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An automated system for epilepsy detection using EEG brain signals based on deep learning approach

Ihsan Ullah[a], Muhammad Hussain[b,*], Emad-ul-Haq Qazi[b], Hatim Aboalsamh[b]

[a] Insight Centre for Data Analytics, National University of Ireland, Galway, Ireland
[b] Visual Computing Lab, Department of Computer Science, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia

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A B S T R A C T

Epilepsy is a life-threatening and challenging neurological disorder, which is affecting a large number of people all over the world. For its detection, encephalography (EEG) is a commonly used clinical approach, but manual inspection of EEG brain signals is a time-consuming and laborious process, which puts a heavy burden on neurologists and affects their performance. Several automatic systems have been proposed using traditional approaches to assist neurologists, which perform well in detecting binary epilepsy scenarios e.g. normal vs. ictal, but their performance degrades in classifying ternary case e.g. ictal vs. normal vs. inter-ictal. To overcome this problem, we propose a system that is an ensemble of pyramidal one-dimensional convolutional neural network (P-1D-CNN) models. Though a CNN model learns the internal structure of data and outperforms hand-engineered techniques, the main issue is the large number of learnable parameters, whose learning requires a huge volume of data. To overcome this issue, P-1D-CNN works on the concept of refinement approach and it involves 61% fewer parameters compared to standard CNN models and as such it has better generalization. Further to overcome the limitations of the small amount of data, we propose two augmentation schemes. We tested the system on the University of Bonn dataset, a benchmark dataset; in almost all the cases concerning epilepsy detection, it gives an accuracy of $99.1 \pm 0.9\%$ and outperforms the state-of-the-art systems. In addition, while enjoying the strength of a CNN model, P-1D-CNN model requires 61% less memory space and its detection time is very short (< 0.000481 s), as such it is suitable for real-time clinical setting. It will ease the burden of neurologists and will assist the patients in alerting them before the seizure occurs. The proposed P-1D-CNN model is not only suitable for epilepsy detection, but it can be adopted in developing robust expert systems for other similar disorders.

1. Introduction

Epilepsy is a neurological disorder affecting about fifty million people in the world (Megiddo et al., 2016). Electroencephalogram (EEG) is an effective and non-invasive technique commonly used for monitoring the brain activity and diagnosis of epilepsy. EEG readings are analyzed by neurologists to detect and categorize the patterns of the disease such as pre-ictal spikes and seizures. The visual examination is time-consuming and laborious; it takes many hours to examine one-day EEG recording of a patient, and it requires the services of an expert. As such, the analysis of the EEG brain signals of patients puts a heavy burden on neurologists and reduces their efficiency. These limitations motivated efforts to design and develop automatic systems to assist neurologists in classifying epileptic and non-epileptic EEG brain signals.

Recently, a lot of research work has been carried out to detect the epileptic and non-epileptic signals as a classification problem (Gardner, Krieger, Vachtsevanos, & Litt, 2006; Meier, Dittrich, Schulze-Bonhage, & Aertsen, 2008; Mirowski, Madhavan, LeCun, & Kuzniecky, 2009; Sheb & Guttag , 2010). From the machine learning (ML) point of view, recognition of epileptic and non-epileptic EEG signals is a challenging task. Usually, there is a small amount of epilepsy data available for training a classifier due to infrequently happening of seizures. Further, the presence of noise and artifacts in the data creates difficulty in learning the brain patterns associated with normal, ictal, and non-ictal cases. This difficulty increases further due to inconsistency in seizure morphology among patients (McShane, 2004). The existing automatic seizure detection techniques use traditional signal processing (SP) and ML techniques. Many of these techniques show good accuracy for one problem but fail in performing accurately for others e.g.

* Corresponding author.
E-mail addresses: Ihsan.ullah@insight-centre.org (I. Ullah), mhussain@ksu.edu.sa (M. Hussain), qulhaq@ksu.edu.sa (E.-u.-H. Qazi), hatim@ksu.edu.sa (H. Aboalsamh).

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they classify seizure vs. non-seizure case with a good accuracy but show poor performance in case of normal vs. ictal vs. inter-ictal (Zhang, Chen, & Li, 2017). It is still a challenging problem due to three reasons, i) a generalized model does not exist which can classify binary as well as a ternary problem (i.e. normal vs. ictal vs. inter-ictal), ii) less available labeled data, and ii) low accuracy. To help and assist neurologists, we need a generalized automatic system that gives good performance even with fewer training samples (Andrzejak et al., 2001; Sharmila & Geethanjali, 2016).

Exiting methods for the detection of seizures use hand-engineered techniques for feature extraction from EEG signals. Some methods use spectral (Tzallas et al., 2012) and temporal aspects of information from EEG signals (Shoeb, 2009). An EEG signal contains low-frequency features with long time-period and high-frequency features with a short time period (Adeli, Zhou, & Dadmehr, 2003) i.e. there is a kind of hierarchy among features. Deep learning (DL) is a state-of-the-art ML approach that automatically encodes hierarchy of features, which are not data dependent and adapt to internal structure of the data; it has shown promising results in many applications. Moreover, features extracted using the DL models have shown to be more discriminative and robust than hand-designed features (LeCun & Bengio, 1995). In order to improve the accuracy in the classification of epileptic and non-epileptic EEG signals, we propose a method based on DL.

The recent emergence of DL techniques show significant performance in several application areas. The variants of deep CNN i.e. 2D CNN such as AlexNet (Krizhevsky, Sutskever, & Hinton, 2012), VGG (Simonyan & Zisserman , 2014) etc. or 3D networks such as 3DCNN Ji, Xu, Yang, & Yu, 2013), C3D (Tran, Bourdev, Fergus, Torresani, & Paluri, 2015) etc. have shown outstanding performance in many fields. Recently, 1D-CNN has been successfully used for text understanding, music generation, and other time series data (Cui, Chen, & Chen, 2016; Ince et al., 2016; LeCun, Bottou, Bengio, & Haffner, 1998; Zhang & LeCun, 2015). The end-to-end learning paradigm of DL approach avoids the selection of a proper combination of feature extractor and feature subset selector for extracting and selecting the most discriminative features that are to be classified by a suitable classifier (Andrzejak et al., 2001; Hussain, Aboalsamh, Abdul, Bamatraf, & Ullah, 2016; Sharmila & Geethanjali , 2016; Zhang et al., 2017). Although the traditional approach is fast in training as compared to DL approach, it is far slower at test time and does not generalize well. Trained deep models can test a sample in a fraction of a second, and are suitable for real-time applications; the only bottleneck is the requirement of a large amount of data and its long training time. To overcome this problem, an augmentation scheme needs to be introduced that may help in using a small amount of available data in an optimal way for training a deep model.

As an EEG recording is a 1D signal, we propose a pyramidal 1D-CNN (P-1D-CNN) model for detecting epilepsy, which comprises of far fewer number of learnable parameters. The amount of available data is small, therefore, to train a P-1D-CNN, we propose two augmentation schemes. Using trained P-1D-CNN models as experts, we design a system as an ensemble of P-1D-CNN models, which employs majority vote strategy to fuse the local decisions for detecting epilepsy. The proposed system takes an EEG signal, segment it with fixed-size sliding window, and pass the sub-signals to base P-1D-CNN models (Fig. 2) that process them and give the local decisions to the majority-vote module. In the end, the majority-vote module takes the final decision (Fig. 1). It outperforms the state-of-the-art techniques for different problems concerning epilepsy detection. The main contributions of this study are: (1) data augmentation schemes, (2) an automatic system based on an ensemble of P-1D-CNN deep models for binary as well as ternary EEG signal classification, (3) a new approach for structuring deep 1D-CNN model and (4) thorough evaluation of the augmentation schemes and the deep models for detecting different epilepsy cases.

The rest of the paper is organized as follows: In Section 2, we present the literature review. Section 3 describes in detail the proposed system. Model selection, data augmentation schemes, and training of P-1D-CNN model are discussed in Section 4. Section 5 presents results; Section 6 discusses the results and compares them with those by the state-of-the-art methods. In the end, Section 6 concludes the paper and present the future directions.

2. Literature review

The recognition of epileptic and non-epileptic EEG signals is a classification problem. It involves extraction of the discriminative features from EEG signals and then performing classification. In the following paragraphs, we gave an overview of the related state-of-the-art techniques, which use different feature extraction and classification methods for classification of epileptic and non-epileptic EEG signals.

Almost all existing methods for epilepsy detection are based on hand-engineered feature extraction techniques. Chua, Chandran, Acharya, and Lim (2011) used Higher Order Spectra (HOS) and power spectrum based features for the automated detection of epilepsy. The authors used the Gaussian Mixture Model (GMM) as a classifier and obtained the classification accuracies of 93.11% and 88.78% with HOS and power spectrum based features, respectively. In another study, Chua, Chandran, Acharya, and Lim (2009) used SVM classifier with HOS based features and achieved an accuracy of 92.67%. Acharya, Vinitha Sree, and Suri (2011) used cumulants for the automated detection of epilepsy. They extracted the HOS cumulants from Wavelet Packet Decomposition (WPD) coefficients and obtained an accuracy of 98.5% with SVM classifier.

Subasi (2007) proposed a method to classify normal vs epileptic EEG brain signals. In this method, EEG brain signals are decomposed into different frequency sub-bands using the discrete wavelet transform (DWT). Four statistical features are extracted from DWT coefficients and are passed to a modular neural network (called Mixture of Experts-MEs) for classification. They reported a sensitivity of 95%, specificity of 94% and accuracy of 94.5%. In another study (Acharya et al., 2012), the authors used SampEn, ApEn and two-phase entropies and a Fuzzy classifier; they reported a specificity of 100%, accuracy of 98.1% and sensitivity of 99.4%. Martis et al. (2013) used features derived from intrinsic Time-Scale decomposition (ITD) and decision tree classifier. This method achieved an accuracy of 95.67%, a specificity of 99.50% and a sensitivity of 99%. In (Acharya et al., 2013), authors proposed a method for the automated classification of EEG brain signals into three different classes, i.e., ictal, normal and interictal. They used Continuous Wavelet Transform (CWT) for feature extraction and SVM as a classifier. Results indicate that this method obtained an accuracy of 96%.

Swami, Gandhi, Panigrahi, Tripathi, and Anand (2016) extracted hand-crafted features such as Shannon entropy, standard deviation, and energy. They employed the general regression neural network (GRNN) classifier to classify these features and achieved maximum accuracy, i.e., 100% and 99.18% for A-E (non-seizure vs. seizure) and AB-E (normal vs. seizure) cases, respectively on Bonn dataset. However, maximum accuracy for other cases like B-E, C-E, D-E, CD-E, and ABCD-E is 98.4%. In another study, Guo, Rivero, Dorado, Rabunal, and Pazos (2010) achieved the accuracy of 97.77% for ABCD-E case on the same dataset. They used artificial neural network classifier (ANN) to classify the line length features that were extracted by using discrete wavelet transform (DWT). Nicolaou and Georgiou (2012) extracted the permutation entropy feature from EEG signals. They employed support vector machine (SVM) as a classifier and achieved an accuracy of 93.55% for A-