Epileptic Seizure Stage Classification from EEG Signal Using ResNet18 Model and Data Augmentation

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***Abstract*—Epilepsy is a widespread neurological disorder nowadays. It can occur to people of any age and any physiological condition. For the proper treatment of epilepsy, the accurate detection of epileptic seizures is crucial. There are many procedures available, and research is still going on. This study focuses on detecting and classifying epileptic seizures from EEG signals using the Convolutional Neural Network. For this purpose, data augmentation was implemented on EEG signals first. We divided the raw signal into four parts of 5 seconds and then rearranged it with four different combinations. We have applied Continuous Wavelength Transform in these newly formed signals to construct the scalogram images. These images were later classified using ResNet-18. The stages classified were Ictal vs. Interictal, Normal vs. Ictal, Normal vs. Interictal. We found the accuracy of 98.4%, 99.1%, and 98.2%, respectively. The accuracy and acceptance of the method can be developed further by applying different epileptic datasets and tuning other neural network parameters.**

***Index Terms*—Epilepsy, Continuous Wavelet Transform, Data Augmentation, ResNet18**

I. Introduction

Brain is the most vital organ of the human body. It is the center of communication between the organs of the whole body. The brain is a major part of the central nervous system alongside the spinal cord and consists of cells that are called neurons. Epilepsy is defined as a neurological disorder that results from abnormal activities of the brain, thus the central nervous system. It is a chronic disease and can occur irrespective of age and gender. Epilepsy is said to occur when at least two seizure events are diagnosed [1]. A seizure is an event that is caused by unusual electrical activity and overexcitement of neurons [2]. Seizures can occur multiple times repeatedly and often leads to the uncontrolled movement of the body and unconsciousness.

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Epilepsy and seizures are common diseases across the world. According to the World Health Organization (WHO), the estimated number of people diagnosed with epilepsy is no less than 50 million and this number is increasing gradually [3]. That is why it is very important to take proper treatment of epilepsy. Seizure events are typically divided into stages like preictal, ictal, interictal, postictal, etc. Where the ictal event represents the occurring of seizure and interictal denotes the interval between two consecutive seizure events. To provide the proper treatment and removing the chances of further seizure complications, it is very important to diagnose the stages timely and precisely [4].

The most common medium of diagnosing epilepsy is the Electroencephalogram (EEG) signals. EEG is the method of recording the electrical activity of the brain. Like the Electroencephalogram (ECG) signal gives us information about the heart, the EEG signal provides information about brain activity. Thus, in context, it helps to identify the stages of seizures. Manual processes are most used in diagnosing of seizure stages. Neurologists often scrutinize the signals and provide decision which is cumbersome and also not accurate always. Thus, an automatic and computer-based accurate detection system of epileptic seizures can contribute a lot to the epileptic seizure detection problem.

There are many types of research going on in this field, and some of them are very successful. Different approaches have been made to reach the accurate detection of epileptic seizures. Most of them are getting better results by applying machine learning and deep learning methods.

Acharya et al. gained 88.67%, 90.00%, and 95.00%, accuracy respectively for a three-class classification of normal, preictal and seizure stages by applying a 13-layer deep convolutional neural network by [2] Yuan et al. have achieved 96.50% accuracy while binary classifying of ictal and interictal stages using a feed forward neural network with an extreme machine learning algorithm [5]. A CNN and transfer learning-based algorithm is proposed by Raghu et al. for 8-class seizure classification, and they have achieved 82.85% accuracy using GoogleNet and 88.30% accuracy using the Inceptionv3 algorithm [6].

The Support Vector Machine (SVM) has been widely used in researches. In the study of Acharya et al. [7], SVM with Radial Basis Function kernel gave the best result of accuracy 96.00% among the other used algorithms to detect three classes of seizures. The researchers of the study [8] also achieved the highest accuracy of 97.19% from the least-square SVM. A similar approach to our study got 95.83% accuracy by using the AlexNet algorithm in scalogram images of EEG signals [9].

Here we are proposing such a model that can automatically detect the different ictal and interictal stages of seizures from the EEG signal. Firstly, we have augmented the raw EEG data. To augment, we have taken the 20 seconds data from the overall 23.6 seconds and then divided it into four parts of 5 seconds each. Then, we have shuffled the four parts in separate combinations to generate four different signals. We have applied CWT in those newly formed signals to generate the scalogram images. Lastly, these scalogram images were given to ResNet18 model for classification.

II. Methods and Materials

A. Data Source

For the work we have collected the open access EEG data from the University of Bonn, Germany [9]. It contains EEG signals of five classes named A, B, C, D, and E. Where A, B are the normal EEG signals collected from five healthy patients. C, D contains interictal seizure stage EEG data, and E contains ictal or seizure events data collected from five epileptic patients. Every five classes contain 100 EEG signals of 23.6 seconds with a sampling rate of 173.61 Hz. The signals are collected from continuous multi-channel EEG recordings, and the artifacts were removed by visual inspections.

TABLE I
DATASET SUMMARY

Dataset Class	Dataset Description
A	Relax and eyes open(normal).
B	Relax and eyes closed(normal).
C	From hippocampal formation (interictal).
D	Within the epileptogenic zone (interictal).
E	Seizure activity (ictal).

B. Data Augmentation

Data augmentation is the procedure of increasing the total amount of existing data points for analysis. It is one of the most popular techniques used to increase the total size of the data points while using a less dataset. It helps to work with the same dataset without completely changing it and provides a better result. It allows us to apply machine learning and neural network models even on small datasets. There are different techniques available for data augmentation according to the data type. Most of them are used for signals and images [11]. For augmenting the images, techniques like rotating, zooming, spatial transformation, etc. are used, and for augmenting the signal, bootstrapping, resampling signals, etc. are used.

The EEG dataset has five sections that contains 500 samples of 23.6 seconds each with the sampling frequency of 173.6 Hz [10]. For each sample in the dataset, we have a total of 4097 data points. However, with this small dataset, it is not proper always to apply a CNN model as over-fitting can occur. To achieve better accuracy, we have applied a data augmentation technique so that the size of the entire dataset increases. To do that, we first clipped off the first 1.7 seconds and the last 1.9 seconds from each sample, as shown in Fig.1. After clipping and removing the total of 3.6 seconds (625 Data Points), we have a data set of 20 seconds long and has 3472 Data points.

By creating a dataset of 20 seconds, we can divide it into four parts of 5 seconds each. This is depicted in Fig.2. These four parts of each sample are permutated and combined to make four different signals named signals 1,2,3,4. Through this process, we have made four different samples of the same signal, and as it is from the same patient, no interpatient overlapping happened. These increased number of samples have helped to prevent overfitting and achieve a better result.

The array formed by concatenating the four parts is used to generate the scalogram images to understand the part at which the changes are happening by stretching the wavelets to observe the slow changes in signal and scaling the wavelets to capture abrupt changes in the signal by using the "PyWavelets" python package. Generating 4 signals from a single patient increases the number of scalograms images which increases the accuracy of ResNet 18 model.

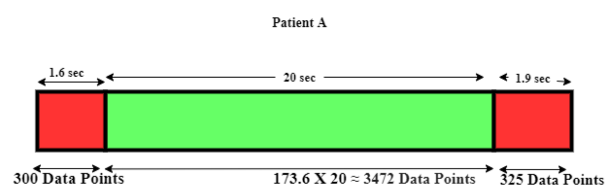

Fig. 1. Dataset after clipping 3.6 seconds

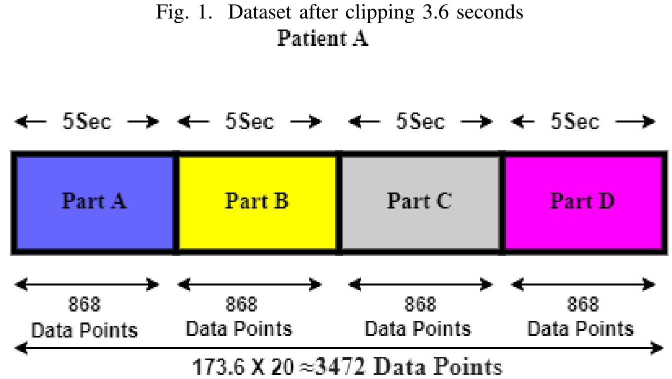

Fig. 2. Diving the Dataset into Four parts

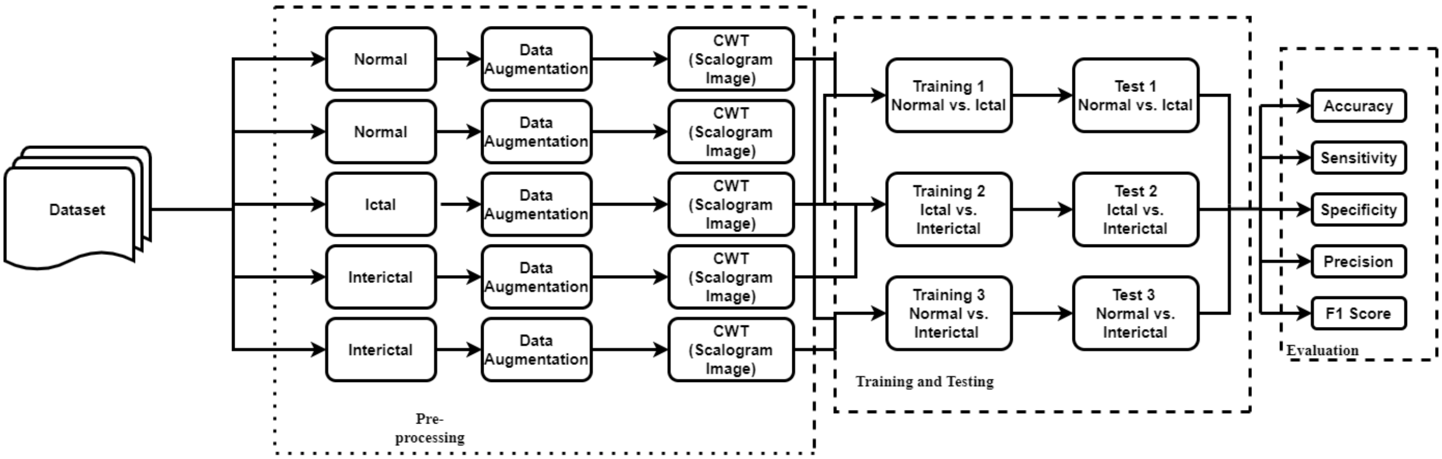

Fig. 3. Algorithm Flowchart

C. Scalogram Images

Fourier Transform helps us to visualize the frequency domain from a time-domain representation or vice versa. It decomposes the signal into its frequency domain without providing any information about its time domain. It is not possible to determine the band of frequencies which are part of a signal at a specific moment of time. As a result, it never gives the complete picture of the signal; that's why we have used CWT.

CWT uses wavelets function that helps us to choose the one that fits best with the features in which we are interested to observe. The most common wavelets for CWT are "Mexican Wavelets", Morlet Wavelet", and "Gaussian Wavelets," all together called as "Mothers Wavelets." These Mother Wavelets divide the 1D to ND time series or image into scaled components, which are based on scaling and shifting which generates the scalograms.

To increase the robustness of ResNet18 model, we can combine the scalograms from 2 different classes and giving as an input to train and to test the model for detection. Out of 3 different conditions among 5 classes, we can make three combinations of scalograms as shown in Fig.1 which are:

- Normal vs. Ictal .
- Ictal vs. Interictal.
- Normal vs. Interictal.

After combining the two classes of different stages the total number of scalograms generated from each combination are:

- Without Data augmentation - 400 scalograms.
- With Data augmentation - 400 X 4 = 1600 scalograms.

D. Model

The processing of EEG signals can be improved by using deep learning methods. Convolutional Neural Network(CNN) is most commonly used methods to analyze visual images. CNN is a part of a deep neural network and is based on learning directly from given data. It consists of 3 layers which are a convolutional layer, a pooling layer, and a fully connected layer. Convolutional and pooling layers are responsible for feature extraction and fully connected layer for the classification process. We can connect these three layers in various ways to create new deep learning models, but a large dataset will be required to train the CNN model, which is difficult. To get the pre-trained model on large dataset, we use a technique called transfer learning methods are used. Weights generated from pre-trained CNN models were used in transfer learning, and users have to train the last fully connected layers.

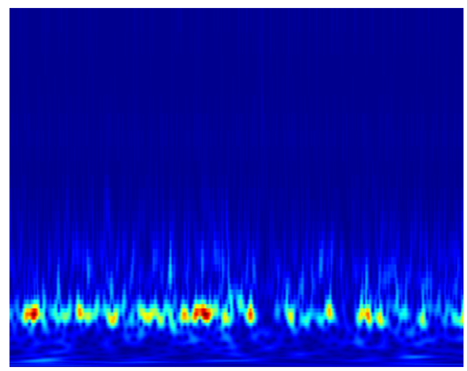

Fig. 4. Scalogram Image genrated by proposed algorithm

The performance of CNN increases if we develop deep layers because it increases its flexibility to adapt to any space increase because of its bigger parameter space to explore. However, it is seen after some depth the performance of CNN degrades and its gradient from where the loss function is evaluated reduces to zero after several applications of the chain rule. This is called the vanishing gradient problem.

In Resnet, the gradient can flow directly because each layer not just feed the next layer but also to the layers which are few steps away. Due to this larger gradient can also propagates through initial layer through back propagation, which solves the vanishing gradient problem. The pre-trained CNN model takes up a specific input sizes images, So we need to resize the our scalogram images according to the ResNet18 model.

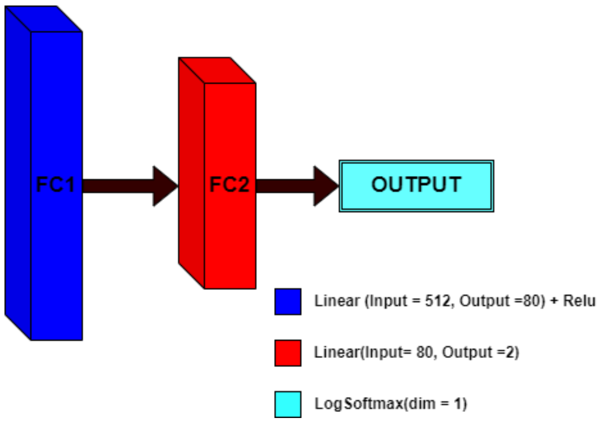

Fig. 5. ResNet18 Layer Description

ResNet-18 as the name suggests has 18 layers which takes 224 X 224 X 3 size of images as an input to the input layer. To reduce the overfitting of data, it takes the help of data augmentation as well as dropout maintenance. The images constructed by CWT which are used to train and test the model.

By using an 80:20 split ratio for training and testing of ResNet18 model, we have a total of approximately 1280 and 320 scalograms for testing and training, respectively in case of data augmentation. In our experiment we have used the Resnet 18 model in which the input is first passed through a linear transformation to the incoming data followed a 'relu' which applies the rectified linear unit function element-wise. The output of 'relu' is again passed through a linear transformation, and finally a output is defined as a LogSoftmax function will be computed as shown in Fig5. We have used the The cross-entropy loss of the CNN outputs was chosen as the model optimization objective function during training. Based on the backpropagated error from the output cross-entropy loss, the Adam optimizer was used to update the trainable parameters of the CNN at a learning rate of 0.001. For The increased number of scalograms used for training and testing improves the generalization capability and robustness of our algorithm. .

E. Evaluation

To evaluate the performance of the ResNet 18 model we have calculated parameters like accuracy, sensitivity, specificity. F1 score and precision are also calculated. These are the mathematical measurements of the model's performance, where accuracy is the ratio of accurately detected samples to total number of samples. Specificity and sensitivity are the measurements of correctly classifying of two different classes, which are negative and positive respectively by definition.

$$Accuracy = \frac{TruePositive + TrueNegative}{Totalnumberofsamples}$$

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive}$$

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative}$$

$$Precision = \frac{TruePositive}{FalsePositive + TruePositive}$$

$$F1Score = \frac{2(PrecisionXSensitivity)}{Precision + Sensitivity}$$

III. Results

Different seizure classification performed on the above mentioned datset using ResNet18 model. The proposed model performance is evaluated using classification accuracy, specificity, sensitivity, precision, F1 score. The classification accuracy of our Resnet18 model for class ictel vs. Interictal is 88.75%, normal vs. Ictal 88.33%, normal vs. Interictal 85.83%. The performance of model with data augmentation for class inter vs. Interictal is 98.33% for normal vs. Ictal is 99.17% , normal vs. Interictal is 97.92%. The other performance parameter of proposed model is mentioned in Table III, and Table IV.

A. ResNet18 and without data augmentation

TABLE II
Without Data Augmentation

Class	Acc.	Spec.	Sens.	Prec.	F1 Score
Ictal vs. Interictal	88.75	89.07	88.43	88.33	88.70
Normal vs. Ictal	88.33	90.35	86.50	85.83	88.03
Normal vs. Interictal	85.83	92.85	86.44	86.66	89.64

B. ResNet18 and data augmentation

TABLE III
With Data Augmentation

Class	Acc.	Spec.	Sens.	Prec.	F1 Score
Ictal vs. Interictal	98.33	97.54	99.15	99.16	99.15
Normal vs. Ictal	99.17	98.36	100	100	99.17
Normal vs. Interictal	97.92	98.32	97.52	97.50	97.74

C. Comparision

TABLE IV
Comparison

Names	B-E	C-E	D-E
Roy et al. [9]	97.5	98.75	97.5
Acharaya et al. [12]	98.55	98.47	97.5
Ours(with data augmentation)	99.1	98.4	98.2

The classification accuracy of our proposed algorithm is 99.1% between normal (set A, set B), interictal (set C, set D), and ictal (set E).

IV. Conclusion

This study shows the approach of classifying the different stages of epileptic seizures from scalogram images of EEG signal using ResNet-18 model of CNN. The data augmentation technique was used to increase the total number of scalogram images. Two stages of epileptic seizure, Ictal and Interictal were classified alongside normal stage. The three stages were classified separately as a part of binary classification procedure. The Ictal vs Interictal showed the best result of 98.33 % accuracy. The Normal vs Ictal showed 99.17% and the Normal vs Interictal showed the less accuracy with 97.92%. With the more handy and accurate approach these problems can be solved. Then it will be easier to detect epileptic stages fast and its treatment procedure will be more comprehensive.

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