Two-stage approach based on combination of one-class SVM and CNN for epileptic seizure identification

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***Abstract*—Many automated EEG seizure detection methods are able to perform well in terms of precision but fail to keep reasonable recall producing a lot of false positives. To solve this, we propose a two-stage framework combining classical outlier detection methods and neural networks, utilizing real-world EEG data. The first stage uses a one-class support vector machine to filter non-seizure activity, followed by a convolutional neural network to distinguish between false positives and true seizures. Evaluation of metrics tailored for epilepsy detection showed improved precision, with a slight decrease in recall for the proposed approach, suggesting that it may improve the performance of clinical decision support systems.**

***Index Terms*—Multi-stage approach, convolutional neural network, epileptic seizure detection, clinical decision support system, EEG**

I. Introduction

Epilepsy is a chronic neurological disorder causing recurrent seizures, which affects over fifty million people [1]. Nowadays, effective treatment relies on early and accurate diagnosis, primarily using electroencephalography (EEG) —- non-invasive method for measuring electrical brain activity [2]. Usually, to diagnose epilepsy, a doctor manually analyzes the patient's EEG recording in order to find the patterns associated with this condition. Despite the fact that such inspection is precise it's very laborious and time-consuming. Therefore, automated tools in the form of Clinical Decision Support Systems (CDSS) are needed for efficient seizure detection [3].

Previous studies on this topic have used a wide range of different methods to solve this problem, including statistical approaches [4], [5], time-frequence analysis [6]–[9] and various machine learning (ML) methods [10]–[14]. The convolutional neural networks used in this study are no exception as well [15]. However, most of these studies utilize limited publicly available datasets, which contain significantly fewer artifacts and noise than real EEG recordings, leading to overoptimistic results.

In our previous studies, we focused on frequency characteristics and temporal dynamics of epileptic EEGs using wavelet transforms and outlier detection techniques [16], and showed that seizures represent extreme events, suggesting outlier detection techniques for this task. However, while these methods are able to find most of the seizures, the number of produced false positives remains a big issue.

In this study, we aim to improve the precision and maintain the recall of our model by using a two-stage approach. We combine a one-class support vector machine (OCSVM) with a convolutional neural network (CNN) to achieve this. Additionally, we have adjusted the evaluation procedure to better reflect the specific requirements of the task. Finally, we utilize a real-world EEG dataset from a clinical setting to train and compare our models.

II. Materials and methods

A. Dataset

The employment of a real EEG dataset in this study was made feasible thanks to the collaboration with the National Medical and Surgical Center named after N.I. Pirogov in Moscow, Russia. All patients provided written informed consent, and the study followed the Helsinki Declaration and local medical regulations. The "Micromed" encephalograph at a 128 Hz sampling rate with 25 channels according to the "10–20" scheme [17] was used. The dataset contains EEG recordings collected from 83 patients between 2017 and 2019, with recording durations from 8 to 84 hours and each patient had from 1 to 5 seizures during the recording session. Once the dataset had been collected, an experienced epileptologist manually annotated all epileptic seizures, which we used as the ground truth for model training.

In our previous study, we observed that the predictions of OCSVM were unsatisfactory for 16 particular patients due to an extreme amount of artifacts in the data [16]. Consequently, we decided to exclude these 16 subjects and keep the data from the remaining 67 subjects for further analysis.

B. Preprocessing

In this study, we work with EEG signals in the time-frequency domain. The transformation of raw signals was done via continuous wavelet transform (CWT) with complex Morlet wavelet as mother wavelet [18], [19]. The wavelet power (WP) spectra in the 1–40 Hz range were used as input for the models:

$$W_n(s,\tau) = \int_{-\infty}^{\infty} x_n(t)\psi^*_{s,\tau}(t)dt, \qquad (1)$$

$$w_n(s,\tau) = |W_n(s,\tau)|^2, \qquad (2)$$

where $n = 1, 2, \ldots N$ is the number of the channel ($N = 25$), $\psi_{s,\tau}(t)$ is a basis function derived from the mother wavelet ψ_0, $W_n(s,\tau)$ are the coefficients of CWT, * corresponds to complex conjugation, and $w_n(s,\tau)$ is the WP of a signal $x_n(t)$.

C. Seizure detection

To demonstrate the effectiveness of the developed approach, we compare it to two one-stage models based on ML and DL approaches. Namely, we used OCSVM and CNN in a standard one-stage fashion as base models. The OCSVM baseline treats seizure detection as an outlier detection problem and uses a Gaussian kernel and 10-fold cross-validation for training, similar to [16]. The WP defined in 2 and averaged over the 2-5 Hz frequency band, 25 EEG channels, and 60-second time intervals, is used as input for the OCSVM model.

In the case of the single-stage CNN model, we reformulated the original task into the image classification task of 10-second time intervals after CWT. With this formulation, we used a CNN based on the ResNet-18 architecture [20] with modifications to the first and last layers to ensure correct input processing. Additionally, as CNNs generally perform better when input data has a distribution with a zero mean and unit variance we used the normalized logarithm of the WP as CNN input. We trained a one-stage CNN model for 10 epochs, where at each epoch 100 training examples per patient were used, with approximately 50% containing epileptic activity. Other training hyperparameters included a learning rate of 0.001, a batch size of 4, binary cross-entropy as a loss function, and the Adam optimizer.

As mentioned earlier, the two-stage approach combines OCSVM and CNN. In the first stage, OCSVM performs a rough filtration by predicting ”suspicious” 60-second segments that may contain epileptic activity. In the second stage, these ”suspicious” segments are fed into the CNN model, which refines OCSVM predictions on 10-second segments. The main difference in CNN training for the two-stage approach is in the way training examples are sampled. For the CNN from the two-stage method, we use half of the examples from actual seizures and half from OCSVM false positives, keeping the other parameters the same as for the one-stage CNN.

D. Evaluation

During the analysis of baseline CNN predictions, we found many short predictions (less than 50 seconds long). These predictions make little sense because seizure durations typically exceed 40 seconds (in our dataset average duration is more than 100 seconds). Therefore, to smoothly decline these short predictions, we applied a median filter with a kernel size of $K = 7$.

Usually, seizure detectors are evaluated as binary classifiers of fixed time intervals. However, in reality, seizures, aren't isolated 10-second intervals. Our analysis of models' predictions supports this statement. We observed that predictions of the same class tend to cluster together which is a good sign as it reminds natural EEG patterns. To employ this observation we used an algorithm to convert a series of 10-second predictions into segments of varying lengths. This algorithm involves two steps: first - merge neighboring segments of the same class, second - merge positive segments separated by a single negative prediction.

However, with the last step, the usage of classical metrics based on the confusion matrix becomes problematic since the number of true seizure segments and predicted seizure segments may be not equal. To solve this problem we need to modify the procedure of accounting TP, FP, and FN predictions. Proposed rules are illustrated in Fig. 1. Specifically, we treat the predicted segment as TP if one or more predicted segments within or intersect a T-second range ($T = 60$ in this study) of a true seizure (Fig. 1A). We call segment FP if it is outside of T-second range of true seizure (center of Fig. 1B), and we call true seizure FN if there is no prediction within T-second range of this seizure (edges of Fig. 1B). With these rules, we can evaluate the performance of the models with standard metrics for classification: $recall$, $precision$, and F_1.

III. Results

In this section, we compare the performance of the proposed two-stage approach with one-stage OCSVM and one-stage CNN. All the metrics are shown in Table I. We can see that both one-stage models result in a similar performance, with slight differences in $recall$, and similar $precision$.

More specifically the one-stage OCSVM produces a high $recall$ of 0.9020, indicating it successfully identifies the majority of true seizures. However, its $precision$ is low at 0.1176 which is also reflected by a high number of false positives ($FP = 345$). The one-stage CNN demonstrates a very high recall of 0.9608, which means that it detects nearly all presented seizures. However, similar to OCSVM, it also has

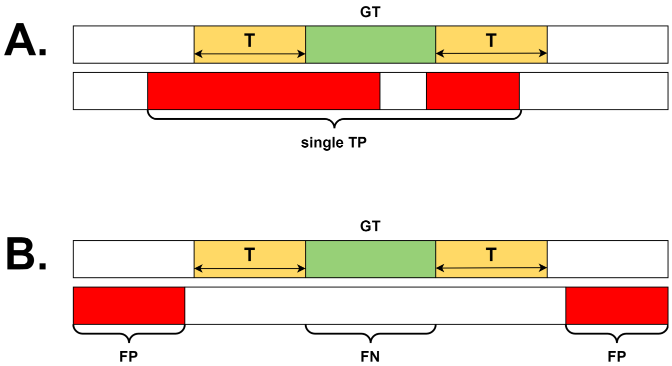

Fig. 1. Rules for counting TP, FP, FN. Green corresponds to true seizures, yellow — to T-second range of seizures, and red — to predictions. (A) multiple predicted segments in T-second range of seizure are counted as one TP; (B) predicted segments outside T-second range of seizure are counted as FP, true seizure without any predictions in its T-second range is counted as FN.

a low precision of 0.1273, indicating a considerable number of false positives as well ($FP = 336$).

The proposed combination of OCSVM and CNN yields significantly improved $precision = 0.5733$, with approximately 10 times fewer false positives ($FP = 32$) than any of the two one-stage approaches. While the $recall$ is slightly reduced compared to the individual models at 0.8431, it remains relatively high, indicating that most seizure events are still correctly identified. The F_1 of 0.6825 reflects a well-balanced performance between $precision$ and $recall$, indicating that the proposed two-stage approach is the most effective among the three evaluated. At the same this approach results in slightly more FN predictions which may be a limitation for some applications.

TABLE I
COMPARISON OF ONE-STAGE MODELS AND TWO-STAGE APPROACH

Model	$precision$	$recall$	F-score	FN	FP	TP
One-stage OCSVM	0.1176	0.9020	0.2081	5	345	46
One-stage CNN	0.1273	0.9608	0.2248	2	336	49
Two-stage	0.5733	0.8431	0.6825	8	32	43

IV. CONCLUSION

In this study, we proposed a two-stage seizure detection algorithm where OCSVM is used for data filtering in the first stage, and in the second stage, CNN is used to refine OCSVM predictions. The proposed two-stage approach showed a slight decrease in $recall$ but a significant increase in $precision$, which produces and as a result has a significant $precision$ improvement. This method may enhance CDSS quality by efficiently handling large-scale real EEG datasets with minimal false positives.

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