A novel epileptic seizure detection system using scalp EEG signals based on hybrid CNN-SVM classifier

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***Abstract*— Epilepsy is a neurological disorder that affects more than 2% of the world's population. Encephalography (EEG) is a commonly clinical tool used for the diagnosis of epilepsy. However, traditional approaches based on visual inspection of EEG signals are tedious and complex. Thus, several automatic seizure detection approaches based on machine learning techniques have been proposed. In this study, a hybrid model for the detection of epileptic seizure is proposed, where convolutional neural network (CNN) is used for automatic feature extraction of EEG signals and support vector machines (SVM) is used for epileptic seizure classification. The proposed approach was evaluated using the Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) dataset. Experimental results showed that the accuracy of the combined CNN-SVM model outperforms the CNN baseline model. The proposed approach provides a substantial increase in seizure prediction performance in terms of sensitivity compared to both classical machine learning approaches and CNN model that have been presented in the previous studies.**

Keywords—Epilepsy, EEG, CNN, SVM, Classification

I. INTRODUCTION

EPILEPSY is a neurological disease identified by recurrent sudden seizures resulting from abnormal electrical brain activity. This disease is usually diagnosed through the visual analysis of EEG recordings as it contains relevant information about brain activities.

Epileptic seizure detection using this approach is a challenging and time-consuming task. Hence, various research works were carried out to develop an automatic system for the detection of epileptic seizure.

Recently, machine learning has made a revolution in the epileptic seizure detection area by addressing the high complexity of EEG signals [1]. Its tools make the distinction and evaluation of seizure characteristics easier.

Until recent years, classical machine learning techniques have been the widely used option for the automatic detection of epileptic seizure [2]. The performance of these approaches relied extensively on hand-engineered techniques for feature extraction. The big challenge is the selection of the appropriate features from EEG signals [3]. The selected features are then fed to a classifier to detect the epileptic seizures.

This issue of manual feature engineering was solved through the development of deep neural networks (DNNs). This latter does not require hand-crafted feature extraction step as it is done automatically and implicitly. Among the different types of DNNs, CNN has attracted the interest of researchers for epileptic seizure detection [1].

This paper proposes a new method to detect epileptic seizure using scalp EEG signals. The presented approach proposes a CNN-SVM hybrid model that takes advantage of CNN to overcome the complexity of feature extraction, and benefits from the effectiveness of SVM in classification. A further evaluation is done by comparing the CNN-SVM model with CNN-based model.

The rest of this paper is organized as follows. A related works for epileptic seizure detection in EEG is surveyed in Section II. Section III explains the proposed method. Experimental evaluation of the combined CNN-SVM approach as well as the results are given in Section IV. A conclusion of this paper is given in Section V.

II. RELATED WORKS

The feature extraction process is a key that determines the classification accuracy.

In literature, the hand-crafted techniques used for feature extraction from EEG signals are generally applied considering either time domain, frequency domain, or time-frequency domain [4]. Tessy et al. [5] have used two time domain features for EEG signal analysis namely line length and energy. These features were used for three classification algorithms such as quadratic discriminant analysis, k-nearest neighbors (KNN) and linear discriminant analysis. The performance evaluation of these classifiers in the seizure detection showed an outperformance of KNN classifier with an accuracy of 94%. A thorough analysis of feature extraction from EEG signals from time, frequency and time-frequency domains was presented in [6]. In this work a total of 52 features from the three domains were extracted. In order to recognize the epileptic state, 10 classification models and a feature selection method were used. Comparing to the state-of-the-art classifiers, these models achieved similar results.

Despite the fact that traditional approaches using hand-engineered features have achieved high performance in epileptic seizure detection, the manual extraction of features may limit its performance when dealing with a complex and large dataset [7]. These limitations have motivated some recent studies to exploit deep learning algorithms for seizure detection. Acharya et al. [8] have suggested a deep CNN) with 13-layer to detect 3 classes (normal, preictal and seizure). This approach achieved an accuracy of 88.67%. The work in [9] proposed the processing and classification of raw EEG signal using long short-term memory (LSTM) networks without any pre-processing step. The evaluation results of this approach showed an average accuracy of 95.54%. An autoencoder-based multi-view model for the automatic seizure detection using scalp multichannel EEGs was recently introduced in [10]. The developed system reached an accuracy of 94.37%.

Though epileptic seizure detection using deep learning achieved promising results, it still needs improvement. Thus, in this work CNN was used as a trainable feature extractor which is found effective in the analysis of EEG signals [2]. SVM classifier was used for the classification.

III. Proposed system design

In this section, the proposed approach is briefly introduced. Then, the theory of CNN and SVM classifiers are presented. Lastly, the proposed hybrid CNN-SVM model for epilepsy detection is described.

A. Approach overview

A preprocessing step is needed before inputting the EEG signals to CNN for feature extraction.

As CNN requires a data with an image format, short-time Fourier transform (STFT) is used to obtain a matrix of two dimension from the raw EEG signals. The used STFT allows CNN to extract features from both frequency and time domains.

In order to facilitate and improve the feature extraction an approach based on moving window is usually done [11]. This technique divides the raw EEG data into epochs (i.e. segments of smaller duration) [12]. In this study, the STFT was used on 30 seconds windows of raw EEG signals.

The fully connected layers of CNN are replaced by SVM to perform classification. The extracted features from CNN are given to SVM as a feature vector.

Because each patient has his characteristic (age, gender, seizure types, etc.), it is necessary to build a specific model for each patient [4]. Using this patient-specific approach, the model will be trained and tested for each patient individually.

The whole process of the proposed approach is described in Fig. 1.

Fig. 2 (a) shows the general workflow of the proposed approach to detect epileptic seizure. This approach is compared with the baseline model based on CNN (b).

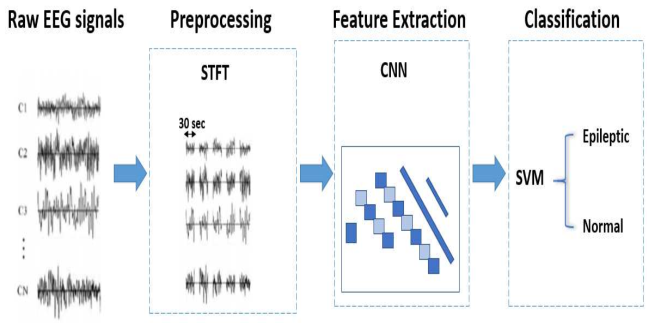


Fig. 1. Proposed approach

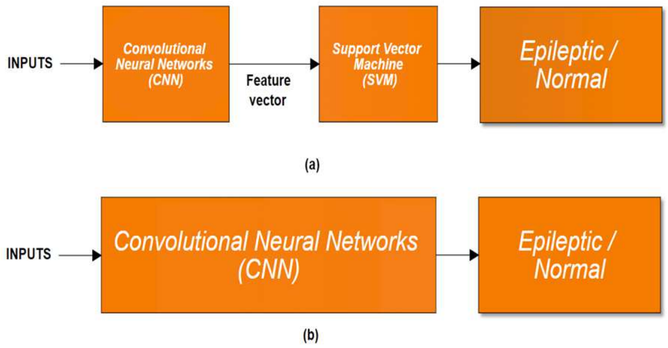


Fig. 2. Framework of the proposed approach (a), workflow of the baseline model (b)

B. Convolutional Neural Networks

Convolutional neural networks (CNN) can be considered as the composition of two parts: a part for the automatic feature extraction and a part for classification.

Generally, the CNN's architecture consists of 3 layers [13]: convolution, pooling and fully connected layers. In the convolution layers, a convolution operation is done to the input data using convolution filters. The pooling layers reduce the spatial dimensions of the input for the next convolutional layer. At last, the fully connected layers which convert the feature maps into a feature vector in order to classify the extracted features.

The CNN used in this work is composed of 3 convolution layers each one is followed by rectified linear activation function (ReLU) and max pooling layer.

The first convolution layer has 16 n filters of size (5×5) and stride of ($1 \times 2 \times 2$), where n refers to the number of EEG channels. The two others convolution layers consist respectively of 32 and 64 filters both of size (3x3) and stride of (1×1).

At last, two fully connected layers with a dropout of 0.5 were used. These fully connected layers have respectively 256 and 2 neurons.

Fig. 3 exhibits the adopted CNN architecture in this work.

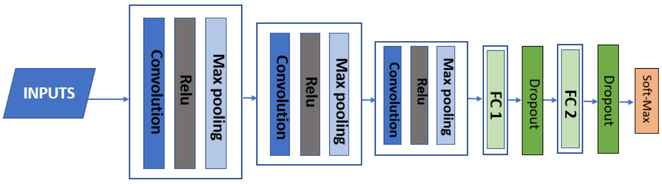


Fig. 3. CNN architecture

C. Support Vector Machines

Support vector machine (SVM) is a statistical method that has been recently successfully applied to many applications. It is a binary classification algorithm. Its goal is to find an optimal separator also called hyperplane of two data classes. This is done through a nonlinear transformation using kernel functions as shown in Fig. 4. The margin is the distance between the separation boundary and the closest data points (support vectors). The essence of SVM is to find the optimal hyperplane that maximizes this margin [14].
The hyper-parameters of SVM classifier determine its performance. For this reason, a method named grid search is used on this work which helps to build the SVM model while finding the best combination of its hyper-parameters.

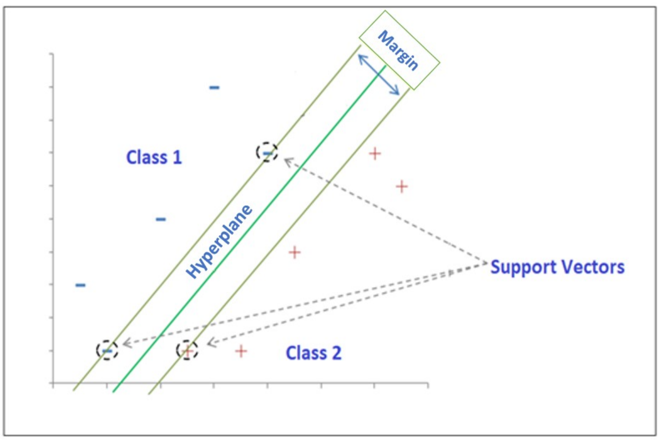


Fig. 4. The concept of SVM classifier

D. Combined CNN-SVM model

In this section, the proposed architecture based on combined CNN-SVM for epileptic seizure detection is described (Fig. 5).
After CNN's training, the SVM classifier is used instead of the fully connected layers for the classification of epileptic seizure. The SVM classifier was trained per-patient where the high-level features are extracted from CNN for every patient.
Given a test set, the classification is done by SVM using the features extracted automatically from the trained CNN.
The output values of the pooling layers of CNN are considered as the feature vectors that will be fed as input of SVM classifier.
The intention of such hybrid model is the combination of the advantages of CNN and SVM. Using this combined model, the classification efficiency of SVM classifier is used to boost the CNN's classification capability.

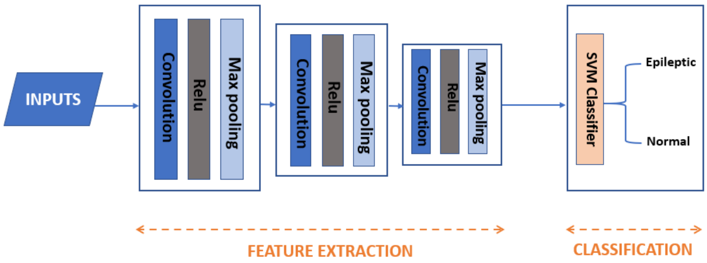


Fig. 5. Architecture of the combined CNN-SVM model for epileptic seizure detection

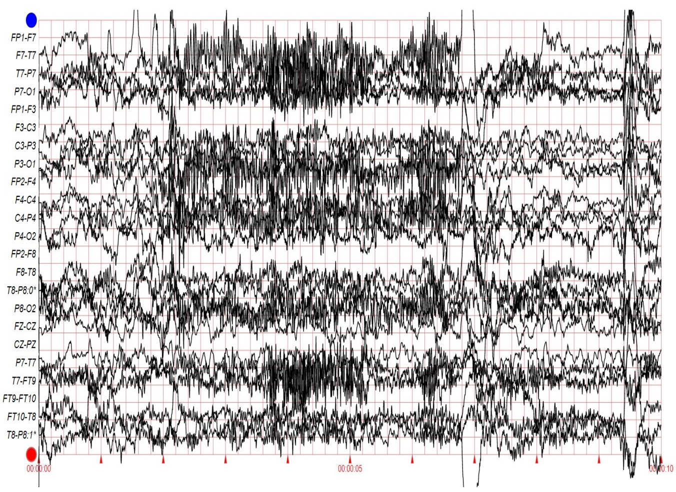
IV. Experimental evaluation

To assess the effectiveness of the proposed epileptic seizure detection system, experiments were performed on the CHB-MIT dataset.

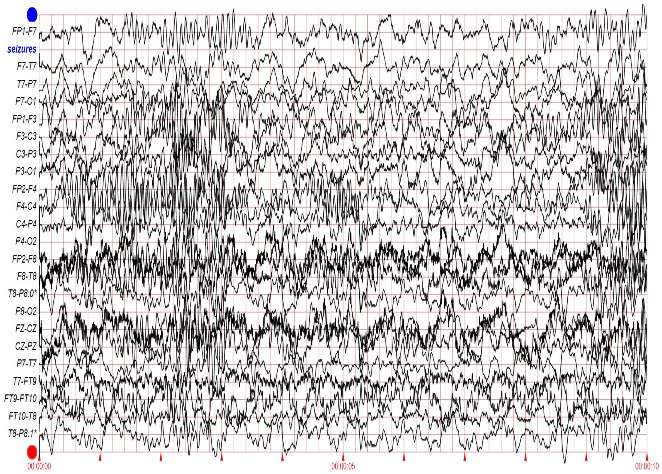
This section introduces the dataset and experimental protocols and discusses the obtained results.

A. Dataset

The database CHB-MIT is collected from the Children's Hospital Boston. It is an open access dataset available on PhysioNet that contains scalp EEG (sEEG) data from 23 patients. The EEG recordings consist of 23 channels. Each case contains between 9 and 42 .edf files.
Fig. 6 shows an example of EEG recordings for normal and seizure state.
In this work, only patients having less than 10 seizures per day are considered. Besides, the analysis of EEG signal made the system computationally expensive as it takes in consideration all the EEG channels. Therefore, only 7 patients are considered.
A detailed description for the chosen patients is given in Table 1.



(a)



(b)

Fig. 6. Example of normal (a) and seizure (b) EEG recordings

TABLE I. SUMMARY OF THE DATASET USED IN THIS WORK

Patient ID	Gender	Number of seizures
1	F	7
2	M	3
5	F	5
19	F	3
20	F	8
21	F	4
23	F	7

B. Results

Experimental studies were carried to explore the efficiency of the proposed model for epileptic seizure detection based on hybrid CNN-SVM.

All experiments in this study were carried out on a laptop computer with Intel Core (TM) i5-8250U CPU @ 1.60GHz, and NVIDIA GeForce MX 150. The model was built using python 3.7.

CNN model was trained and tested for each patient individually. The number of samples in the training and test datasets is presented in Table 2.

The seizure detection performance differed among the subjects. However, the obtained accuracy was above 90% for all subjects for both the baseline CNN and combined CNN-SVM models.

As shown in Table 3, the achieved accuracy using the proposed combined model was superior (for patients 2, 5, 20 and 21) or comparable (for patients 19 and 23) to the accuracy of the baseline CNN model.

Compared to the CNN model, the accuracy of the combined CNN-SVM was poor for some patients (patient 1). This can be explained by a couple of possibilities. Firstly, for this patient, the inter-ictal EEG (between seizures) may have contained features similar to those in seizure state leading to a bad performance of the CNN-SVM model in the discrimination between normal and epileptic classes. Second, the existence of some confusing artifacts at the onset of seizure or during the seizure period which may cause false detection.

Fig. 7 shows an example of the receiver operating characteristic (ROC) curve of CNN-SVM and CNN models for patient 21. This curve shows the trade-off between true positive rate and false positive rate. In this example, the CNN-SVM model indicates a better performance than CNN model as the ROC curve is closer to the top-left corner.

In addition, the area under the ROC curve (AUC) was used as a comparison criterion between the proposed model and the baseline CNN model. This metric is a measure of sensitivity versus specificity of a given classifier. It reveals the classifier's capability in the distinction between classes.

In overall, for most of the patients, the performance of the proposed CNN-SVM model has been found superior than CNN model, as the achieved AUC values are the highest (Fig. 8).

Furthermore, the performance of this work was evaluated through a comparison with some previous studies utilizing the CHB-MIT dataset for the detection of epileptic seizure (Table 4). Some of these previous works used deep learning models and others used hand-crafted features-based approach. This comparison is based on the metric of sensitivity also known as recall which measures the proportion of the detected seizures from the total seizures.

Authors in [15] and [16] used CNN model for epilepsy detection. Compared to [16], the proposed model showed an obvious better sensitivity results for all patients. While, the sensitivity of the CNN-SVM model outperforms [15] for patients 1, 2 and 5 and achieved almost similar results for the rest of patients.

On the other hand, in [17] several classical machine learning classifiers namely random forest (RF), k-nearest neighbors (KNN) and naïve bayes was used for the detection of epileptic seizure. Compared to these classifiers, this work achieved almost better sensitivity for all the patients.

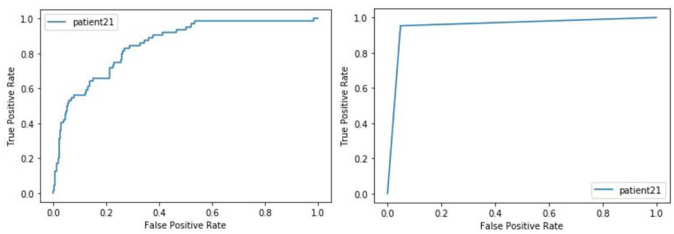


Fig. 7. ROC curve of CNN-SVM (right) and CNN (left) classifiers for patient 21.

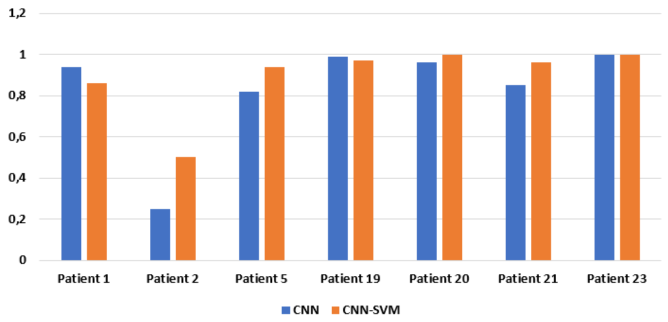


Fig. 8. A per-patient performance comparison of CNN-SVM and CNN classifiers for AUC metric

TABLE II. THE TRAINING AND TEST DATASETS FOR EACH PATIENT

Patient ID	**Training set**	**Test set**
1	2350	750
2	2562	1045
5	1956	422
19	3114	1131
20	2610	577
21	3132	768
23	1896	395

TABLE III. ACCURACY OF THE COMBINED CNN-SVM MODEL AND CNN MODEL FOR EACH PATIENT

Patient ID	**Accuracy**	
	CNN	***CNN-SVM***
1	100	95
2	91.9	94
5	91.87	94
19	99.9	99
20	97.24	100
21	93.68	96
23	100	100

TABLE IV. COMPARISON OF STATE-OF-THE-ART TECHNIQUES WITH THE PROPOSED METHOD ON THE CHB-MIT DATASET

Patient ID	**Sensitivity**					
	CNN [15]	***CNN [16]***	***RF [17]***	***KNN [17]***	***Naïve bayes [17]***	***This work***
1	85.7	96.88	99.4	97.5	99.9	99
2	33.3	99.73	99.7	98.7	97.4	100
5	80	59.36	98.7	96.8	97.4	99
19	100	99.9	99.7	99.7	99.8	100
20	100	98	98.8	99.6	99.1	100
21	100	87.65	98.4	99	99.4	99
23	100	93.42	99.5	99	89.4	100

V. CONCLUSION

Epileptic seizure detection is a classification problem that has been exhaustively studied over the last decades. This article proposed the combination of the learning ability of CNN and the generalization ability of SVM classifier. Hence, the feature extraction part was done using CNN to minimize the feature engineering and the seizure detection (epileptic/ normal) was performed by SVM.

The proposed combined CNN-SVM model was validated using scalp EEG data. Comparing to the baseline CNN model, the proposed approach gives a better accuracy result. Comparing to the previous studies using the same dataset (CHB-MIT database), this approach gives the best results.

This model can be improved and used for seizure detection wearable device.

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