Epileptic EEG Classification Using Synchrosqueezing Transform with Machine and Deep Learning Techniques

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***Abstract*—Epilepsy is a neurological disease that is very common worldwide. In the literature, patient's electroencephalography (EEG) signals are frequently used for an epilepsy diagnosis. However, the success of epileptic examination procedures from quantitative EEG signals is limited. In this paper, a high-resolution time-frequency (TF) representation called Synchrosqueezed Transform (SST) is used to classify epileptic EEG signals. The SST matrices of seizure and pre-seizure EEG data of 16 epilepsy patients are calculated. Two approaches based on machine learning and deep learning are proposed to classify pre-seizure and seizure signals. In the machine learning-based approach, the various features like higher-order joint moments are calculated and these features are classified by Support Vector Machine (SVM), k-Nearest Neighbor (kNN) and Naive Bayes (NB) classifiers. In the deep learning-based approach, the SST matrix was recorded as an image and a Convolutional Neural Network (CNN)-based architecture was used to classify these images. Simulation results demonstrate that both approaches achieved promising validation accuracy rates. While the maximum (90.2%) validation accuracy is achieved for the machine learning-based approach, (90.3%) validation accuracy is achieved for the deep learning-based approach.**

***Index Terms*—CNN, EEG, SST, SVM, Time-Frequency Analysis**

I. Introduction

Epilepsy is one of the most common neurological diseases caused by disruption of brain normal activity as a result of abnormal electrical activity temporarily occurring in the brain nerve cells. It is characterized by epileptic seizures that occur suddenly and spread to the whole or a certain part of the brain. According to the statistics of the World Health Organization, there are more than 50 million epilepsy patients worldwide and approximately 2.4 million people are diagnosed with epilepsy every year. EEG which records the electrical activity of the brain is preferred to use to obtained detail information about epilepsy because it is a low cost, non-invasive and effective technique. On the other hand, it is time-consuming to follow up long-term epileptic EEG recordings for expert neurologists and establish the correct diagnosis [1]–[4]. Therefore, many automated algorithms have been developed for the classification and detection of epileptic seizures. These developed algorithms are divided into two groups based on deep learning and machine learning.

Many studies were carried out using the machine learning approach for the classification and detection of epileptic seizures. In [1], the high classification accuracy was obtained utilizing the symplectic geometry decomposition approach based on the non-linear transformation proposed to the detection of epileptic seizures using SVM classify. In [2], the automated seizure detection method was performed using the complete ensemble empirical mode decomposition (CEEMD) based approach. Using obtained intrinsic mode functions (IMFs), the statistical and spectral features were calculated and the Quadratic Discriminant classifier was used for the classification process. In another computer-aided diagnostic technique, the discrete wavelet transform (DWT) and arithmetic coding approaches were used to distinguish seizure and seizure-free signals. Obtained features were classified by machine learning methods such as SVM multi-layer perceptron (MLP), NB, and kNN [5]. In [3], The Fourier synchrosqueezed transform (FSST) based approach was performed to classify seizure and seizure-free EEG signals. In this approach, the absolute values of FSST were calculated for each EEG signal. Using these absolute FSST values, non-overlapping 5 different frequency sub-bands were calculated. Gray-level co-occurrence matrix (GLCM) of these five sub-bands were obtained as features. The SVM and kNN classifiers were utilized to evaluate the performance of the conducted study.

Additionally, there are many studies in which neural network-based classification is performed. In [6], the Epileptic seizure detection approach based on the tunable-Q wavelet transform (TQWT), entropies, Particle swarm optimization (PSO) and Artificial Neural Network (ANN) was introduced.

Furthermore, there are many studies performed in this field based on deep neural networks (DNN) and convolutional neural networks (CNN). Raghu et al. conducted a CNN based study using Temple University Hospital EEG data set. Their

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multi-class classification approach included seven different Epileptic seizure types and normal EEG signals. They calculated Short-Time Fourier Transforms (STFT) of EEG signals and the images of Spectrograms using STFTs were used as the input for CNN. Different networks such as AlexNet, VGG16, VGG19, SqueezeNet, GoogLeNet, Inception-v3, DenseNet-201, ReNnet-18, ResNet-50, and ResNet-101 were used to obtain a suitable network for the proposed approach. The maximum performance accuracy (88.30%) was achieved using the Inception-v3 network [7]. In a DNN-based approach, the stacking ensemble-based deep neural networks model was used to predict epileptic seizures. Public Bonn EEG data set was utilized for the proposed study and the average accuracy value of 97.17% was obtained [8]. Madhavan et al. [9] produced FSST and wavelet SST (WSST) matrices to detect focal EEG signals used in epileptogenic areas and trains CNN via these matrices. The obtained results show that the accuracy of the model they have proposed is about 99%. In [10], authors have used FSST as a data augmentation technique and trained the data they created with CNN. Their results showed that FSST is more stable and provides more accurate results.

In this paper, SST based classification model for epileptic EEG data is introduced. The magnitudes of SST matrices are used for both feature extraction in the machine learning-based approach, and to obtain the images to be used as the input in the deep learning (DL)-based approach.

II. Materials and Methods

In this study, SST analysis is performed to distinguish pre-seizure and seizure EEG segments. 10-channel epileptic EEG signals are used, that are labeled as "pre-seizure" and "seizure" by expert neurologists. The TF representations of EEG segments are obtained using SST for each EEG channel separately. Higher-order joint TF moments are calculated using the magnitude of SST to generate the feature sets. Then, machine learning algorithms such as SVM, kNN, and NB are used for the classification. In addition, the three-dimensional TF representations obtained by SST were saved as images and used as input of CNN. Finally, the performance of the machine learning-based and deep learning-based approaches were evaluated.

A. EEG Dataset

In this study, we were used epileptic EEG data of 16 epilepsy patients recorded using surface electrodes at Izmir Katip Celebi University School of Medicine Department of Neurology. EEG signals were obtained from the Neurofax EEG device that has 18 different channels and a sampling frequency of 100 Hz. According to the International 10-20 electrode placement system, EEG signals were recorded from electrode positions of Fp1-F7, F7-T1, T1-T3, T3-T5, T5-O1, Fp1-F3, F3-C3, C3-P3, P3-O1, Fp2-F8, F8-T2, T2-T4, T4-T6, T6-O2, Fp2-F4 F4-C4, C4-P4, P4-O2. However, only EEG data recorded from the temporal and frontal lobes (Fp1-F7, F7-T1, T1-T3, T3-T5, Fp1-F3, Fp2-F8, F8-T2, T2-T4, T4-T6, Fp2-F4) were used for our study. In order to use these EEG data for the proposed study, Ethical Approval was obtained by Izmir Katip Celebi University Non-Invasive Clinical Research Ethics Committee in 08.08.2019 and numbered 296.

B. Synchrosqueezing Transform

SST, is a method that can be used for TF analysis of nonlinear and non-stationary processes based on continuous wavelet transform (CWT) or Short-time Fourier Transform. In the proposed study, STFT based SST was performed to analyze pre-seizure and seizure EEG segments [3], [11]. The EEG signals used in the study are divided into 1-sec EEG segments and the SSTs of these EEG segments are obtained by following the steps below.

Let $x(u)$ be the signal to be analyzed and $g(u-t)$ is the window function. SST process starts by taking STFT.

$$X(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty} X(\xi)G(\omega-\xi)e^{j\xi t}d\xi \tag{1}$$

Here, $X(\xi)$ is the Fourier Transform of analyzed signal $x(u)$, $G(\omega-\xi)$ is the Fourier transform of window function $g(u-t)$, and $X(t,\omega)$ Short-time Fourier transform of analyzed signal.

In SST method, the energy concentration is advanced by the squeezing procedure. In order to obtain usually neglected instantaneous frequency (IF) information from STFT, the derivative of $X(t,\omega)$ is calculated with respect to time [3], [11].

$$\omega_0(t,\omega) = -j\frac{\partial_t X(t,\omega)}{X(t,\omega)} \tag{2}$$

In the SST approach, the STFT coefficients that have the same frequency information are collected where they should appear, by using instantaneous frequency ω_0(t, ω). The SST $T(t,\eta)$ is formulated by using synchrosqueezing operator $\int_{-\infty}^{\infty}\delta(\eta-\omega_0(t,\omega))d\omega$ [3], [11].

$$T(t,\eta) = \int_{-\infty}^{\infty} X(t,\omega)\delta(\eta-\omega_0(t,\omega))d\omega \tag{3}$$

An example SST magnitude spectra for pre-seizure and seizure EEG segments are given in Fig. 1.

C. Machine Learning Based Approach

In the machine learning-based approach, high order joint moments were calculated as features by using the magnitude of SST and various machine learning algorithms such as SVM, kNN, and NB were used for classification. The supervised machine learning method SVM which has the linear kernel function was used for the proposed approach [1], [3]. Additionally, Euclidean distance measure was used for the kNN classifier and k=10 was chosen [3], [5]. For the NB classifier, the Gaussian kernel was used [5]. Moreover, to evaluate the performance of classifiers, 5-fold Cross-Validation (CV) method was utilized [12].

Higher order joint TF moments based feature set: The higher-order joint TF moments $< n^i\ \omega_k^j >$ are calculated as

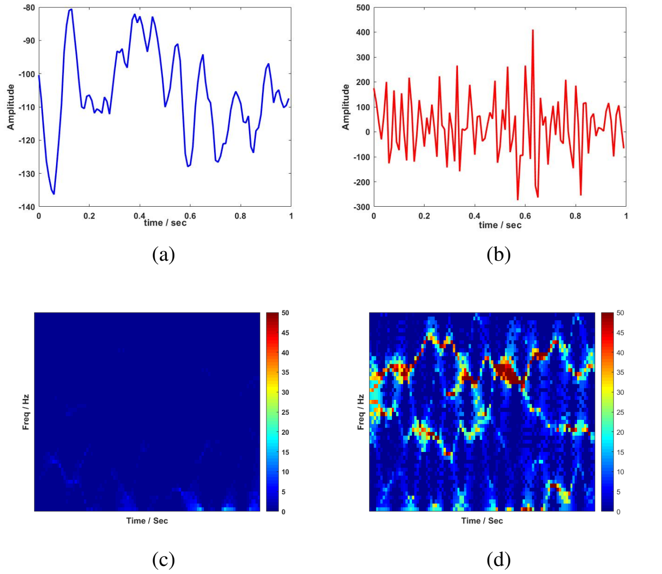

Fig. 1: One second long EEG segments, (a) pre-seizure, (b) seizure, magnitude SST of (c) pre-seizure EEG segment, (d) seizure EEG segment.

the feature set using the magnitude square of the obtained SST matrix.

$$< n^i\ \omega_k^j >= \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} n^i \omega_k^j |T(n, \omega_k)|^2, \quad i, j = 1, \ldots, 4 \tag{4}$$

Here, $T(n, \omega_k)$ is the TF representation of the EEG segments obtained using SST, N is the length of the EEG segments, and $\omega_k = \frac{2\pi}{N} k,\ k = 0, \ldots, N-1$.

The log-normalization approach is used to reduce the dynamic range of joint TF moments [13],

$$\overline{< n^i\ \omega_k^j >} = \log(\frac{< n^i\ \omega_k^j >}{i!j!}), \qquad i, j = 1, \ldots, 4, \tag{5}$$

1x16 log-normalized joint moment $\{\overline{< n^i\ \omega_k^j >}\}$ feature vector is obtained for each pre-seizure and seizure EEG segments.

D. Deep Learning Based Approach

In this study, similar simulations are conducted to compare machine learning and deep learning based classifier performances. The CNN architecture was used in deep learning based approach. The RGB images were obtained to use as input for the CNN approach from all SST matrices calculated and used in the above method.

1) SST Image Representation: The obtained each SST matrix corresponding to a one-second EEG segment is converted into a 1356x1071 dimensional, 300 DPI RGB image. The axis, title and legend information of these images were omitted, as they may cause inaccurate information during classification. During this process, no pre-processing or feature extraction is necessary. Then, all SST images were lossless scaled to 32x32 RGB images using the OpenCV library. Then, one-second SST images obtained from each patient's 10-channel EEG data are labeled as pre-seizure and seizure.

2) Deep Learning Based Architecture: CNN is a deep learning subclass and a kind of artificial neural network and used for diagnostic purposes in biomedical image classification, segmentation and object detection. The aim of CNN is to create feature maps from hyperparameters within the images and to learn the information on these maps using multiple structures such as convolution layers, pooling layers, and fully connected layers [14]. In this study, the SST images were created to distinguish pre-seizure and seizure epileptic EEG signals. By using CNN architecture, SST images were classified. As such, EEG segments are represented using high temporal and spectral resolution images and effectively classified by the CNN structure.

The CNN architecture was designed in four layers. First of all, the input data were subjected to convolution, the Rectified Linear Unit (RELU), and then pooling. This process was repeated 4 times and the output is connected to the fully connected layer. Finally, normalization was performed via a Softmax function. Each convolutional layer has a 4x4 kernel size, the stride of 2, and a filtering count of 10, 20, 50 and 100, respectively. After every convolution layer, RELU is applied to the feature maps. After that, a max-pooling operation that has 4x4 kernel with the stride of 2 is applied to RELU outputs. The softmax function is used for the binary classification of pre-seizure and seizure EEG classes.

III. Performance Evaluation

Statistical metrics such as Accuracy (ACC), Precision (PRE), Recall (REC or Sensitivity), and F_1 score were used for performance evaluation.

$$\begin{aligned} ACC &= \frac{TP + TN}{TP + FN + FP + TN} * 100\% \\ REC &= \frac{TP}{TP + FN} * 100\% \\ PRE &= \frac{TP}{TP + FP} * 100\% \\ F_1 Score &= 2 * \frac{PRE * REC}{PRE + REC} * 100\% \end{aligned} \tag{6}$$

Here, the number of data which is a sample of the pre-seizure class and assigned by the classifier as the sample of the correct class is represented by True Positive (TP); however, the number of data assigned as a member of the seizure class is represented by False Negative (FN). Additionally, the number of data which is a sample of the seizure class and assigned by the classifier as the sample of the same class is represented by True Negative (TN), but the number of data that mistakenly assigned as the sample of the pre-seizure class is represented by False Positive (FP) [3], [12].

IV. Experimental Results and Discussion

In this paper, using the SST method, deep learning-based and machine learning-based approaches were proposed to classify pre-seizure and seizure epileptic EEG signals. The comparison of both machine learning (ML)-based and deep learning (DL)-based approaches, are given using performance metrics like accuracy, precision, recall, and F_1 score in Table I.

TABLE I: Performance results (%) for pre-seizure and seizure EEG signal classification

	ML-Based			DL-Based
Metrics	**SVM**	**kNN**	**NB**	**CNN**
Training ACC	90.6	90.2	89.3	99.97
Validation ACC	90.2	90.2	89.4	90.3
PRE	85.99	86.48	82.32	90.85
REC	86.08	88.41	89.43	86.38
F_1score	86.03	87.44	85.73	88.56
ROC AUC	0.96	0.96	0.96	0.95
Duration of Each Iteration	5.01sec	0.70sec	8.14 sec	1 sec

Performance evaluation results of ML-Based approach was given in Table I, and the confusion matrix is shown in Fig.2. In the ML-based approach, the joint TF moment based feature set was used as an input of classifiers. Using this feature-set, the maximum classification accuracy of 90.6% is achieved with the SVM classifier. While the SVM and kNN methods algorithms yield the highest validation accuracy of 90.2%, the NB method achieved 89.4% validation accuracy. On the other hand, the maximum REC value (89.43%) was obtained using the NB classifier. However, the maximum PRE (86.48%) and F-score (87.44%) values are achieved using the kNN algorithm. Additionally, the minimum iteration duration (0.70 sec) is provided with the kNN algorithm.

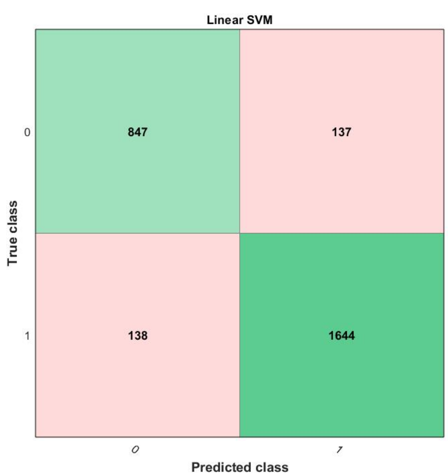

Fig. 2: Confusion matrix of the proposed SVM classifier

All deep learning classification experiments were carried out with Nvidia GeForce RTX 2080 Ti GPU and 64 GB RAM by using Cuda 10.1, cudart64-101.dll, and Tensor Flow 2.0 library. In the training step, batch size, optimization learning rate, test size, image layer count, and EPOCH count are selected as 128, 1e-3, 20%, 3, and 50, respectively. Thanks to the proposed CNN architecture, training accuracy of 99.97% and the validation accuracy of 90.3% were achieved. Training loss was about zero, and validation loss was found to be 0.7221. The F1 score was found as 0.8856. Training performance of the proposed deep model is given graphically in Fig.3.

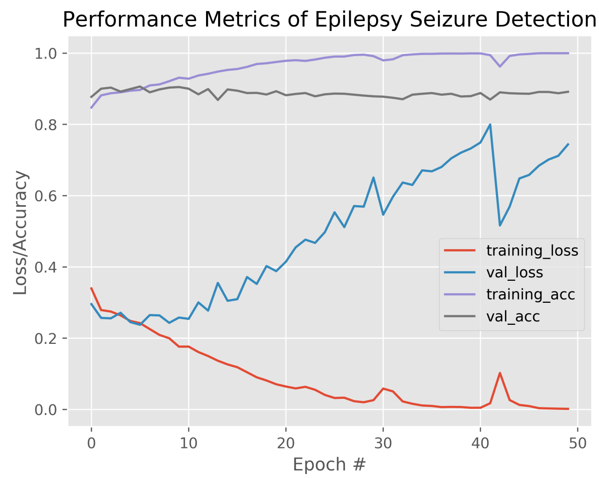

Fig. 3: Performance of trained CNN model.

As shown in Fig.3, training and test accuracies are over 90%. Also, as the number of Epoch increases, the value of training loss decreases. Note that the validation loss increases regardless of the number of Epochs which is undesired. As seen in the confusion matrix given in Fig.4, and the performance metrics in Table I, the model is not actually over-fitted. The reason of the increasing validation loss is considered to be the limited time resolution of the SST images, because the sampling rate of EEG recordings is 100 Hz.

Furthermore, the performance of the ML-based and the DL-based approaches was compared. Although DL based models have higher training costs, the iteration duration of the proposed DL-based model is shorter than the proposed ML-based approach. While validation ACC, REC, and F-score values are similar in both approaches, PRE (90.85%) and training ACC (99.97%) values are higher in the DL-based approach.

The obtained results from the proposed ML-based method and the DL-based method are promising compared with other recently published papers [15], [16]. Also, better classification results were obtained with empirical mode decomposition (EMD)-based feature extraction studies which have higher computational complexity [17], [18]. Despite of this, using SST images as input for CNN architecture has a new perspective on future approaches.

V. Conclusion

In the proposed study, 10-channel pre-seizure and seizure epileptic EEG signals of 16 patients were used. Synchrosqueezed Transform was applied using 1sn EEG segments

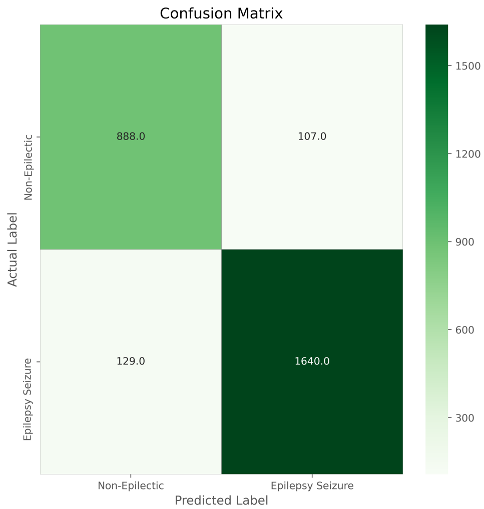

Fig. 4: Confusion matrix of the proposed CNN architecture.

and TF representations were obtained for each EEG segment. In the ML-based approach, the higher order joints TF moments were calculated as features using these SST matrices. Machine learning algorithms such as SVM, kNN, and NB were used to classify this feature set. On the other hand, 3D RGB images were obtained using magnitude of SST matrices and used as input data for the CNN architecture to determine whether EEG signals belong to the pre-seizure or seizure classes. In addition, both ML-based and DL-based proposed methods, demonstrate a high performance rates in classifying our pre-seizure and seizure segments. However, the DL-based approach provided better training ACC than the ML-based approach.

In our future and ongoing studies, we aim to compare SST based approach with other high-resolution TF analysis methods. Additionally, the different feature extraction methods and different machine learning algorithms for the ML-based approach, and also the different CNN architecture for the deep learning-based approach may be used.

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