DEEP LEARNING BASED EPILEPTIC SEIZURE TYPE DETECTION

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Article History: Received: 12.12.2022 **Revised:** 29.01.2023 **Accepted:** 15.03.2023

Abstract

World Health Organization estimates that 50 million people suffer from epilepsy, a neurological disorder. While electroencephalography (EEG) is useful for monitoring and diagnosing epilepsy patients' brain activity, it requires the analysis of a trained professional in order to identify any signs of epileptic activity in the recordings. Obviously, this is a slow and laborious approach. The primary goal of this investigate is to progress a perfect that can foretell the nature of an oncoming seizure.The main focus of the projected approaches is to enhance classification accuracy of epileptic seizure signals and the prediction rate. And also in this study, we projected scheme is based on Convolutional Neural Network-(CNN) with deep learning for classification. This procedure inspired by biological neural networks and are used in statistics and cognitive science. In this project we find the five kind of Seizures as Absence Seizures, Myoclonic seizures, Tonic seizure, Colonic seizure and Atonic Seizures.

Keywords: Convolutional Neural Network, Epileptic Seizure Type Detection, deep learning, flask framework.

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DOI: 10.31838/ecb/2023.12.s3.043

1. Introduction

Soft computing techniques can be used to find seizures caused by epilepsy in EEG signs. First, the EEG signals are broken into their individual subcomponents using techniques like Wavelet and FastICA. Then, BPNN is used to find the epileptic seizures [1]. The EEG signal is split into subcomponents by the feature extraction tool based on how statistically independent the non-Gaussian source signals are. These separate parts help train the BPNN and are used to figure out if a seizure is happening [2]. Neurons, which are nerve cells, make up more than 10 billion of the brain's cells. The network of neurons in the brain works very well as a system for processing information. With the help of electric currents, Neurons in the nervous system process and send information through the membranes [3]. So, the information sent by these electric and magnetic fields is picked up from the scalp's surface. Small electrodes were placed on the scalp to measure these electric fields caused by the movement of neurons. Electroencephalogram then amplifies and records the differences in potential between these electrodes (EEG) [4]. At the same time, Magneto encephalogram (MEG) is used to measure the small magnetic fields made by neurons in the brain [5].

The abnormality should be found early on so that the right steps can be taken in time to stop the impending seizure. Epilepsy can be predicted very well with the help of an automated analysis and a reliable universal seizure predictor [6]. Also, by automating the way these kinds of neurological problems are found, the neurologist's workload can be greatly abridged, the response time to the infection can be improved, and the right treatment can be given at the right time [7]. Also, if used to diagnose epilepsy, an automatic seizure detection system can be used as a second view in totaling to the doctor's visual inspection of the EEG [8].

People can also lose consciousness because of seizures. Seizures may be caused by a group of brain cells releasing a lot of electricity at once. Different parts of the brain can cause brain cells to discharge too much. Seizures can last anywhere from a few seconds of jerking muscles to a few hours [9 and 10]. This is why epileptic seizure detection needs to be done automatically.

A. Organisation and Contribution of this study

The remains part of this paper is organized the literature section and problem statement after we will give the proposed section, and also, we will get the results of our proposed system is demonstrated in next section. And finally, we describe the conclusion of our study. The chief contribution of our study is to determine the Epileptic Seizure Detection and its Type by using deep learning-based convolution neural network.

Literature survey

A.T. Tzallas, et al. [11] showed that the time-frequency investigation was a good way to classify EEG fragments for seizures. To figure out the (PSD) of each piece, a short-time Fourier transform and a few time-frequency spreads are used. ANN is used for feature extraction, estimating the fragmentary energy of the signal section on certain time-frequency windows, and grouping the EEG portion. The results show that the projected method is limited because the obtained sets of features don't give enough information to effectively classify these sets because of the high number of misclassifications.

N.B. Karayiannis, et al. [12] showed how to deal with seizure sections in the neonatal EEG by showing the features of the EEG procedure cascaded with a neural system. Based on the power spectrum, a rule-based procedure picks out short parts of EEG designs that are likely to be epileptic. This was improved by making models of neural systems that show how the results of an algorithm depend on the features in the power spectrum. Some obvious pseudosinusoidal seizure sections were chosen as seizure sections by the rule-based calculation, which made a higher number of false discoveries. This is because the cascaded scheme was not used.

Recurrent Convolutional Neural Networks (RCNN) were suggested by A.R. Ozcan and S. Ertürk [13] as a way to predict seizures in people with epilepsy. For the outline of analytic and treatment systems that will prevent or stop epileptic seizures, it is important to come up with convincing ways to predict them. In this study, the features extracted from the multi-channel EEG signals using different methods were turned into a multi-spectral picture arrangement based on where the electrodes were placed. With the multi-spectral picture groupings that have been collected, RCNN are ready to find spatial and temporal connections in the multi-channel EEG motions before an epileptic seizure.

J. Birjandtalab et al. [14] came up with the frequency field features (standardised in-band power spectral density) to get data out of signals. We put together a learning method based on multilayer perceptrons to improve the accuracy of finding. In this work, the most accurate model is the multilayer perceptron with two hidden 40-layer layers. The thinking behind this is that as the sum of hidden layers grows, the problem of the model being too tight gets worse. This makes it harder to figure out how much the cross-approval error is.

Y. Park, et al. [15] made a (PPA) for predicting seizures by using spectral power from EEG and SVM classification in a number of ways. Preprocessing, highlight extraction, SVM order, and postprocessing are all parts of the proposed PPA. During preprocessing, artefacts are taken out of iEEG recordings, and these recordings are also preprocessed in bipolar and time-differential ways. Features of the spectral intensity of raw, bipolar, or possibly time-differing iEEG are taken out of a sliding 20-second-long window that is half covered. Cost-sensitive

SVMs are used to set up is used to do optimization and testing outside of the model.

Problem statement

EEG is one of the major tools for identifying epileptic seizures. There is a need for an efficient automated technique for segmenting the epileptic seizure signals such as focal, non-focal, preictal, interictal and ictal signals from the database since some of methods are dependent on the manual operations.

- Features extracted from the signals are less if the number of signals in the database is low. Hence low database causes low performance in the signal classification.
- In a large dataset, the method used for EEG classification system failed to achieve better classification performance by means of error rate. The error rate can be minimized by using the optimal feature in the system.
- Some techniques have achieved higher classification in the seizure detection, but these methods have the ability to classify only in the uniform pattern database and most of the EEG signal databases are not available in the uniform pattern.

Many biomedical that EEG is the essential biomedical signal applied in neurological clinics. EEG records electrical activity of brain and determines the actions of patient's epileptic seizure, which affects almost 1% of world population. The human ability of classifying and identifying the focal signal and non-focal signal is naturally significant, but it the time. Manual recognition consumes more time for EEG signals and also it is only applicable for small EEG datasets. So an automatic epileptic seizure system has created an attention among the applications.

Electrode Placement

Electrodes are small metal discs that are usually made of gold, tin, stainless steel, or they are coated with silver chloride (AgCl). The electrodes, which are put on the scalp 10 after a conductive gel has been put on it, send signals to the differential amplifiers. The relationship between the locations of the electrodes is shown in an international guide for placing electrodes on the scalp. The EEG is a record of the brain's activity, which is a worry because the brain has thousands of neurons. The pattern of brain activity depends on how excited a person is. If a person is excited, EEG records fast wave patterns; otherwise, it records slow waves.

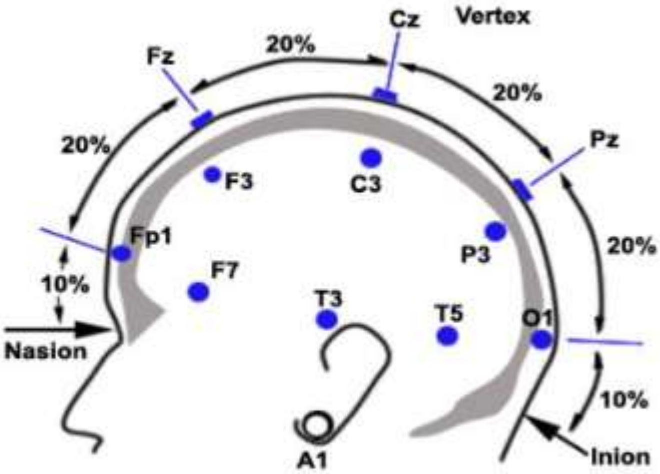

Figure 1: Placement of electrodes for recording EEG signal

The EEG is used to record brain activity for things like sleep research and to figure out what's wrong with people with dementia, epilepsy, tumours, schizophrenia, etc. Figures 1 show how 10–20 electrodes are placed from above and from the side. For figuring out where on the hemisphere a site is, it has a number, a letter, and another letter. The letters T, C, F, O, and P stand for temporal, central, frontal, occipital, and parietal. For easier identification, a made-up lobe, like the central lobe, is used.

B. Signal Frequencies

The recorded waveforms of EEGreplicate the cortical electrical activity. The signal intensity of EEG is quite small, measured in microvolts( ). The signal frequency of EEG is typically around 10μV to 100μV and 10mV to 20mV when measured from the scalp. Each stimulus or mental activity causes activation of a certain group of neurons that are specialized for processing a received stimulus type. For a person with brain disorder, different groups of neurons will be activated for similar activity performed on a person without any disorder. The brain potentials are broadly classified into spontaneous brain potentials and event potentials.

Proposed System

In this section we detailed describe about our proposed model, Using deep learning and a Convolutional Neural Network, the proposed system can accurately categorize data. This algorithm is based on biological neural networks, which are employed in both statistics and cognitive science (the brain being viewed as especially important in the central nervous system). These can be represented as mathematical functions that are set up to represent, just as the interconnection of neural systems from different input variables to the output does (dependent variables). Absence atonic seizure are the five seizure types identified in this work.

In the absence of a large enough training set, entropy-based methods like spectral entropy struggle mightily. Complete ensemble EMD with adaptive noise is very accurate even with a large EEG dataset, but it can only be applied to data with uniform patterns and not all data with non-uniform patterns. Sometimes, manual evaluation or adjustments to the training data are required, but this process must be carried out mechanically. Due to the nature of biogeography-based optimization, only a subset of available EEG channels can be used for data collection and analysis.

C. Dataset Description

In this section we describe about the dataset description of our proposed model, In the EEG recording, each "chunk" is 1 second long and contains 178 data points, each of which represents the value of an individual electrode. A total of 11500 data points have been accumulated (23 x 500 = 11500 rows), with each record containing 178 data points for 1 second (178 columns). The final column is labelled "y 1=Absence Seizures." Myoclonic seizures (2), tonic-clonic (3), tonic-clonic (4), and atonic (5) seizures. To select a model, we first divide our data set into train and test sets. The data in this case is divided into a 70% training data and a 30% test data set. The train test split model is being used in this split process. We now have xtrain xtest and ytrain ytest as a result of the separation.

Data Pre-processing

In this section, we talk about the pre-processing methodology we used on the dataset; this is the process we went through to modify the data before feeding it into the algorithm. Data Raw data is transformed into a usable data set through the use of preprocessing methods. Whenever data is compiled from various sources, it is typically done so in a raw format that makes analysis difficult, if not impossible.

Classification of seizures

Epilepsy is a neurological disorder that lasts for a long time and is marked by seizures that are caused by abnormal, excessive, brain. An epileptic seizure can cause anything from short-term memory loss to violent movements [11]. People can tell when someone is having an epileptic seizure because their muscles move quickly and their minds change. People can also lose consciousness because of seizures. The seizures happen when a group of brain cells sends out a lot of electricity. Seizures can last anywhere from a few seconds of jerking muscles to a few hours. Figure 2 shows a graphical representation of how seizures are grouped.

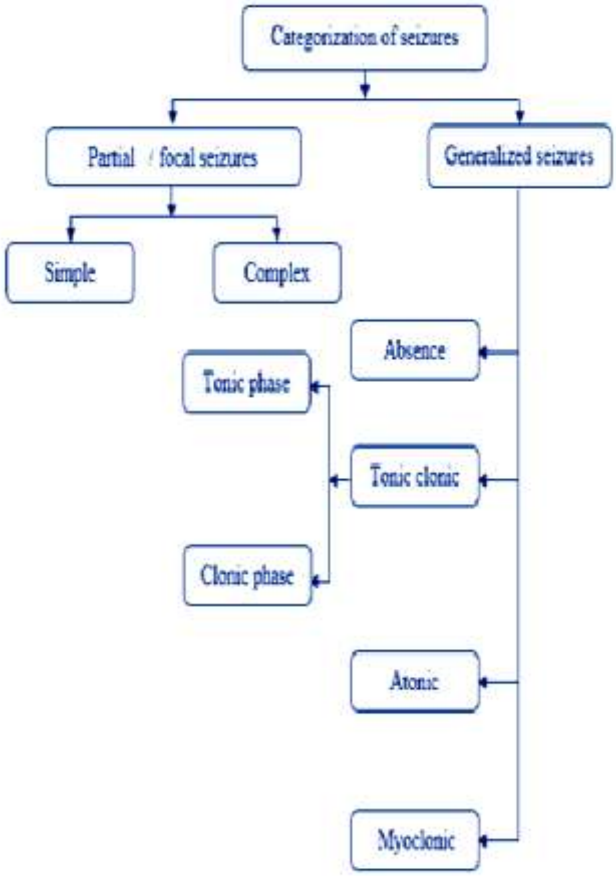

Figure 2: Seizure classification

D. Proposed Convolution neural network

CNN is a standard, state-of-the-art Deep neural network (DNN) classifier that uses vectors to classify data without knowing the input's topology. The CNN method first pulls out the small features at a higher resolution. Then, the small features are turned into larger, more complex features at a lower resolution. CNN is a computer model that can learn on its own. It is driven by the central sensory systems of animals, especially the brain. CNN system is made up of a network of interconnected "neurons" that can learn values from data fed into the system.

NN is used to solve a wide range of problems that are hard to solve with rule-based programming, just like other ML techniques. Usually, a CNN is described by three things: parameters, connections, and an activation function that changes the weight of a neuron's input into an activation of its output. Each input's results are added to those of the following input to determine the updated weight. The sums are biased, and the function is used to send each one to its destination. A function is the most common type of activation function used.

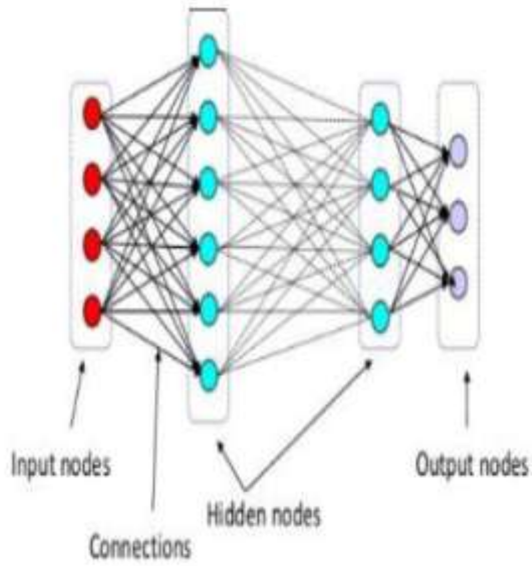

Figure 3: Structure of Deep neural network

DNN usually works as a feed-forward network. It is an pre-training procedure that trains layers one at a time. Here, the data flows from the input layer to layer without any looping function. One of the main benefits of DNN classifier is that it has a very low chance of missing values during classification. In the pre-training stage, the DNN technique only runs one layer. In figure 3, you can see how DNN is put together.

2. Results and Discussion

A Core i5 with 4GB of RAM powered the machine. We utilized Scikit-learn, an open-source deep learning toolkit written in Python. Running the software requires the usage of an Integrated development environment (IDE). The data was divided into ten parts using the 10-fold method. A confusion matrix is a special table construction that allows, in the machine learning field and more specifically the statistical classification problem. The rows and columns of the matrix indicate the actual and anticipated instances of each class, respectively (or vice versa).

TP: Patients who were diagnosed as unwell were in fact sick.

FP: Patients who were in fact healthy were mistakenly classified as ill.

TN: Patients that were healthy were accurately classified as such.

FN: Patients who were actually sick were mistakenly classified as healthy.

Table 1: Confusion matrix for Binary forecast

Predicted labels)	**Algorithm outputs/labels**	
	without disease (Negative/0)	**with disease (Positive/1)**
Patient without-disease (False/0)	TN	FP
Patient with-disease (True/1)	FN	TP

E. Performance Metrics

Our proposed model classification performance by using some metrics, it is discussed in this section.

1. Sensitivity (SE): Breast cancer risk is distinct as the likelihood that an separate would develop the disease and die from it.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (1)$$

2. Specificity (SP): In order to avoid developing breast cancer, the chance of certain outcomes is specified as TN.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (2)$$

3. Accuracy (AC): It's based on the likelihood of getting correctly categorized results.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (3)$$

4. F-score: The F-score is the mean of the replica's sensitivity and specificity, which is used to assess its performance.

$$\text{F} - \text{score} = 2 \cdot \frac{\text{Sensitivity}\cdot\text{Specificity}}{\text{Sensitivity+Specificity}} \quad (4)$$

4.3. Performance Analysis of Proposed CNN for different validation

In this section, the validation of projected method is carried out by changing the percentage of training dataset and testing dataset. Initially, In the experimental analysis of proposed method for 70% of training data and 30% of testing data in terms of numerous metrics.

Table Ii: Comparisons Analysis Of Proposed Method With Existing Machine Learning Modules

Models	**Sensitivity**	**Specificity**	**F-score**	**Accuracy**
Support Vector Machine	91	89	91	90.56
Random forest	93	90	93	91.21
Proposed Method	96	98	97	97.56

In Table 2 and figure 4 represent that the comparisons analysis of proposed method with existing machine learning modules. In this comparisons analysis we evaluate totally three models as Support Vector Machine, Random Forest and Proposed Method. In this comparisons analysis the proposed model (CNN) reached the better results than other compared model.

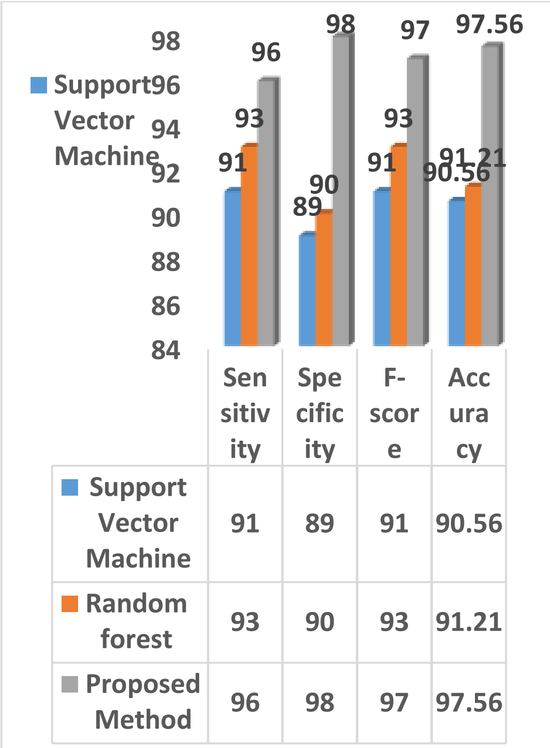

Figure 4: graphical representation of proposed with existing models

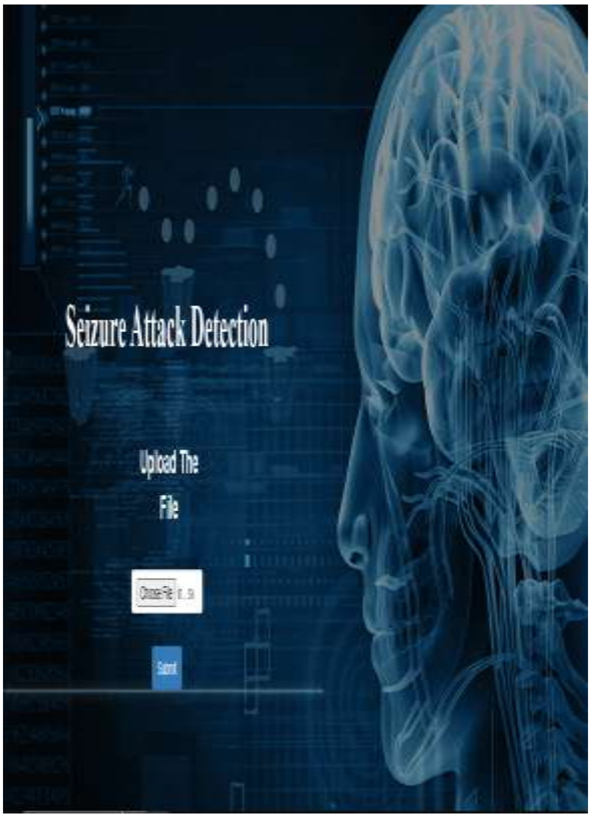

Figure 5: visualization of flask framework

In above figure 5 represent that the visualization of flask framework, in this analysis, we used HTML and CSS module to visualize the Seizure types

3. Conclusion

The determination of this study is to analyze and classify EEG signals to detect seizures. Electrical brain activity measured by an EEG can be interpreted to reveal the mental processes at play during any given activity. One's reaction to a given position varies with the mental state signals it receives. Therefore, a variety of mental illnesses can be remedied through the methodical and stringent examination of these signals. There are now state-of-the-art machines that can read these signals based on what we know about them. However, it can be extremely challenging for medical specialists to diagnose and conclude on any particular neurological disease after reviewing the recordings. As a result, there is a large market for a computer-based model that can accurately identify a particular neurological disease based on analysis of these signals, and plenty of opportunities for computer scientists to develop such a model. In this dissertation, In this proposed system, we find out the Epileptic Seizure Type Detection by using proposed system is based on CNN with deep learning for classification. This algorithm inspired by biological neural networks and are used in statistics and cognitive science. In this project we find the five kinds of Seizures with good accuracy. And also, we used we used HTML and CSS module to visualize the Seizure types with help of flask framework.

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