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Seizure Type Classification Using EEG Based on Gramian Angular Field Transformation and Deep Learning

Anand Shankar[1], Samarendra Dandapat[2], and Shovan Barma[1]

[1]*Dept. of Electronics and Communication Engineering, Indian Institute of Information Technology Guwahati, Assam, India,*
[2]*Dept. of Electrical and Electrical Engineering, Indian Institute of Technology Guwahati, Assam, India*
Emails: anand.shankar@iiitg.ac.in; samaren@iitg.ac.in; shovan@iiitg.ac.in

***Abstract*—classification of seizure types plays a crucial role in diagnosis and prognosis of epileptic patients which has not been addressed properly, while most of the works are surrounded by seizure detection only. However, in recent times, few works have been attempted on the classification of seizure types using deep learning (DL). In this work, a novel approach based on DL has been proposed to classify four types of seizures — complex partial seizure, generalized non-specific seizure, simple partial seizure, tonic-clonic seizure, and seizure-free. Certainly, one of the most efficient classes of DL, convolution neural network (CNN) has achieved exemplary success in the field of image recognition. Therefore, CNN has been employed to perform both automatic feature extraction and classification tasks after generating 2D images from 1D electroencephalogram (EEG) signal by employing an efficient technique, called gramian angular summation field. Next, these images fed into CNN to perform binary and multiclass classification tasks. For experimental evaluation, the Temple University Hospital (TUH, v1.5.2) EEG dataset has been taken into consideration. The proposed method has achieved classification accuracy for binary and multiclass — 3, 4, and 5 up to 96.01%, 89.91%, 84.19%, and 84.20% respectively. The results display the potentiality of the proposed method in seizure type classification.**

***Clinical relevance*—gramian angular summation field, seizure types, convolution neural network.**

I. INTRODUCTION

In recent times, most of the works focused on the epileptic seizures classification using EEG recordings [1–4]. In contrast, types of different seizures have not been analyzed extensively, which is very important to epileptic seizures diagnosis and prognosis [5]. Indeed, in the accurate classification of seizure types, discriminative features among different seizure types need to be well-defined, which is very challenging [6]. Aside from that, only a few studies have focused on the classification of seizure types [5–7]. However, it is very challenging to classify seizure types using EEG signals by traditional methods [7]. Therefore, an automatic and accurate classification of seizure types is very important and advances the diagnosis practice and epileptic patient's conditions.

Certainly, advancements in DL algorithms have been efficiently improved the automatic classification performances in the field of biomedical signal processing and image recognition [1]. Indeed, DL algorithms bypass the hand-crafted features engineering, which improves computational efficiency [3–4]. The automatic feature extraction capabilities of CNN make it efficient and extremely useful in the field of image classification [4]. The seizure type classification using traditional machine learning, in [2], four classes of seizure types have been discriminated by support vector machine classifier based on statistical features extracted from decomposed components of EEG by empirical mode decomposition with an accuracy of 95%. In [5], 8 types of seizures have been discriminated by constructing 2D images from 1D EEG by spectrogram. Actually, the images of multiple channels have been vertically concatenated before feeding into different DL models. The classification accuracy achieved up to 82.14%, 76.81%, 79.71%, and 84.04% by CNN, VGG19, VGG16, and AlexNet models respectively. In [6], the weighted $F1$–score 90.1%, 80.7%, 86.6%, and 72.2% have been achieved by classifiers k-nearest neighbor (k–NN), stochastic gradient descent, XGBoost, and CNN respectively to classify 8 classes of seizure type. In [7], 8 classes of seizure types have been discriminated by a neural memory network with a weighted $F1$-score of 94.5%. However, very limited attempts have been made in the classification of seizure types [5–7].

In this direction, CNN architecture, an efficient class of DL, evidenced significant performance in 2D image-based classification including epileptic seizures detection [1–2]. However, the performance of CNN greatly depends on the large number of diverse input datasets [3]. Hence, successful implementation of CNN can be performed by constructing several 2D images from 1D EEG [4–5]. Therefore, in this study, 2D images have been encoded from 1D EEG signal by gramian angular summation field (GASF) transformation [8]. Besides, it analyzes the EEG signal in the polar coordinate system, while preserving the temporal dependency [9]. The generated images can be directly fed into the CNN pipeline for feature extraction and classification. Therefore, in this work, the proposed idea employed an efficient 2D image generation technique, gramian angular field transformation and CNN pipeline to classify seizure-free and four classes of seizure type using EEG signals.

This paper has been structured as follows: Section II consists of an introduction, followed by an experimental setup in Section III. Next, Section IV discussed the analysis of experimental results. Finally, paper concluded in Section V.

II. PROPOSED METHOD

The outline of the proposed idea has been displayed in Fig. 1. First, 2D images from each EEG segment of seizure types have been generated by GASF transformation. Then, images

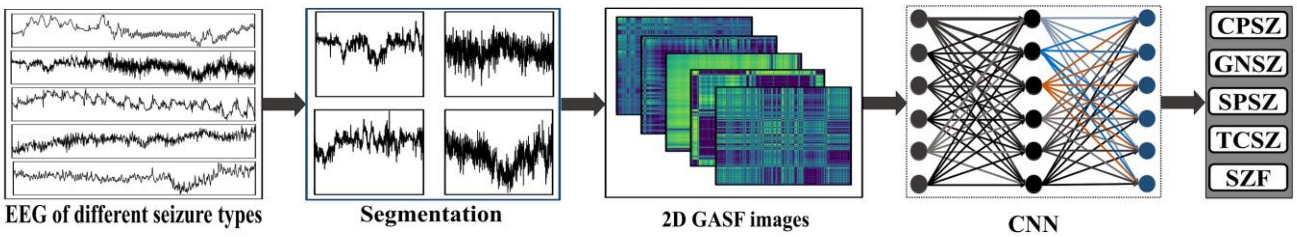


Fig. 1. The outline of proposed work to classify seizure-free and four class of seizure types based on 2D images constructed from EEG.

have been directly fed into the CNN pipeline. Further, binary and multi-class classification have been evaluated to analyze the seizure types. The details of the proposed method described below:

A. Processing

The EEG signals of the dataset have been free from noise and different artefacts. Further, the whole signals have been segmented with pre-defined length to get meaningful information as well as minimize the computational practice [1]. In addition, it provides a large number of diverse samples which is required for successful deep learning applications [3–4]. Therefore, based on a certain duration, the EEG signals have been segmented with 50% overlapping. Now, each segment has been encoded into a 2D image by GASF transformation.

B. Gramian Angular Summation Field

The 1D time series can be transformed into a 2D image by the application of an efficient and widely used imagining algorithm — gramian angular field (GAF) transformation [8–10]. The GAF provides an efficient way to analyze 1D time series in the polar coordinate system [9]. Besides, the encoding process in the polar coordinate system is bijective and preserved the temporal dependency [10–11]. For GAF transformation, suppose $s(t)$ (1) is a time series having m number of samples;

$$s(t) = t_1, t_2, t_3, t_4, \ldots t_m \tag{1}$$

Next, $s(t)$ has been scaled to a range of [-1, 1] by (2), as normalization can improve the performance of algorithms and minimize the bias issue in dataset [3], [10].

$$\tilde{t}_i = \frac{(t_i - \max(s(t))) + (t_i - \min(s(t)))}{\max(s(t)) - \min(s(t))} \tag{2}$$

Now, scaled samples are transformed to the polar coordinate system by (3);

$$\begin{cases} \theta_i = \cos^{-1}(\tilde{t}_i) & -1 \le \tilde{t}_i \le 1 \\ r_i = \dfrac{i}{m} & i \in m \end{cases} \tag{3}$$

where, θ_i and r_i are the inverse value of cosine function and radius of t_i in the polar coordinate system respectively. However, the cosine angle varies in the range of [0, π] as samples of $s(t)$ have been scaled in the range of [-1, 1]. Subsequently, time correlation among sample points is measured by the trigonometric functions and construct a gram matrix which is computed by (4). In this way, GASF can transform 1D time series to the 2D image through scaling of data, transformation of coordinate, and functions of trigonometric.

$$GASF = \begin{bmatrix} \cos(\theta_1 + \theta_1) & \ldots & \ldots & \cos(\theta_1 + \theta_m) \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ \cos(\theta_m + \theta_1) & \ldots & \ldots & \cos(\theta_m + \theta_m) \end{bmatrix} \tag{4}$$

C. Convolution Neural Network

The self-learning capability of CNN achieved great success and paving new ways in the field of biomedical signal and image processing [1]. Indeed, CNN resourcefully analyzes input data and extracts meaningful features to classify the specific input [2]. The proposed CNN architecture and its layers — convolutions, batch normalization, max-

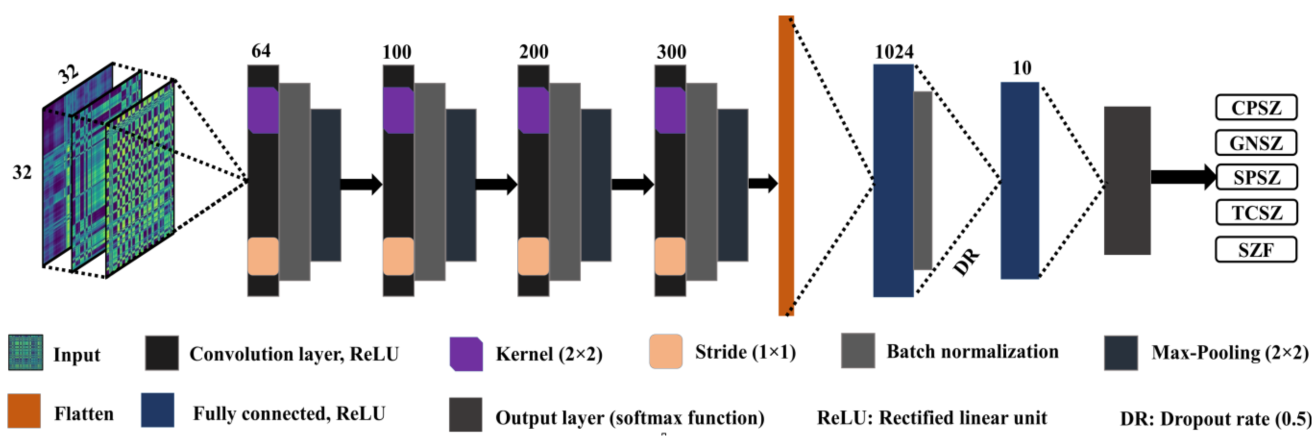


Fig. 2. The proposed CNN architecture for classification of seizure types.

pooling (M_P), fully–connected (FC), dropout, and an output layer with empirically tuned have been illustrated in Fig. 2. The CNN autonomously extracts multiple features from the input by performing convolution operations by kernel functions [3]. Next, the outcome of convolution has been fed into the ReLU function, which makes the neural network sparse, reduces the computational burden, and improves efficacy [4]. Further, batch normalization has been used with convolution and fully connected layers to minimize the internal covariance shift issue as well as speed up the model training practice [1]. Besides, it also efficiently advances model convergence speed, stability, and performance. The M_P layer learns smooth and sharp features as well as aggregates the features map that improves the efficacy and robustness of the model [3]. After that, features have been flattened and fed into the FC layer to compile the feature vectors of the preceding layer. In addition, dropout layer has been used to reduce the over-fitting issue and improves the model performances [4]. Finally, the output layer having a softmax function produces the probability of specific input classes. Now, 2D images have been directly fed into the CNN to classify seizure-free and four types of seizures.

III. EXPERIEMNTAL METHODOLOGY

A. Data

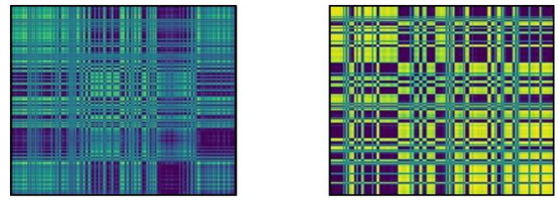
For evaluation of the proposed idea, a well-known EEG dataset of Temple University Hospital (TUH, v1.5.2) has been taken into consideration [12]. The different recording processes (unipolar and bipolar montages techniques) and sampling rates have been adopted to capture EEG signals. In this work, EEG recorded with average reference (AR) unipolar montages of 19 common channels — C3, C4, Cz, F3, F4, F7, F8, FP1, FP2, Fz, O1, O2, P3, P4, Pz, T3, T4, T5, and T6 with a sampling rate of 250Hz have been taken into account. EEG recording of four seizure types along with seizure-free has been utilized for validation. The description of EEG dataset has been summarized in Table I, in which first and second column represents seizure types and the duration of EEG recording (s) respectively. In total, EEG recordings of 18 patients have been considered.

B. Experiment

The EEG recording of each channel has been segmented in the length of 10s with 50% overlapping. Further, 2D images have been constructed from each EEG segment. In Fig. 3 (a) and (b), GASF images constructed from an EEG segment of channel C3 of CPSZ and GNSZ have been shown respectively. Certainly, the difference between the images can

TABLE I
DATASET DESCRIPTION

Seizure types	Duration (s)
Complex partial seizure (CPSZ)	1448.48
Generalized non-specific seizure (GNSZ)	1606.16
Simple partial seizure (SPSZ)	1328.50
Tonic clonic seizure (TCSZ)*	517.17
Seizure-free (SZF)	1386.11



(a) (b)

Fig. 3. The images constructed by GASF transformation from an EEG segment of channel C3 of (a) CPSZ and (b) GNSZ respectively.

be observed. However, from Table I, it can be noticed that the duration of TCSZ recording is very small compare to other seizure types, hence a random oversampling technique has been applied to generate the balance training samples. As CNN architecture required a fixed size of the inputs, therefore all the images have been resized into 32x32 before using as input.

The data-driven CNN pipeline has been employed to learn and extract potential features and classify the seizure types. The model has been trained by Adam ($\beta1$= 0.9, $\beta2$ =0.99, decay rate =10^{-6}) optimizer and categorical cross-entropy as loss function. The learning rate, number of epochs, and size of batch have been tuned to 0.0001, 50, and 16 for all classification tasks. Now, for evaluation of CNN pipeline, the dataset has been split in the ratio of 80:20 for training and testing samples. Besides, 20% of training samples have been used for validation. Finally, binary and multi-class classification tasks have been evaluated by the CNN pipeline.

IV. RESULTS AND DISCUSSION

The 2D images generated by GASF transformation from 1D EEG segments have been used to train the CNN model. In this work, a total of 26 classification tasks (binary (10), and multi-class (16)) have been executed. Further, the classification accuracy (A_{cc}) and weighted $F1$–score ($F1$) have been evaluated by (5) and (6) respectively to validate the proposed idea.

$$A_{CC} = \frac{tp + tn}{tp + fp + fn + tn} \tag{5}$$

$$F1 = 2 * \frac{P * R}{P + R} \quad \begin{cases} P = \dfrac{tp}{tp + fp} \\ R = \dfrac{tp}{tp + fn} \end{cases} \tag{6}$$

where, tp, tn, fp, and fn represents true positive, true negative, false positive, and false negative respectively, while P and R denote precision and recall respectively.

The normalized confusion matrix recorded in classification of CPSZ, GNSZ, SPSZ, TCSZ, and SZF has been shown in Fig. 4. The performance metrics (PM) of binary classification tasks have been summarized in Table II, in which the first and second column represents seizure types, followed by A_{cc} and $F1$ respectively. It has been noticed that maximum A_{cc} and $F1$ have been achieved in the classification of SPSZ and SZF to 96.01% and 96.0% respectively. The performance metrics for the classification of three classes of seizure types have been listed in Table III. The maximum A_{cc}

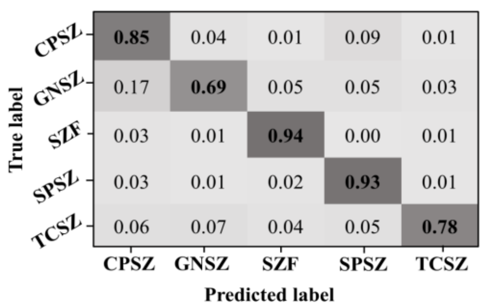


Fig. 4. The normalized confusion matrix obtained in classification of CPSZ, GNSZ, SPSZ, TCSZ, and SZF.

and $F1$ have been recorded up to 89.91% and 90.0% respectively for the classification of CPSZ, SPSZ, and TCSZ. In Table IV, performance metrics have been listed for the classification of four (top) and five classes of seizure types respectively. The maximum A_{cc} and $F1$ have been recorded 84.19% and 84.0% respectively to classify GNSZ, SPSZ, SZF, and TCSZ. In addition, the classification A_{cc} and $F1$ achieved up to 84.20% and 84.0% in the case of CPSZ, GNSZ, SPSZ, TCSZ, and SZF. A comparative study with recent works has been summarized in Table V. As displayed, the proposed method is very much efficient for the classification of seizure types.

V. Conclusions

In this work, GASF transformation and CNN have been employed to classify four classes of seizure type — CPSZ, GNSZ, SPSZ, TCSZ, and SZF using EEG. The binary and multiclass classification tasks have been performed, and maximum accuracy achieved up to 96.01% for binary classification, while accuracy recorded up to 89.91%, 84.19%, and 84.20% for 3, 4, and 5 classes of seizure types respectively. The proposed idea can efficiently discriminate seizure types and seizure-free using EEG signals with favourable experimental performance.

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TABLE II: PM OF BINARY CLASSIFICATION

Seizure types		PM (%) A_{cc}	PM (%) $F1$
CPSZ	GNSZ	84.51	85.0
	SZF	92.51	93.0
	SPSZ	92.85	93.0
	TCSZ	92.49	90.0
GNSZ	SZF	90.04	90.0
	SPSZ	95.00	95.0
	TCSZ	85.76	85.0
SPSZ	SZF	96.01	96.0
	TCSZ	92.15	92.0
TCSZ	SZF	91.08	92.0

TABLE III: PM OF CLASSIFICATION OF 3 SEIZURE TYPES

Seizure types			PM (%) A_{cc}	PM (%) $F1$
CPSZ	GNSZ	SZF	76.87	77.0
		SPSZ	81.35	82.0
		TCSZ	79.87	80.0
	SPSZ	TCSZ	89.91	90.0
	SZF	SPSZ	88.47	88.0
		TCSZ	78.50	78.0
GNSZ	SZF	SPSZ	88.10	88.0
		TCSZ	82.50	82.0
	SPSZ	TCSZ	87.71	88.0
SPSZ	SZF	TCSZ	86.88	87.0

TABLE IV: PM FOR CLASSIFICATION OF 4 AND 5 SEIZURE TYPES

Seizure types					PM (%) A_{cc}	PM (%) $F1$
4–class						
CPSZ	GNSZ	SZF	SPSZ		79.62	80.0
		SZF	TCSZ		79.05	79.0
		SPSZ	TCSZ		79.67	80.0
	SZF	SPSZ	TCSZ		84.18	84.0
GNSZ	SPSZ	SZF	TCSZ		84.19	84.0
5–class						
CPSZ	GNSZ	SPSZ	SZF	TCSZ	84.20	84.0

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TABLE V: A COMPARATIVE ANALYSIS

Works	Methods	PM (%) A_{cc}	PM (%) $F1$
[5]	EEG, basic CNN	82.14	-
	EEG, AlexNet	84.06	-
[6]	EEG, FFT, CNN	72.20	-
	EEG, FFT, *k*-NN	88.40	-
This work	**EEG, GASF, CNN**	**96.01**[a]	**96.0**[a]
		89.91[b]	**90.0**[b]
		84.19[c]	**84.0**[c]
		84.20[d]	**84.0**[d]

Note: [a]: binary, [b]: 3– types, [c]: 4– types, [d]: 5– types of seizure