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An automated & enhanced epileptic seizure detection based on deep learning based architecture

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***Abstract*---**A precise seizure detection system allows epileptic patients to receive early warnings before a seizure occurs. It is critical for people who are drug-resistant. To find the very minimal time before seizure onset, traditional seizure prediction techniques rely on variables collected from electroencephalography (EEG) recordings and classification algorithms. Such methods cannot achieve high-accuracy prediction due to the information loss of hand-crafted features and the limited classification capabilities of regression and other algorithms. Kernels are employed in the early and late stages of the CNN RNN architecture with VGG 16 in the convolution and max-pooling layers, respectively. The suggested hybrid model is tested using the CHB-MIT scalp EEG datasets. The total sensitivity, false prediction rate, and area under the receiver operating characteristic have all yielded positive results.

***Keywords*---**deep learning, wearable device, seizure prediction, CNN, RNN, VGG16, CHB-MIT scalp EEG dataset.

Introduction

A chronic as well as non-contagious brain disease is Epilepsy that affects around 50 million individuals worldwide. Almost all of the patients are from low- and middle-income countries. On the other hand, 75% of them do not receive the care they require. The symptoms of this disease are recurrent and only last a few

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minutes. Seizures of involuntary movement involving a the entire body or a section of it. It's also sometimes accompanied by a loss of appetite. Consciousness and control of bowel or bladder function.Functional and structural neuroimaging modalities are two key types of screening approaches in the treatment of epileptic seizures. Functional neuroimaging provides physicians and neurologists with crucial information on brain function during epileptic seizures. On the other hand, structural MRI (sMRI), diffusion tensor imaging (DTI) are two of the most important neuroimaging techniques in structural format. EEG models are most favoured among clinicians, according to research on epileptic seizure diagnosis. The diagram below in Figure 1 depicts the categories of Seizures.

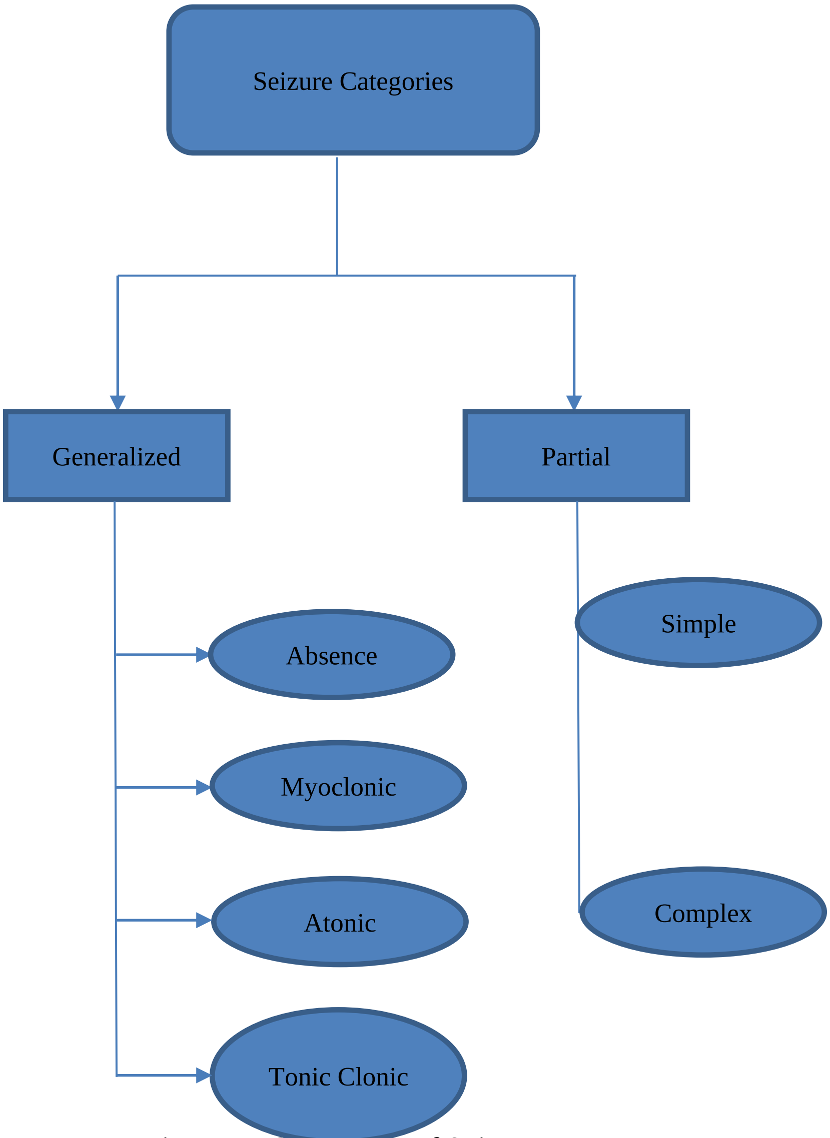

Figure 1. Categories of Seizure

Medical professionals rely on visual inspection of EEG plots to detect seizures. Because this method extracts enough time, dependable automatic detection methods must be developed. Given its current demonstrated reliability and excellent performance, deep learning is a realistic alternative. Convolutional neural networks are used in this publication to study deep learning. By acting directly on the raw EEG data, such networks do not necessitate feature extraction prior to detection, which speeds up the detection process. EEG is a sort of brain recording that can be classified into two categories: scalp EEG and non-scalp EEG. Intracranial EEG is a type of EEG that is recorded inside the skull. The EEG of the scalp is recorded by connecting an electrode to the scalp. Intracranial EEG can be examined by implanting electrodes in the brain during a procedure or surgery. Many variables interfere with scalp EEG. Filtering or noise from seizures can help with seizure identification. The scalp and the skull However, scalp EEG is a better choice because it is easier to monitor than intracranial EEG a more typical sort of signal used to diagnose and treat intracranial EEG is better for epilepsy than intracranial EEG. As a result, the EEG dataset in this study is made up of scalp EEGs. Despite the fact that deep learning approaches produce promising results in many applications, The method splits an intensity image generated by EEG data into two categories: epileptic and category of healthy. The learning of pattern is based on intensity pictures, which collect data from all of the electrodes used.

Related Work

There has been a lot of previous work in the field of EEG signal identification. Almost all of the work is around manually extracting signal features by dividing the signal into frequency, temporal, and wavelet-based domain components. There hasn't been much research into using raw EEG signals on a CNN (without feature extraction or handpicking). The authors developed an FPGA-based automated seizure detection system using the CHB-MIT database. An ant colony optimization technique is combined with a rule-based classifier was employed as the classifier. After testing on a different dataset, they were able to obtain 98.9% accuracy. The dataset used was CHB-MIT. The time it took to detect whether a seizure was about to happen affected their detection accuracy (delay).

A new study demonstrated that deep learning (DL) for epilepsy detection, which automatically encodes EEG patterns connected to seizures, is significantly more successful than standard feature selection and classification methods. In one of the earliest deep learning experiments on epilepsy diagnosis, a convolutional neural network (CNN) was used for feature extraction in an image-based representation of EEG signals, followed by Long Short Memory units (LSTM) for classification. The technique was tested for subject-specific accuracy using the CHBMIT dataset. According to the linked literature, training CNN models needs skilled neurologists manually labelling a huge amount of EEG data. As a result, as highlighted by the majority of the authors, the major issues limiting the performance of these deep-learning seizure detection methods are the amount of training data, which may not be sufficient, and the feature space of seizures, which can vary significantly across different patient EEG recordings and even within the same patient. Transfer-learning systems are now under examination, despite their apparent potential in addressing the problem of a lack of data for epileptic seizure detection. In the realm of seizure detection, neural networks have recently gained more attention. CNNs have the ability to learn nonlinear local features with increasing complexity that are successful. The complexity of processing grows as it passes from input. Originally, CNNs were referred to as a collection of convolutional and convolutional neural networks.

The original CNN's stacking layers were then transformed into a larger architecture known as Alex Net, CNN's unique functionality fundamental features. The Inception-V1 architecture (GoogLeNet) was the first to be introduced, and it comprises processing stages that memorise spatial patterns to convey channel correlation. With fewer network parameters, the architecture allowed for the learning of more pattern features. The Xception architecture, which is similar in idea, then merges the coded features with a point-wise convolution. It is unique in that it does not employ layer non-linearity. This study aims to explore if an original CNN design built on separable depth-wise layers can detect epilepsy in EEG data. In contrast to earlier CNNs, this one employs convolution as the first layer to generate a frequency component representation of the raw signal This is compatible with feature extraction from signal decomposition in filter banks. This design is examined here to discriminate between intervals in EEG data, which is relevant to cross subject modelling. Cross-subject modelling, as opposed to patient-specific models, can dramatically expand the algorithm's applicability by allowing it to interpret data from unknown subjects. The CHB-MIT and Ubonn databases, both of which are freely available, were used to test this CNN architecture. It achieved high performance, with 92.82 % (5 patients in CHB-MIT) and 99.70 %.

Background

Deep Neural Networks

The algorithm called back propagation is used by deep neural networks (deep learning). They look for complicated patterns in data. Multilayer neural networks with an unsupervised learning strategy for the first layer are known as deep neural networks. As a result, the model's depth and complexity are reduced by getting features on its own. The CNN outperformed the multilayer perceptron and other machine learning models used in the picture analysis. Kernels are the building blocks of CNNs to produce and output, convolve with the input image features. Feature maps are the results. The weights used in the kernel's convolution with the picture are the same as those used in the kernel's convolution with the entire input image. When compared to fully-connected neural networks, this leads in a large reduction in parameters while keeping the fundamental characteristics. To reduce data dimensionality, CNNs use sub-sampling or pooling layers, which take the maximum or average of image feature sub-spaces. Fully-connected layers, often called as dense neurons, may also be included in the architecture.

Convolutional neural network

The purpose of a CNN is to learn the right representations of the incoming data attributes. Weight distribution and grouping are the two key differences between a CNN and an MLP. Convolution nuclei are utilized to produce distinct feature maps. Each next is connected to a function map neuron in the following layer. Furthermore, the nucleus is shared by all spatial positions of the inputs in order to generate the function diagram. For classification, one or more complete bound layers are employed for multiple Convolution and grouping layers. A collection of n cores $W = w_{1,} w_{2,} w_{3,} \ldots . w_{n,}$ and their biases $B = b_{1,} b_{2,} b_{3,} \ldots . b_{n,}$ are converted as inputs at each CNN layer. A new yz function map is generated via convolution between the values of data and each core.$yz_1 = \sigma(wz_1 - 1) * (y_1 - 1) + (bz_1 - 1)$ During the CNN learning phase, a tiny window travels across the inputs, allowing the bias and weight values to be modified. To learn properties and recognize data, fully linked feed-forward neural networks can be employed. Given the large values of input involved with photographs, in where every pixel is a unique vector, a large number of neurons, also in a shallow architecture, will be required. Different stages, including as convolution, maximum grouping, and flattening, are frequently used in this network. The diagram below in Figure.2 depicts the layers available in CNN.

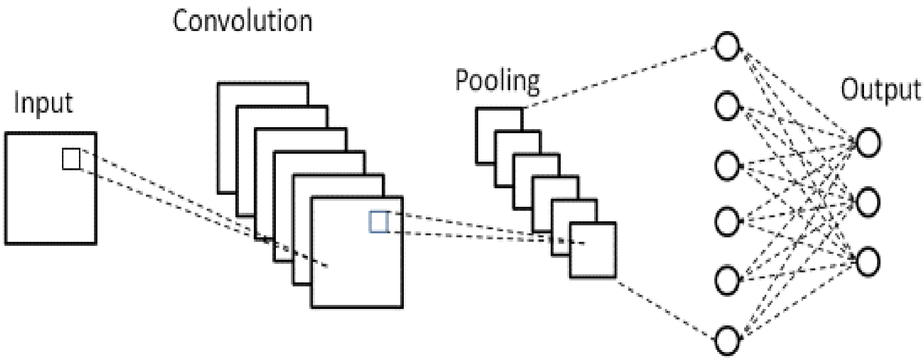

Figure 2. Layers of CNN

- Convolution layer: the characteristics and patterns are derived from the data.
- Grouping: It minimizes the dimensionality of every feature map but retains the information which is important.
- Flatten: To insert data into the next layer, flatten it into a one-dimensional matrix. To make a single lengthy and flatten the output of the Convolutional layers with a feature vector.
- Fully Connected: These form of layers associates with each neuron to other neuron in the next layer.

Wearable seizure detection EMG based device

The wearable devices used to aid mild or chronic seizure. The gadget was put on the brachial biceps muscle to measure surface EMG signals. This small gadget is easily concealed beneath the patient's clothing The location was chosen based on previous experience the number of seizures that the patient has expressed. The wearable gadget is affixed to a hypoallergenic hydrogel patch with three implanted

surface EMG electrodes that is self-adhesive. This device was created specifically for it. The separation between the recording electrodes was 20 millimeters. The wearable device was equipped with a lithium polymer battery. The sampling rate was 1,024 Hz. A slightly altered rendition of the method for detecting seizures was integrated into the device. In a nutshell, the electrophysiologic biomarker. The early phase of GTCS is marked by an increase in amplitude and frequency.
EMG signal oscillations of high frequency (>150 Hz).

Figure 3. Wearable device for Seizure detection

The wearable devices listed above in Figure 3 may be comfortably worn from hours to days. From the figure 3 depicted above A denotes the wearable device, B, C denotes wearable device connected to a self adhesive patch having electrodes. D denotes remote control of the wearable device.

Methodology

CHB-MIT Scalp EEG Database

The CHB-MIT scalp EEG database is a collection of recorded seizures from intractable seizure patients. The data of EEG is collected and Each recording has a multi resolution and numerous recordings. Among the twenty patients For each example, the number of recordings is between the ages of 10 and 45. There are 660 files in total. At least one seizure was recorded in 139 of them. The duration is lengthy, most files are one hour long. In the recording, the electrodes were placed one of the standard EEG signal recording systems. As a result, the EEG raw signal files have 21 channels are labelled.

Data Preprocessing

Before executing feature extraction or classification activities, data processing is required. The EEG data recorded in general are redundant and contain unwanted noise and distortions. To make the data appropriate for further processing, these uncertainties must be filtered out. Because of preprocessing, EEG signals will only contain useful signal-related information, in combination with external noise (typically caused by electrode movement), contaminate actual EEG recordings, lowering signal quality and affecting classification accuracy. This stage turns the EEG signal data into a two-dimensional table format to aid processing and provide crucial information for seizure detection. Various feature selection models are employed to process the incoming data. This research used a supervised, preprocessed, restructured dataset with class features and probable class values.

Extracting Features

To minimise feature values, relevant features from a specific region of the input signal are eliminated at this step. Raw EEG signals have a wide range of signal properties, including quality and length. They also experience discrepancies in the EEG readings due to motion artefacts and background noise. To solve this challenge, feature extraction algorithms are employed to choose only the features that are required. The EEG signal data's data dimensionality is likewise reduced using DL techniques. DL-based models are used to extract features.

Detection

The hybrid CNN-RNN network is utilized for detection, and it is developed with a convolutional stack comparable to VGG16 but with a few small variations in the layer structure. Three layers make up the hybrid CNN-RNN architecture: a transcription layer, recurrent layers, and a convolutional layer The VGG16 architecture for convolutional layers excludes fully-connected layers from the system architecture design. The recurrent layers then transform these properties into a labelling sequence that distinguishes different forms of EEG data.

VGG 16 architecture

On the ImageNet dataset, VGG16 was shown to be the best performing model. Let's have a look at the architecture of this setup. A fixed size 224 by 224 image with three channels – R, G, and B – is regarded the input to any of the network configurations. The only pre-processing done is to normalise each pixel's RGB values. Every pixel is subtracted from the mean value to achieve this. Signals are transmitted via a first stack of two convolution layers with a very small receptive size of 3 × 3 before being activated by ReLUs. There are 64 filters in each of these two layers. The padding is 1 pixel, while the convolution stride is fixed at 1 pixel.

The spatial resolution is preserved in this arrangement, and the output activation map is the same size as the input image dimensions. The activation maps are then run via spatial max pooling with a stride of 2 pixels over a 2 x 2-pixel window. The size of the activations is reduced by half. In the suggested hybrid architect's primary layers, convolutional layers combine CNN and RNN to extract features associated to epileptic seizures. The convolutional layer's performance is also passed on to the RNN layers, which are used to distinguish between different signal patterns. Convolutional layers outperformed RNNs in detecting local and regional trends in this study. The architecture of VGG16 is given below in Figure 4.

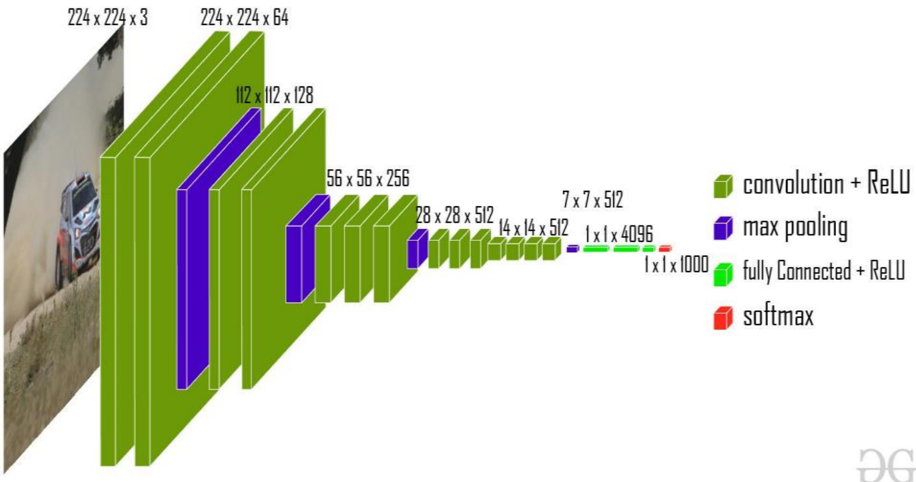

Figure 3. VGG 16 Architecture[11]

Additionally, the CNN layers' convolution operation allows the RNN to operate faster, allowing it to recognize more different patterns. To restore the system's accuracy and efficiency, the suggested solution blends in features with CNN-RNN. EEG data is used to detect epileptic seizures. The three convolution layers discussed above make up the CNN-RNN architecture. To reduce the dimensionality of the obtained features, use one maximum pooling layer for feature extraction. Vectors with features, as well as the collected attributes, are converted to FC using a fully connected (FC) layer. The LSTM model is used to extract RNN features, which are then combined with CNN layers and hand-crafted features. Last but not least, the FC layers are used for data classification.

Simulation Results

We simulated the works that attained state-of-the-art performance after analysing it using traditional criteria. This study looks at the various metrics for evaluation. We used 20% of each participant's samples for testing and the rest of the samples to train the model. The average and standard deviation of individual statistic are generated in a proper sequence using ten independent runs with various initializers.

Metrics

The four criteria used are mentioned as follows to evaluate the performance. Accuracy is termed as the percentage of correctly identified samples divided by entire samples.

$$Accuracy = \frac{TR+TN}{TP+FN+TN+FP}$$

The fraction of entire samples labeled as Category-A that genuinely correspond to that category is defined as precision. The smaller the system's False Alarm Rate, the greater the Precision (FAR).

$$Precision = \frac{TP}{TP+FP}$$

The recall rate is the proportion of all Category-A samples that are ultimately categorised as A. The system's capacity to identify anomalies is reflected in the recall rate.

$$Recall = \frac{TP}{TP+FN}$$

True Positive, False Positive, True Negative, and False Negative are represented by TP, FP, TN, and FN, respectively. Seven of the patients had exceptional Sensitivity and AUC values, with 99 % sensitivity, while subject chb01 has the best results, with 100 % sensitivity and AUC. The Table 1 below depicts the performance of the dataset for the hybrid method with giving values of Sensitivity and AUC as given below.

Table 1
Performance of CHB-MIT dataset

CHB MIT Dataset	CNN+STFT		CNN+ FFT		(CNN+RNN+VGG16)	
	SEN %	AUC	SEN %	AUC	SEN %	AUC
Chb-01	86.7	-	-	0.945	100	1.00
Chb-05	81.0	-	-	0.987	99.8	0.99
Chb-06	81.0	-	-	0.935	99.9	0.97
Chb-08	-	-	-	0.922	99.9	1.00
Chb-10	33.4	-	-	0.856	98.9	0.99
Chb-14	80.1	-	-	-	99.0	0.99
Chb-22	-	-	-	0.878	99.7	0.99

From the table 1 given above the sensitivity and AUC values of our proposed models have outperformed the compared models like CNN+STFT and CNN+FFT. In the first category of Chb-01 our model has achieved the maximum sensitivity of 100% which is a overwhelming performance and the other models too have given the performance which has depicted satisfied results. The Figure 3 below depicts the ROC curve for the seven patients with one model reaching a maximum AUC of 1.00 for Chb01 and CHb08 respectively

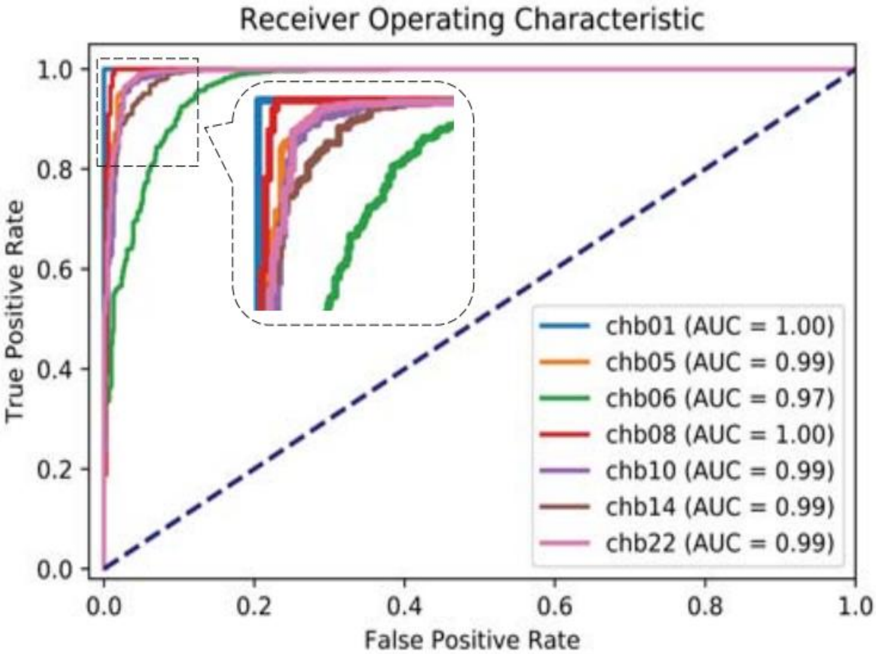

Figure 3. ROC curves from CHB-MIT dataset

Our model has strong ability to differentiate samples of the datasets, as shown in Fig. 3 Our model has achieved great capacity for the list of cases given, as seen the curves. The values of ROC also have given phenomenal performance values in the proposed model.

Conclusion

This study describes the CNN RNN architecture with VGG 16 for seizure detection. The CNN model is fed raw EEG data as input instead of more generally recognised as the variables of frequency. The suggested design takes advantage of the Redundancy in the time axis of an EEG signal while conserving information for early-stage in the channel axis processing, keeping in mind the signal's unique features. Experiments on commonly used benchmark datasets show that the suggested architecture has a enhanced sensitivity, tremendous AUC score, and FPR. Furthermore, employing raw signals lowered data processing complexity, resulting in shorter execution times, lower power consumption, and more silicon space in the upcoming hardware module.

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