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# Mathematical model for epileptic seizures detection on an EEG recording

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***Abstract.*** *Purpose* of this study — analysis of the possibility of using convolutional neural networks as a model for detecting epileptic seizures on real EEG data *Methods.* In this paper, wavelet analysis is used for time-frequency analysis. To localize epileptic discharges, the task of detecting them was reduced to the classification task and the ResNet18 architecture of neural network was used. Techniques were used to augment and balance the biomedical data dataset under consideration. Wavelet analysis is used for time-frequency analysis. To localize epileptic discharges, the problem of their detection was reduced to the classification task, and the ResNet18 neural network architecture was used. Techniques were used to augment and balance the considered biomedical dataset. *Results.* Convolutional neural network can be successfully used to detect epileptic seizures, a method of postprocessing the results of primary detection is proposed to improve the quality of the model. It is shown that the developed model demonstrates high accuracy in comparison with other methods based on classical machine learning algorithms. The value of the $F_1$-score metric reaches 0.44, which is a high value for classification of the real biological data. *Conclusion.* The presented model based on a convolutional neural network for detecting epileptic seizures on an EEG recording can become the main one in medical decision support systems for epileptologist.

***Keywords***: EEG, time-frequency analysis, neural networks.

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## Introduction

Epilepsy is a chronic neurological disorder that manifests itself in the form of rare repetetive seizures caused by abnormal activity in the brain. A seizure is understood as abnormal activity of neurons in the brain, which can be accompanied by loss of consciousness, uncontrolled movements or other negative manifestations. At the time of 2016, more than 50 million people worldwide suffered from epilepsy [1]. However, it is worth noting that with timely detection and proper treatment, up to 70% of patients achieve a state of remission [2, 3]. To date, the main diagnostic tool for epilepsy is electroencephalography.

Electroencephalography (EEG) is a non-invasive measurement of the electrical fields 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, as a specialist needs to analyze a huge amount of data. For example, in some cases, the patient may stay in the clinic from several days to several weeks for long-term monitoring. This will require the analysis of hundreds of hours of EEG recordings [4]. The availability of an automated tool for detecting epileptic seizures on an EEG recording could significantly speed up the screening process, free the doctor from laborious work, and also provide an alternative opinion. Building such clinical decision support systems (CDSS) is currently an urgent and important scientific task [5, 6].

Today, there is a large amount of research in the field of EEG data analysis, and the detection of epileptic seizures is no exception [7]. In part of the papers, statistical models [8, 9] are used to identify seizures. But there are a large number of papers where various machine learning algorithms are used [10–12]. Recently, the deep learning industry has been actively developing, where neural networks show the best results in solving problems using data from various modalities, including images, texts and audio signals. As a result, many researchers are trying to apply artificial neural networks to the task of detecting epileptic seizures [13, 14].

However, most often the research and evaluation of the proposed models is carried out on publicly available data, among which the most common datasets used are Bonn-Barcelona EEG [15] and CHB-MIT [16]. However, these datasets have certain disadvantages that prevent the production of models ready for use in everyday non-invasive monitoring conditions. Thus, [15] contains data from invasive EEG monitoring of patients suffering from pharmacoresistant focal epilepsy, which is very different from how modern noninvasive EEG monitoring is carried out. The dataset [16] contains data on only 23 patients under the age of 22, including 5 men. This may not be a representative sample enough, as it is known that EEG data is highly variable from patient to patient [17].

In this paper, the question is investigated: whether an approach based on convolutional neural networks can be used as a model for detecting epileptic seizures on real EEG recording data. To get an answer to this question, a dataset of noninvasive monitoring data is used, where all data were provided by the National Medical and Surgical Center named after N.I. Pirogov (Moscow), recorded using one device and marked up by one epileptologist, as well as frequency analysis methods. To localize seizures on the EEG, a hybrid approach is used, where first the signal is translated into the time-frequency domain using a continuous wavelet transform and then a convolutional neural network is used.

## 1. Methods

The general scheme of the study is shown in Fig. 1, where an oval is used to indicate data at various stages of processing, and a rectangle is responsible for indicating the stages of working with data. The dotted line indicates the optional use of the block. Each individual step will be discussed later in the article.

**1.1. Information.** The work uses data provided by the N.I. Pirogov National Medical and Surgical Center of the Ministry of Health of the Russian Federation (Moscow, Russia). All medical procedures were carried out at the Center in accordance with the Helsinki Declaration and the medical rules of the Center and were approved by the medical expert commission. All patients gave written informed consent before participating. The dataset includes anonymized data from long-term patient monitoring in the Department of Neurology and Clinical Neurophysiology from 2017 to 2019. Monitoring was carried out 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 necessary to make a correct diagnosis. The data contains records of 83 patients diagnosed with focal epilepsy. Epileptic foci were found in the frontal, temporal, or parietal regions of the left, right, or both hemispheres. From one to five epileptic seizures were recorded in each patient during the follow-up. EEG signals were recorded with a sampling rate of 128 Hz over 25 channels according to the international 10–20 [18] system. An example of the data is shown in Fig. 2.

**1.2. Time-frequency analysis.** The analysis of the signals was performed using the continuous wavelet transform (CWT) [19]. The CWT performs convolution for each of the 25 EEG signals $x_n(t)$ with the basic function $\psi(\eta)$:

$$W_n(f,t_0) = \sqrt{f}\int\limits_{-\infty}^{\infty} x_n(t)\psi^*(f(t-t_0))dt, \quad n=1,2,\ldots,N, \tag{1}$$

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

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

where $\omega_0 = 2\pi$ — the central frequency of the wavelet, which describes its general behavior, determined by approximating the wavelet with a sine wave.

Next, the power of the obtained spectrum in the frequency range of 1...40 Hz was considered:

$$\hat{W}_n(f,t) = |W_n(f,t)|^2, \quad n=1,2,\ldots.N, \tag{3}$$

**1.3. Mathematical model.** The detection of epileptic seizures on the EEG recording was reduced to the classification of disjoint segments of the EEG recording of a fixed length (in this work — 10 seconds) after the wavelet transform. These segments can be considered as 25-channel images and, therefore, the task is to classify these images. In this formulation, the dominant position is occupied by neural networks, which since the advent of AlexNet [20] in 2012 have occupied leading positions in various benchmarks, such as ImageNet [21]. Therefore, the neural network of the ResNet-18 [22] architecture was chosen as a mathematical model, which is the standard choice for the classification problem.

Neural networks tend to converge faster and more stable when the input data is normally distributed with a near-zero mean and limited variance. However, the overall power distribution

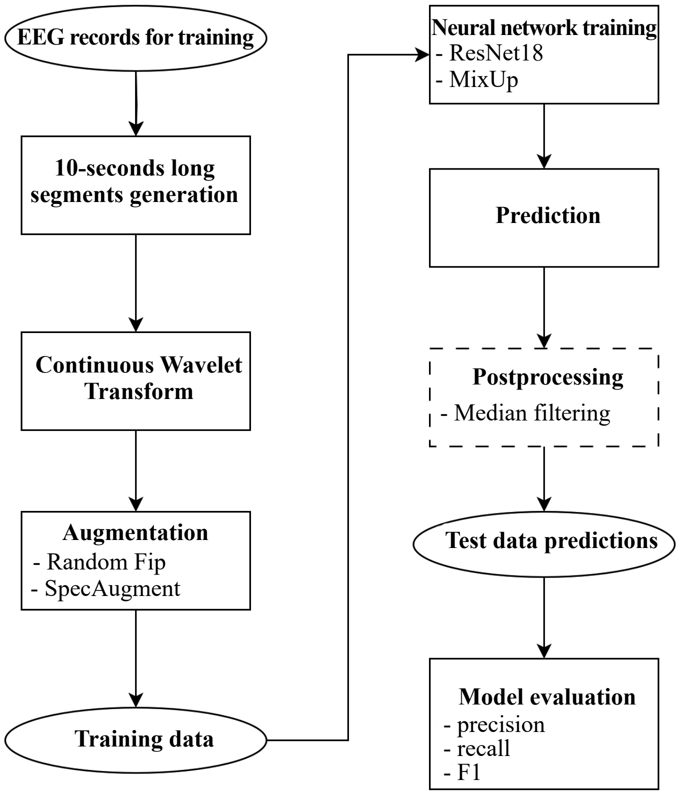


Fig 1. Study scheme. The oval represents data at various stages of processing. The rectangular block describes the data processing steps. The dotted line indicates the optional use of the block

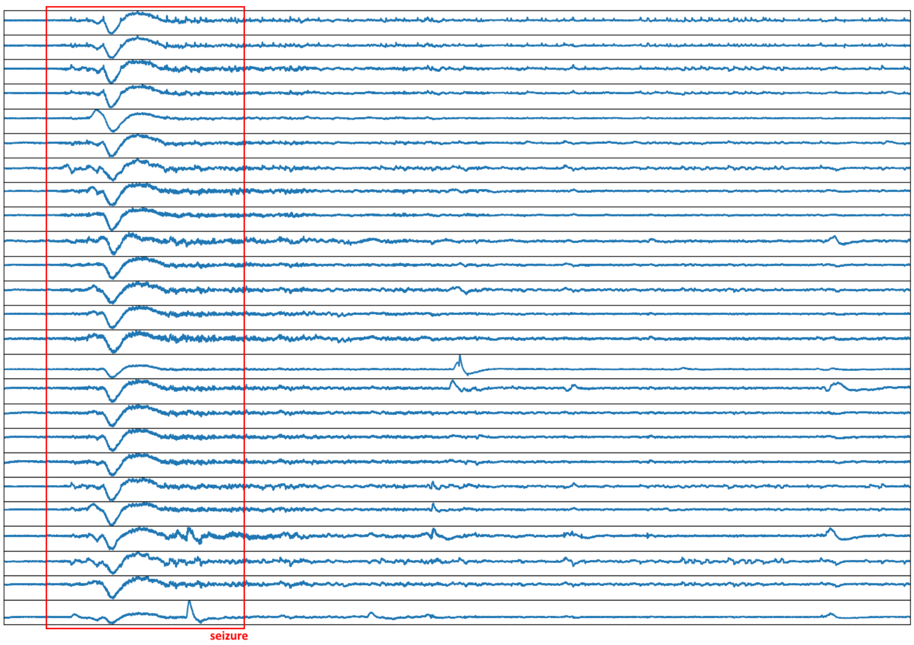


Fig 2. EEG record from the dataset with a seizure, which is highlighted in red (color online)

of the spectrum is asymmetric, close to exponential, due to the fact that many values are close to zero. Therefore, the input for the network was normalized logarithm of the power of the spectrum:

$$\hat{W}_n^{\log}(f,t) = \log(\hat{W}_n(f,t)), \tag{4}$$

$$\hat{W}_n^{\text{norm}}(f,t) = \frac{\hat{W}_n^{\log}(f,t) - \mu(\hat{W}_n^{\log})}{\sigma(\hat{W}_n^{\log})}, \tag{5}$$

where $\mu(X) = \frac{1}{|X|}\sum_{x\in X} x$ — average value, $\sigma(X) = \sqrt{\frac{1}{|X|}\sum_{x\in X}(x-\mu(X))^2}$ — standard deviation.

In order to get better results and accelerate the convergence of the model [23], pre-trained weights of the corresponding architecture are usually used, trained on the classification task on a dataset of color images (such pre-trained weights are usually present in all modern software packages). However, color images have 3 channels, and the available EEG data after the wavelet transform is 25 channels. To solve this problem, a special initialization scheme for the first convolutional layer of the neural network was implemented. Each filter of the first convolutional layer of the pre-trained network was averaged along the channel dimension of the input image. Then, for each filter, the corresponding "average"was duplicated 25 times. This approach made it possible to use the parameters of the pre-trained model and start training with a good initial approximation.

The available dataset is highly unbalanced — more than 99% of the total recording time corresponds to the normal condition of the patient. Therefore, during network training, an equal number of segments containing and not containing an epileptic seizure were randomly selected. In this study, 100 segments containing normal activity and 100 segments containing epileptic activity were selected for each patient.

The training of the network was carried out on the data of 34 patients, testing — on the data of 45 patients and 4 records were excluded from consideration, as they revealed flaws in the markup at the stage of analysis of the initial data. For example, the records of two patients had one seizure lasting 1000 seconds at the end of the recording, which is several times longer than the maximum duration of the seizure in all remaining records. Another 2 records were excluded from consideration after consulting with a doctor due to the significant number of artifacts during EEG registration.

Model Training Parameters:

- number of epochs — 10,
- learning rate — 0.001,
- butch size — 4,
- optimizer — Adam.

Binary Cross Entropy was used as a loss function for the neural network:

$$\text{BCE} = -\frac{1}{N_{\text{data}}}\sum_{i=1}^{N_{\text{data}}}(y_i\log(x_i) + (1-y_i)\log(1-x_i)), \tag{6}$$

where $N_{\text{data}}$ — number of training examples, $x_i$ — model prediction, $y_i$ — true label.

**1.4. MixUp and augmentation.** Augmentation techniques and the MixUp [24] approach were used to improve network performance. The MixUp approach allows you to increase the number of unique examples in the dataset by mixing the available data in a certain proportion. This allows you to get the linear behavior of the model in the intervals between the training

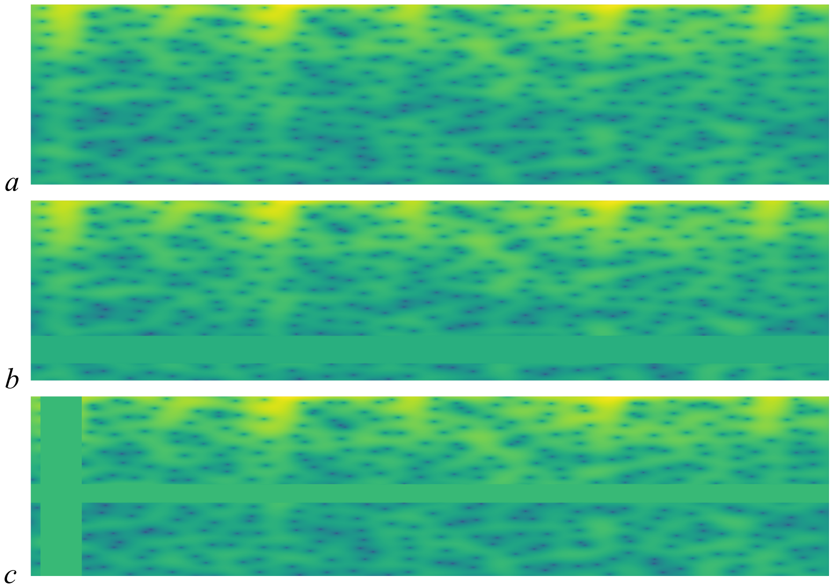

Fig 3. Example of SpecAugment. *a* — source; *b* — frequency masking; *c* — time and frequency masking (color online)

examples. This improves the stability of the network, as it allows you to use examples for training that are difficult to obtain in real life. Experiments show that when using MixUp, the acceptance boundaries move linearly from class to class [24]. Mathematically, MixUp can be written as follows:

$$\begin{cases} \widetilde{x} = \lambda x_i + (1-\lambda)x_j, \\ \widetilde{y} = \lambda y_i + (1-\lambda)y_j, \end{cases} \tag{7}$$

where $(\widetilde{x}, \widetilde{y})$ — a new training example, $(x_i, y_i)$ and $(x_j, y_j)$ — two random training examples from the dataset, $\lambda$ — the value from the beta distribution, that is, $\lambda \sim \mathrm{B}(\alpha,\alpha)$, $\lambda \in [0,1]$. In this paper, $\alpha=1$.

Augmentations are techniques for increasing the variability of a dataset by using transformations on the source data. This allows you to get more stable and accurate solutions. In this work, random reflection of the spectrum power of a 10-second time interval was used as augmentations, as well as the SpecAugment [25] approach — a simple augmentation method originally proposed for the speech recognition task. SpecAugment is applied directly to the power of the spectrum and consists in masking blocks of frequency channels and/or masking blocks of time channels, that is, replacing the original values of the block with 0 or the average value of the spectrum power. In Fig. 3 shows an example of using this augmentation, where the original values are replaced by the average. Here is the original power of the spectrum (Fig. 3, *a*), the power of the spectrum using frequency masking (Fig. 3, *b*) and the power of the spectrum using frequency masking and time masking (Fig. 3, *c*).

**1.5. Post-processing.** Based on the training data, the threshold for assigning a segment to a positive or negative class was selected. After receiving the network predictions, a large number of false positive network responses were observed only on one consecutive interval of 10 seconds. In Fig. 4 this observation is demonstrated: 2 false positive triggers, indicated by pink columns, each trigger lasts for 10 seconds. This is a serious problem, since with the actual use of such a model, the doctor will need to spend a huge amount of time viewing false «suspicious»

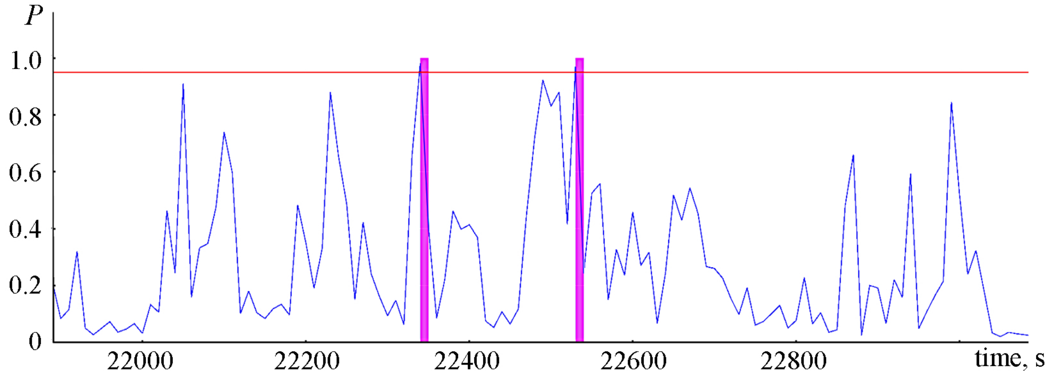


Fig 4. Dependence of the network's confidence on time. Red line shows the classification threshold, pink columns are single 10 seconds long false positives (color online)

segments that actually do not contain abnormal activity.

To solve the problem of a large number of single false positives, the distribution of the duration of seizures was considered. This is shown in Fig. 5. To build the model, the durations of all seizures in all patients were calculated. It can be seen from the distribution that the minimum duration of an seizure is more than 40 seconds, and the average duration of an seizure is more than 100 seconds. Therefore, in order to minimize the number of single false predictions, it was decided to apply post-processing. To do this, a median filter with a kernel size of $k = 7$ was used. This approach, in contrast to the selection of heuristic rules for assigning a segment to a false positive, makes it possible to smooth the signal as a whole and obtain less stochastic predictions.

To assess the quality of the model, standard quality metrics for the classification problem were used — *precision* ($P$), *recall* ($R$) and $F_1$, based on errors of the 1st and 2nd kind that occur when checking statistical hypotheses:

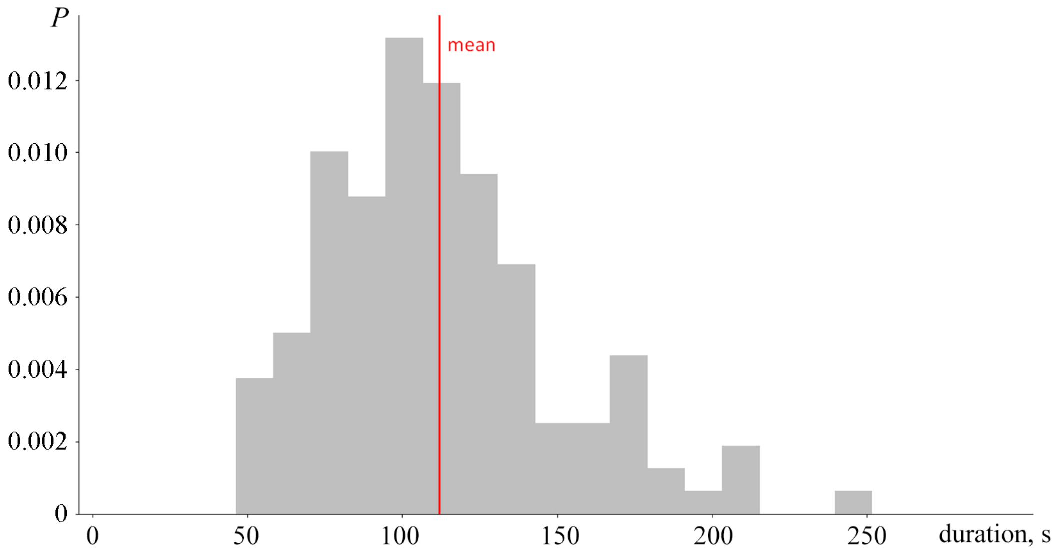


Fig 5. Estimation of the probability density function (PDF) of the distribution of the duration of epileptic seizures in the data set used. Red vertical line shows average seizure duration (color online)

Table 1. Training results of the model

| Subset | *precision* | *recall* | $F_1$ |
|---|---|---|---|
| Train | 0.7771 | 0.7794 | 0.7782 |
| Test | 0.1903 | 0.7199 | 0.2495 |
| Test, median filter $k = 7$ | 0.4196 | 0.7308 | 0.4382 |

$$P = \frac{TP}{TP + FP}, \tag{8}$$

$$R = \frac{TP}{TP + FN}, \tag{9}$$

$$F_1 = \frac{2 \cdot P \cdot R}{P + R}, \tag{10}$$

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, $FN$ is the number of false negative predictions of the model.

## 2. Results and discussion

In this paper, a model was proposed for the detection of epileptic seizures based on the convolutional neural network of the ResNet18 architecture. In Fig. 6 shows examples of seizures that the proposed model recognized as truly positive (Fig. 6, *a, b*) and false positive (Fig. 6, *c, d*). For clarity and compactness of the display, it was decided to visualize the original signal and the power of the spectrum (formula (3)) after baseline correction, only for the Cz channel, which corresponds to the central electrode located on the median sagittal plane of the skull.

The results of network train on training and test sets are presented in the table 1. From the table 1 it can be seen that when switching from the training set to the test set, there is a significant decrease in the *precision* metric, and with it $F_1$. This is due to the fact that during training, 100 segments of normal and epileptic activity were randomly selected for balancing the dataset, and during the testing phase, the entire record is divided into consecutive 10-second segments. Considering that the average recording duration is more than 12 hours and more than 99% of recordings are normal activity, on inference the number of segments containing normal activity is many times higher than their number during training. Consequently, the number of false positive positives also increases, which is reflected in a decrease in the value of the *precision* metric.

It follows from the table 1 that median filtering significantly improves the results of the proposed model. The improvements are most noticeable in the *precision* metric. This is a natural result, since the median filter is especially effective in impulse noise reduction, which is what single false positives of the model are.

To demonstrate the effectiveness of the proposed method, the table 2 provides a comparison with the methods proposed in [26, 27], which are based on classical machine learning algorithms and use the same data set.

The model proposed in this paper, without the use of postprocessing, reaches the value of the metric $F_1 = 0.2495$. This surpasses the result presented in [26], where the authors generate features manually for subsequent classification using a random forest algorithm. The results demonstrated by our model are also comparable to the results presented in [27]. In it, the authors

Table 2. Comparison of models

| Model | *precision* | *recall* | $F_1$ |
|---|---|---|---|
| Random Forest [26] | 0.0533 | 0.7867 | 0.0933 |
| One-class SVM [27] | 0.1270 | 0.7697 | 0.2058 |
| ResNet-18 | 0.1903 | 0.7199 | 0.2495 |
| ResNet-18 медиан. фильтр. $k = 7$ | 0.4196 | 0.7308 | 0.4382 |

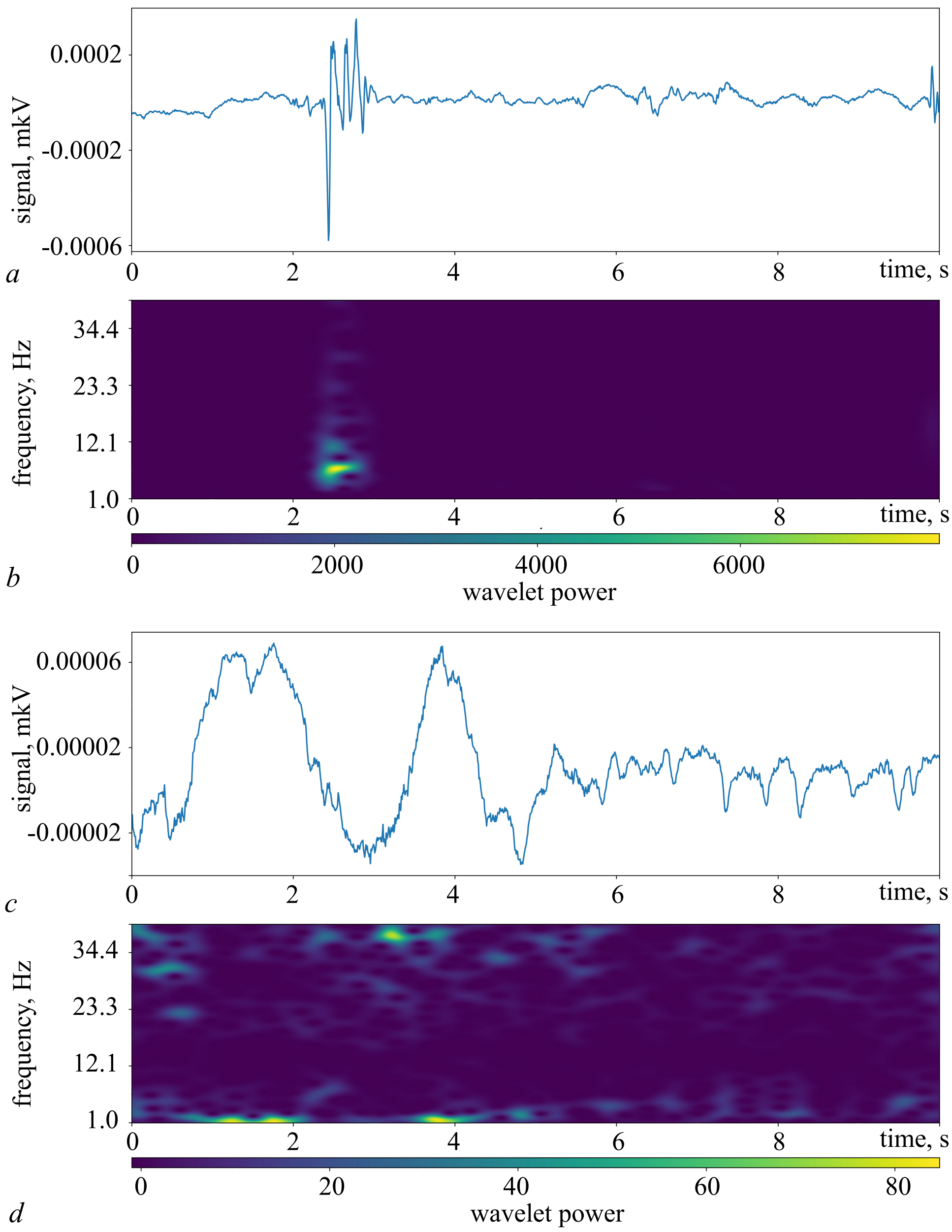


Fig 6. An example of seizures that developed model detects: *a* — the original signal of a true positive segment; *b* — the power of the spectrum of a true positive segment; *c* — the original signal of a false positive segment; *d* — the power of the spectrum of a false positive segment (color online)

solve the problem of detecting seizures as an outlier detection problem using a single-class SVM [28].By adding a post-processing step, the results are significantly improved. The final value of the $F_1$ metric is 0.4382. This surpasses the results in [26, 27] and demonstrates the effectiveness of the proposed method.

Another important task is to create brain-computer interfaces for non-drug interruption of epileptic seizures [29], which are based on predicting the formation of an seizure by EEG/ECoG signals and subsequent brain stimulation by the interface [30, 31]. The proposed model can be effective for solving this problem, since the classification is carried out in short (up to 10 seconds) intervals. However, there is a problem of the need to calculate the wavelet spectra over the entire frequency range. This leads to a large expenditure of machine time. Therefore, further optimization is necessary to use the algorithm in real time. It is important to analyze the most significant frequency range over which the restoration of the wavelet spectrum is necessary.

## Conclusion

In this work, the effectiveness of using a convolutional neural network to detect epileptic seizures on EEG recordings was demonstrated. Augmentation techniques and a special training scheme were used to obtain a high-quality solution. The table 2 shows that the proposed model based on the convolutional neural network of the ResNet18 architecture with a median filter for postprocessing is generally superior to models based on classical algorithms (despite a small loss in the *recall* metric). The proposed model does not require manual feature generation. This is an advantage over classical approaches. The proposed model does a good job of identifying segments containing an seizure, but there are problems with false positives. This is due to the complexity of the original signal — great variability within the recording of one patient and between the recordings of several patients. Among all the seizures of all patients, the model marked at least one segment as epileptic, which means that when the doctor looks at such "suspicious"segments, not a single seizure will be missed. This is a key criterion for the applicability of the model as a clinical decision support system (CDSS).

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