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APPLIED RESEARCH

# Classification of Epileptic Seizures by Simple Machine Learning Techniques: Application to Animals' Electroencephalography Signals

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This work involved experimental animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Bogomoletz Institute Committee for Biomedical Ethics, and performed in line with the international and national regulations on the use of experimental animals, in particular the Convention of the Council of Europe dated March 18, 1986 and the "Law of Ukraine on the Protection of Animals from Brutal Treatment" dated February 21, 2006.

**ABSTRACT** Detection and prediction of the onset of seizures are among the most challenging problems in epilepsy diagnostics and treatment. Small electronic devices capable of doing that will improve the quality of life for epilepsy patients while also open new opportunities for pharmacological intervention. This paper presents a novel approach using machine learning techniques to detect seizures onset using intracranial electroencephalography (EEG) signals. The proposed approach was tested on intracranial EEG data recorded in rats with pilocarpine model of temporal lobe epilepsy. A principal component analysis was applied for feature selection before using a support vector machine for the detection of seizures. Hjorth's parameters and Daubechies discrete wavelet transform coefficients were found to be the most informative features of EEG data. We found that the support vector machine approach had a classification sensitivity of 90% and a specificity of 74% for detecting ictal episodes. Changing the epoch parameter from one to twenty-one seconds results in changing the redistribution of principal components' values to 10% but does not affect the classification result. Support vector machines are accessible and convenient methods for classification that have achieved promising classification quality, and are rather lightweight compared to other machine learning methods. So we suggest their future use in mobile devices for early epileptic seizure and preictal episode detection.

**INDEX TERMS** Epilepsy, single-channel intracranial encephalographic data, PCA, SVM, automated system, rats.

## I. INTRODUCTION

Epilepsy is a chronic noncommunicable disease of the brain. Currently, around 50 million people worldwide suffer from epilepsy [1]. It is characterized by recurrent seizures that are accompanied by loss of consciousness and partial or generalized convulsions. If epileptic seizures are not stopped or if repeated seizures occur one after the other, severe brain injury or even death can result [2]. Currently, the majority of epilepsy cases are effectively managed with various pharmacological therapies. In high-income countries, up to 70% of people living with epilepsy could become seizure-free

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with the appropriate use of antiseizure medications; however, in low-income countries, this percentage is substantially lower [1]. Meanwhile, around 30% of patients worldwide have drug-resistant epilepsy (DRE) [3]. In some circumstances, surgery may be advantageous for these patients, but only for focal epilepsy cases [4].

Unfortunately, ensuring safety during seizures remains an urgent issue for the large number of patients suffering from DRE. During seizures, most people are unable to provide proper self-care, and external help is required. Usually, only qualified medical personnel can provide the necessary assistance to such patients to save their health and, in some cases, their lives. A mobile system for detecting and prediction of epileptic seizures in real-time is one of the options for solving this issue. Such a system should detect a pathological activity that precedes the seizure by analysis of electroencephalography (EEG) signals and should warn the patient about potential danger. The patient can warn others about the impending attack, take prescribed medications, and take the least traumatic position.

Automatic detection of epileptic seizures started its way a long time ago [5]. New efficient approaches become available today due to new achievements in hardware and data analysis. Concepts of portable devices for this purpose have already been created [6], [7]. However, not all of them have yet received practical clinical use, although there are studies in which such portable devices are used to collect data [8]. All these devices use software that collects the data, extracts EEG signal's features, and classifies the patient's state to be ictal, pre-ictal, or some other one.

The field of epileptic seizure detection and prediction faces several significant challenges. Foremost among these challenges is the complexity of numerical methods required for accurate signal classification. These intricate numerical techniques often result in performance issues, affecting the reliability and stability of seizure prediction devices. As a result, there is a pressing need to develop classification methods that offer computational efficiency while exploring informative EEG signal features. Furthermore, resilience issues, such as autonomy and artefacts, pose significant challenges [9].

In this paper, we present an approach for signal classification (Fig. 1) designed to be suitable for mobile devices. Our approach leverages simple yet effective classic signal classification methods, including Principal Component Analysis (PCA) and Support Vector Machine (SVM). We apply this approach to the detection of epileptic seizures in rats using the pilocarpine model of epilepsy and intracranial single-channel EEG signals. Intracranial EEG signals exhibit a higher signal-to-noise ratio and lower artefact levels when compared to signals obtained from the scalp, making them a valuable source for extracting informative features.

We demonstrate the efficiency of our proposed approach and provide a comparative analysis with other established methods. Our study addresses the existing challenges in epileptic seizure classification, offering a promising solution

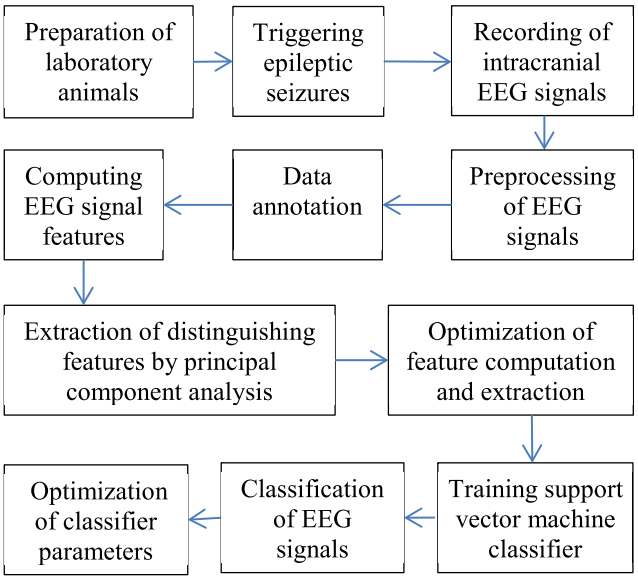


**FIGURE 1.** Research stages diagram.

that balances computational efficiency and informative feature extraction.

The paper is organized as follows: Section II contains a short overview of EEG signal classification; Section III describes electrophysiological experimental procedures and data used for classification; Section IV describes features used for data classification; Section V describes informative feature extraction approaches; Section VI describes data classification approaches applied in this work; Section VII gives a short result analysis and conclusions.

## II. EEG SIGNALS CLASSIFICATION

Work on the possibility of detection and predicting epileptic seizures in real time using brain interfaces appeared quite a long time ago [10]. Over time, works began to appear with a more systematic analysis of the application of the classification task e.g. [11] is a survey with more than 200 references. Indeed, the challenge of predicting impending epileptic seizures to warn patients has led to the development of new diagnostic tools and treatments for epilepsy. This task is not trivial and requires consideration of additional details e.g. the relationship between epileptic spikes and seizures [12]. The authors developed a new automated spike detection method to investigate this relationship by considering seizure severity and the spatial distribution of the spike frequency.

Nowadays a lot of different approaches for the automatic classification of EEG signals, including detection of epileptic seizures are reported [13] which we will discuss in the following paragraphs. Approaches that were implemented in practice are of greatest interest.

A system using an edge device as part of the Internet of Medical Things [14] operates in real-time and provides training accuracy of up to 99.4% with almost perfect sensitivity and specificity. This system uses Petrosian's fractal dimension for feature extraction and a computationally intensive ordinary kriging model is used as a classifier.

Conversion of annotated EEG signals to images and consecutive application of convolutional neural networks (CNN) for image classification provides a classification accuracy of 94%-96% [15]. Such methods offer new opportunities for the early detection of epileptic activity [16]. Deep learning techniques, such as CNN, have demonstrated an accuracy of about 97% without the need to extract distinguishing features of epileptic events [17]. Additionally, new algorithms have been proposed for real-time monitoring and prediction of epileptic seizures, which could greatly enhance patients' quality of life [18]. Another important development is the use of hybrid models and approaches that combine deep learning techniques with traditional algorithms. Application of the classifier trained using an animal model to human EEG signals achieves an F1-score of 93% [19]. Studies have also been conducted on the use of signal processing methods to improve the quality of EEG signals before their classification [20]. Other approaches based on CNN achieve a classification accuracy of about 99.5%, as shown in studies such as [21]. Another group reported a classification accuracy of up to 91% using a similar approach and a different dataset [22]. According to [23], since 2020, about 78% of novel EEG classification approaches use deep learning.

Introduction of new signal features for classical classification approaches is also of interest. An EEG signal sample shifting [24] demonstrated accuracy rates of 99%, 98%, and 100% for normal vs. inter-ictal, inter-ictal vs. ictal, and normal vs. ictal classifications respectively. The review [25] discusses seizure localization methods based on EEG signals. An EEG epileptic signal classification algorithm based on an enhanced Radial Basis Function (RBF) [26] demonstrated accuracy up to 92% and robustness against errors, making it a promising approach for improving the reliability and precision of seizure detection in clinical settings. Multifractal detrended fluctuation analysis [27] is a unique approach that extracts a feature vector for further classification. The authors claimed that epileptic seizure classification accuracy can reach 99% using such an approach. Genetic programming [28] was applied to extract a new feature vector from a set of statistical signal components. Then these new features were used by a k-nearest neighbour (k-NN) classifier. The accuracy of epileptic seizures detection achieved 99% for the dataset used by the authors. It should be noted that different classifiers and/or different datasets could result in deviations in the detection accuracy. A line length algorithm [29] can be used for detecting pre-ictal events. Classification accuracy of this approach was found to be 89%, while sensitivity and specificity were 90% and 88% respectively.

Great interest is attributed to mobile EEG classification devices. Today there are many commodity installations of Brain-Computer Interfaces (BCI) available on the market. For example, EMOTIV EPOC+ allows recording electroencephalographic data in real-time. There is an interest in using such devices together with additional computing accelerators for data processing [30].

Special attention is paid to EEG data recorded during long-term time intervals. For example, a seizure detection algorithm based on two measures of nonlinear and linear dynamics, adaptive short-term maximum Lyapunov exponent (ASTL max) and adaptive Tiger energy (ATE) is presented [31]. The algorithm was tested on long-term (0.5–11.7 days) continuous EEG recordings from five patients with a total of 56 seizures, showing an average sensitivity of 91% and an average specificity of 0.14 false positives per hour.

Of particular interest are works in which the performance of the classification is analysed. The recent article [32] analyses several factors affecting the performance of seizure prediction models, focusing on post-processing aspects, seizure onset period (SOP), and seizure prediction horizon (SPH). In addition, this study provides some new directions and proposals for building high-performance forecasting models in the future.

In addition to the approaches mentioned above, there are even more complicated implementations of algorithms for the calculation and selection of features and their classification. Despite good reported classification quality such algorithms have their shortcomings. Results obtained using deep learning neural networks and other complex classification approaches with large degrees of freedom depend significantly not only on the trained dataset but also on the number of iterations used to train it. In this paper, we suggest an EEG signal classification approach that does not require large datasets and no significant computing power.

## III. INTRACRANIAL EEG SIGNALS

Non-invasive scalp electroencephalography, which uses electrodes placed on the scalp to measure the electrical activity of large, synchronously firing populations of neurons in the brain, is the most common type of EEG recording in humans. In the case of small animals with experimental epilepsy, the same technique can be used with minor modifications. However, due to parasite capacitances, signal filtering through bones and soft tissues, poor electrical contact with the skin, and other factors, the signal-to-noise ratio in such electrophysiological recordings is very low. It is well known that as a result of this distortion, the EEG signal loses a significant amount of information that could be used to predict epileptic discharges. The intracranial EEG (iEEG), also known as electrocorticography (ECoG) using subdural electrodes or stereotactic EEG (sEEG) using depth electrodes is much more suitable for this purpose. The iEEG signal provides precise information about the temporal dynamics of neural networks at the millisecond scale. It has been suggested that human iEEG recordings despite of some technical and ethical problems have a huge potential for providing information on brain function as well as various pathological states [33].

In the study presented here, we used EEG signals recorded in Bogomoletz Institute of Physiology, National Academy of Sciences of Ukraine. In the following paragraphs we are briefly describing the experimental set-up, steps taken to trigger epileptic seizures, preparation of the animals etc.

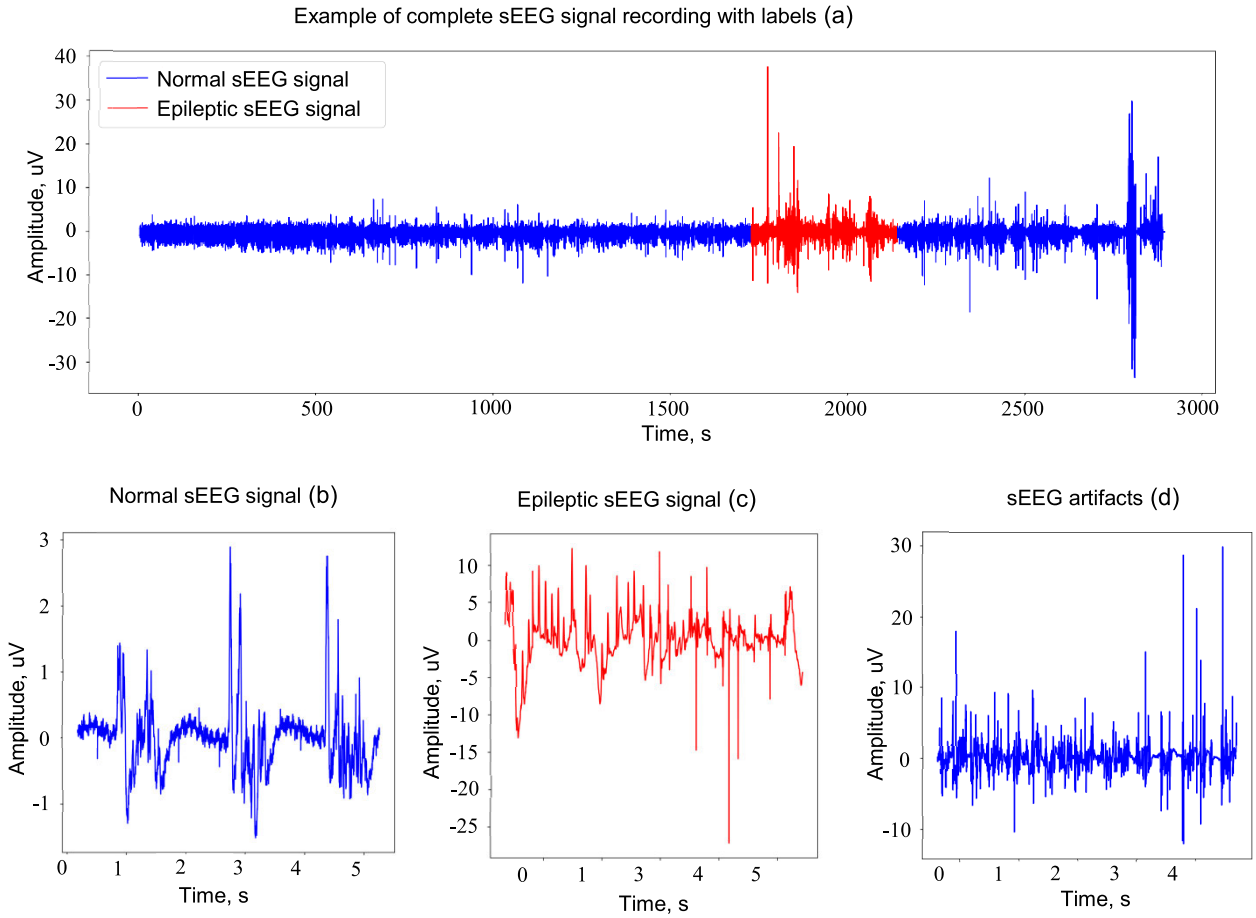


**FIGURE 2.** Examples of different typical EEG signals: labelled record after pre-processing (a); non-epileptic signal segment (b); epileptic signal segment (c); spiking artefacts segment (d).

The signals were recorded using the lithium-pilocarpine model of epilepsy in rats, which is a well-established model of human temporal lobe epilepsy [34]. The recordings were conducted on 60- to 90-day-old Wistar rats in accordance with international and national regulations on the use of experimental animals, in particular the Convention of the Council of Europe dated March 18, 1986 and the Law of Ukraine on the Protection of Animals from Brutal Treatment dated February 21, 2006. Animals were kept in a room with controlled temperature and light cycle (22°C, light phase started at 20:00 and lasted 12 h), food and water were available ad libitum. All experiments were performed in the dark phase. Rats were given an intraperitoneal injection of lithium chloride (127 mg/kg) 20-22 hours before pilocarpine administration. The first dose of pilocarpine was 30 mg/kg, followed by 10 mg/kg every 30 minutes as long as seizures did not occur. If rats did not have seizures after receiving a total dose of 60 mg/kg of pilocarpine, they were removed from the experiment. Seizures were stopped one hour after epilepsy induction with a diazepam (40 mg/kg) injection.

sEEG recordings (30-80 min long) were made from 13 rats anesthetized with 1.5 g/kg urethane injected intraperitoneally using a standard experimental procedure [35]. Skin and periosteum were removed from the skull. The dura was cut and removed. A burr hole 0.5 mm in diameter was drilled in the skull above the hippocampus. A wire electrode 50 $\mu$m in diameter (California Fine Wire, Grover Beach, CA, USA) for extracellular field potential (EFP) recordings was inserted into the application cannula 0.2 mm diameter, (Plastic One, Roanoke, VA). The tip of the recording electrode was extended for approximately 100 $\mu$m from the cannula ending. The application cannula with the recording electrode was positioned into the CA1 pyramidal cell layer of the hippocampus under stereotaxic and electrophysiological guidance (3.8 mm posterior, 2.5 mm lateral and 2.0 mm below dura). Reference and ground electrodes were implanted into the cerebellum. After stabilization of the signal (5-10 min), EEG monitoring was conducted. sEEG signals were recorded by using a differential amplifier (A-M Systems, Carlsborg, WA, USA) and digitized at 416 kHz using an A/D converter (NI USB-6009, National Instruments, Austin, TX, USA). All data were partitioned into about 60 sweeps of one minute for each animal.

The data underwent an initial filtration using the EEGLAB toolbox [36], removing noise and artefacts of biological nature. The first filtration step involved rejecting the 50 Hz

power line component. Then a high-pass filter with a cut-off frequency of 1 Hz and a low-pass filter with a cut-off frequency of 40 Hz were applied to remove slow drifts and high-frequency noise, which are standard in EEG pre-processing to ensure the quality of the signals. Reference electrode interpolation was performed to correct potential issues with specific electrodes. Finally, electromyogram (EMG) and electrooculogram (EOG) artefacts were filtered using Independent Component Analysis (ICA) based filters.

Regions of ictal and pre-ictal states were labelled by experts. The data were combined into a single array and standardized for more convenient processing. Fig. 2 shows examples of typical annotated signals coloured blue and red. Red labelled signal regions correspond to epileptic seizures (epileptic signal) while signal regions without seizures (normal signal) are labelled blue. Some spiking artefacts presumably associated with electrode mobility were still present in the signals after the prior filtering and were also labelled by experts. Examples of normal and epileptic signals are provided in Fig. 2. An example of a single annotated recording is displayed in Fig. 2a. The normal signal is coloured blue, while seizure segments are coloured red. A normal signal (Fig. 2b) corresponds to the normal rhythms of a rat's brain while epileptic signal patterns (Fig. 2c) differ significantly. The recorded signals have large variations in amplitude. The informative signals (Fig. 2b, 2c) should be distinguished from the artefacts that remained after the pre-processing stage (Fig. 2d) and which are presumably associated with the movement of the electrodes that may be present in the normal and in the epileptic signal.

For further analysis the combined data records were partitioned into epochs from 1 to 21 seconds long. Epochs' duration determines signal frequency resolution. To investigate the influence of the epochs' duration on data classification metrics we performed 11 different classification experiments. In 1st experiment we set the epoch's duration to 1 second; in 2nd experiment to 3 seconds; in 3rd experiment to 5 seconds and so on up to 21-second-long epochs in the last i.e. the 11th experiment. EEG signals' durations (Fig. 2a) are approximately several thousand seconds, so there are approximately $10^2$-$10^3$ epochs for each rat's signal depending on the epoch duration.

## IV. SIGNAL FEATURES

A set of 13 statistical characteristics was calculated for each epoch to be used as features for data classification. The following statistical parameters were used: mean signals' value (1), standard deviation of signal values (2), modulus of signal values difference (3), and skewness (4), where parameter $m$ is mentioned in (5). The mean value and standard deviation are widely used for detecting anomalies in EEG signals, as epileptic seizures are often accompanied by significant deviations from normal brain activity [37]. The modulus of signal values difference captures sharp changes in amplitude, which are particularly important when analysing epileptic seizures, where rapid and strong changes in neural activity are observed [38]. Skewness quantifies the asymmetry of the signal distribution, which can indicate pathological brain states such as epileptic seizures. An asymmetric distribution may signal a shift in neural activity coherence, potentially marking the transition to seizure states [39].

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{1}$$

$$\sigma = \sqrt{m_2}, \tag{2}$$

$$A = \sum_{n=1}^{N} |x_n - x_{n+1}|, \tag{3}$$

$$g_1 = \frac{m_3}{m_2^{3/2}}, \tag{4}$$

$$m_i = \frac{1}{N} \sum_{n=1}^{N} (x[n] - \bar{x})^i \tag{5}$$

Additionally, Hjorth parameters activity, mobility, and complexity [40] were computed. The Hjorth 'Activity' (6) parameter describes the average energy (variance) of the signal, which is crucial in EEG analysis, as increased signal energy is often observed during seizure onset. This parameter highlights changes in the overall signal power associated with pathological brain conditions [37]. Mobility describes the frequency shift corresponding to the power spectral density maximum of the signal. Epileptic seizures are known to produce significant changes in the frequency spectrum, making this parameter vital for accurate seizure detection [41]. Complexity describes variations of mobility and reflects the degree of similarity between the signal and harmonic oscillation. Epileptic seizures often lead to increased signal complexity due to the chaotic nature of brain activity during these events [42].

$$\text{Activity}(x) = m_2(x(t)), \tag{6}$$

$$\text{Mobility}(x) = \sqrt{\frac{m_2(\frac{dx(t)}{dt})}{m_2(x(t))}} \tag{7}$$

$$\text{Complexity}(x) = \sqrt{\frac{\text{Mobility}(\frac{dx(t)}{dt})}{\text{Mobility}(x(t))}} \tag{8}$$

In addition to the characteristics in amplitude-time representation the description of the data in time-frequency representation based on discrete Wavelet transform (DWT) [43] is used. The continuous wavelet transform is defined as follows:

$$\text{CWT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) * \psi\left(\frac{t-\tau}{s}\right) dt, \tag{9}$$

where $\text{CWT}(\tau, s)$ is the result of the continuous wavelet transforms at time offset $\tau$ with scale $s$, $x(t)$ is the signal under analysis, $\psi((t-\tau)/s)$ is the wavelet function scaled and shifted in time. Small values of $s$ correspond to high-frequency components, while large values correspond to low-frequency ones. Parameter $\tau$ is a time shift of the wavelet, allowing analysis of frequency spectrum at different moments in time. In this work the discrete wavelet transform

was computed as follows:

$$\begin{aligned} \mathrm{cA}_{k+1}(i) &= \sum_{j=0}^{N-1} h_j \mathrm{cA}_k (2i+j), \\ \mathrm{cD}_{k+1}(i) &= \sum_{j=0}^{N-1} g_j \mathrm{cA}_k (2i+j), \\ \mathrm{cA}_0(i) &= x(i), \end{aligned} \tag{10}$$

where $\mathrm{cA}_k(i)$ represents approximation coefficients of signal $x(i)$ at a scale $k$ and discrete time sampling offset $i$ that effectively encapsulates the low-frequency components of the signal, $\mathrm{cD}_k(i)$ represents detail coefficients that accentuate the high-frequency details of the same signal at the scale $k$ and discrete time offset $i$. The wavelet function $\psi$ from (9) is not used in closed form but is applied implicitly by successive application of low-pass filter $h_j$ and high-pass filter $g_j$ [43]. Instead of scaling the wavelet function $\psi$ (9) the signal $x(i)$ (or its approximation component $cA$) is decimated in half after convolution with filters $h_j$ and $g_j$ at each scaling stage $k$.

Coefficients of filters $h_j$ and $g_j$ were specially chosen to obtain the Daubechies wavelet transform of order $N = 5$ [44]. The Daubechies fifth order wavelet is asymmetric and has orthogonal among others properties [45]. This wavelet is mentioned in literature to be efficient for epileptic seizure feature extraction [46].

Mean value, standard deviation, and signal energy of the approximation $\mathrm{cA}_1$ and detail $\mathrm{cD}_1$ coefficients were used in this work as additional features for epileptic signal detection. Examples of such coefficients for a randomly taken epileptic signal are provided in Fig. 3a and Fig. 3b respectively. A signal of 1000 seconds duration demonstrates rarely encountered spikes in the detail component when the signal undergoes drastic changes. The first order only scaling ($k = 1$) was used because its detail and approximation coefficients correspond to the highest possible time resolution.

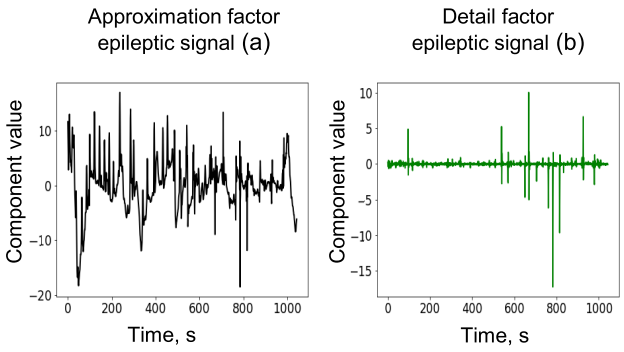


**FIGURE 3.** The first order scaling wavelet components for a 1000 seconds epileptic signal: approximation (a) and detail (b).

## V. INFORMATIVE FEATURES EXTRACTION

A large number of signal features significantly influence the performance requirements of a classification system and also may reduce classification quality. Thus, extraction of informative signal features is an essential stage of data classification for simple machine learning approaches. In this work principal component analysis (PCA) [47] is applied for transition into a space of informative characteristics.

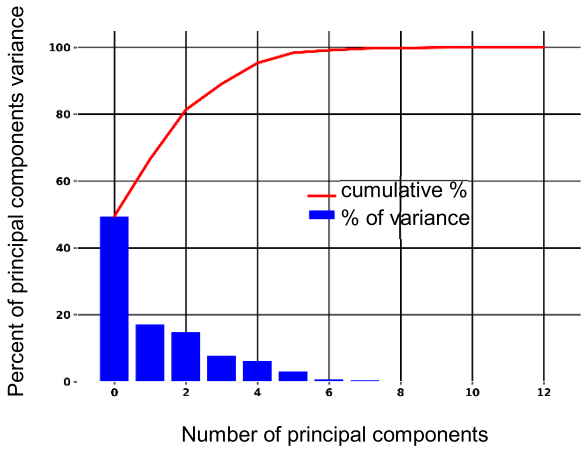


**FIGURE 4.** Variances of principal components.

We applied PCA based on a singular value decomposition (SVD) procedure that decomposes the original data matrix $X$ into a product of three matrices, $X = USV^t$, where $U$ is a matrix formed by orthonormal eigenvectors of matrices $XX^t$, $V$ is a matrix formed by orthonormal eigenvectors of matrices $X^tX$, $S$ is a positively defined diagonal matrix of singular values and $X^t$ is a transposed $X$ matrix. The resulting matrices provide a new set of features, i.e. principal components, or scores (matrix $T$) and contributions of old features into new ones, or loadings (matrix $P$) $T = US$ and $P = V$. New features are sorted in order of their variances (diagonal values of matrix $S$ or $T^tT$).

The procedure described above is applied for each epoch's duration. The example of a normalized variance of each principal component and the cumulative percent of variances are displayed in Fig. 4. Fig. 4 reveals that up to 6 principal components are required to capture 95% of the total variance.

The contributions of the original features to the principal components 1-13 are visually depicted in Fig. 5. The original features are: mean signals' value (*Mean*), standard deviation of signal values (*STD*), modulus of signal values difference (*Abs diffs*), skewness (*Skew sign*), Hjorth activity (*Hjorth activ*), Hjorth mobility (*Hjorth mobil*), Hjorth complexity (*Hjorth complex*), mean value of detail component (*cD mean*), standard deviation of detail component (*cD std*), signal energy of detail component (*cD energy*), mean value of approximation component (*cA mean*), standard deviation of approximation component (*cA std*), signal energy of approximation component (*cA energy*) correspond to horizontal axes. Principal components' numbers correspond to vertical axes. Contributions of the original features into principal components are described by colour. Significant contributions correspond to colours different from red. Notably, most of the original features have significant contributions to the first 3 principal components. This experience underscores that,

in our case, selecting only specific statistical features for classification would not be meaningful. No clearly defined group of original features exists for making classifications. Reducing the data dimension by eliminating original signal features is not advantageous, as it could result in a significant loss of valuable information.

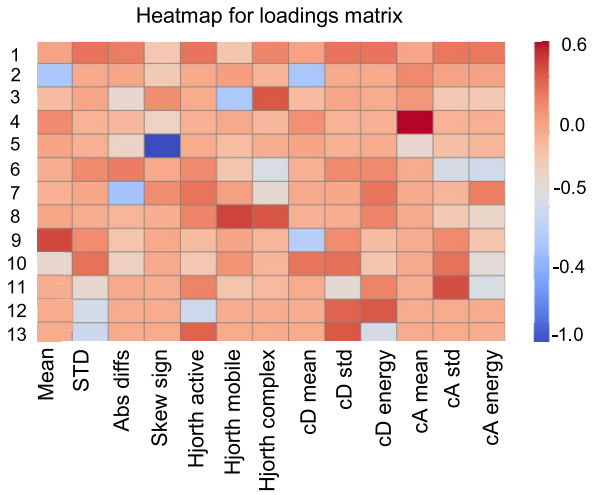


**FIGURE 5. Contribution of original statistical features into principal components.**

The distribution of the first three principal component values in the new features space is displayed in Fig. 6. The red dots present the ictal signal, while the blue dots present the normal signal.

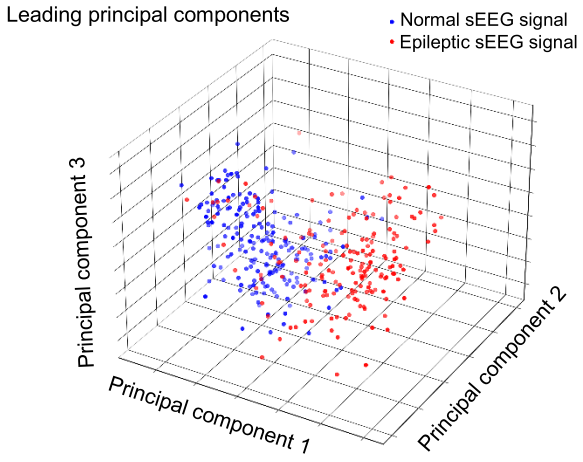


**FIGURE 6. Distribution of the three leading principal components for normal and epileptic signals.**

## VI. SVM CLASSIFICATION

Support vector machines (SVM) [48] are a powerful and straightforward approach for binary data classification. The fundamental concept behind this method is to identify a hyperplane that optimally separates data points in the feature space into two distinct classes. Notably, the hyperplane is constructed in non-linear coordinates, implying that the distance between different data points $i$ and $j$ in the feature space is calculated as $d^2 = K(x_i, x_j)$, where $d^2$ represents the squared distance, $x_i, x_j$ denote feature value vectors for data points $i$ and $j$, and $K(x_i, x_j)$ signifies the kernel function.

The process of constructing the hyperplane within the feature space occurs during the training phase of the algorithm and necessitates prior knowledge of the training dataset classification. Once the hyperplane is determined, it can classify new data.

In the work presented here we considered Gaussian (11), sigmoid (12), and linear (13) kernels that are widely used due to low computing resource requirements. The SVM was trained using annotation information in the dataset.

$$K\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right) \tag{11}$$

$$K\left(x_i, x_j\right) = \tanh\left(a x_i^T x_j + r\right) \tag{12}$$

$$K\left(x_i, x_j\right) = a x_i^T x_j + r \tag{13}$$

SVM is used in the present work because it has been extensively applied and proven successful in the classification of epileptic EEG signals due to its effectiveness in handling high-dimensional data, small, and imbalanced datasets [49]. Its accuracy in distinguishing between ictal (seizure) and non-ictal (normal) EEG states is reported to be over 96% [37]. In many studies in epilepsy detection SVM outperforms multilayer perceptron and probabilistic neural networks [50], as well as k-nearest neighbours (KNN) and decision trees (Random Forest, etc.) [51], and also naïve Bayes [52]. SVMs are robust to over-fitting [53], unlike CNNs, KNNs, and decision trees because they require fewer hyper-parameters to tune. Another advantage of SVM is its low resource requirements, as it only stores a relatively small number of support vectors rather than a large number of coefficients, or the entire training set, unlike CNNs, KNNs and decision trees. This makes SVM ideal for deployment on portable devices with limited resources [54].

Classifier testing was conducted to identify the optimal classifier kernel and assess classifier accuracy. Given the limited size of the dataset, the following testing methodology was employed: data records for each single rat were used as the training sets, while the data of the remaining 12 rats served as the test sets. All 13 different classifiers were trained using the 13 training sets, each corresponding to one of the 13 rats. Subsequently, each classifier underwent testing using the test sets from all rats, resulting in an accuracy matrix with dimensions of $13 \times 13$. An accuracy matrix for 1-second epochs is presented in Tab.1. In this matrix, columns represent classifiers trained on a specific rat's dataset (e.g., column 1 corresponds to a classifier trained on Rat 1), while rows indicate the classification accuracy when testing the classifier on datasets from other rats. Diagonal cells show within-subject (training) performance. Off-diagonal cells reflect the classifiers' performance on data from different rats, highlighting the performance generalizability across subjects.

**TABLE 1.** Example matrix with accuracy values for each pair of training and testing sets for a 1-second epoch and gaussian kernel.

| | Data set and corresponding classifier number for training | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data set number for testing | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 1 | 99,2% | 45,7% | 54,3% | 54,3% | 54,3% | 45,7% | 54,3% | 54,3% | 54,3% | 45,7% | 54,3% | 54,3% | 54,3% |
| 2 | 25,8% | 93,6% | 25,8% | 25,8% | 25,8% | 74,2% | 25,8% | 25,8% | 25,8% | 74,2% | 25,8% | 25,8% | 25,8% |
| 3 | 99,1% | 0,9% | 100,0% | 99,1% | 99,1% | 0,9% | 99,1% | 99,1% | 99,1% | 0,9% | 99,1% | 99,1% | 99,1% |
| 4 | 86,2% | 4,1% | 95,9% | 99,6% | 95,9% | 4,1% | 95,9% | 95,9% | 95,9% | 4,1% | 95,9% | 95,9% | 95,9% |
| 5 | 85,1% | 14,9% | 85,1% | 85,1% | 99,9% | 14,9% | 85,1% | 85,1% | 85,1% | 14,9% | 85,1% | 85,1% | 85,1% |
| 6 | 24,3% | 75,6% | 24,5% | 24,5% | 24,5% | 100,0% | 24,4% | 24,5% | 24,5% | 75,5% | 24,5% | 24,5% | 24,5% |
| 7 | 88,7% | 11,3% | 89,0% | 89,0% | 89,0% | 11,1% | 95,7% | 89,0% | 89,0% | 11,0% | 89,0% | 89,0% | 89,0% |
| 8 | 85,4% | 14,1% | 85,9% | 85,9% | 85,9% | 14,1% | 85,9% | 100,0% | 85,9% | 14,1% | 85,9% | 85,9% | 85,9% |
| 9 | 52,4% | 47,6% | 52,4% | 52,4% | 52,4% | 47,6% | 52,4% | 52,4% | 100,0% | 47,6% | 52,4% | 52,4% | 52,4% |
| 10 | 43,9% | 56,1% | 43,9% | 43,9% | 43,9% | 56,1% | 43,9% | 43,9% | 43,9% | 100,0% | 43,9% | 43,9% | 43,9% |
| 11 | 98,2% | 1,8% | 98,2% | 98,2% | 98,2% | 1,8% | 98,2% | 98,2% | 98,2% | 1,8% | 100,0% | 98,2% | 98,2% |
| 12 | 99,2% | 0,8% | 99,2% | 99,2% | 99,2% | 0,8% | 99,2% | 99,2% | 99,2% | 0,8% | 99,2% | 100,0% | 99,2% |
| 13 | 95,8% | 3,4% | 96,6% | 96,6% | 96,6% | 3,4% | 96,6% | 96,6% | 96,6% | 3,4% | 96,6% | 96,6% | 100,0% |
| Average | **75,6%** | **28,4%** | **73,1%** | **73,3%** | **74,2%** | **28,8%** | **73,5%** | **74,1%** | **76,7%** | **30,3%** | **73,2%** | **73,1%** | **73,3%** |
| Confidence interval | **±17,1%** | **±17,7%** | **±16,7%** | **±16,6%** | **±16,6%** | **±17,8%** | **±16,5%** | **±16,%6** | **±17,0%** | **±17,7%** | **±16,6%** | **±16,6%** | **±16,6%** |

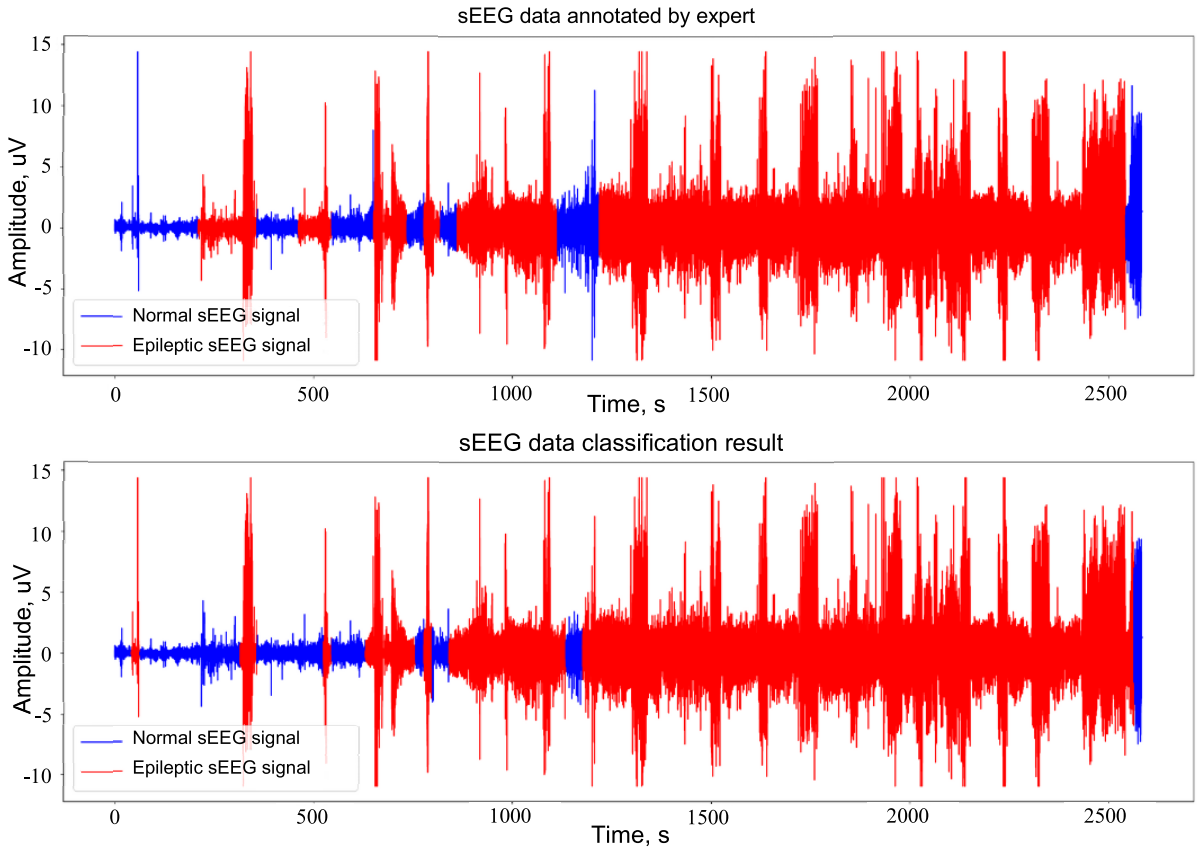


**FIGURE 7.** Comparison of epileptic seizures annotated by the expert (top) and detected by the classifier (bottom).

Accuracy is a product of sensitivity and specificity. Sensitivity was computed as a percentage of correctly classified seizure epochs. Specificity is a percentage of non-seizure epochs that were classified as non-seizure.

The average accuracy of each of the 13 classifiers was determined by calculating the mean values within the respective columns of the accuracy matrix. A confidence interval with a confidence probability of 0.95 is also provided for

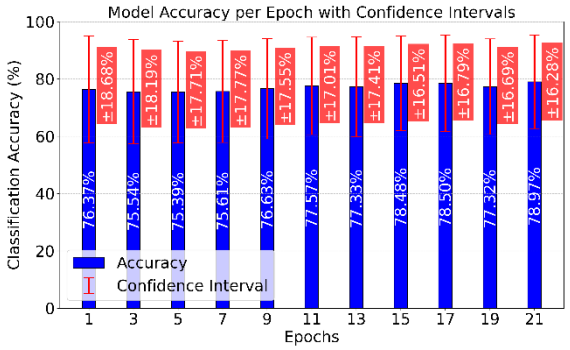


**FIGURE 8. Classification accuracy of the classifier number 9 for different epoch durations in seconds.**

each classifier. The best classifier was identified as the one exhibiting the highest average classification accuracy. This approach ensures that classifiers are evaluated for their ability to generalize across independently recorded datasets without data leakage.

This testing procedure was performed for the 11 data epoch durations and all 3 SVM kernels. The highest classification accuracy was achieved with the Gaussian kernel at 77%, followed by the linear kernel at 74% and the sigmoid kernel at 73%. Notably, the best classifier, number 9, demonstrated consistently high performance across all SVM kernels and epoch durations. For the optimal classifier i.e. 9, see Tab.1, sensitivity and specificity were 90% and 74%, respectively.

The classification accuracy of the best classifier, number 9 (Tab. 1), across different epoch durations in seconds (Fig. 8) demonstrates that altering the epoch duration has a negligible impact on the overall classification accuracy. The accuracy values (Fig. 8) range from 75.39% to 78.97%, which is significantly smaller than the accuracy confidence interval (Tab. 1, Fig. 8).

Classifiers number 1 and number 5 have very low classification accuracies. To check a possible over-fitting occurrence a regularization parameter[1] of the SVM was changed. Changing of the regularization parameter did not change the behaviour of these classifiers, which means there was no over-fitting i.e. the behaviour of these classifiers is stable and is determined by the data. The best classifier trained using data of just one rat provides decent performance for almost all the rats in the dataset.

A comparison of classification results with data annotated by the expert is displayed in Fig. 7. Epileptic seizures are displayed in red and normal states are displayed in blue. One can see that most time intervals containing epileptic seizures are correctly classified, but some normal states are classified as epileptic seizures. Amplitude fluctuations that correspond to the movement of electrodes are sometimes classified as epileptic seizures. Epileptic seizures are not always detected at the beginning and at the end of signal epochs. Start and end time moments of subsequent short epileptic seizures are not always accurately detected.

[1]The regularization parameter controls the trade-off between classification error for all samples and distance from all samples to the margin between classes. A classifier with a large regularization parameter tries to construct an interclass margin for separation of maximum samples even if samples of different classes are very close to each other. Using a small regularization parameter makes classifier constructing interclass margins as far as possible from most samples of different classes and close samples of different classes may be classified as the same class.

## VII. CONCLUSION AND PERSPECTIVES

In this study, we combined the principal component analysis with the support vector machine approach for the detection of epileptic seizures in rats. The proposed approach can classify epileptic seizures using EEG signals with sufficient accuracy for certain practical applications. Such applications include mobile devices for electrophysiological data sampling, devices for epilepsy seizure detection and prediction, etc.

The classification of the EEG dataset using all original signals' statistical features provides nearly the same classification results as the classification using a smaller number of features enriched by PCA: sensitivity is 90%, and specificity is 74%. These classification results were achieved using the Gaussian kernel function that provided the best classification performance in our investigation. Epoch duration does not significantly change classification results. Thus, the longest epoch of 21 seconds is recommended due to performance considerations. The proposed optimization of the informative features extraction from the statistical feature set provides a significant reduction of computing performance requirements that is of interest for mobile EEG applications.

The reported specificity of 74% implies a moderate rate of false positives, which could indeed present challenges in scenarios requiring real-time monitoring. However, this study's results are intended as a proof of concept for potential usage in lightweight, portable devices aimed at early seizure detection or laboratory research, where high sensitivity is paramount to minimize the risk of missing a seizure.

It is also worth noting that the specificity observed in this study may be influenced by the limited size and variability of the dataset. With larger, more diverse datasets, specificity is expected to improve, making this approach a promising candidate for future development in both laboratory and practical seizure detection systems.

The classification approaches discussed in this article were not trained and tested using large human datasets and thus they are not ready for clinical applications. However, they may be applied in laboratory electrophysiological research. They are also promising for analysing of human EEG data for further investigations of practical applicability. Successful applications of classifiers trained on animal models to human EEG signals classification are reported [19], making the presented approach promising for future clinical applications.

Classification performance of the proposed approach appears to be slightly lower than performance of some approaches described in literature such as the approaches based on artificial neural networks. This difference may be referred to the small dataset applied in current work, used features, specifics of data annotation, classification approach,

etc. But, in order to allow real-time detection of epileptic seizures using body-worn sensors the processing of the measurements requires to be rather lightweight. We envision that this can be achieved using the approaches researched here and most probably not when using neural networks. In any case, an introduction of new features should improve the classification performance of approaches considered in this work. Such additional features may be potentially revealed using realistic microscopic modelling of epileptic activity in biological neuronal networks [55]. It is also will be interesting to apply tensor models that potentially could further reduce computational load without compromising classification accuracy. Examples of such models are PARAFAC [56] and TUCKER [57] that offer decomposing of EEG signals into lower-rank components for dimensionality reduction.

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