CNN-LSTM Network for Epileptic Seizure Detection

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Abstract

Frequent epileptic seizures result in memory impairment, damage to human brain and so on. Medical experts generally use Electroencephalography (EEG) to diagnose the epilepsy. Visually detecting epileptiform abnormalities is time-consuming and prone to error. The purpose of this work is to help clinicians by providing them computer aided detection system to detect epileptic seizures.

Epileptic seizures are usually diagnosed by identifying the sharp spikes in the electroencephalography (EEG) signal. Deep learning-based automated systems techniques have shown appreciable performance in the area of neurological disease detection. In this paper, the authors presented a model having layers of 1D-Convolutional Neural Network (CNN) and long short-term memory (LSTM) for epileptic seizures detection. The authors have obtained a maximum detection rate of 100% between seizure and non-seizure EEG signals using CNN- LSTM network only in 20 epochs. The robustness of the proposed model, has been checked by adding noise to the EEG waveforms.

The proposed methodology will be beneficial for neurologists for real-time seizure detection.

Keywords: Convolutional Neural Network, Classification, Electroencephalography, Epileptic Seizures, Long Short-term memory, Long Short-Term Memory.

1. Introduction

Epilepsy is rapidly progressing into a serious neurological condition. It affects about 50 million people, and 100 million people are affected at some point in their lives [1]. In epilepsy, the patient experiences the symptom of more than one seizure. An epileptic seizure is a brief, excessive electrical discharge of brain neurons. The brain may experience this aberrant condition partially or develop in general. It causes a brief loss of consciousness that lasts anywhere from a few seconds to a few minutes. Seizures are particularly dangerous since they can strike at any time and without warning. This can result in significant injuries such as fractures and burns, as well as death [2].

Electroencephalography (EEG) is the most used technique for seeing and capturing brain activity. This method involves implanting electrodes on the scalp to monitor the electrical activity of the brain. [3]. In non-invasive EEG systems, electrodes are positioned or affixed to the scalp's surface; in invasive EEG systems, electrodes must be surgically inserted or penetrated into the scalp. Electrodes continuously record the voltage variations of the contact surface brought on by brain activity. However, it takes a lot of time and requires an EEG specialist to visually evaluate and annotate EEG information. Consequently, it is crucial to create automated seizure detection and prediction techniques in order to raise the standard of clinical care and diagnosis.

Researchers of different domains, specifically, computational neuroscience and machine learning, are assiduously putting forward new solutions for better seizure detection. Many attempts have been made to recognize epileptic seizure activity automatically utilizing handmade features followed by machine learning approaches. Mustafa et al. [4] has used only time-frequency statistical features of delta band followed by Random Forest classifier for detection of seizures. In another work [5], Haralick features of gamma band has been extracted followed by Decision tree classifier. The fundamental drawback of handmade feature extraction approaches is that an expert is needed to identify the most appropriate group of defining features.

The paper is composed as follows: In Sec. 2 previous works done in the area of healthcare using deep learning has been detailed. Sec. 3 presents the Bonn dataset description followed by description of LSTM and CNN. In Sec. 4 experimental results have been tabulated and compared with previous studies. Sec. 5 conclude the paper.

2. RELATED WORK FOR HEALTHCARE IN DEEP LEARNING

Deep learning's greater capacity to discover patterns has several prospective uses in healthcare and medicine. Search for "deep learning in healthcare" turns up more than 250,000 entries in google scholar, demonstrating that In the literature, this possibility has not gone undiscovered. The applications range from drug research to phenotyping in the field of healthcare.

Biomedical imaging is one field that has attracted a lot of attention, and development in deep learning for medical imaging has been heavily influenced by architectures based on convolutional neural networks. A convolutional neural network designed for radiology called CheXNet was more accurate than professional radiologists at identifying pneumonia in chest X-rays [6]. A subset of 420 chest X-rays were utilized to compare CheXNet's performance against that of four radiologists. It was discovered that CheXNet outperformed the radiologists on average and on three of the individual radiologists' F1 ratings. It used a 3D convolutional autoencoder that has already been trained to identify Alzheimer's disease and mild cognitive impairment from MRI scans, and it performed better than earlier research. It utilised a 3-dimensional convolutional autoencoder that had already been trained to identify diseases such as Alzheimer's and mild cognitive disorders from MRI images, and it did so with a performance that was superior to that of the time's leading technology. Alzheimer's disease was identified by Hosseini-Asl et al. [7] utilizing structural brain MRI data. Like this, Gulshan et al.'s [8] analysis of retinal fundus photographs revealed the presence of Diabetes-related retinopathy and macular edema. It made use of an InceptionV3 architecture and discovered that the deep learning technique had performance that was on par with ophthalmologists in terms of sensitivity and specificity. Convolutional neural networks have shown potential in the semantic segmentation of medical images. A fully convolutional network dubbed U-Net was developed by Ronneberger et al. [9] to segment the neuronal areas in images from brain electron microscopy. Additionally, Deep learning has been employed.

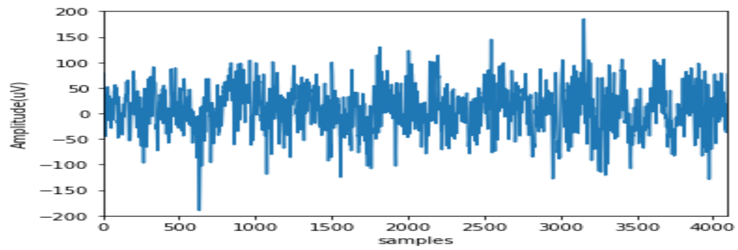
The identification of epileptic seizures has also been accomplished using deep learning. On the Bonn dataset, Acharya et al. [10] categorized seizures using a 13-layer CNN model. 1D pyramidal CNN model proposed by Ullah et al [11] have shown promising results on EEG waveforms. Arpana et al. [12] have compared three 1D CNN models comprising only two convolutional layers. Gupta et al.[13] has also used 1D CNN model on Bonn EEG dataset and obtained good results only in 20 epochs. The main drawback of CNN models are they cannot retain memory of time-series EEG waveforms. So, there is a chance they miss some important features of these biomedical signals.

Recurrent Neural Network (RNN) can remember information about the past as it uses previous values as inputs. LSTM a variant of RNN has been widely applied in detection of seizures [14], [15]. In [16], authors have presented LSTM model for the detection of epilepsy. In this paper, authors have combined the temporal capabilities of LSTM with spatial features of CNN to enhance the detection rate of seizures and robustness of the model. In the next section the proposed methodology has been explained.

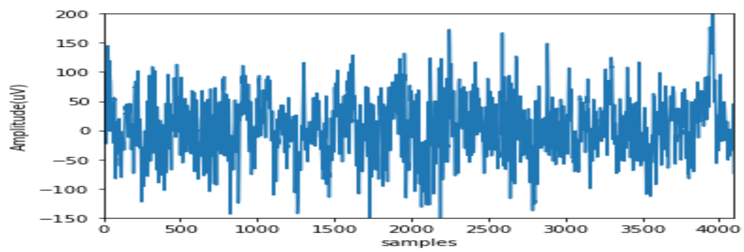
3. METHODOLOGY

3.1 Dataset

The University of Bonn in Germany's benchmark EEG database is used to classify EEG time-series [17]. The EEG database has five categories (A–E) and is freely accessible online. Each group has 4096 samples and is made up of 100 single channel EEG segments recorded at 173.61 Hz for 23.6s. A visual analysis of the EEG data was done in order to remove significant artifacts brought on by muscle movements or eye blinking. EEG segments also need to meet a weak stationary requirement. Using the conventional international 10-20 surface EEG technique, Groups (A) and (B) were recorded. Five healthy participants engaged in these stets with their eyes open and closed in (A) and (B), respectively. For the (C), (D), and (E) groups, five epileptic patients were chosen for prior to surgery examination utilizing intracranial electrodes. In the epileptogenic zone (D) and in (C), depth electrodes were symmetrically implanted to record from the hippocampus emergence of the opposing brain's hemisphere. The contacts of all electrodes were used to collect segments for Group E. While segments in group (E) contain seizure activities, segments in groups (C) and (D) have inter-ictal interludes. Examples of several sets from the Bonn dataset according to Figure 1.



(a)



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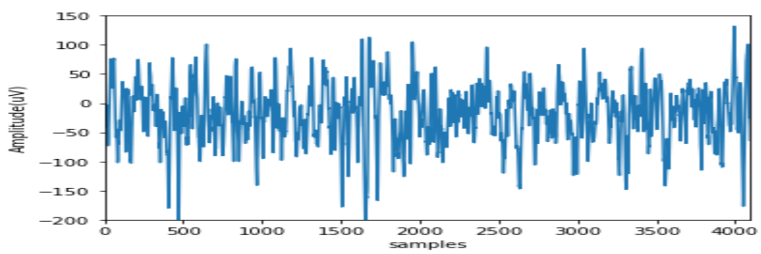

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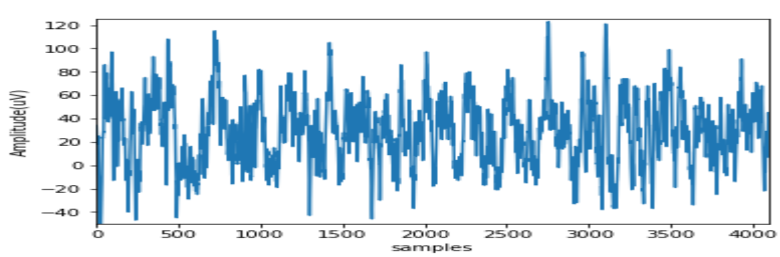
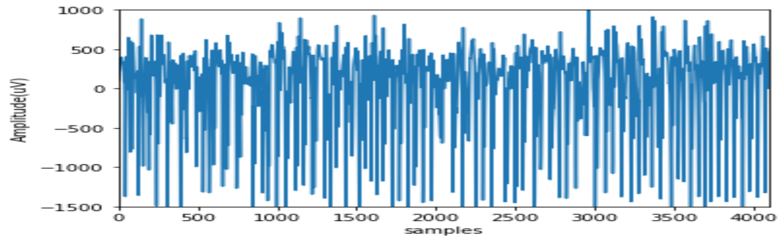


(d)



(e)

Figure 1. Segment of group (a) A, (b) B, (c) C, (d) D and (e) E

3.2 Long Short-Term Memory

The recurrent neural network (RNN) architecture has been used to solve the long-range reliance problem in a couple of different ways. The long short-term memory (LSTM), developed in [18], is one such architecture. A subtype of RNN known as an LSTM has a hidden state, a cell state, a sequence of inputs, and—if desired—a sequence of outputs.

An LSTM cell encapsulates its computations into 'gates' that are composed of weight multiplication and non-linearity, contrary to a vanilla RNN cell, which consists of a fully connected network with recurrent connections. The gates in the cell state, an LSTM's primary information highway, control how data is updated. An LSTM has gates of three different types: forget, input, and output the amount of the current state of the cell to be contributed to the current hides state is determined by the output gate., the input gate determines amount of the new input must be utilized to change the cell state, and the forget gate defines how much of the previous cell state should be forgotten.
The gates are written mathematically as:

ft = σ(Wf · [ht-1, xt] + bf) (1)
it = σ(Wi · [ht-1, xt] + bi) (2)
ot = σ(Wo · [ht-1, xt] + bo) (3)

where the activation function is represented by σ and the forget, input, and output gates' respective outputs are represented by ft, it, and ot, respectively.
The previous cell state is multiplied by the forget gate output, along with the input gate's previous concealed state, to update the current cell state. A single cell's LSTM architecture is depicted in Figure 2.

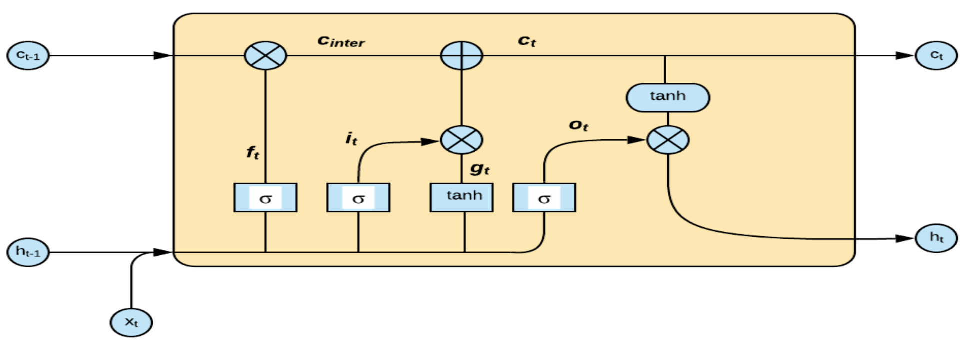


Figure 2. shows the LSTM architecture, with c_{t-1}, c_t, h_{t-1}, h_t *and* x_t standing for previous cell state, current cell state, prior hidden state, current hidden state, and current input, respectively.

3.3 Convolutional Neural Networks

The idea of receptive fields in neuroscience served as the basis for CNNs, a type of neural network. They have had a lot of success with image classification as well as computer vision. A CNN performs the convolution process differently from a feed-forward neural network. The kernel-specific matrix used in the convolution process is a feature extraction technique.

A convolution adopts as input a matrix and outputs a new matrix having an identical shape as the input matrix. Convoluting the kernel across the input means adding up each component of the Hadamard product (multiplying the kernel by the area of the input that corresponds, element by element), which yields the components of the output matrix. In Figure 3, the convolution procedure is displayed. The kernel the Hadamard product's total is computed. and thus forth at each step by sliding one column to the right (referred to as a stride). When the kernel meets the right edge, it moves down a row, after that it restarts on the left. When the kernel hits the bottom edge, the convolution process is complete. The convolutional process is just a moving total of the input that is weighted.

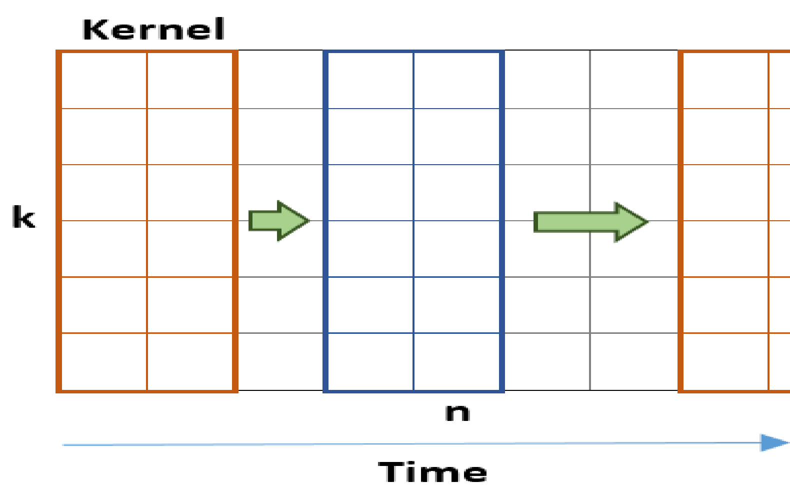


Figure 3. Operation of 1D convolution

In Figure 3,For the convolutional layer is x is input of length n as well as the kernel is w of length k.A max-pooling procedure is commonly performed after the convolutional operation in a CNN. Max pooling builds matrices by gathering data from localized spatial regions of the input, much like convolutions do. On the other hand, max pooling is independent of any kernel. It just reports the majority of a defined window that is moved across a 1D input.

The convolutional process extracts visual features while referring to classification of image. Basically, seeking out specific characteristics in that area of the image, like edges and corners, is how you convolve a kernel across an image. Complex features like eyes, noses, are first learned by the higher convolutional layers. and other anatomical aspects when convolutional layers are stacked. As a result, in the field of image classification, CNN has experienced significant success, where it is at the forefront of excellence presently. Convolutional layers have been typically used for tasks involving visual images, but their application in language models has increased and they are beginning to outperform recurrent networks due to their significantly lower computational cost.

The proposed strategy combines the advantageous features of CNN and LSTM. The architecture of CNN-LSTM is given in Table 1.

4. RESULTS AND DISCUSSION

Using Tensorflow and keras library of Python, the proposed CNN-LSTM deep learning model's efficacy has been evaluated. For training the model, As the loss function, the categorical cross-entropy function was used. This loss function still makes parameter updates possible even when a neuron's output is saturated, making it particularly well-suited for classification tasks. The Adam mini-batch optimization technique was used to find the cross-entropy function averaged across the training set. Using the k-fold cross validation method, the dataset was split into training and test sets before the model was started and trained [19]. An Intel(R) Core (TM) i7-4790CPU@3.6GHz; 8GB RAM; and 64-bit OS system were used for the training. The model underwent 20 epochs of training with a batch size of 32.

The different groups of the Bonn dataset were combined to perform classification task. In this experiment for execution, total nine data clusters have been formed. Accuracy, sensitivity, and specificity has been employed to evaluate the effectiveness of the approach suggested. Data cluster A-E (healthy with eyes open - seizure) achieved the maximum result of 100% for all three metrics. While data cluster C-E (interictal-seizure) obtained 97% accuracy. For three class classification 93.67% accuracy has been achieved. Table 2 shows the results obtained using the proposed model.

Table 1. Architecture of proposed CNN-LSTM model

```
_________________________________________________________________
Layer (type)                 Output Shape              Parameters
=================================================================
conv1d_1 (Conv1D)            (None, 4095, 3)           12
_________________________________________________________________
lstm_1 (LSTM)                (None, 4095, 64)          17408
_________________________________________________________________
batch_normalization_1        (None, 4095, 64)          256
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 4093, 6)           1158
_________________________________________________________________
global_average_pooling1d_1   (None, 6)                 0
_________________________________________________________________
dense_1 (Dense)              (None, 100)               700
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 202
=================================================================
Total parameters: 19,736
Trainable parameters: 19,608
Non-trainable parameters: 128
```

Table 2: Results obtained using proposed CNN-LSTM structure on Bonn EEG dataset

Data clusters	**Accuracy**	**Sensitivity**	**Specificity**
A-E	100	100	100
B-E	99	99	99
C-E	97	95	99
D-E	97	97	97
AB-E	99.49	100	99
CD-E	97.45	96.89	98
ABCD-E	95.81	96.36	95.25
AB-CDE	94.82	92	97.65
AB-CD	91	86.5	95.5
B-D-E	93.67	91	95

ADASYN was used to balance the imbalanced data clusters [20]. To evaluate the robustness of the recommended CNN-LSTM model, authors have added Gaussian noise of different standard deviation (σ) to the EEG waveforms.

Figure 4 presents the performance metrics obtained for different values of σ. It can be observed from the figure shown the results has not been degraded after the inclusion of noise.

Figure 4. Performance metrics for different values of Gaussian noise

Table 3 shows the comparison with previous existing techniques implemented on Bonn EEG dataset. The proposed model CNN-LSTM shows the promising result.

Table 3: Comparison with other methodologies applied on Bonn EEG dataset

Scenario	**Reference**	**Methodology**	**Accuracy (%)**
A-E	[21]	Time frequency statistical features and RF	98
	[22]	Matrix determinant and MLP	97.1
	[23]	Haralick features and Naïve Bayes	99
	This study	CNN-LSTM	100
B-E	[21]	Time frequency statistical features and KNN	93.5
	[24]	GModPCA and SVM	95.8
	[23]	Haralick features and Naïve Bayes	98
	This study	CNN-LSTM	99
C-E	[21]	Time frequency statistical features and Naïve Bayes	96
	This study	CNN- LSTM	97
D-E	[21]	Time frequency statistical features and KNN	91.5
	[25]	Time frequency statistical features and CNN	96.75
	[23]	Haralick features and Naïve Bayes	96
	This study	CNN-LSTM	97
B-D-E	[25]	Time frequency statistical features and BiLSTM	88.9
	This study	CNN-LSTM	93.67

5. CONCLUSION

An automated system using combination of CNN and LSTM layers to detect epileptic seizures has been presented. The deep learning model was used to distinguish between various combinations of two-class classification and one three class classification (healthy, interictal, and ictal). In order to examine the entire dataset for testing purposes, K-fold cross-validation was done. The classification accuracy was found to be 100% for the proposed model only in 20 epochs. As well as model's robustness has been presented by adding noise in the data. The categorization of the proposed model on a big dataset could be a future direction for this research.

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