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Classifier for Detecting Outliers in Epileptic Seizures

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Abstract—The authors consider a classifier for detecting seizures on electroencephalogram records. The classifier is based on a one-class support vector machine, due to features of brain activity during epileptic seizures. A transparent feature selection procedure is used to improve the interpretability of the classifier.

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INTRODUCTION

Epilepsy is a group of neurophysiological diseases characterized by the onset of seizures that can range from short episodes with no clinical manifestations to prolonged convulsive attacks [1, 2]. According to global statistics, epilepsy is one of the most common neurophysiological diseases [3]. Attacks are accompanied by involuntary movements and a state of temporary incapacity, posing a danger to both the patient himself and those around him. Patients with epilepsy are also more prone to cognitive and behavioral disorders [4]. Epilepsy can be treated surgically or with medication, but both require prior diagnosis [5].

Specialists face many problems when diagnosing epilepsy. It has a variety of causes (e.g., heredity, brain injury, stroke, tumor), and the exact cause often remains unknown [6, 7]. This results in many manifestations of epilepsy, which (along with the random nature of the onset of seizures) greatly complicates diagnosis [8].

One of the most common ways of diagnosing epilepsy is to study electroencephalogram (EEG) [9]. Patients are observed in a hospital for long periods of time during such studies, and their EEG data is deciphered by an expert searching for epileptiform activity that emerges spontaneously or as a result of ongoing functional tests. This means of diagnosis is very reliable, but its main drawback is the need to decipher the EEG. A generally accepted means is visual analysis with manual interpretation of the EEG. Manual EEG decoding requires considerable effort even from an expert neurophysiologist and can be influenced by the human factor. This field of medicine therefore needs reliable automated means of EEG diagnostics. The fully automatic detection of EEG seizures would seem to be the most attractive option, but even modern means in this area have a high probability of misdiagnosis. Such mistakes can negatively impact a patient's physical and mental health, resulting in the need for additional treatment and rehabilitation. A possible solution to this problem is the partial automation of diagnostics, in which an automated algorithm analyzes the data and obtains preliminary results, but the final decision is made by an expert. This principle underlies the construction of medical decision support systems (MDSSes) [10].

METHODS

A promising area for developing ways of diagnosing epilepsy is machine learning [11]. When detecting epileptic seizures, the EEG data are usually divided into two classes: seizures and non-seizures (normal activity) [12, 13]. However, the distribution of examples according to class is often highly biased: only several minutes of epileptic activity are observed in tens of hours of recorded EEGs. Figure 1 shows an example of a long EEG recording for a patient with epilepsy. The figure clearly shows that the 24-h EEG recording (Fig. 1a) contains only two epileptic seizures (Figs. 1b and 1c) with a total duration of 140 s (~0.16% of the entire recording). There is thus a class imbalance in the epileptic EEG data, in which classical models show poor accuracy of classification for the class less represented (in this case, seizures). This is because many classical models are based on the assumption of equal distributions of examples between classes.

It should be noted that the problem of class imbalance arises when training an algorithm, resulting in discussions of two main types of machine learning algorithms: supervised and unsupervised. Supervised algorithm is trained on pre-labeled data in order to then independently label new unlabeled data [14]. In diagnosing epilepsy, the EEG recordings with epileptic activity are pre-marked by an expert, and then can be used to train a machine learning algorithm [15]. A review of the literature shows that most modern ways of detecting seizures are based on supervised learning [16]. Such means usually have higher accuracy of classification, but they face certain problems: a high prob-

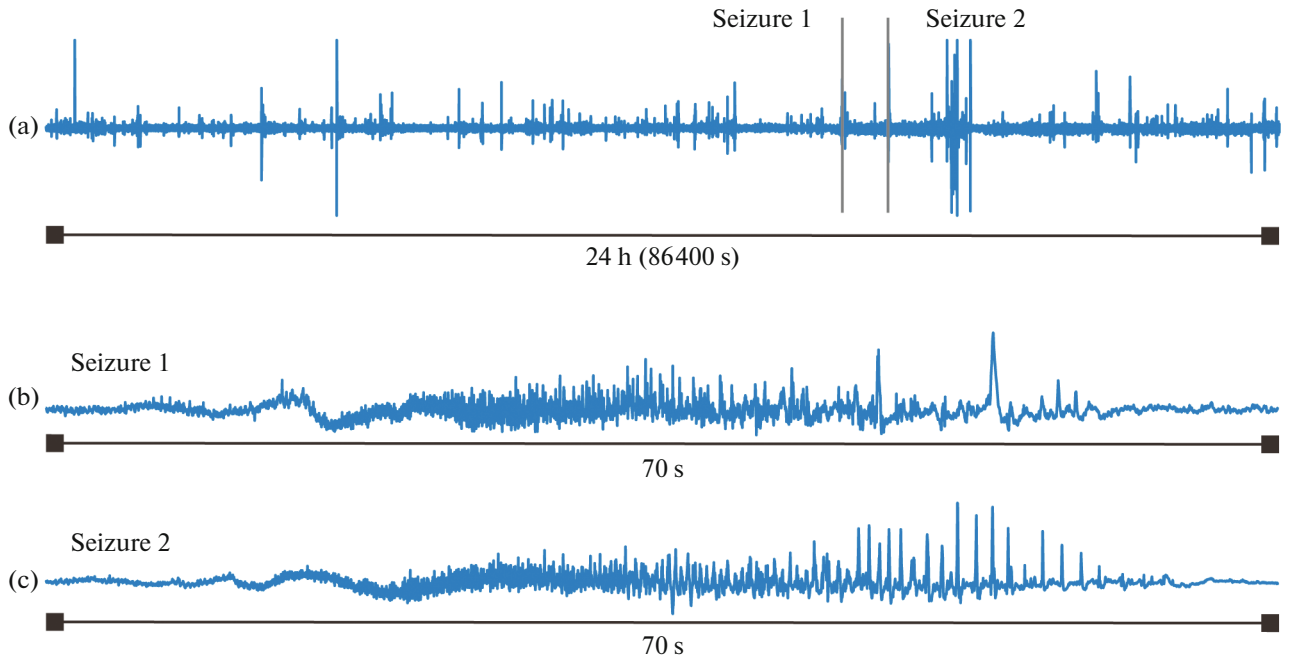

Fig. 1. Example of a daily EEG recording with two seizures (indicated by vertical grey stripes). One of the EEG channels shows (a) a full recording lasting 24 h and (b, c) two epileptic seizures lasting 70 s each.

ability of overfitting the algorithm is added to the problem of class imbalance. As mentioned above, the EEG data in epilepsy can vary greatly, and the lack of representation of epileptic activity results in poor reproducibility of the pattern of epileptic seizures. To solve this problem, we must use a large set of variable EEG data when training the algorithm, and the collection of such data is a complex task in itself. A more practical solution to this problem could be to use unsupervised learning [17], in which a set of unlabeled data is analyzed, clustered, and divided into classes (e.g., background EEG activity and seizures).

In this work, we propose using an unsupervised machine learning algorithm to solve the problems of class imbalance and the possible overfitting of the classifier. The unbalanced classes in an epileptic EEG are so pronounced that there is only one class of normal activity, while examples of seizures are considered anomalies or outliers. In machine learning, one of the most popular ways of finding outliers is one-class Support Vector Machines [18]. This option has proven to be reliable in analyzing a variety of biological data [19, 20].

Machine learning in problems of diagnosis usually results in the development of classifiers, interpretable or non-interpretable. Non-interpretable classifiers classify data without explaining how they work. Such classifiers are typically the ones most promising and provide high accuracy of 99–100%. However, algorithms of this type of classifiers often cannot be interpreted by a human [21, 22]. This means non-interpretable classifiers cannot be used to obtain new knowledge about gathered data. Interpretable classifiers act as an alternative: their accuracy of classification is lower on average, but the algorithms and results of the work can be interpreted by a human [23, 24].

One way to make a machine learning algorithm more interpretable is through a transparent feature selection procedure. For multichannel EEG data, a set of features can be obtained from the spatial–frequency–time domain that together comprise a multidimensional feature space [25]. A feature selection procedure is needed because having many features negatively affect computational costs. This procedure is most often performed automatically, and features are selected on the basis of maximum relevance or minimum redundancy. To provide greater interpretability, however, the feature selection procedure can be based on knowledge of the frequency–time structure of an EEG.

In selecting features for the classifier, we used results from our earlier studies of epileptic EEGs. In terms of frequency, we had already shown that epileptic seizures manifest as spikes in the energy of a continuous wavelet transform (CWT) averaged over a certain area of the spatial–frequency–time domain [26, 27]. As a feature, we used the average CWT energy in the 2–5 Hz range of frequencies over 25 EEG channels and in 60-s time intervals.

RESULTS AND DISCUSSION

We tested a classifier based on a one-class SVM (support vector machine) using the average CWT

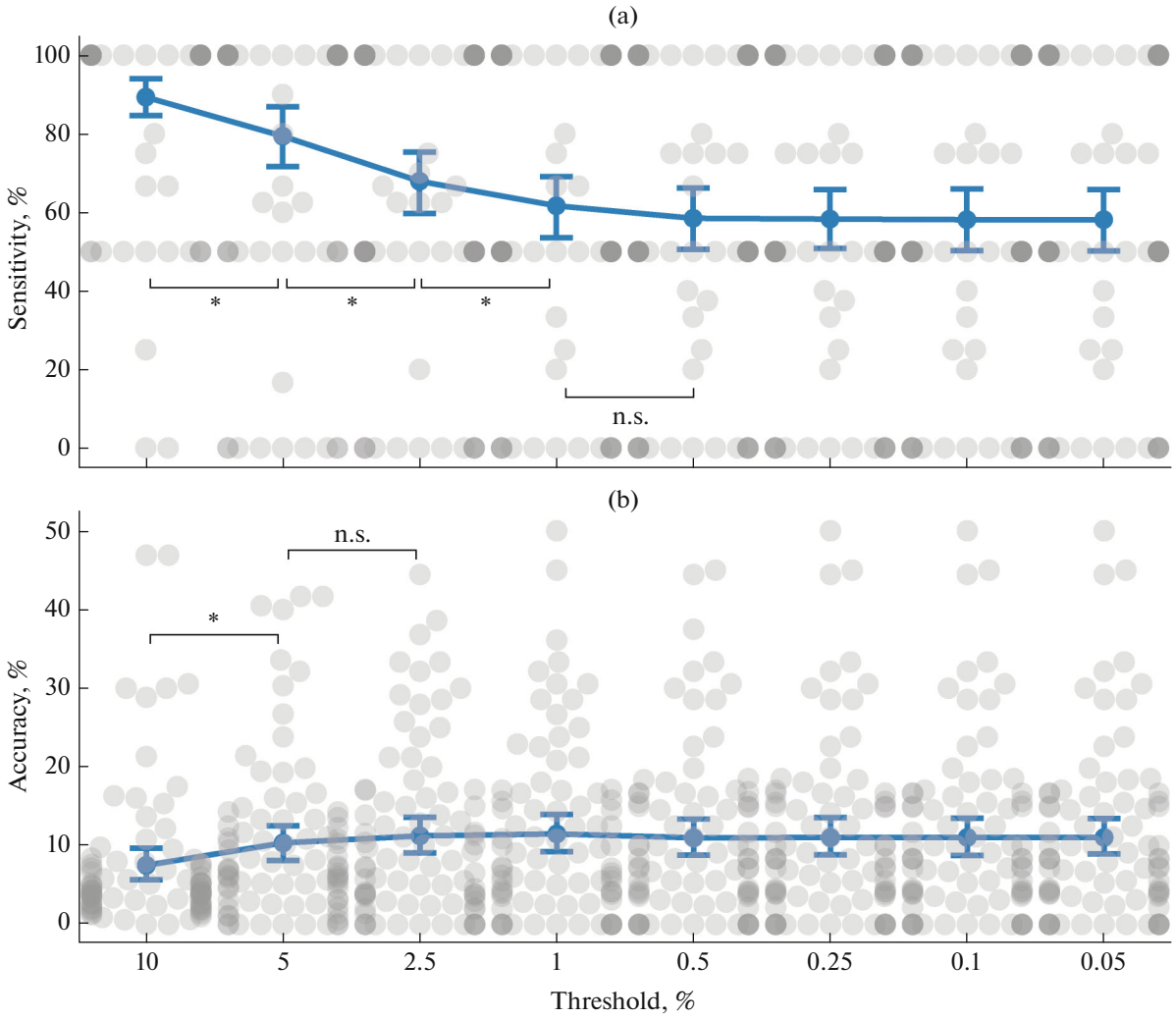

Fig. 2. Dependence of the (a) sensitivity and (b) accuracy of the classifier on the threshold value. A statistically significant difference is marked with an asterisk (*); a non-significant difference is labeled n.s.

energy as a feature. This classifier was tested on a set of data recorded in 83 patients with various forms of focal epilepsy. To evaluate the performance of the classifier, we calculated such indicators as sensitivity (true positive rate, TPR) and accuracy (positive predictive value, PPV):

$$\mathrm{TPR} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FN})100}\%, \quad (1)$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FP})100}\%, \quad (2)$$

where TP (true positive) is the number of correctly recognized seizures, FP (false positive) is the number of falsely recognized seizures, and FN (false negative) is the number of missed seizures.

For the classifier, we also considered two hyperparameters that can affect the efficiency of classification:

(1) Threshold, the expected percentage of outliers in the training data. We considered the values 10, 5, 2.5, 1, 0.5, 0.25, 0.1, 0.05%.

(2) Type of training, the strategy used in training and testing the algorithm. We considered cross-validation (CV) and sliding control (leave-one-out, LOO). In the former, the data set for one subject is divided into k fragments: $k-1$ fragments are used to train the classifier, and the classifier is tested on the kth fragment. In the latter, data on 82 adult subjects are used for training, and the data of the 83rd are used for testing the classifier.

Statistical analysis was performed using the Wilcoxon test to determine the optimal hyperparameter values for the classifier.

Figure 2 shows the dependence of the sensitivity and accuracy of the classifier on the threshold value. As can be seen from Fig. 2, the sensitivity and accuracy changed considerably as the threshold fell, but the

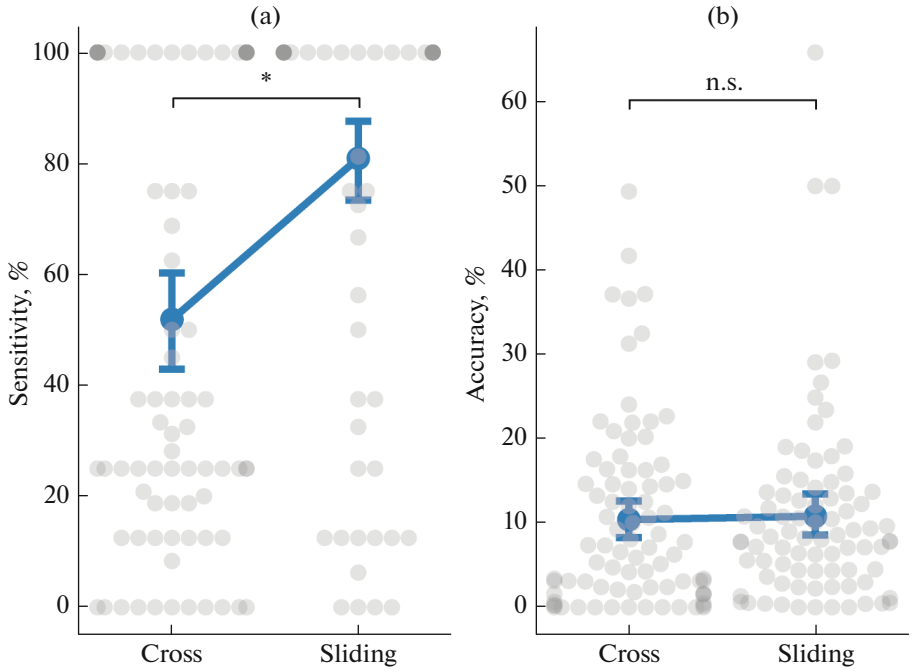

Fig. 3. Dependence of (a) sensitivity and (b) accuracy of the classifier on the type of training: cross-validation or sliding control. A statistically significant difference is marked with an asterisk (*); a non-significant difference is labeled n.s.

change ceased to be significant at a certain point. The sensitivity fell along with the threshold, and the drop remained significant down to the 1% threshold (Fig. 2a). The accuracy rose as the threshold fell, but its significance remains only up to 5% of the threshold value (Fig. 2b). The threshold value of 5% can thus be considered optimal, since the accuracy stops growing and the sensitivity remains high.

Figure 3 shows the dependence of the classifier's sensitivity and accuracy on the type of training: cross-validation and sliding control. Figure 3a shows that the sensitivity for cross-validation is much higher ($p = 3.18 \times 10^{-7}$) than for sliding control: TPR = 76.97 ± 4.40 versus TPR = 39.96 ± 5.20. At the same time, the accuracy is not significantly different ($p = 0.12$) for cross-validation and sliding control: PPV = 12.70 ± 1.47 and PPV = 9.30 ± 1.72 respectively (see Fig. 3b). Cross-validation is clearly a more appropriate type of training for a classifier.

CONCLUSIONS

We selected the optimal values for classifier hyperparameters. The final sensitivity of the classifier was TPR ~ 77%, and the PPV accuracy was ~13%. This accuracy may seem low, but we must take into account the considerable length of EEG recordings—in some cases, around 80 h. A classifier with such characteristics can be used in an MDSS [28]. For example, we can replace analysis of the entire EEG record with that of episodes highlighted by the classifier. The work of an expert is still required in this approach, but the amount of analyzed data is considerably reduced. The work of the expert is also reduced, shortening the time of making a diagnosis for a particular patient.

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COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest. The authors declare that they have no conflicts of interest.

Statement of compliance with standards of research involving humans as subjects. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants involved in the study.

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