Classification of Ictal and Preictal Seizure using EEG Signals based on Convolutional Neural Network

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***Abstract*—Epilepsy is a neurological disorder in which normal brain activity is affected. Electroencephalography (EEG) is a gold standard to predict epilepsy seizures. Manual inspection of EEG signals to detect various seizure phases is a major challenge therefore, need for some mechanism to automate seizure prediction to ease the work of clinicians is required. Moreover, Epilepsy patients suffer difficulties in social gatherings as the seizure is unpredictable which can cause anxiety, fear, etc in them. To overcome these challenges, automatic seizure prediction is vital. The present work encompasses the channel selection and data augmentation methods to create a system that automatically classifies two phases of seizure-ictal and preictal using a 1D Convolutional Neural Network (CNN) model. Instead of using all channels of EEG signals, a subset of channels is used in this work to analyze its effect on performance. Data augmentation is used to increase the datasets which got limited due to channel selection. The model achieves the best performance with the help of the 1D CNN model. It achieves an accuracy of 99.62%, specificity of 99.76%, and sensitivity of 99.70% on the CHB-MIT dataset. This work shows that a subset of channels with greater importance can improve the robustness of the seizure prediction system. This in turn saves the time to set up the electrodes on the scalp of the patients. Various data augmentation schemes can be used to compensate for the limited dataset. Usage of models like 1D CNN are suitable for designing low-power seizure prediction systems.**

***Index Terms*—EEG signals; Epilepsy; CNN; Channel Selection; Data augmentation; Deep learning model**

I. Introduction

Epilepsy is a brain function disorder brought by excessive neuronal firing that affected more than 50 million people across the globe as per World Health Organization (WHO). Among the patients, an estimated 70% of persons with epilepsy might live without disease if they get proper care and treatment [1]. Electroencephalogram (EEG) technique is mainly used in the diagnosis of epilepsy and it captures the brain activities and thus able to detect the alleged seizures, and unusual spikes. Almost all epilepsy patients, with a few exceptions, will exhibit recognizable EEG variations during an epileptic seizure (ictal phase) [2]. Most epilepsy patients exhibit recognizable interictal (or between-seizure) epileptiform discharges (IEDs), also known as spike and wave, spike and sharp-wave, or sharp-wave discharges [3]. Apart from the ictal and interictal phase, there are two more seizure phases namely the preictal and postictal phase which occurs before and after an ictal state. EEG signals can be recorded using either non-invasive or invasive techniques [4]. The unpredictable nature of seizure is a major concern among the patients, i.e. there is no way to know when a seizure will begin or what will cause it to start [5]. The primary objective of seizure prediction is to foresee a seizure by immediately triggering an alert. The development of effective seizure prediction algorithms may lead the way for the design of seizure-suppressing drugs or the development of restricted-loop systems that, automatically, trigger some seizure-neutralizing procedure. It may lessen any aftereffects like fear or social exposure [6]. Thus, seizure prediction has the potential to enhance epilepsy care, and hence, the quality of life for those who have epilepsy. It can be achieved by the classification of EEG signal data. A classification problem in EEG can be done using traditional machine learning (ML) algorithms in which features are extracted manually from the EEG signals and predicted with the help of a classifier. Nowadays, deep learning-based algorithms are popular to extract features from EEG signals automatically. In this work, we present a deep learning model based on a 14-layered 1D CNN. The contributions of the proposed work are mentioned below:

i. We have proposed a lightweight CNN model with fewer parameters that consume less power which in turn is suitable for handheld devices.
ii. We reduced computational cost by incorporating channel

selection methods which also helps in avoiding overfitting that occurs due to the use of unwanted EEG data.

iii. We compensated for the limited dataset by applying suitable data augmentation techniques

II. Related Work

The development of deep learning techniques has proved its capacity to solve many complex problems in a wide range of applications such as in the field of medicine for disease classification [7], in the field of security for biometrics [8]. Normally, CNN refers to a two-dimensional CNN that is used for image classification, however, it has shown its ability to solve other kinds of tasks involving time series data like EEG signals. In the work of Salman, the EEG BONN dataset is converted into 2D data and passed into a 2D CNN model for the classification of normal vs interictal vs ictal [9]. Other 2D CNN architectural models like AlexNet, GoogleNet, VGGNet, ResNet, etc. are made to use for Epilepsy prediction in the works of Roy et al. and Shoka et al. [10], [11]. On the other hand, 1D CNN has also been widely used for text data, and 1D signals like the output from human activity monitoring systems, music generation systems, EEG machines, etc. Acharya et al. claims that their work is the first one to apply CNN for seizure prediction [12]. The authors proposed a 1D CNN architecture that uses the BONN dataset in which raw single-channel EEG signals are made input to the classifier and hence feature extraction step is eliminated. A pyramidal 1D CNN (P-1D-CNN) architecture has been introduced by Ullah et al. 2018 which is an ensemble of CNN models to predict epilepsy detection using the BONN dataset [13]. The authors have claimed that their model required 61% fewer parameters compared to standard CNN models. The authors made use of data augmentation techniques to handle the smaller size of the dataset which helps to achieve a good performance. Kurdthongmee et al. combined two CNN architectures from the works of Acharya et al. and Abiyev et al. to make an optimized model capable of classifying normal, preictal, and seizure [12], [14], [15]. The shallow layers helped to predict abnormalities more quickly and the proposed system achieved good performance upon application to the BONN dataset. Deepa et al. applied Min-max normalization on the pre-processed CHB-MIT dataset before passing it into the prediction model [16]. The authors used Bidirectional Long Short Term Memory (LSTM) to achieve the classification of ictal and preictal. The present work proposes a CNN-based classification model for the prediction of Epilepsy based on ictal and preictal seizure phases. The various channel selection and data augmentation methods have been applied in the proposed model and the performance of the same has been validated. The CHB-MIT dataset has been used to validate the proposed model for seizure prediction. The remainder of the paper is organized as follows: The used datasets and the proposed approaches are introduced in Section III. Experimental analysis is explored in Section IV, whereas in Section V, results and discussions are explained. Finally, Section VI concludes the paper and the future scope.

III. Materials and Methods

A. Dataset

CHB-MIT dataset is one of the widely used multi-channel EEG data for epilepsy prediction [17]. It consists of scalp EEG readings from 22 pediatric epilepsy patients ranging from 1.5 to 22 years of age. The EEG data has been sampled at 256 samples per second. Except for a few subjects, most files contain 23 EEG signals taken from the scalp. The dataset can be freely downloaded from https://physionet.org/content/chbmit/1.0.0/ in the form of 'edf' files. However, the CHB-MIT dataset contains heavily uneven and distorted data, therefore data has to be pre-processed before passing into the prediction model. Hence, in this proposed work, a balanced pre-processed version of the dataset is utilized.

B. Data Pre-processing

Data normalization is one of the pre-processing approaches in which the data is scaled or transformed to ensure that each feature contributes equally [18]. The Min-max normalization linearly scales the un-normalized data to predefined lower and upper bounds, where the data is usually rescaled between 0 and 1. In the proposed model, MinMaxScaler normalization has been applied to the dataset. Two channel selection methods are incorporated in which first method is based on variance by Duun-Henriksen et al. [19] and secondly, a subset of channels has been formed based on the works of Stevenson et al. and Zhang et al. [20], [21]. From first method, three channels such as FT9-FT10, F7-T7, and F3-C3 of maximum variance were chosen. In the second case, channels such as FP2-F8, F8-T8, and T8-P8 are chosen since they are known to be prominent for epilepsy seizure prediction tasks based on the past literature. Further, data augmentation schemes suitable for 1D EEG signals have been implemented to improve the accuracy of the prediction model. It has been done by taking the EEG signal and breaking it into small chunks of the same window size. We segmented EEG signals into different lengths to feed into the model. In the first case, the entire signals are partitioned into non-overlapping chunks of 4097. After partitioning, the signal at the end of each channel that is less than 4097 is discarded. In the second case, a sliding window strategy is used to create chunks of smaller signals with two different lengths 512 and 1024 are implemented inspired by the work of Ullah et al. [13]. Three data augmentation schemes based on varying window size and stride are applied. As per Scheme-1, a window size of 512 and a stride of 64 (overlapping portion between consecutive segments) is being adopted to segment the train and test sets into further smaller segments to be fed into the model. In Scheme-2, the same window size of 512 and a stride of 128 are used. Finally, in Scheme-3, a new window size of 1024 is used, whereas the stride size is kept constant i.e., 128.

C. Proposed Methodology

Fig. 1 shows the strategy that has been chosen to build the prediction model which combines the above-described methods. After Min-Max Normalization, channels are selected,

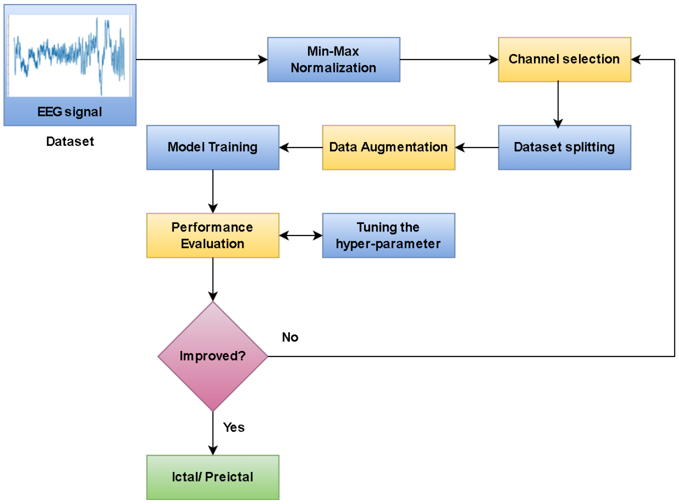


Fig. 1: Flowchart of the proposed methodology

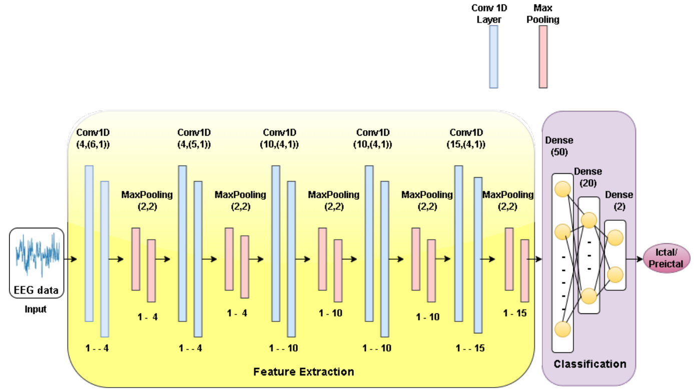


Fig. 2: Architecture of the Proposed 1D CNN

followed by splitting the data into train and test sets. Then, the data augmentation is applied before passing the data into the model. Finally, performances are evaluated, and based on that, the process is repeated until an optimized solution is achieved, in which no further improvement is visible.

The use of a 1D CNN for seizure prediction offers several advantages over other models such as efficient processing in which 1D CNNs are specifically designed to handle sequential data such as time series signals in which they are good at capturing temporal dependencies and patterns in the signals. In the case of seizure prediction, where the input is often EEG data, a 1D CNN can effectively extract important features from the signal. The convolutional layers in a 1D CNN perform local feature extraction by sliding a small filter/kernel across the input signal which allows the network to capture local patterns and variations in the EEG signal, which is useful for identifying seizure activity. The ability to focus on local features makes 1D CNNs well-suited for detecting localized changes in the signal associated with seizures. 1D CNN model has been used in the proposed model which was designed to have a lesser number of layers and parameters and thus minimize the computing cost without compromising the performance. In comparison to more complex models like recurrent neural networks (RNNs) or LSTM networks, 1D CNNs typically have fewer parameters. which makes them computationally lighter and faster to train, especially when working with medium to large datasets.

Figure 2 illustrates the diagrammatic representation of the proposed 1D CNN algorithm. The feature extraction part consists of five convolution layers and max pooling layers arranged alternately followed by a flattened layer. Each convolution layer is with 4 filters in the initial two layers 10 in the latter two layers and followed by a layer with 15 filters. The filter sizes decrease as the learning goes deeper with sizes such as 6, 5, 4, etc. The size of all four max-pooling layers is 2 × 2 which helps to decrease the size of the features. The EEG data in the form of one dimension is fed as the input into the convolutional layers. Finally, the last 3 layers consist of dense layers having sizes 50, 30, and 2 followed by a Softmax layer and a classification layer. The choice of layers and parameters are done based on several experiments to have a lightweight model without compromising the performance.

IV. Experimental analysis

In this work, various experiments that combine two channel selection methods and three data augmentation schemes are conducted. The dataset includes two classes namely ictal and preictal. Data pre-processing is done using a workstation with a 3.70 GHz processor Intel processor and 64 GB RAM and the Jupyter Notebook using Python version 3.7.8. The model has been trained and tested using Google Colab's GPU. Keras, which is an open-source neural network Python library that runs on top of Tensorflow has been used for this work. 1D CNN has been used for both feature extraction and classification. The list of hyperparameters that helped to improve the models' performance is listed in Table I. Appropriate regularization has been used in the last few layers of the 1D CNN model. SeLu was used as the activation function in all convolution layers.

TABLE I: Hyper-parameters used in the experiments

Hyperparameters	Values
Optimizers	Adam
Regularizations	L1, L1-L2
Batch size	100
Learning rate	0.001

The performance of each proposed model is evaluated by determining the accuracy, sensitivity, and specificity which are defined below from Equations (1) - (3), where TP is True Positive, the number of correctly predicted seizures and TN is True Negative, which is the number of non-seizures prediction which is same as the actual value. FP is False Positive and FN is False Negative which denotes the incorrectly predicted classifications. FP is the number of incorrect predictions as seizure where it is non-seizure in reality. Finally, FN tells the number of non-seizures predicted incorrectly by the classifier [22].

$$Accuracy(Acc) = \frac{TP + TN}{TotalSamples} \quad (1)$$

$$Specificity(Spe) = \frac{TN}{TN + TP} \quad (2)$$

$$Sensitivity(Sen) = \frac{TP}{FN + TP} \quad (3)$$

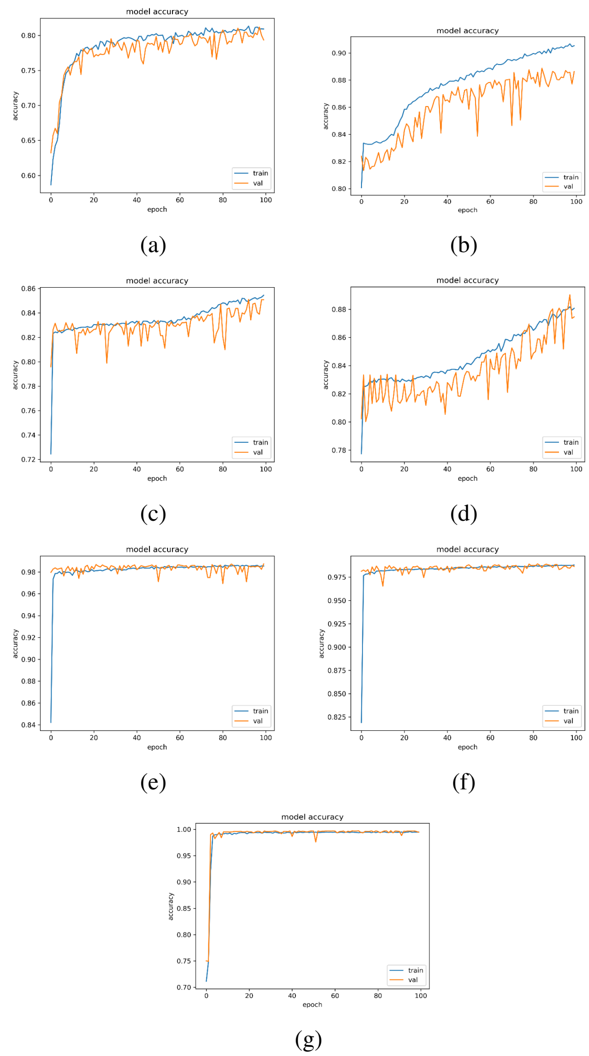
V. Results and Discussion

In the presented model, EEG data of the CHB-MIT dataset were classified using 1D CNN. Initially, all 23 channels were used to train and test the model. Later, two channel selection methods were used whereas in first case channels were chosen bsed on variance using ictal data, in which the top 3 maximum channels were selected and in second case, a subset of three channels that are different based on previous works are selected. To compensate for the limited dataset, three data augmentation schemes were used. As per Scheme-1, a window size of 512 and a stride of 64 (overlapping portion between consecutive segments) is being adopted to segment the train and test sets into further smaller segments to be fed into the model. In Scheme-2, the same window size of 512 and a stride of 128 are used. Finally, in Scheme-3, a new window size of 1024 is used, whereas the stride size is kept constant.

The accuracy curves for all seven experiments are shown in Fig.3 from 3a to 3g and the loss curves are shown in Fig. 4 from 4a to 4g. It is noted that the accuracy of the models from 3a – 3d converged after 80 epochs, whereas models from 3e – 3g converge after 20 epochs itself and gave better accuracy. In terms of loss, except for model 4b, other models converge after 20 epochs, whereas the former converges after 60 epochs.

TABLE II: Result of the proposed models for seizure prediction

Channels	Data Augmentation	No: of Chan-nels	Acc (%)	Spec (%)	Sen (%)
All 23 channels	NA	78.68	74.41	79.10	
FT9-FT10, F7-T7, F3-C3	Window size=512, stride=64	3	88.63	90.00	88.00
	Window size=512, stride=128	3	86.72	89.80	87.00
	Window size=1024, stride=128	3	86.00	86.00	87.00
FP2-F8, F8-T8, T8-P8	Window size=512, stride=64	3	98.95	99.25	99.00
	Window size=512, stride=128	3	98.69	98.40	99.00
	Window size=1024, stride=128	3	99.62	99.76	99.70



(a) (b) (c) (d) (e) (f) (g)

Fig. 3: Accuracy curve for cases that use (a) all channels, (b) - (d) channel selection method 1 and data augmentation schemes- 1, 2, and 3 respectively, (e) - (g) channel selection method 2 and data augmentation schemes-1, 2, and 3 respectively.

The results of various experiments of the proposed models are presented in Table II. The initial experiment was conducted using all channels in which no channel selection and data augmentation methods were used, which gave an accuracy of 78.68%. Later, the accuracy was improved by 10-20% by the application of channel selection methods in which only a few prominent subsets of all 23 channels were considered, followed by the three data augmentation schemes. Hence, combining both methods proved to be effective in improving the accuracy of the prediction model. Among the channel selection methods, proposed models that used the channels FP2-F8, F8-T8, T8-P8 showed better performance compared to the ones that used the variance method. Further, the model in which data augmentation scheme-3 whose window size is 1024 and stride 128 gave the best accuracy of 99%, a specificity of

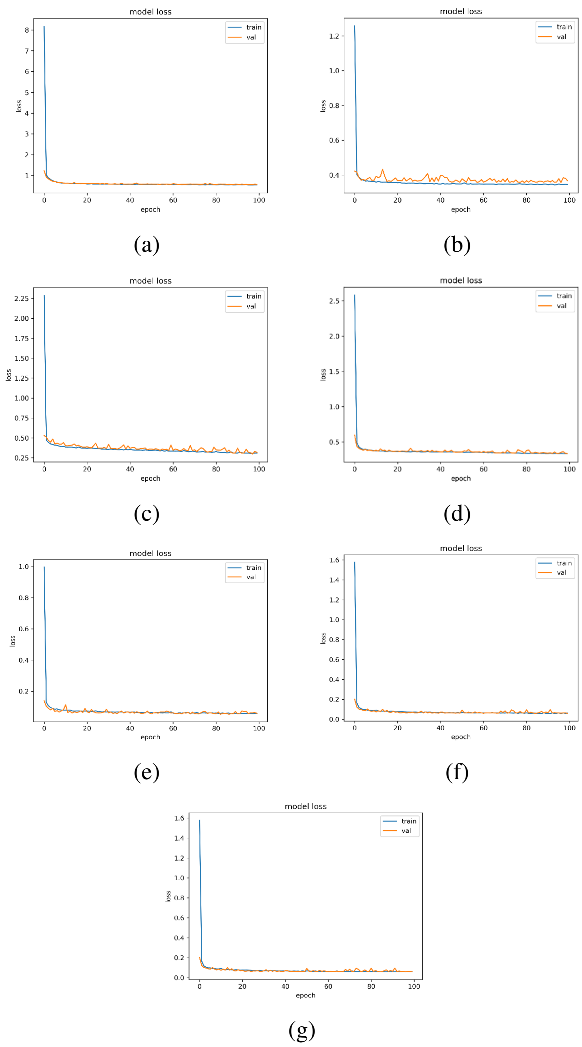


Fig. 4: Loss curve for cases that use (a) all channels and (b) – (g) channel selection method 1 and data augmentation schemes- 1, 2, and 3 respectively, (e) - (g) channel selection method 2 and data augmentation schemes-1, 2, and 3 respectively.

99.76%, and a sensitivity of 99.70%.

A comparison of other similar published works is made with our proposed model which is detailed in Table III. Zhang et al. used the channel selection method for CHB-MIT based on previous literature and then used pre-trained models such as VGG16, VGG19, and ResNet50. Pre-trained models, especially those trained on large-scale datasets like ImageNet, may not be specifically optimized for seizure prediction tasks. The features learned by the pre-trained model may not be directly applicable to the unique characteristics of EEG data and seizure patterns. In contrast, 1D CNNs can be designed and trained specifically for seizure prediction, allowing for better domain adaptation. Zhang et al. and Hussein et al. have used a vision transformer model using a 2D image form of EEG data in which the former used STFT and the latter used CWT to convert the 1D EEG data into a 2D form. Transformer models tend to have a higher computational cost compared to traditional CNN architectures as the Transformers involve self-attention mechanisms which in turn utilize significant computational resources and memory. Thus, it may limit their practicality, particularly if resources such as processing power or memory are constrained. Usman et al. have utilized the power of an ensemble model for seizure prediction, however, ensemble models require training and fine-tuning multiple individual models, which can be time-consuming and require additional effort. Maintenance of an ensemble model involve managing multiple components, which can be more challenging compared to a single 1D CNN model. Hence, it can be seen that the proposed model is better than the other state-of-the-art methods by considering the practical application in a real-time environment.

TABLE III: Comparison analysis of the proposed model with existing state-of-the-art methods

Previous works	Model/ Technique	Accu (%)	Spec (%)	Sen (%)
Zhang et al. [21], 2020	STFT + VGG16, VGG19, ResNet50	97.00, 98.20, 96.17	-	-
Usman et al. [23], 2021	Ensemble(SVM, CNN, LSTM)	-	95.65	96.28
Zhang et al. [24], 2022	STFT + Vision Transformer	94.6	89.8	-
Hussein et al. [25], 2022	CWT + Vision Transformer	-	-	99.80
Proposed model	**14-layer CNN**	**99.62**	**99.76**	**99.70**

VI. Conclusion and Future Work

An automatic seizure prediction system is proposed that combines various methods such as channel selection and data augmentation to improve the performance of the 1D CNN model. The advantage of using deep learning methods is to prevent manual feature extraction and feature selection methods. This work shows that all channels do not necessarily improve the accuracy of the system, instead, a subset of channels with greater importance can contribute to creating a robust epilepsy detection system. This in turn saves the time to set up the electrodes on the scalp of the patients. Various data augmentation schemes are used to compensate for the dataset which got limited after channel selection. Among the experiments,the proposed model achieves better accuracy, specificity and sensitivity of 99.62%, 99.76% and 99.70% respectively. Simple models like 1D CNN are easy to train and they are suitable for designing low-power seizure prediction systems which makes this model to be used in real. As a future work, one can analyze various other state-of-the-art deep learning algorithms which can solve the seizure prediction problem efficiently.

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