127-132

ეპილეფსიური შეტევების დეტექციის ინტერპრეტაცია და დახასიათება ღრმა სწავლების დამუშავებით

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ანოტაცია. ელექტროენცეფალოგრაფია (EEG) მნიშვნელოვან როლს ასრულებს შეტევებისა და ეპილეფსიის დეტექციაში. თუმცა, EEG-ის სკანირება და ინტერპრეტაცია გარკვეულ შეზღუდვებს შეიცავს, ექსპერტებისა და პროფესიონალების მხრიდან. ამ კვლევის მიზანია EEG-ის ინტერპრეტაციის შესაძლო მეთოდის შეთავაზება, რომელიც დამახასიათებელია ღრმა სწავლების პროცესისთვის, რათა შემცირდეს პროფესიონალებისთვის შრომატევადი სამუშაო და გაუმჯობესდეს სიზუსტე და შესაძლებელი გახდეს დიაგნოზის დასმის ავტომატიზება. გამოიყენება 54 პაციენტის სკალპის EEG მონაცემები CHP-MIT (ბოსტონის ბავშვთა საავადმყოფო და MIT უნივერსიტეტი) და MCG (მედიკლუბი, საქართველო) EEG მონაცემთა ნაკრებიდან, რომლებიც შეიცავს 20 არხს. კვლევა ჩატარდა CNN-ზე დაფუძნებული კონვოლუციური ნეირონული ქსელების ResNet და EfficientNet მოდელებით EEG სიგნალზე, რათა განხორციელებულიყო შეტევების დეტექციის კლასიფიკაცია და დახასიათება, გაზრდილიყო შედარებითი მაჩვენებლები, როგორიცაა სპეციფიკურობა, სენსიტიურობა და სიზუსტე. ResNet მგრძნობელობის, სპეციფიკისა და სიზუსტის ქულა მრავალარხიანი კვლევისას საშუალოდ იყო: 76.28 სპეციფიკურობაში, 76.69 მგრძნობელობაში და 76.95 სიზუსტეში. მგრძნობელობის, სპეციფიკისა და სიზუსტის EfficientNet ქულა მრავალარხიანი კვლევისას საშუალოდ იყო 89.64 სპეციფიკურობაში, 87.75 მგრძნობელობაში და 87.99 სიზუსტეში.

საკვანძო სიტყვები: ეპილეფსია; CNN; ღრმა სწავლა.

The date of review 07.02.2025
The date of submission 10.02.2025
Signed for publishing 16.06.2025