Epileptic Seizure detection from EEG signals using Deep Learning

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I. Introduction

Epilepsy is a central nervous system disorder causing seizures in which brain activity becomes abnormal due to the release of abnormal discharge of brain neurons. Seizures are those periods of time when the patient experiences loss of awareness, unusual behavior, and sensation. Some symptoms may include staring spells, loss of consciousness, uncontrolled jerking movements, etc (Mayo Clinic, 2021). It is observed that epilepsy can possibly start either in childhood or in people over 60 years of age. Moreover, it is only during seizures, we can spot epilepsy otherwise, they appear the same as able-bodied people (NHS, 2020).

According to the World Health Organisation (WHO), roughly 50 Million people worldwide are diagnosed with epilepsy, making it the most common neurological disease. However, if treated with utmost care at least 70% can lead to a seizure-free life. The unpredictability of seizures is the main cause of disability or even death at times. Therefore, it is extremely important to build and develop an appropriate mechanism for early detection (WHO, 2022).

Electroencephalogram (EEG) is effective, non-invasive, and crucial in detecting seizures and recording the activity of brain neurons (Yousefi and Hosseini, 2022). Identification of characteristic brain signals (features) is instrumental for intervention and accurate prediction of seizures and the onset of seizures (Tian et al., 2019). As accurate detections are key to preparing for treatment beforehand, EEG signals are preferred as they provide real-time data. Since the abnormality in the signals can be sparse, and neurologists will have to spend vast amounts of time capturing seizures, visual inspections can be time-consuming. With the advancement of machine learning methodologies, the development and improvement of computer-aided seizure detection systems would serve as a valuable clinical tool that will study EEG in a much more efficient manner.

The proposed methodology begins by signal preprocessing the raw EEG signals using a bandpass filter followed by a median smoothing filter. Then, by applying Discrete Wavelet Transform, important features are extracted from the signal, and finally, a deep Convolution Neural Network model is applied for accurate binary classification.

This work begins by analyzing recent and existing research in this area in Section II. Section III details the dataset used in this study and Section IV proposes the seizure detection algorithm using wavelet transform-based feature extraction from EEG signals and deep learning. Section V details the implementation and Section VI discusses the results of the experiment. Finally, Section VII concludes the manuscript.

II. Literature review

Numerous studies have been conducted on effective and efficient feature selection techniques and classification techniques to accurately detect an epileptic seizure from EEG signals. This review aims to analyze the various techniques implemented on different datasets and study each methodology and its efficiency which help guide this work.

Chen et al. (2020) proposed a unified framework for the early detection and diagnosis of epileptic seizures from EEG signals. The raw data is preprocessed using a mean filter then status change is detected in the EEG signal using autoregressive moving average (ARMA) to extract dynamic characteristics and quantify the deviation between the real and predictive value on the basis of which null hypothesis testing is applied. Feature extraction using EMD and SVD is applied. These are then fed to a pairwise one-class SVM classifier with the first SVM being trained on epilepsy or non-epilepsy data and the other on normal or abnormal class data. The resulting pair of class labels determine epilepsy, normal, or other brain activity.

Tian et al. (2019) proposed a deep multi-view based learning for EEG-based epileptic seizure detection method. The study constructs an initial multiview. The EEG raw data forms the time-series domain, by using Fourier transform to generate a frequency series domain [4-30Hz] and using wavelet transform to generate a time-frequency domain. Then on each of these domains, CNN is applied for deep multi-view feature extraction. Finally, a multi-view classifier Multi-View Takagi-Sunego-Kang fuzzy system is trained on the features extracted‒resulting in a generalized and robust model and low detection delay.

Mardini et al. (2020) proposed a method for detecting epileptic seizures from EEG signals in combination with machine learning classifiers. Signal preprocessing includes applying bandpass filters and smoothing methods. Then 54-DWT mother wavelets are applied with high-level decomposition for each wavelet to generate sub-bands and derive statistical and non-linear features. The set of features are selected and reduced using the Genetic algorithm. Finally, the selected features are applied to classifiers SVM, ANN, KNN, Naive Bayes.

Zhang et al. (2022) proposed a method for detecting epileptic seizures using Bidirectional Gated Recurrent Unit Network. The EEG signal is preprocessed by segmenting without overlapping then applying wavelet transform and decomposing it in 5 scales. Scales in the frequency range [3-30Hz] are reconstructed. Then, the signal is subdivided and the relative energies of the signal components of the wavelet are calculated. Higher relative energy denotes the occurrence of a seizure. Thereby, a feature matrix is calculated and inputted into the Bi-GRU which learns long-term dependencies through bidirectional gating mechanism and is classified based on a threshold.

Yousefi and Hosseini (2022) proposed a single instruction simplified method for the purpose of epileptic seizure diagnosis from EEG signals to compare data with and without wavelet transform. In the preprocessing step, low pass filters are applied to the raw EEG data, then in the feature extraction step, frequency domain and time domain features are extracted using band filters. Finally, the features are fed through an MLP classifier which performed better than pure wavelet transform-based methodology.

Xiong et al. (2021) proposed a deep-learning model to detect epilepsy using EEG signals. The model contains two core concepts: the 2D representation of the features and the scalability of the network. The model creation is composed of these five steps: 1. The time decomposition of the signals into smaller slices 2 Feature extraction using wavelet transform and fast Fourier transform 3. Features were represented in 2D using the time and frequency features. 4. Deep learning on the normalized images to obtain deep features. EfficientNet is used here.

Gómez et al. (2020) proposed an automatic way to detect seizures using imaged-EEG signals. To represent the data as images they took the amplitude as the pixel value in an image. Two dimensions were taken, they were the vertically aligned EEG channels and the temporal dimension. A fully convolutional network(FNC) was used. FNC is an extension on a CNN, which can process EGG signal recordings that are of different lengths. Strategies like dropout, where random connections are dropped and L2 regularization was used to prevent the model from adapting to the trained data. Finally, fine-tuning which is a transfer learning strategy to make up for the limited amount of data available was used.

Wei et al. (2018) proposed a method that includes using a new 3D CNN whose inputs are multi-channel EEG signals. Sliding window was used here. The successive relationship of the different electrodes was selected according to the adjacent degree of the electrodes and the corresponding 2D EEG images were fused to form a 3D multi-channel image. CNN was used for feature extraction. To reduce the overfitting group normalization and dropout strategy was used. According to this paper, the main advantage they have over others is the full utilization of the multi-channel signal information and hence will serve as a benchmark for future work based on multi-channel EEG.

Wei et al. (2018) proposed an improved model for the automatic detection of epileptic seizures. In this paper, using channel and multi-channel EEG recordings are investigated. The recordings are preprocessed using the Butterworth filter, which helps reduce noise from environmental factors and those generated by artifacts due to movement in the body. Time splitting is also used here to split the signal, one slit includes 4s split with 50% overlap. For feature extraction, they use DWT to decompose the signals and extract features, temporal and spectral being the two most important followed by 30 others. Multiple classifiers were constructed which included traditional ones like KNN, SVM and fuzzy learning algorithms. All classifiers were tested and compared. The KNN and FRNN gave the best results.

Avcu et al. (2019) proposed SeizNet, a deep Convolutional Neural Network (CNN) for seizure detection. This method proved to be an efficient way of detecting with a lesser number of channels required for accurate detection, it was equipped with additional dropout layers and batch normalization after every convolutional layer so as to avoid model overfitting, as an activation function, ReLU is used.

Zhou et al. (2018) proposed a convolutional neural network (CNN) based on raw EEG signals to differentiate between the 3 segments for epileptic seizure detection namely, ictal, preictal, and interictal with an aim to compare the performance of time & frequency domain signals. A CNN method was designed with not more than 3 convolutional layers, as to avoid imbalance between lesser samples during the ictal and preictal whereas a relatively high number of samples during the interictal period.

Chatzichristos et al. (2020) proposed a method based on a fusion of multiple attention-gated U-nets, using LSTM (Long Short-Term Memory) network. This U-net architecture contains three distinct attention-gated U-nets, each with a different perspective on the EEG signal and focusing on channels with the most relevant information. They have been distinguished by the filtering and pre-processing techniques applied to the EEG data. The evaluation metrics consisted of sensitivity and false alarms and it has outshined various methodologies with a relatively good score in terms of sensitivity and false alarms.

Subasi, Kevric and Abdullah Canbaz (2017) proposed a very robust, adaptive, and efficient hybrid SVM classifier for the classification EEG data. It uses genetic algorithms (GA) and particle swarm optimization (PSO) to figure out the optimum parameters for the SVM during the training period. DWT was applied to the EEG signals to decompose them into frequency sub-bands. With the help of discrete wavelet transform (DWT) sub-bands which were generated, statistical features are extracted, helping in pre-processing of training and validation sets. All input variables are normalized to avoid domination of an attribute. For training, 10-fold cross-validation is applied and then evaluated on the validation set. To avoid overfitting, iterations are stopped upon reaching maximum validation accuracy.

Jana, Sharma and Agrawal (2020) have proposed a methodology by integrating spectrograms and 1D-CNN. The method is divided into 3 segments namely EEG data filtering, Spectrogram feature matrix generation, and 1D- convolutional network. It applies 1D-CNN on the spectrogram data which is generated after filtration of EEG signal data using Butterworth filter and passed through a 2s time window. The CNN model consists of 3 layers. Precisely, these layers work mainly for batch normalization, dropouts, ReLU function, and pooling.

P. Thuwajit et al. highlight EEGWaveNet, an innovative method for EEG seizure classification. The proposed model consists of three primary modules: Multiscale Convolution, which captures valuable intrachannel features; Spatial-Temporal Feature Extraction, responsible for extracting spatial-temporal features across different scales; and Classifier, which employs fully connected layers and a binary classification activation function. The model's effectiveness is demonstrated by comparing it with seven state-of-the-art baseline methods, showcasing its strong performance in EEG-based seizure detection tasks.

III. Dataset

This work adopts data from the Bonn University EEG Database It contains 500 EEG signal recordings, 100 recordings grouped into a class. Each recording represents a single subject/person. All signals were sampled at 173.61 Hz sampling frequency resulting in 4097 datapoints in 23 seconds. The categories y are as follows ():
5 - healthy subjects (eyes open), i.e. the patient had their eyes open during EEG signal recording, 4 - healthy subjects (eyes closed), i.e the patient had their eyes closed during EEG signal recording, 3 - seizure-free recording from the hippocampal formation in the hemisphere opposite the epileptogenic zone, 2 - seizure-free recording from the epileptogenic zone, 1 - Recording of seizure activity. (Andrzejak et al., 2001)

For the purpose of binary classification, y = {0, 1} where the files containing class labels as either 2, 3, 4, or 5 were relabeled as 0 denoting a non-seizure sample whereas a file having class label 1 denoted a seizure sample.

IV. Methodology

Figure 1 shows the overall workflow of the methodology for the classification of an epileptic seizure from an EEG signal.

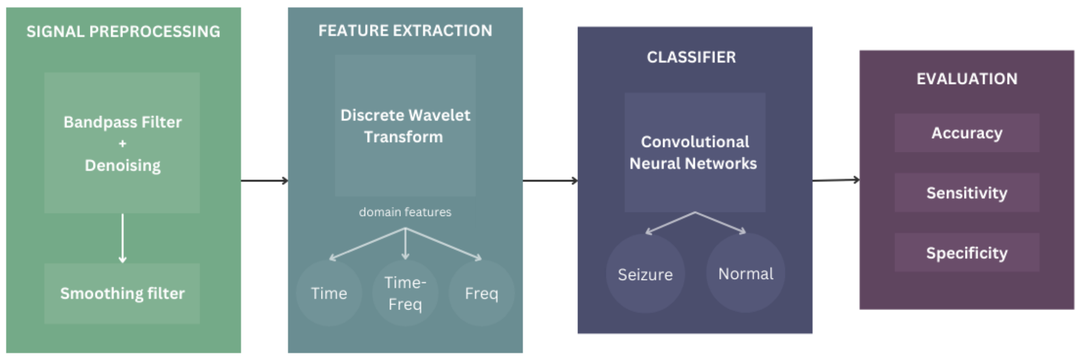

Figure 1: Architecture diagram of the methodology

It is a three-step process containing signal preprocessing, feature extraction, and classification. Finally, the results are evaluated by accuracy, specificity, and sensitivity metrics.

Signal Preprocessing

The raw EEG signals obtained from the dataset are contaminated with noise. The raw EEG data is preprocessed in two steps, first by applying a bandpass filter on it and denoising the data, and then by applying a smoothing filter on it. Signal preprocessing results in a transformed signal with low noise/redundant features.

Denoising and Bandpass filtering

Bandpass filtering is applied to the transformed signal to extract frequency components within a specific frequency range. This is done to capture important signals useful in differentiating between a seizure and normal brain activity (Yousefi and Hosseini, 2022). Simultaneously, it enables denoising and the removal of small amplitude components of the signal regardless of frequency resulting in a low signal-to-noise ratio (Barclay, Bonner and Hamilton, 1997).

A bandpass filter works by combining a low-pass and a high-pass filter into a single filter to filter out frequencies that are too low or too high thereby only allowing frequencies within a certain range to remain (Kuphaldt, 2015). By filtering out frequencies, we are aiming at eliminating noise and artifacts such as removing heart signals related to pulse artifacts and low-frequency noise, such as building vibrations and nearby electromagnetic field noise, and AC powerline high frequency (Jiang, Bian and Tian, 2019).

The Butterworth filter is popularly used as a bandpass filter and is an analog filter design producing the best output response with no ripple in the pass or stop band resulting in a maximally flat filter response. Additionally, by design, the Butterworth filter can simultaneously denoise (Electronics Tutorials, 2013).

This work made use of a Butterworth filter of order 2, and lower frequency limit of 1Hz, and an upper-frequency limit of 40 Hz as suggested by previous works and the Bonn University.

Smoothing

The smoothing filter works by removing the high-frequency noise and artifacts regardless of amplitude (Barclay, Bonner and Hamilton, 1997).

After experimenting with the median filter and the Savitzky–Golay filter using various parameters, this work made use of a median filter with window size three for filtering based on the suggestions in existing works as well as experimentations. The median filter is a non-linear filter that calculates the mean value of the sequence of data at the processed point and its surroundings (Kawala-Sterniuk et al., 2020). The median filter is robust and efficient in eliminating spikes caused by noise and outliers, and delicately smoothing the signal (Anomaly, 2015).

Feature Extraction and Discrete Wavelet Transform

In this work, Discrete Wavelet Transform (DWT) is applied to the preprocessed EEG signal. While Convolution Neural Network (CNN) can be directly used on raw EEG signals as a feature extractor, the noise generated during recording would affect classification accuracy (Hassan, Hussain and Qaisar, 2022). Wavelet transforms are widely used to efficiently extract features for interpretation from transient signals. Two methods of wavelet transform include the Continuous Wavelet Transform (CWT) and the DWT but the drawback of the CWT is that it generates a lot of redundant information making DWT a better choice as a wavelet transform (Hassan, Hussain and Qaisar, 2022).

Additionally, the ability of DWT to find patterns in signals and to be applied to non-stationary EEG signals has proved it to be suitable for localizing transient events which can occur as spikes during epileptic seizures (Subasi, et al., 2017). DWT converts the time-series signal into a time-frequency domain signal (Tian et al., 2019) and provides a good trade-off between time and frequency localization (N. Sun, et al. 2007). The signal is decomposed into frequency components in different scales (Zhang et al., 2022). Features are then extracted from various sub-bands generated (Mardini et al., 2020). These features are statistical and entropy-based features in the time domain, frequency domain, and time-frequency domain (Feudjio et al., 2021). The coefficients calculated in these scales are selected to perform single-scale signal reconstruction and feature extraction (Zhang et al., 2022).

This work implements Daubechies wavelet of order 4 (db4). The order 4 (or also 2) of the Daubechies wavelet is better suited for signals with sharper, more abrupt changes which matches the property of EEG signals for seizure identification (Mallat, 2008). A level 5 decomposition is used which gives a good resolution (Santoso et al., 1996).

Classification

CNN is implemented for binary classification of EEG non-seizure vs seizure signals. The CNN architecture is using reference from Hassan, Hussain and Qaisar, (2022) , where we have added an additional dropout layer: Conv1D layer: This is the first layer of the CNN and it is responsible for detecting local patterns in the input data. The layer has 11 filters, each of size 5, and uses the ReLU activation function.

- MaxPooling1D layer: This layer performs down-sampling by taking the maximum value over a pool size of 4. Another Conv1D layer: This is the second convolutional layer and it has 7 filters, each of size 5, and also uses the ReLU activation function.
- Another MaxPooling1D layer: This layer performs another down-sampling operation, using the same parameters as the first MaxPooling1D layer.
- Flatten layer: This layer flattens the output from the convolutional layers into a 1D array, which can be passed to the fully connected layers.
- Dense layers: These are fully connected layers that perform classification based on the patterns detected by the convolutional layers. The first dense layer has 50 units with ReLU activation function, while the second dense layer has 20 units with ReLU activation function.
- Dropout layer: This layer is used to prevent overfitting by randomly dropping out some of the units in the previous dense layer during training.
- Output layer: This is the final layer of the network and has one unit with sigmoid activation function. It outputs a probability value between 0 and 1, representing the likelihood of the input belonging to a particular class.
- The model is compiled using the binary cross-entropy loss function, the Adam optimizer, and accuracy as the evaluation metric.

V Implementation

The model was implemented in Python v3.7 with the help of additional frameworks and libraries such as keras v2.8.0 and tensorflow v2.8.2, numpy, pandas, scipy.signal and Scikit-learn. All codes were run on Intel(R) Xeon(R) CPU @ 2.20GHz in Google Colab. The Python 3 Google Compute Engine backend was used for the Python codes. 12.7GB System RAM and 107.7GB disk space was allocated on Google colab.

V. Results and Discussion

The proposed model was tested on the chosen dataset. We trained our model in 1000 epochs with a learning rate of 0.001. The model training and testing loss graph and accuracy graph is seen in Figure 2.

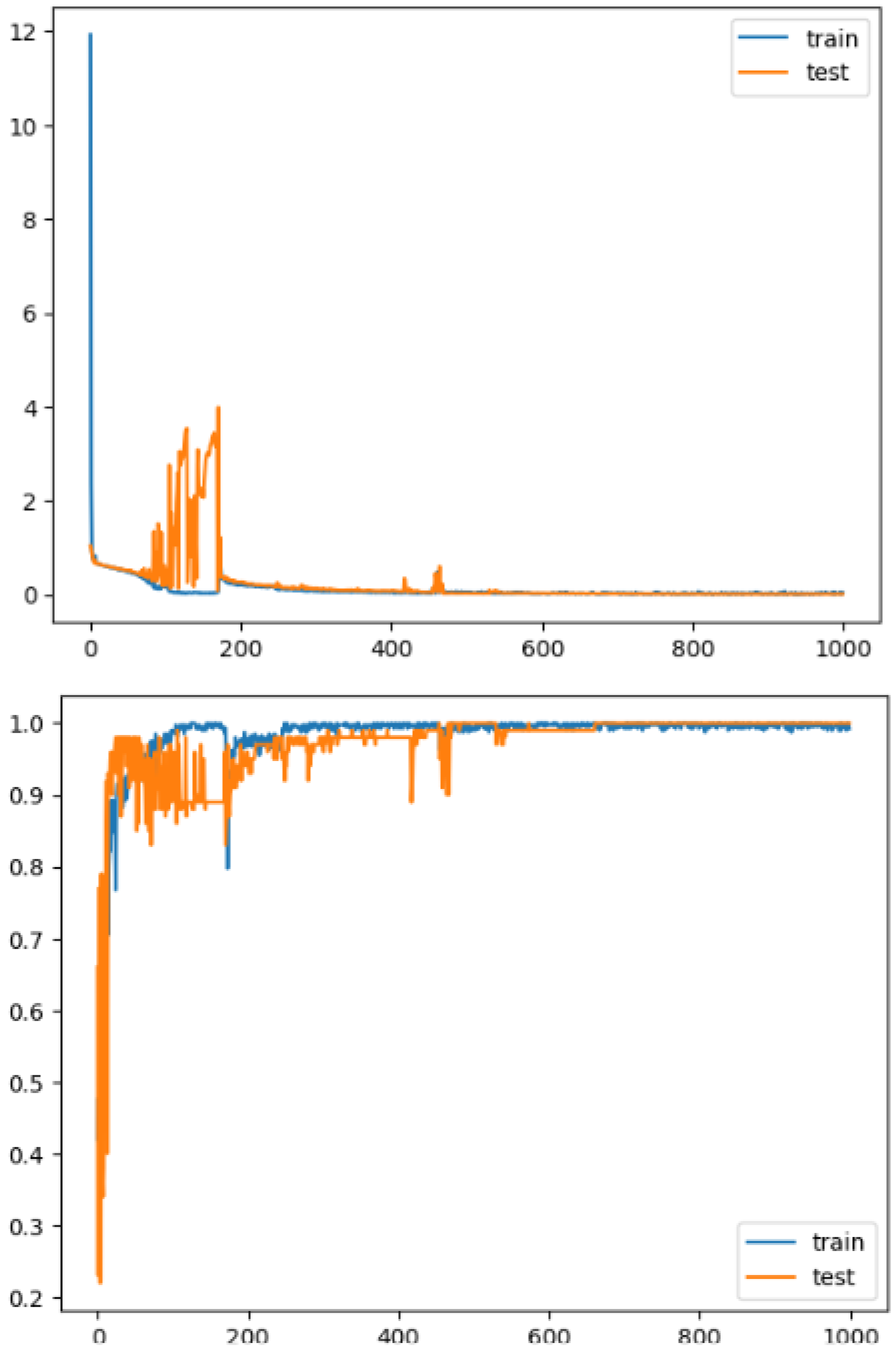

Figure 2: Train-Test loss graph and Train-Test accuracy graph

The model was evaluated on Specificity, Sensitivity, and Accuracy scores as noted in Table 2. Additionally, metrics for Precision, Recall, and F1-score have been detailed in Table 3 for each of the 2 classes, seizure, and non-seizure as seen in the Python scikit classification report (Figure 2).

Metrics	**Score**
Accuracy	1.00
Sensitivity	1.00
Specificity	1.00

Table 1: Performance of proposed model

Metrics	**Score**	
	Seizure	**Not Seizure**
Precision	1.00	1.00
Recall	1.00	1.00
f1-score	1.00	1.00

Table 2: Performance of proposed model for each class

```
print(classification_report(Y_test,y_pred1))

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        78
           1       1.00      1.00      1.00        22

    accuracy                           1.00       100
   macro avg       1.00      1.00      1.00       100
weighted avg       1.00      1.00      1.00       100
```

Figure 2: Classification report for the model

The results of the proposed methodology on the chosen dataset from Bonn University are compared against existing works on the same dataset as seen in Table 3. Binary classification of non-seizure vs seizure EEG sample was the chosen result from the object of the selected papers to be compared. The comparison metric used is accuracy which was found to be a uniform metric across the works compared.

Yousefi and Hosseini (2022) preprocessed the raw EEG signals, applied feature extraction using wavelet transform and then applied MLP classifier. Chen et al., (2017) decomposed and reconstructed the signal while extracting features using DWT and classified it using SVM with RBF kernel as the classifier. Ullah et al. (2018) make use of an ensemble of pyramidal one-dimensional deep convolutional neural network (P-1D-CNN) model while Acharya et al. (2018) made use of a deep 13-layer CNN model for feature extraction and classification.

Reference	**Accuracy (%)**
Yousefi and Hosseini (2022)	95.5%
Chen et al., (2017)	99.33%
Ullah et al. (2018)	99.7%
Acharya et al. (2018)	88.7%
Proposed	**100%**

Table 3: Performance comparison with existing works

VI. Conclusion

In conclusion, the methodology presented for the classification of epileptic seizures from EEG signals is a three-step process, starting with signal preprocessing, followed by feature extraction using Discrete Wavelet Transform (DWT), and finally classification using a Convolutional Neural Network (CNN). Signal preprocessing involves denoising and bandpass filtering using a Butterworth filter and smoothing using a median filter. Feature extraction is performed using DWT with the Daubechies wavelet of order 4, and a level 5 decomposition is used. Finally, the CNN architecture is based on the work of Hassan, Hussain, and Qaisar, (2022), with an additional dropout layer, is used as another layer of feature extraction while simultaneously being a powerful classifier. The accuracy, specificity, and sensitivity metrics are used to evaluate the results. The methodology has proved to be effective in accurately identifying seizures from EEG signals with 100 percent accuracy.

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