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Detection of Epileptic Seizures using EEG Signals

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***Abstract*—Epilepsy is a neurological disorder which causes abnormal brain activity such as seizures. Electroencephalogram (EEG) signals are recordings of the electrical activity of brain, which are used extensively in many medical applications, including detection of epileptic seizures. Traditionally, neurologists made inferences by visual inspection. However, this was usually very time consuming and the results are subject to the expertise of the reader. Hence, automatic epileptic seizure detection techniques are needed, which are able to provide high quality results in a short time. In this paper, an approach has been proposed that uses Discrete Wavelet Transform to convert the EEG signal into the time-frequency domain. Approximation and detail coefficients were obtained after the discrete wavelet transform of EEG signals. Then, various features are extracted and then classification is carried out on a number of classifiers including convolutional neural networks, random forests etc for the detection of epilepsy seizure.Results show that our processing technique and the combination of features extracted provide far superior results than those obtained by applying the classifiers on the EEG signals directly. In our work, an accuracy of 99.29 was achieved which outperformed the conventional epileptic seizure detection techniques. The proposed approach is tested on Bonn University's EEG signal dataset.**

***Index Terms*—EEG, Epilepsy, Seizure Detection, Discrete Wavelet Transform, CNN, Neural Network**

I. Introduction

EEG (Electroencephalogram) [1] is a way through which we can retrieve information regarding the physiological situation of a patient. EEG is a non-invasive testing method which contains a lot of information about the state of a patients health. Through EEG, complicated dynamics of brain can be comprehended. EEG signals are very essential for detecting disorders like epilepsy seizures. The World Health organisation has stated in a report that more that 50 million people worldwide suffer from epilepsy [2]. Manual detection of epileptic seizures is an extremely time-consuming and laborious task, and it is also subject to the expertise of the neurologist. Accurate and timely diagnosis is extremely important so that patients can start with the treatment procedure as early as possible.

Epileptic seizures are caused by disruption in the neuron firing mechanism [3], i.e. abnormalities in the electrical signals generated by the brain. Since electroencephalogram (EEG) signals record the electrical activity of the brain, hence it is natural to use these signals for the task of detecting epileptic seizures. Lot of research in the domain of analysis of EEG and it's classification is based upon the fact that processing of information in the brain is exhibited in the EEG signals as the transitions of electrical-activity in time and frequency dynamically. Hence, wavelet transforms are very effectively used for capturing the smallest of these transitions in the EEG signals.

Analysis of EEG signals is usually not an easy task, due to their non-linear and non-stationary nature. [4]. Therefore, automated ways are being developed extensively for the purpose of detection of epilepsy seizures. Discrete Wavelet Transform (DWT) is an appropriate tool for dealing with such signals, since it localizes the signal in both the time and the frequency domains. That is why it is preferred over some other methods like Fourier Transform which do not provide temporal resolution.

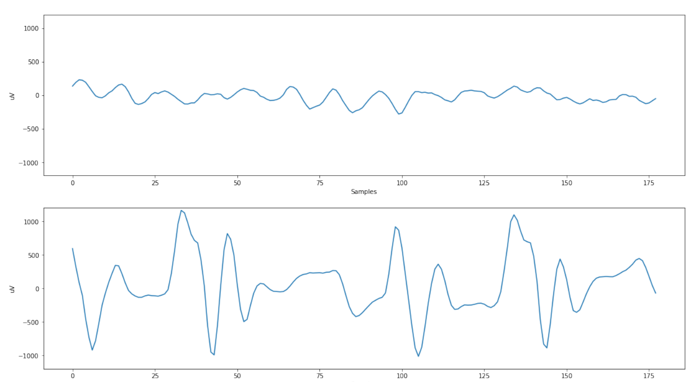

Fig. 1: (upper) EEG signal without seizure; (lower) EEG signal with seizure

In Figure 1, two signals from the dataset have been shown; one without seizure and the other with the seizure. In this paper, the Bonn University Dataset [5] has been used.

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The rest of the paper is organized as follows. In section II, other relevant work utilizing EEG signals has been discussed. In section III, the proposed algorithm has been discussed. Then section V presents the results obtained without any pre-processing as well as results with our algorithm. Finally, section VI concludes this work.

II. Related Work

In the past few years, analysis of EEG signals has remained a topic of great interest for researchers. In [6], research has been conducted on frontal EEG asymmetry and emotion by applying Fourier Transform to raw EEG signals. Similarly, [7] has also used Fourier Transform for conducting further analysis on these signals. The basic problem with these approaches is that Fourier Transform can only localize the signal in frequency, not in both time and frequency simultaneously.

To overcome this problem of Fourier Transform, short-time Fourier Transform (STFT) was developed. STFT divides the entire signal into windows, and applies Fourier Transform to each window. In [8], the authors have used STFT for epileptic seizure detection. [9] also uses STFT to analyze background activity for autism. This approach succeeds in localizing a signal in both time and frequency to some extent. However, it is still highly dependant on the window size, and moreover, that window is the same for all frequencies.

Discrete Wavelet Transform (DWT) has the ability to localize a signal in both time and frequency simultaneously. It has been used widely for the analysis of EEG signals in the time-frequency domain [10] [11] [12]. In [10] epileptic seizures have been detected using DWT and Artificial Neural Network (ANN).

Empirical Mode Decomposition (EMD) is another algorithm that provides time-frequency representation of the signals. In this, the signal is broken down into many Intrinsic Mode Functions (IMFs). This technique has also been extensively used for EEG signal analysis [13] [14] [15].

In [16], approximation of entropy as well as energy has been used for the purpose of detecting seizure and spikes. DWT along with feature extracted like Hjorth variance has been used in [17]. Various other features have also been used like relative energy,amplitude index of fluctuation, variation coefficient [18] and the variances of wavelets [19]. Lacunarity along with the index of fluctuating [20] have also been explored. In [21] EMD (empirical-mode-decomposition) has been used. In [22] Fractal analysis has been used. IN [] fuzzy systems have been used.

III. Proposed Work

The complete process of the method has been described in Figure 2.

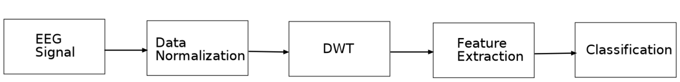

Fig. 2: Schematic representation of proposed method

The raw EEG signal is first normalized, as described in Equation 1.

$$Normalize(x) = \frac{x - m}{s} \quad (1)$$

where x is the signal, m is the mean of the signal and s is the standard deviation. Normalizing the data decreases its variance and makes the model less susceptible to change in scale.

After that, Discrete Wavelet Transform is applied to the normalized data. Different types of wavelets could be used in DWT. We used Daubechies 4 (db4) wavelet with decomposition till level 4 (Figure 3). DWT is effectively used for the purpose of decomposition of a signal into approximation-coefficents and detail-coefficients. 1st level of decomposition is obtained after which further decomposition can be carried out into similar approximation and detail coefficients [23]. In our work, 4 levels of decomposition has been carried out. Further extraction of features can be carried out from detail coefficients.

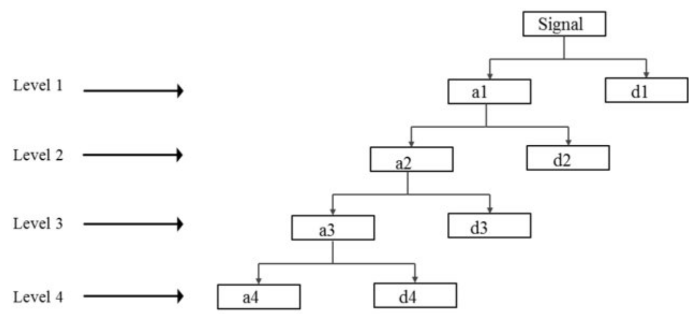

Fig. 3: 4-level DWT decomposition tree [24]

On decomposition of the signal at any one level, we get a vector of detail coefficients and a vector of approximation coefficients. The approximation coefficient vector is obtained by making the signal go through a low-pass filter, while the detail coefficients vector is obtained by making the signal go through a high-pass filter. As can be seen from Figure 3, finally we get four vectors of detail coefficients (d1, d2, d3 and d4) and a vector of the approximation coefficients (a4).

Now, we need to extract features from these coefficients. We have extracted features from all the coefficients so that any significant information from the original signal is not lost. We have extracted seven features, which have been explained below. Each of these metrics was calculated for all the coefficient vectors. In the equations below, x is the coefficient vector and N is the number of elements in x.

1) **Mean**:

$$Mean(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (2)$$

2) **Standard Deviation**:

$$Standard\_Deviation(x) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - m)^2}{N}} \quad (3)$$

where m is $Mean(x)$.

3) **Root Mean Square**:

$$Root\_Mean\_Square(x) = \sqrt{\frac{\sum_{i=1}^{N}(x_i^2)}{N}} \qquad (4)$$

4) **Skew**: Skew is a measure of the asymmetry in the data.

$$Skew(x) = \frac{\sum_{i=1}^{N}(x_i - m)^3/N}{s^3} \qquad (5)$$

where s is $Standard\_Deviation(x)$.

5) **Kurtosis**: Kurtosis is a measure of outliers in the data.

$$Kurtosis(x) = \frac{\sum_{i=1}^{N}(x_i - m)^4/N}{s^4} \qquad (6)$$

6) **Maximum Fractal Length (MFL)**:

$$MFL(x) = log_{10}\left(\sqrt{\sum_{i=1}^{N-1}(x_{i+1} - x_i)^2}\right) \qquad (7)$$

7) **Coefficient of Variation**: It signifies the variations in the amplitude of the signal.

$$V_c(x) = \left(\frac{Standard\_deviation(x)^2}{Mean(x)^2}\right) \qquad (8)$$

8) **Shannon Entropy**: Entropy is the degree of uncertainty. Shannon Entropy is the capacity of the information present in the data.

$$H(x) = -\sum_{i=1}^{N} P(x_i)log(P(x_i)) \qquad (9)$$

where P(X) is the probability mass function for the EEG signal.

All these features were appended, and then passed through various classifiers which are described as follows. In Logistic Regression, a variable (binary dependent) is modelled using a logistic function. In SVM (Support Vector Machine), a hyperplane is used to separate categories. For instance, a linear straight line will be the hyperplane in case of a 2 dimensional plane by which the plane is divided into two parts. However, transformations can be carried out on the hyperplanes known as 'kernels'. In KNN (K-Nearest-Neighbours), the closest 'k' training instances are used for the predictive analysis. In Randome forests, multifarious decision trees are constructed during the training. It is an Ensemble learning method. Xg-boost is a library (open source) for gradient boosting. It is also an Ensemble Learning method. ANN refers to Artificial Neural Networks which are computational systems designed to replicate the information processing abilities as that of human neurons. CNN (Convolutional Neural Network) is an important part of Deep Learning consisting of multiple types of layers like Convolutional Layer, Pooling Layer and Fully Connected Layers.

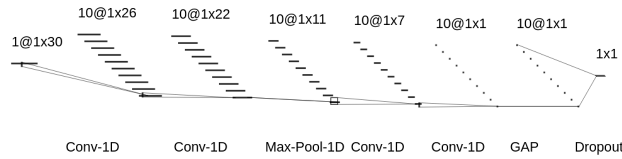

Fig. 4: 1D-CNN Architecture

IV. Dataset

The Bonn University Dataset [5] has been used. The dataset originally had 5 sets (A,B,C,D and E). All of these sets consisted of 100 single channel EEG recordings of length 23.6 seconds. We divided these signals into segments of 1 second, each containing 178 data points. Out of these 5 sets, only set 5 had EEG data for epileptic seizures. Hence, we modelled this as a binary classification problem, where samples from sets A, B, C and D represent the non-seizure class, while samples from set E represent the seizure class. Recording of these EEG signals was done through an amplifier with 128 channels. The frequency of sampling was 173 Hz.

V. Results

Results were taken for the following classifiers (Table I) - Logistic Regression, Support Vector Machine (SVM) with gaussian as well as linear kernels, K-Nearest Neighbours (KNN), Random Forest, Xgboost, Artificial Neural Network (ANN), and 1-D Convolutional Neural Network (CNN) (Figure 4).

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 80)                14320
_________________________________________________________________
dense_2 (Dense)              (None, 80)                6480
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 81
=================================================================
Total params: 20,881
Trainable params: 20,881
Non-trainable params: 0
```

(a) For raw EEG signal

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 15)                465
_________________________________________________________________
dense_5 (Dense)              (None, 15)                240
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 16
=================================================================
Total params: 721
Trainable params: 721
Non-trainable params: 0
```

(b) For proposed approach

Fig. 5: Number of parameters in ANN

Another important point to note is the number of parameters in ANN and CNN for Raw EEG Signal and for the proposed method. The proposed method produces better results for

```
Layer (type)                 Output Shape              Param #
=================================================================
reshape_2 (Reshape)          (None, 178, 1)            0
_________________________________________________________________
conv1d_5 (Conv1D)            (None, 169, 50)           550
_________________________________________________________________
conv1d_6 (Conv1D)            (None, 160, 50)           25050
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 80, 50)            0
_________________________________________________________________
conv1d_7 (Conv1D)            (None, 71, 50)            25050
_________________________________________________________________
conv1d_8 (Conv1D)            (None, 62, 50)            25050
_________________________________________________________________
global_average_pooling1d_2 ( (None, 50)                0
_________________________________________________________________
dropout_2 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 51
=================================================================
Total params: 75,751
Trainable params: 75,751
Non-trainable params: 0
```

(a) For raw EEG signal

```
Layer (type)                 Output Shape              Param #
=================================================================
reshape_1 (Reshape)          (None, 30, 1)             0
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 26, 10)            60
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 22, 10)            510
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 11, 10)            0
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 7, 10)             510
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 3, 10)             510
_________________________________________________________________
global_average_pooling1d_1 ( (None, 10)                0
_________________________________________________________________
dropout_1 (Dropout)          (None, 10)                0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 11
=================================================================
Total params: 1,601
Trainable params: 1,601
Non-trainable params: 0
```

(b) For proposed approach

Fig. 6: Number of parameters in CNN

both ANN as well as CNN with significantly less number of parameters (Figure 5 and Figure 6).

TABLE I: ACCURACY ON VARIOUS CLASSIFIERS

Classifier	Raw EEG Signal	Proposed Approach
Logistic Regression	80.96	**97.57**
SVM (Gaussian Kernel)	79.04	**97.88**
SVM (Linear Kernel)	83.04	**97.64**
KNN	92.18	**97.54**
Random Forest	96.14	**98.43**
Xgboost	97.23	**98.26**
ANN	95.12	**97.56**
CNN	79.04	**99.29**

Table II shows the comparison of our most accurate classifier with a few other approaches. In [25], both wavelet based features (energy, entropy, mean, minimum, maximum and standard deviation) and statistical features from raw signal (interquartile range and mean absolute deviation) have been extracted, and then a linear classifier has been used for classification of the data. In [26], raw EEG signal has been normalized and fed to a 13-layer 1-D Convolutional Neural Network (CNN). In [12], DWT has been applied and statistical features (average power, standard deviation and mean absolute value) have been extracted. Then k-nearest neighbour (KNN) algorithm is used to classify the data. In this, the test data points are assigned to a class based on the ”k” nearest training data points in the feature vector space. [27] explored the Hermite transform for processing of the EEG signal. Permutation entropy, histogram features and statistical features were extracted from the decomposed signal and passed to least-square support vector machine (Ls-SVM) for classification. In [28] the authors have attempted to extract the temporal features of the EEG signal using an architecture of the family of Recurrent Neural Networks, called Long Short Term Memory Networks (LSTM). The authors of [29] have used a 1-D Residual Convolutional Neural Network (Res-CNN) on raw data. Res-CNN consists of CNN-like layers but with residual blocks i.e. blocks with skip connections, which typically allow training deeper networks with richer representation of the data.

TABLE II: Comparison with other approaches

Reference	Method	Accuracy (%)
-	Raw Signal + Xgboost	97.23
Ahammad et al [25]	DWT + Linear Classifier	84.20
Acharya et al [26]	Raw Signal + CNN	88.67
Sharmila et al [12]	DWT + k-NN	97.10
Siuly et al [27]	Hermite Transform + LS-SVM	97.60
Ahmedt et al [28]	Raw Signal + LSTM	95.54
Lu et al [29]	Raw Signal + Res-CNN	99.00
Our approach	DWT + CNN	**99.29**

VI. Conclusion and Future Work

The results exhibit that our proposed approach has improved the accuracy of the epileptic seizure detection by a significant amount. Decompoisition of signals using discrete wavelet transform followed by appropriate extraction of features lead to the improvement in the accuracy of detection of epileptic seizure detection. An accuracy of 99.29 percent is achieved in our approach which is considerably much better as compared to conventional classification methods.

In the future, meta-heuristic algorithms can be used to extract the best subset of features. The use of Huang-Hilbert transform in place of DWT can also be explored. Combination of wavelet transforms can also be explored.

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