Two-stage model for epileptic seizures detection on EEG recordings

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***Abstract*—The purpose of this study is to analyze the applicability of a two-stage model based on convolutional neural networks to improve the quality of seizure detection on real EEG data. Wavelet analysis is used for time-frequency analysis. To localize epileptic discharges, the seizure detection task was reduced to the classification task where the prediction process consists of two steps: the first model provides coarse predictions which are refined by the second model trained on the first model's errors. As a result of using the proposed two-stage model, the F1-score metric was improved by about 2% compared to a single coarse model, and at the same time led to a significant increase in false negative predictions, which shows the tradeoff brought by the considered approach.**

***Index Terms*—EEG, time-frequency analysis, neural networks**

I. Introduction

Epilepsy is a chronic neurological disorder that manifests itself in the form of rare recurring seizures caused by abnormal activity in the brain. As of 2016, more than 50 million people worldwide suffered from epilepsy [1], however, with timely detection and proper treatment, up to 70% of patients reach a state of remission [2], [3]. Nowadays electroencephalography is the main diagnostic tool for epilepsy.

Electroencephalography (EEG) is a non-invasive measurement of the electrical activity of the brain, in which electrodes placed on the scalp register voltage potentials resulting from the passage of current in and around neurons. The most common approach to EEG analysis is visual analysis, which is performed by an experienced epileptologist. This approach is a time-consuming and expensive process since a medical doctor needs to analyze a huge amount of EEG data. The availability of an automated tool for detecting epileptic seizures could significantly speed up the screening process and provide an alternative opinion. Today, the construction of such a clinical decision support system (CDSS) is an important scientific task [4], [5].

There are a large number of studies in the field of EEG data analysis, and the detection of epileptic seizures is no exception [6]. In most works, statistical or classical machine learning models are used to detect seizures [7]–[12]. It is worth noting that with the development of deep learning, many researchers are trying to apply deep neural networks to the task of seizure detection [13]–[15]. It is also worth mentioning that approaches using ensembles of models [16] and multi-stage models [7] are developing and achieving impressive results.

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This paper attempts to answer the question about the applicability of a two-stage model based on convolutional neural networks to improve the quality of seizure detection on real EEG data. To answer this question, frequency analysis methods and the data recorded using a single device and marked up by an epileptologist are used.

II. Data

The data under study was provided by the National Medical and Surgical Center named after N.I. Pirogov of the Ministry of Health of the Russian Federation (Moscow, Russia). All medical procedures were held in the Center in accordance with the Helsinki Declaration and the medical rules of the Center and were approved by the local ethics committee. All patients provided written informed consent before participation. The data set includes anonymized long-term monitoring data of patients in the Department of Neurology and Clinical Neurophysiology between 2017 and 2019. Monitoring was performed during daily activities, including sleep and wakefulness. The duration of the recording varies from 8 to 84 hours, depending on the patient's condition and the number of episodes of epileptiform activity required to make a correct diagnosis. The data contains records of 83 patients diagnosed pathologically with focal epilepsy. Epileptic focuses were found in the frontal, temporal, or parietal regions of the left, right, or both hemispheres. During the observation period, each patient had from one to five epileptic seizures. EEG signals were recorded with a sampling rate of 128 Hz with $N = 25$ channels according to the international "10–20" system [17].

III. Methods

The general scheme of the study is shown in Fig. 1, where the oval is used to indicate data at different stages of processing, and the rectangle is responsible for denoting the specific procedures performed with data. Each individual step will be discussed later in the article.

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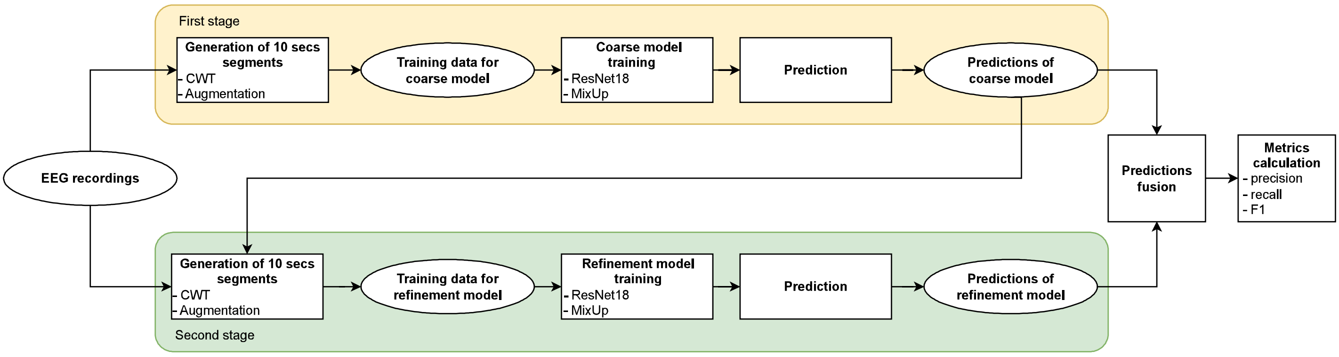

Fig. 1. Modules of the first stage are highlighted in yellow. During this stage, the neural network is trained on the available data, inference is performed, and obtained coarse predictions are saved. Modules of the second stage are highlighted in green. During this stage, the second neural network is trained on data containing the first model's errors, and inference of the second network is performed. Finally, the predictions of both models are aggregated to obtain refined predictions that will be used for metrics calculation.

A. *Two-stage model*

In the problems of classical machine learning, multi-stage algorithms that gradually improve the quality of predictions using information from previous stages [18], [19] are successfully used to solve a wide class of problems and are de facto the standard in the industry. Also, multi-stage models are successfully used in deep learning, for example, in such computer vision tasks as segmentation [20] and alpha matting [21]. In the seizure detection field there also exist works that use multi-stage models to achieve better performance [7], but an approach that combines convolutional neural networks and multi-stage modeling is not so widespread and studied in the seizure detection field.

In this paper, the considered solution consists of two stages illustrated in Fig. 1. Modules related to the first stage of prediction are marked in yellow. During the first stage, the neural network is trained on the available data, inference is performed, and obtained coarse predictions are stored for use in the next stage. The modules of the second stage are highlighted in green. During the second stage, using the predictions of the first network and the ground truth labels, data containing the first model's errors is generated, and training and inference of the second network are performed on this data. Finally, the predictions of both models are aggregated to obtain refined predictions that will be used for the final model performance evaluation.

B. *Models training*

For the sake of simplicity, the neural network training procedure is the same for models from each stage. The detection of epileptic seizures on the EEG recording was reduced to the task of classifying non-intersecting segments of the EEG recording of a fixed length (in this work – 10 seconds) after the continuous wavelet transform (CWT) [22]. These segments can be considered as 25-channel images, and, therefore, the seizure detection task can be considered as an image classification problem. In this formulation, the best performance, in various benchmarks such as ImageNet [23], is achieved by neural networks. Therefore, the neural network of the ResNet-18 [24] architecture was chosen as a model, which is the standard choice for the classification task.

Original data was transformed to input to the network using continuous wavelet transform. The CWT performs convolution for each of the 25 EEG signals $x_n(t)$ [27] with the basic function $\psi(\eta)$:

$$W_n(f,t_0) = \sqrt{f}\int_{-\infty}^{\infty} x_n(t)\psi^*(f(t-t_0))dt, \tag{1}$$

where N is the number of channels in the EEG recording, f is the frequency, t is the time, $W_n(f,t)$ are the coefficients of the wavelet transform. The sign $*$ denotes a complex conjugate function. The Morlet wavelet was used as the basis function of the CWT:

$$\psi(\eta) = \frac{1}{\sqrt[4]{\pi}} e^{j\omega_0\eta} e^{-\frac{\eta^2}{2}}, \tag{2}$$

where $\omega_0 = 2\pi$ is the central frequency of the wavelet. Finally, the power of the obtained spectrum for each channel in the frequency range of 1-40 Hz was considered as an input for the models.

It is important to note that the existing data set is highly unbalanced - more than 99% of the total recording time corresponds to the normal activity. Therefore, during the training of the coarse network from the first stage, for each patient, 50 segments with normal activity and 50 segments with epileptic activity were randomly selected. To train the refinement network from the second stage 100 segments containing the first model's errors were added to 100 randomly chosen segments.

Both models were trained for 10 epochs, with a mini-batch size of 4, a learning rate of 0.001, Adam optimizer, and binary cross entropy as a loss function. To make models more robust and suppress the effects of overfitting SpecAugment [25] and MixUp [26] techniques were used.

C. *Fusion and evaluation*

Once both coarse and refinement models are trained we need to develop a fusion mechanism for their predictions to use a two-stage model. This was achieved in the following way (illustrated in Fig. 2):

- The coarse model trained on the original data predicts whether or not 10-second segments contain epileptic activity
- In case the coarse model predicted that the current segment contains an epileptic activity then we use the refinement model trained on errors of the coarse model to obtain a refined prediction.

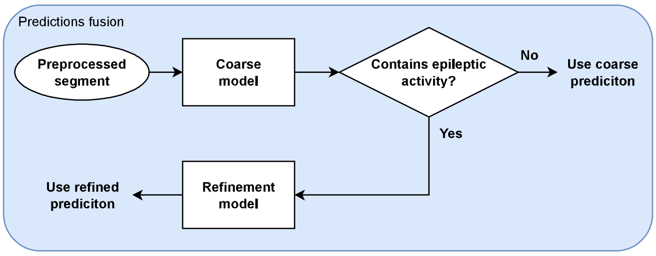

Fig. 2. Predictions fusion mechanism. The coarse model predicts whether or not EEG segments contain epileptic activity. In case the coarse model predicted that the current segment contains an epileptic activity then the refinement model refines prediction

The threshold for assigning a segment to a positive or negative class was selected based on the training data. After receiving the predictions of the coarse network, a large number of false positive network responses were observed only on one consecutive segment of 10 seconds. To solve this problem a median filter with a kernel size of $k = 7$ was used.

After the fusion and filtration were performed the quality of the model was evaluated using standard metrics for the classification task – $precision(P)$, $recall(R)$ and F_1:

$$P = \frac{TP}{TP + FP}, \tag{3}$$

$$R = \frac{TP}{TP + FN}, \tag{4}$$

$$F_1 = \frac{2 \cdot P \cdot R}{P + R}, \tag{5}$$

where TP is the number of true positive predictions of the model, TN is the number of true negative predictions of the model, FP is the number of false positive predictions of the model, and FN is the number of false negative predictions of the model.

IV. Results and discussion

In this paper, a two-stage model based on convolutional neural networks of the ResNet18 architecture was proposed for the detection of epileptic seizures. The results of the proposed model are presented in table I. To demonstrate the effect of the two-stage approach results of a single coarse model were added.

From the table I it can be seen that refinement network addition leads to better average F_1 and $precision$ metrics but at the same time to a significant loss in terms of average $recall$ metric. This is a natural result due to the fact that the

TABLE I
Training results

Model name	$precision$	$recall$	F_1
Coarse model	0.4196	0.7308	0.4382
Two-stage model	0.5339	0.4404	0.4566

coarse model produces a huge amount of false positives and small false negatives and therefore refinement model learns to predict positive class more carefully, which was reflected in the $recall$ metric. On the other hand, the noticeable improvement in the $precision$ metric is a positive event since usually, seizure detection models suffer from too many false positive responses, which makes it impossible to use such models as CDSS.

V. Conclusion

In this paper, the applicability of a two-stage model based on convolutional neural networks to improve the quality of seizure detection on real EEG data was studied. Usage of the proposed approach leads to fewer false positive predictions but at the same time tends to have noticeably more false negatives which increases the probability of missing a true epileptic seizure event. This is the reason why further research is needed to find a solution that can provide fewer false positives without significantly increasing the number of false negatives.

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