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Classifying Single Channel Epileptic EEG data based on Sparse Representation using Shallow Autoencoder

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Abstract— **Patient independent epileptic seizure detection algorithm for scalp electroencephalogram (EEG) data is proposed in this paper. Principal motivation of this work is to integrate neural and conventional machine learning methods to develop a classification system which can advance the current wearable health systems in terms of computational complexity and accuracy. Being based on processing a single channel EEG processing, the approach is suitable for usage with small wireless sensors. A shallow autoencoder model is utilized for sparse representation of the EEG signal followed by k-nearest neighbor (kNN) classifier to categorize the data as epileptic or non-epileptic. Using a single EEG channel an optimum sparsity level is explored in the encoded sample. Attaining an accuracy, sensitivity and specificity of 98.85%, 99.29% and 98.86% respectively, for CHB-MIT scalp EEG database, proposed classification method outperforms state of-the-art seizure detection methodologies. Experiments has shown that this performance was possible by using a sparsity level of 4 in the auto-encoder. Furthermore, use of shallow learning instead of deep learning approach for generation of sparse but effective representation is computationally lighter than many other feature extraction and preprocessing methods.**

I. INTRODUCTION

Epilepsy is a common neurological disorder entitled as a second most common neural disease [1]. Accurate diagnosis of these disorders require developing efficient algorithms to support clinicians with regard to reducing human effort and error. In order to evaluate automatic epileptic seizure detection efficiently, numerous algorithms have been developed and a lot of work has already been proposed in the literature [1] - [11].

Broadly speaking these approaches extract statistical features in the first phase and then use some machine learning model for detection of epileptic seizures [2], [3]. These approaches extract some linear and non-linear discriminative features directly from raw EEG data or after applying some transform like Fast Fourier transforms (FFT) [11] or Common spatial Pattern (CSP) [12]. Different statistical features are then calculated which are used as input to the classification stage. These statistical features include Power Spectral Density, Mean, Standard Deviation, Variance, Minimum, Maximum etc. [3]. Most of these studies extract discriminative features in either spectral domain [2], temporal domain [3] or combined spectral-temporal domain [8]. Dimensionality reduction of these features is usually carried out using Principal Component Analysis (PCA). Dictionary based approaches such as empirical mode decomposition (EMD) are also addressed as feature learning technique [9].

Various machine learning models have been explored in the literature for EEG data classification. List of these models include kNN, Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naive Bayesian classifier and Decision tree. These classifiers learn through some discriminative features present in the data and categorize it in different classes [3]. Trend of evaluating multiple machine learning classifiers in different stages of classification task is also presented in previous studies [12].

Detection of epileptic seizures using deep learning modules is evolving rapidly in recent times. Deep network architectures provide good classification results by paying penalty of intensive resources which is not feasible for developing wearable health systems. Computational complexity of certain approaches is a major disadvantage.

Deep learning approaches for EEG signals classification mostly use stacked autoencoders and deep convolutional neural network (CNN) architectures for unsupervised EEG feature extraction as [4] and [6]. Using raw data directly [5], [7] or some data pre-processing techniques are presented in recent times like FFT base image as input to CNN in [11]. Both, spectral and temporal domain embeddings are integrated into one deep learning model in [1]. Deep network modules mostly use sigmoid function and Softmax classifier [5] - [7]. Consequently, exploring a joint venture of machine learning models and neural networks is desirable.

Some methodologies as in [9], [12] use patient specific features to improve performance which hinders their general use. Moreover, most of these approaches are multi-channel approaches like [1] - [12]. Reducing the number of input channels say to one without compromising on accuracy minimizes the number of EEG electrodes required and the associated computational requirement. Generalized seizure disorder can be picked up by any EEG channel but for focal epilepsy pre-selection of correct location (EEG channel) is important. Hardware approaches targeting wearable health devices [16], [8] have also used multichannel processing Furthermore, many approaches are using statistical features, non-linear computations [16] and wavelets [8] which have

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higher computational complexity. Recently there has been a trend towards single channel based approaches as in [10] which enhances patient acceptability for long duration usage along with available battery life.

In this work we have developed an optimal sparse representation using an autoencoder for seizure detection. This eliminates the need to develop a usual feature extraction stage preceding the classification stage. This adds training load but using shallow network serves our purpose to keep computations and resources lower for the evaluation phase and is the one that is invoked in regular usage. The work is elaborated further in the following section. Section III discuss a brief overview of the EEG database and experimental setup used along with classification performance. Concluding remarks are addressed in section IV.

II. Proposed Method

Our approach is based on using a shallow autoencoder model for sparse representation of EEG data which is classified by a conventional classifier. Figure 1 depicts the block diagram of the proposed approach for processing the EEG data in the test and training phases including generation of sparse representation (encoding), reconstruction (decoding) and classification of EEG data. Proposed algorithm take chunks of 1-sec EEG trial and continuously process them. Segments of 1-30 sec are normally used [5]. For accurate marking at fine granularity we have selected 1 sec segment. Raw EEG signal is directly used as input to autoencoder without any preprocessing and feature extraction stages. The encoded representation or sparse representation is reconstructed by the decoder. Different sparsity levels can be chosen. For each sparsity level it is possible to train the auto-encoder for minimizing the reconstruction error. This encoded sample (sparse representation) is used for classification. The training phase involve both the encoder and decoder but the testing phase involve only the encoder and the classifier.

Additionally, the algorithm deals with processing a single channel at a time. Multichannel implementation provide more information to discriminate the nature of EEG data by paying penalty of intensive resources. However, in our case based on prior training and testing of the system an optimal channel is pre-selected for further use. As discussed in section III performance of our approach still excel the multichannel approaches.

Furthermore, our approach is not patient specific in terms of performance achievement and depict a high average performance over a body of patients. Multiple patients data is used to train classifier and autoencoder for better learning. In order to find the best classifier, we tested first with a Softmax layer and then tried out conventional Machine Learning tools such as Decision Tree, SVM, kNN, LDA. Adding a deep neural net (DNN) module was also a good option to explore, however, it had the drawback of high computational cost for designing wearable health systems. It was found that kNN classifier performed best with respect to our quality measures among all other machine learning classifiers. However, computational complexity of the Decision Tree is the lowest [17] but its quality performance is also lower. kNN can be taken as an optimal compromise.

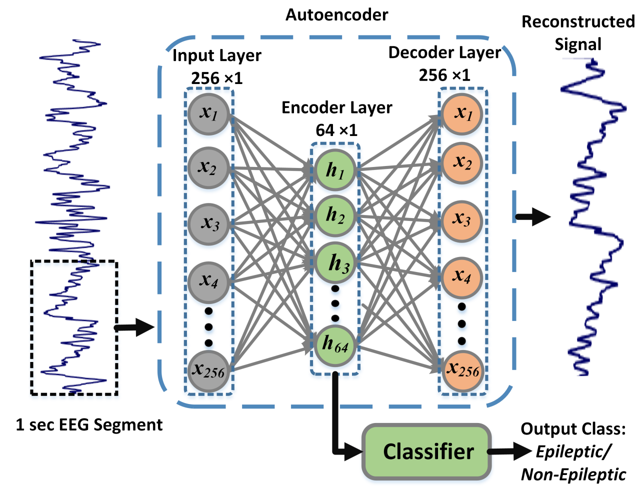

Fig. 1. Proposed work flow

III. Results and Discussion

A. Dataset

In order to examine the effectiveness of the proposed seizure detection method, we are using publicly available PhysioNet scalp EEG database named as CHB-MIT provided by [14]. Dataset was collected at the Children's Hospital Boston, consists of EEG recordings from pediatric subjects with intractable seizures. Recordings grouped into 23 cases, collected from 22 subjects, sampled at 256 Hz. A detailed description of the subject information is also provided in a table which contains the gender and age of each subject [14].

B. Experimental Setup

A shallow autoencoder model for sparse representation of EEG signal along with kNN classifier to label the data as epileptic or non-epileptic is illustrated in Figure 1. Assuming the sampling rate of the database 256 Hz, proposed algorithm is designed to process a 1 sec trial (segment) [7]. Therefore, input layer consists of the signal length 256. Autoencoder compresses the input signal to 64 samples, providing a sparsity level (No. of samples in original signal/No. of samples in sparse signal) of value 4. In order to train the encoder in a better mechanism to provide sparse features which are good representatives of the original signal, a decoder layer is also added to reconstruct the signal and train the system to reduce the difference between original and reconstructed data. Decoder layer reconstructs the signal to its original length of 256.

Choice of linear activation favors an autoencoder model with low computational cost as compared to non-linear functions. Therefore, transfer function for encoder layer is chosen to be saturating linear transfer function (Satlin), whereas, to calculate decoder layer's output from its input, linear function (Purelin) is used [15]. Scaled conjugate gradient

(SCG) is designated to update weight and bias values of the autoencoder. Mean Square Error (MSE) loss function is selected in training phase of the autoencoder to compare the original and reconstructed signal.

In order to categorize the data as epileptic or non-epileptic, Weighted kNN classifier is used with 10 nearest neighbors. One of the major concern regarding affecting the performance of kNN classifier is the choice of hyper-parameter k. Selecting a very small value of k will be sensitive to outliers. On the other hand, if we designate a larger k, then neighborhood may incorporate some features from other classes. Weighted kNN is the choice to handle these uncertain conditions. Kernel function for this uncertainty should be the one whose value must decrease as the distance increase. Considering these conditions, we select Squared Inverse distance weight kernel. Euclidean distance metric for neighbors selection is adopted . In order to encapsulate the uncertain outliers and to deal with incomplete and inconsistent information existing in the features, Exhaustive Neutrosophic set is used to determine the decision criteria [13].

C. Performance Testing

Autoencoder model for sparse representation of the input signal was trained using randomly selected 10,000 non-seizure and 5940 seizure trials from the database. Raw EEG samples of 1 sec duration constituted a trial with no pre-processing and feature evaluation involved. The kNN model was then trained on classifying these encoded samples (sparse representations) as epileptic or non-epileptic segments. In order to test the proposed seizure detection model 3 Million trials (of 1 sec durations) were also extracted from the dataset. The dataset as is usual in real-life data is highly unbalanced towards non-seizure trials (with just less than 11252 seizure trials). Figure 2 shows the channel wise mean testing measures in terms of accuracy, sensitivity and specificity. Hidden size of the encoder is 64 providing sparsity level of 4. Results for each EEG channel shows each of the three quality measure to be above 94%. This demonstrates the effectiveness of the proposed methodology.

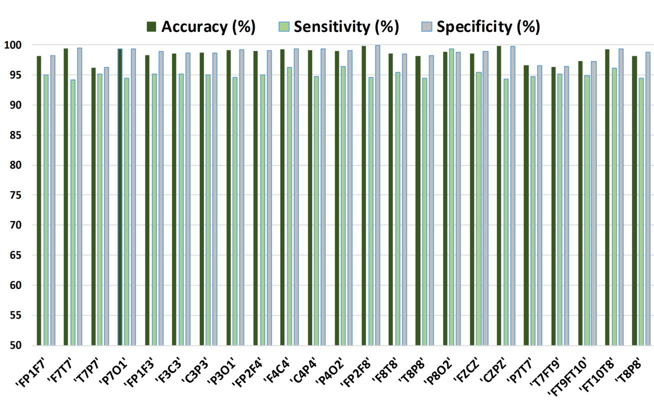

Fig. 2. Channel wise Average Accuracy, Sensitivity and Specificity of all database events with sparsity level 4

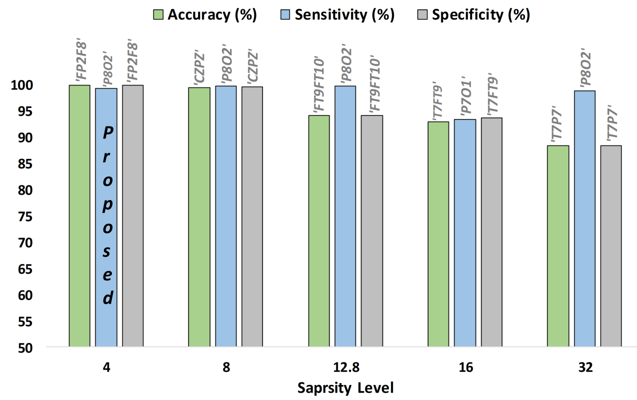

Fig. 3. Best performing channel for each sparsity level with kNN classifier

TABLE I

AVERAGE RECONSTRUCTION ERROR FOR EACH SPARSITY LEVEL

Sparsity Level	4	8	12.8	16	32
Mean Absolute Error	6.24	9.19	11.46	12.90	18.31

Proposed classification algorithm is also tested using multiple hidden sizes of autoencoder providing sparse signals of multiple lengths. Table I shows the average reconstruction error against the increasing sparsity levels. Figure 3 presents accuracy, sensitivity and specificity of the best performing channel at each sparsity level. Statistical census of performance evaluation illustrates that the proposed classification model can be used in different scenarios according to system requirement. Highest sparsity level that is reported 32 corresponding to compressing the input signal of length 256 to 8 samples only. Even for 8 samples, proposed algorithm still provides greater than 98% sensitivity. However, accuracy and specificity maintains above 90% stats up till sparsity level 16. For level 32, both of these stats comes down to 88%.

D. Performance Comparison

In order to illustrate the effectiveness of proposed classification method, results obtained are compared with some state of the art methodologies. Table II encapsulates a comparative analysis of the quality measures achieved by proposed classifier in terms of average classification accuracy, sensitivity and specificity of all EEG channels with some latest existing models. Results listed by proposed algorithm are the average figures achieved with sparsity level 4. Proposed seizure detection method outperforms all the techniques and shows best performance compared to all the listed methods. Moreover, we are using single channel approach and shallow autoencoder having only one encoding layer which is advantageous over these listed techniques in terms of computational cost.

Performance comparison in terms of computational complexity with other seizure detection schemes also aids efficacy to the proposed algorithm. A brief comparison regarding this scenario is also presented in Table II. Single channel, patient independent approach is implemented corresponding

TABLE II
COMPARISON OF CLASSIFICATION RESULTS WITH STATE OF THE ART TECHNIQUES FOR CHB-MIT DATABASE

Ref. - Year	Channels	Features	Classifier	Accuracy(%)	Sensitivity(%)	Specificity(%)
[10] - 2021	1	Band energy	SVM	-	87.60	88.00
[1] - 2020	21	Multiple Spectral and Temporal	CE-stSENet	95.96	92.41	96.05
[2] - 2020	22	30 Statistical features	SVM, kNN and 8 other	86.27	80.32	92.22
[3] - 2020	Multiple	24 Statistical	SVM	94.50	-	-
[4] - 2019	23	SAE	Deep CNN, FC and SVM	92.00	95.00	90.00
[5] - 2019	23	Deep CAE	FC and SoftMax	93.97	-	-
[6] - 2019	23	Deep CNN	Dense and SoftMax	98.05	90.00	91.65
[7] - 2018	Multiple	FFT and Deep CNN	FC and SoftMax	96.10	-	-
[9] - 2018	23	EMD dictionary	SVM	92.90	94.30	91.5
[11] - 2018	21	Deep CNN	SoftMax	-	87.95	86.50
[12] - 2016	23	Poincare section and PCA	LDA and Naive Bayes	94.69	89.10	94.80
Proposed (All channels mean)	**1**	**64 Shallow encoded**	**kNN**	**98.60**	**95.23**	**98.90**
Proposed (Channel 'P8O2')	**1**	**64 Shallow encoded**	**kNN**	**98.85**	**99.29**	**98.86**

to process only one EEG electrode for seizure detection. Whereas, most of the techniques in literature [1] - [12] use multi-channel processing which are definitely resource intensive. Same is the case for hardware modules [16], [8]. Secondly, signal classification using deep network modules such as CNN or stack autoencoders [4] - [7] is also an adverse approach for developing wearable health systems due to entanglement of immense computational power and resources. Applying shallow learning module in this regard is quite suitable and advantageous. The system architecture comprises of only one layer in this approach which reduces resource utilization and time latency. Mapping a 256 samples signal to 64 require only 16384 (256×64) multiplications and addition of 64 biases.

IV. CONCLUSION

We proposed a hybrid approach to detect epileptic seizures in wearable health systems which also outperforms the state of the art methods with detection sensitivity of greater than 99%. Further goal of this work is to develop a classification algorithm which is patient independent, less computation expensive, and suitable for wearable devices yet achieving both high sensitivity and specificity. Unlike the existing multi-channel seizure detection methods in the literature, we proposed and developed single channel model. In order to achieve sparse representation of the EEG signal, a shallow autoencoder model instead of deep network is proposed with only one encoder layer. kNN classifier is further added to categorize the data as epileptic or non-epileptic. Statistical measures achieved by the proposed algorithm demonstrate that our method outperforms state of the art methods and we have the advantage of low computational cost as well.

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