Epileptic Seizure Detection Using Rhythmicity Spectrogram and Cross-Patient Test Set

Palak Handa[1] and Nidhi Goel[2]

***Abstract*— This work proposes an automated epileptic seizure detection pipeline using generated rhythmicity spectrograms and Generic Convolutional Neural Networks (CNN). 1D multi-channel, scalp-EEG signals taken from a publically available EEG database (CHB-MIT Scalp EEG database, version: 1.0.0) were converted to time-variable, non-overlapped and one-sided rhythmicity spectrograms (2D images) through Short-time Fourier transform (STFT) method for patient no. chb01, chb02, chb03 and chb05. A two class, supervised classification between seizure (ictal) and non-seizure images was performed. Thorough cross-patient test set analysis has been presented along with evaluation metrics such as precision, recall, F1-score, and loss and accuracy of the model on the test set. The generic model achieved an average training, validation and test set accuracy up-to 91.89, 88.17 and 61% respectively. An automated epileptic seizure detection system can escalate the process of diagnosis and early decision to surgery which may aid in quality of life (QOL) of diseased patients.**

***Index Terms*— Spectrogram, test set, seizure detection, Q-EEG, signal to image**

I. INTRODUCTION

Epileptic seizures are sudden, uncontrollable electrical disturbances which can be observed through an electroencephalography (EEG) in different parts of the affected brain [1]. Approximately 10 million epilepsy affected patients reside in India [2]. Epileptic seizures are considered one of major public health concerns by WHO [2]. Due to increase in such cases every year and only handful people in neurology, the rate of diagnosis of disorders related to epileptic seizure activity is lower than the recommended rate [2], especially in developing countries like India. Hence, automated detection using deep learning techniques which are able to learn complex patterns from seizure and non-seizure EEG signals can be useful to reduce this burden, facilitate automated diagnosis and improve the quality of life (QOL) of diseased patients.

Signal to image based models like histogram, scalogram, periodogram, variogram, and spectrogram *etc.* are becoming popular in analyzing signals in different biomedical domain. Spectrograms are one such method to convert a series of signals to n*m matrix like image formats. It provides a visualization and understanding of spectral complexities and frequency components in time-frequency domain [3]. It is known to have better temporal and frequency resolution in comparison to Fourier transform [3]. Spectrographic analysis is studied under Quantitative analysis of EEG signals [4]. It has been used as an input image to various deep learning methods in several medical fields such as depth of anesthesia (DOA) [3], brain coma [5], human imagination [6], epilepsy and seizures [8], [9], [10], [11], [12], etc. Deep learning methods have shown remarkable diagnostic accuracy towards understanding complex patterns in medical AI due to their automated complex feature extraction efficacy [8], [9], [10].

Recent studies carried out using deep learning such as convolution neural networks (CNN), LSTM, Residual CNN, Deep neural networks, and transfer learning architectures etc. are trained on raw dataset instead of statistically developed features[8], [9], [10]. Such techniques have achieved higher accuracy levels but also helps in automating the entire pipeline making the pipeline ‘end to end’.

Mathematically, each column of N channel EEG signal can be considered as a sequence represented in equation 1. A Short-time Fourier transform (STFT) of this time series data can be done through equation 2. Power spectral density of this function is achieved by magnitude square of STFT function mentioned in equation 3.

$$x(t) = [x_1, x_2, \ldots\ldots x_h] \tag{1}$$

$$STFT[x(n)](m,\omega) \equiv X(m,\omega) = \sum_{n=-\infty}^{\infty} x(n)\omega(n-m)e^{-j\omega n} \tag{2}$$

$$spectrogram[x(t)](\tau,\omega) \equiv |X(\tau,\omega)|^2 \tag{3}$$

In equation 1, 2 and 3 collectively, h presents the number of seconds of a particular EEG envelope, x(n) is the signal containing n samples, w is the frequency of the signal.

Recent contributions in signal to image conversion with convolutional neural networks has been done using University of Bonn, EPILEPSIAE project and CHB MIT EEG scalp database. Both before mentioned datasets are considered a benchmark dataset for seizure detection and prediction tasks [7].

Mandhouj *et al.* [8] performed epileptic seizure classification of spectrograms developed from University of Bonn EEG signals. Hussein *et al.* [9] generated scalograms from CHB MIT scalp EEG signals and performed seizure prediction using semi-dilated convolutional network (SDCN). An eight class classification of different seizures such as tonic-clonic, clonic, and non-specific seizures *etc.* and non-seizures based on spectrogram representation of 1D EEG signals is discussed in [10]. The work used advanced deep learning models like AlexNet, two variants of VGG and a basic CNN model.

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Toraman [11] classified two different seizure states namely pre-ictal and inter-ictal state using pre-trained classifiers VGG19, ResNet, DenseNet. Yuan *et al.* [12] proposed an auto-encoder based approach for spectrogram based supervised seizure detection. They extracted hand crafted features and developed a channel aware module. Hu *et al.* [13] fused time and frequency domain signal and image features namely mean amplitude spectrum (MAS), mean power spectral density (MPSD) and wavelet packet features (WPFs) into an image and used it as an input to proposed hierarchical neural network (HNN) pipeline. The experiments were done on the public database, CHB-MIT and the private database, iNeuro epilepsy. A topological image of EEG channel was fed to a 3D CNN model in [14] from 16 patients of CHB MIT EEG dataset.

Hussein *et al.* [15] converted the scalp and invasive EEG signals to a scalogram using continuous wavelet transform and proposed a semi-dilated convolutional network for seizure prediction task. Another work analysed the ROC curve of converted EEG signals and sub-bands to images using STFT and naive bayes classifier [16].

Shankar *et al.* [17] generated 2D recurrence plots from Bonn University and CHB-MIT EEG scalp database and used CNN to perform classification. Fourier-based Synchrosqueezing Transform (SST) images were generated from CHB-MIT data to perform seizure detection task [18].

This paper has performed quantitative EEG (Q-EEG) analysis by generating power spectral density based rhythmicity spectrogram from 1D seizure (ictal) and non-seizure EEG segments. A generic CNN with cross-patient analysis has been presented and discussed in Section III. Section II describes the EEG dataset and processing done to perform signal to image conversion and description of generic CNN. Section III presents experimental results and its discussion. Finally, the conclusion is presented in Section IV.

II. Materials and Method

A. EEG Dataset Description

CHB-MIT scalp EEG database is an open access database containing 844 hour of multi-channel scalp-EEG [15]. 23 pediatric patient data has been recorded who suffer from intractable seizures. 198 seizures have been reported at sampling frequency of 256 Hz. There are unique folders for each patient which contains summary of each folder and 1-4 hours of EEG in EDF format. Seizure start and end time in different EDF files is also mentioned in these folders.

B. Signal to image generation

EDF files of patient 01, 02, 03 and 05 available at [19] were downloaded. The dataset has several artifacts such as eye ball, muscle movements etc. Wu *et al.* [20] has listed all such artifact prone channels. Based on that list, specific 15 EEG channels namely F7-T7, T7-P7, P7-O1, F3-C3, C3-P3, P3-O1, F4-C4, C4-P4, P4-O2, F8-T8, T8-P8, P8-O2, FZ-CZ, CZ-PZ, and P7-T7 were chosen for further analysis. Channel-wise ictal and random non-seizure segments were transformed into rhythmic spectrograms through STFT method to generate a balanced, fixed time and length dataset.

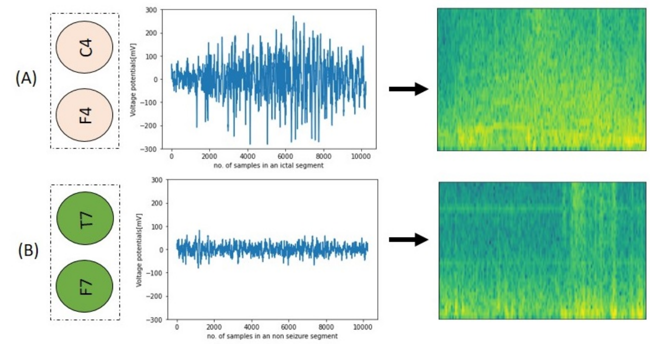

Fig. 1. Spectrogram generation from a 1D EEG signal containing (A) a seizure segment (B) a non-seizure segment.

Fig. 1 shows an example of the developed rhythmicity based spectrograms from 1D seizure and non-seizure EEG signals. In this, two different files suppose (A) and (B) containing a seizure and non-seizure segment were considered. EEG signal measured across a specific channel for e.g., F7-T7 and F4-C4 were extracted and converted to a spectrogram. The original image size obtained was 360*360. Information present outside the spectrogram box was cropped and final input image for generic CNN model was 280*274.

The final dataset consisted of 105 frames from chb01, 30 frames from chb02, 90 frames from chb05 and 75 frames from chb05 separately from both ictal and non-seizure files. The total image frames and ictal time (20 ictal signals) were 600 frames and 25 minutes respectively.

Table I shows the time calculation of 20 seizure segments taken from respective folders available in the original CHB-MIT EEG database. Finally, the dataset was divided into training set (80%), testing set (10%) and validation set (10%). Data augmentation methods such as re-scaling, and flipping (horizontal and vertical) were opted to increase the quantum of the dataset. A seizure segment refers to ictal segments where the seizure started and ended. Similarly, a non-seizure segment refers to any file which has no occurrence of a seizure. No other prior processing was done than extraction of EEG seizure and non-seizure fragments in the above mentioned manner.

C. Generic CNN Model

The generic CNN model has a total of seven layers comprising of two convolution layers (with ReLU activation function) each followed by a max pooling layer, a flattening layer and two fully connected layers (with Sigmoid activation function). The two convolution with pooling layers extract deep features from input seizure and non-seizure images. Each max pooling layer helps in reducing the dimension of the features extracted from each convolution layer. The final feature vector is built using a flattening layer which is fed to two dense layers to finally classify the input image as a seizure or a non-seizure EEG. The last layer performed the binary classification task with an activation layer of softmax

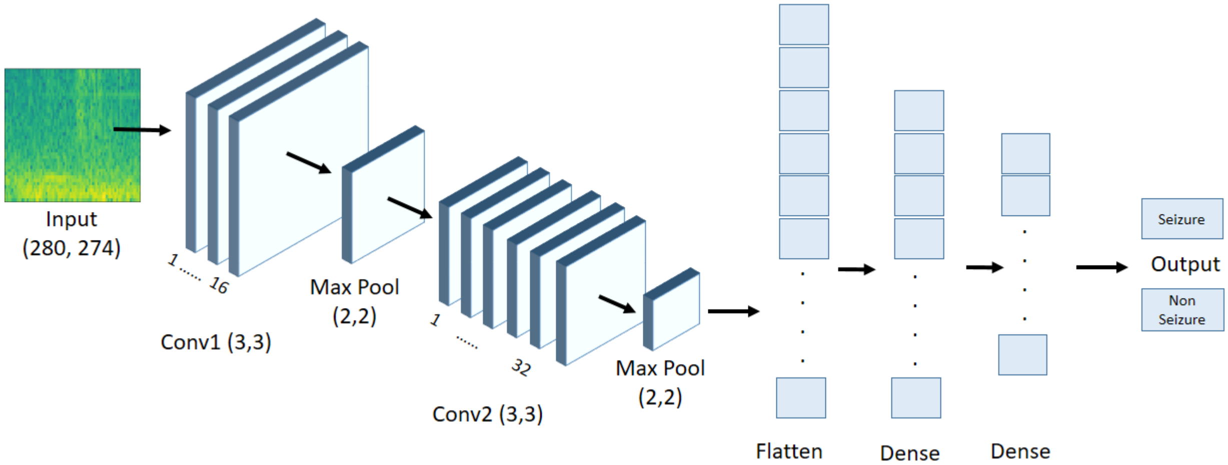

Fig. 2. Generic CNN Pipeline for seizure detection using Rhythmicity Spectrogram.

TABLE I
SEIZURE SEGMENTS INFORMATION

Seizure s.no.	Seizure from folder	Seizure time (in seconds)
1	chb01-03	40
2	chb01-04	27
3	chb01-15	40
4	chb01-16	51
5	chb01-18	90
6	chb01-21	93
7	chb01-26	101
8	chb02-16	82
9	chb02-16+	81
10	chb03-01	52
11	chb03-02	65
12	chb03-03	69
13	chb03-04	52
14	chb03-35	66
15	chb03-36	53
16	chb05-06	115
17	chb05-13	110
18	chb05-16	96
19	chb05-17	120
20	chb05-22	117
—	Total seizure time	25.33 minutes

function by matching them to appropriate labels. Stochastic gradient descent optimizer was used in the training phase.

III. Results and Discussion

There are several types of trends in spectrograms to detect seizures such as amplitude based spectrograms, asymmetric spectrograms, rhythmicity based spectrograms and frequency-amplitude based spectrograms [4]. EEG ictal spikes and frequency changes observed in the CHB-MIT data are much more sudden and frequent as compared to non-seizure states. A rhythmicity based spectrogram can measure rhythmicity of EEG signals at different frequencies and detect those sudden changes where low rhythmicity represents a yellow band and high rhythmicity represents a dark blue/purple band (likely possibility of seizure occurrence). Since spectrograms are prone to detection of artifacts such as muscle/EMG changes, chewing, eye ball movements, this paper used 15 channels in a frequency range from 0 – 40 Hz. Time –variable, one sided, non-overlapped, rhythmicity based spectrograms were developed using short-time Fourier transform (STFT) method from EDF files of Patient no. 01, 02, 03 and 05 as described in section II.

A generic two dimensional Convolutional neural networks was developed for classification between seizure (ictal) and non-seizure spectrographic images. Convolutional layers tried to extract temporal deep features from the input data. The model was run for 15 epochs on training set (480 images) and validated through a validation set (60 images). Batch-wise processed, 16 images (at-a-time) were fed to the Generic CNN.

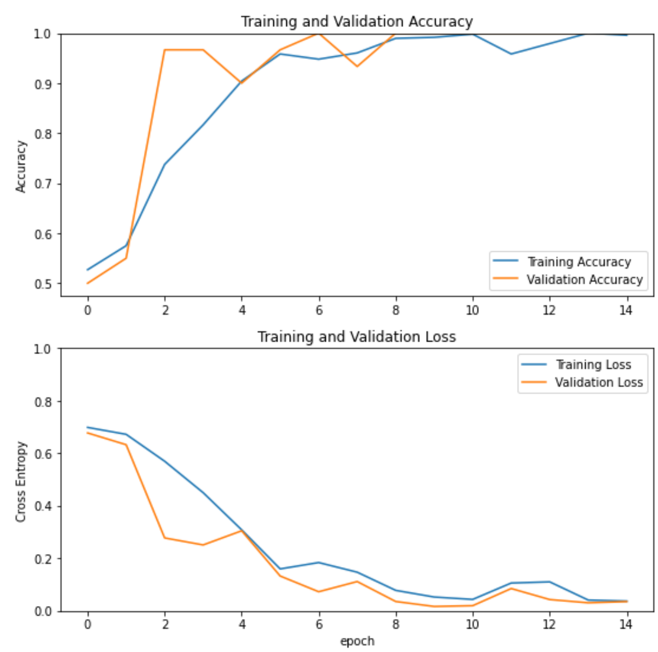

Fig. 3. Training and validation accuracy and loss graph

TABLE II

PERFORMANCE EVALUATION OF GENERIC CNN WITH CROSS-PATIENT TEST SET

Model Configuration	Parameters	Model performance
(A) Training and Validation set: Epochs = 15, Batch size = 16, SGD, learning rate = 0.01, decay = 1e-6, momentum = 0.9	Avg. of Accuracy (%)	91.89
	Avg. of Validation Accuracy (%)	88.17
	Avg. of training loss	0.244
	Avg. of Validation loss	0.1819
	Training time per epoch (in seconds)	14
	Model size (h5 file)	8.93 MB
(B) Test set: SGD, re-runs = 50, Batch size = 16	Avg. of accuracy (%)	61
	Avg. of precision (%)	65
	Avg. of recall (%)	59
	Avg. of F1-score (%)	60

All the model configuration details are mentioned in Table II. The best model after several re-runs with a constant seed was saved. The memory disc space of the model was 8.93 MB. The pipeline was implemented using python scripts (jupyter notebook) on system with 16GB RAM, AMD Ryzen 7 2700 Eight-core processor, NVIDIA GeForce GTX 1050Ti and 4GB RAM graphics card.

Different patient images were used in test set (60 images). A total of 2,337,810 parameters were trained. Obtained average results of model run for 15 epochs have been mentioned in Table II where average of the evaluation metrics refers to the average of all the epochs and no. of times the model was run. In Fig. 3, there was an overall accuracy increase for both validation and training data with the advancement of the epoch. The overall loss of both training and validation decreased with increasing epochs. Evaluation metric of the classification task was done through accuracy, loss, precision, recall and F1-score. An average training and validation accuracy of 91.89 and 88.17 % was achieved with training and validation loss of 0.244 and 0.1819. An average accuracy, precision, recall and F1-score of 61%, 65%, 59% and 60% was achieved on the test set images.

IV. CONCLUSION

Automatic detection of epileptic seizures from EEG signals has been researched widely. Various mentioned state-of-art pipelines have worked upon signal to image conversion methods and classified the images using machine learning and deep learning methods. This paper focused on generating rhythmicity spectrogram for different EEG segments containing seizure and non-seizure activities of patients chb01, chb02, chb03 and chb05 in CHB-MIT database. The generic model achieved an average training, validation and test set accuracy up-to 91.89, 88.17 and 61% respectively. It is a preliminary work of ongoing work to classify seizure and non-seizure EEG signals based on different angle, magnitude and power spectral density rhythmicity spectrogram for CHB-MIT EEG and Siena Scalp EEG database.

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