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Review

# Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy

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ABSTRACT

Nearly one-third of patients with epilepsy continue to have seizures despite optimal medication management. Systems employed to detect seizures may have the potential to improve outcomes in these patients by allowing more tailored therapies and might, additionally, have a role in accident and SUDEP prevention. Automated seizure detection and prediction require algorithms which employ feature computation and subsequent classification. Over the last few decades, methods have been developed to detect seizures utilizing scalp and intracranial EEG, electrocardiography, accelerometry and motion sensors, electrodermal activity, and audio/video captures. To date, it is unclear which combination of detection technologies yields the best results, and approaches may ultimately need to be individualized. This review presents an overview of seizure detection and related prediction methods and discusses their potential uses in closed-loop warning systems in epilepsy.



## 1. Introduction

Epilepsy is one of the most common neurological disorders and occurs with an incidence of 68.8/100,000 person-years [1]. The age-adjusted incidence of epilepsy is estimated to be 44/100,000 person-years [2]. Despite the introduction of new antiepileptic drugs in the last decades, one-third of people with epilepsy continue to have seizures despite treatment [3]. However, even when seizures are well controlled, self-reported quality of life is significantly lowered by the anxiety associated with the unpredictable nature of seizures and the consequences therefrom [4].

Some of the difficulties in managing treatment-refractory epilepsy can be ameliorated by the ability to detect clinical seizures. This information might be useful both in developing accurate seizure diaries and in providing therapies during times of greatest seizure susceptibility. The ability to rapidly and accurately detect seizures could promote therapies aimed at rapidly treating seizures. The capability to detect seizures early and anticipate their onset prior to presentation would provide even greater advantages. These early detection and prediction systems might be able to abort seizures through

*Abbreviations:* SVM, support vector machine; ANN, artificial neural network; PCA, principal component analysis; SEN, sensitivity; SPEC, specificity; FPR, false-positive rate; PPV, positive predictive value.

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**Table 1**
Selected seizure detection systems.

| Author, year | Measuring device/seizures detected | Detection algorithm | Results |
|---|---|---|---|
| *Electroencephalography/electrocorticography* | | | |
| Webber, 1996 [5] | EEG (24–40 channels)/seizures not stated | ANN classification system | SEN of 76% and FPR of 1 event/h |
| Pradhan, 1996 [6] | EEG (8 channels)/seizures not stated | Wavelet transformation feature acquisition, ANN classification | SEN of 97% and SPEC of 89.5% |
| Gabor, 1998 [7] | EEG (8 channels)/seizures not stated | Self-organizing neural network with unsupervised training | SEN of 92.8% and FPR of 1.35 events/h |
| Wilson, 2004 [8] | EEG (8–32 channels)/seizures not stated | Combined algorithm (utilizes matching pursuit, small neural networks, and clustering algorithm) | SEN of 76% and FPR of 0.11 events/h |
| Wilson, 2005 [9] | EEG (single channel selected)/CPS, secondary GS and primary GS | Used a trained probabilistic neural network for rapid detection of seizures | SEN of 89% and FPR of 0.56 events/h |
| Alkan, 2005 [10] | EEG (4 channels)/absence seizures | Comparison of linear regression systems and ANN classification systems | ANN-based systems found to be greater. ANN-based system provided greater accuracy compared with linear regression |
| D'Alessandro, 2005 [11] | Intracranial EEG/seizures not stated | Genetic algorithm for signal processing, probabilistic neural network for classification | 100% prediction of seizures within 10 min prior to onset |
| Arabi, 2006 [12] | EEG/neonatal seizures | Used linear correlation feature selection methods and back propagation neural network for classification. Used in detection of neonatal seizures | SEN of 91% and FPR of 1.17 events/h |
| Casson, 2007 [13] | Ambulatory EEG | Continuous wavelet transform | Over 90% of spike detection |
| Chan, 2008 [14] | Intracranial EEG/PS | SVM system | SEN of 80–98%, FPR of 38% |
| Netoff, 2009 [15] | EEG (6 channels)/PS | Cost-sensitive SVM system | SEN of 77.8%, no false positives detected |
| Chua, 2009 [16] | EEG/PS | Data processing by higher-order spectra analysis followed by classification by the Gaussian mixture model or SVM | Accuracy of 92–93% |
| Mirowski, 2009 [17] | EEG/PS | Variable feature extraction methods used followed by patient-specific machine learning-based classifiers | Convolutional networks combined with wavelet coherence yielded sensitivity of 71% and no false positives |
| Sorensen, 2010 [18] | EEG (3 channels)/GTCS, SPS, CPS | Features classified by matching pursuit algorithm and classified by SVM | SEN of 78–100 and FPR of 0.16–5.31 events/h |
| Chisci, 2010 [19] | EEG (multichannel)/focal seizures | Least-squares parameter estimator for extraction followed by SVM classification | SEN of 100% |
| Peterson, 2011 [20] | EEG (single channel)/absence seizures | Wavelet transform followed by SVM classification used to detect absence seizures using single-channel EEG | SEN of 99.1% and PPV of 94.8% |
| Temko, 2011 [21] | EEG (8 bipolar)/neonatal seizures | Fast Fourier transform used for feature extraction followed by SVM classification. Used to detect neonatal seizures | SEN adjustable, with 89% SEN yielding one false detection/h |
| Acharya, 2011 [22] | EEG/seizures not stated | Higher-order spectra-based feature extraction followed by SVM | Detection accuracy of 98.5% |
| Kharbouch, 2011 [23] | Intracranial EEG/focal epilepsy | Multistep feature extraction system followed by SVM classifier, individualized for patients | Detected 97% of seizures, FPR of 0.6 events/day |
| Liu, 2012 [24] | Intracranial EEG/GTCS, SPS, CPS | Wavelet decomposition-based feature extraction followed by SVM classification | SEN of 94.5% and SPEC of 95.3% |
| Xie, 2012 [25] | EEG (6 channels)/focal seizures, others not stated | Feature extraction by wavelet-based sparse functional linear model and 1-NN classification method | Has 99–100% classification accuracy |
| Direito, 2012 [26] | EEG (multichannel)/focal seizures | Markov modeling classification system. Identified four states — preictal, ictal, postictal, and interictal | Point-by-point accuracy of 89.3% |
| Rabbi, 2012 [27] | Intracranial EEG/GTCS, SPS, CPS | Used fuzzy algorithms for feature extraction for classification | SEN of 95.8% and FPR of 0.26 events/h |
| *Implanted advisory system* | | | |
| Cook, 2013 [28] | Intracranial implanted device/partial-onset seizure | Cluster computing system at NeuroVista (one algorithm for each patient) | SEN of 65%–100% |
| *Electromyography* | | | |
| Conradsen, 2010 [29] | Features extracted from surface electromyography acceleration and angular velocity/seizure-like movements performed by healthy volunteers | Classification based on SVM | SEN of 91–100% and SPEC of 100% |
| Conradsen, 2012 [30] | Electromyography and motion sensor features/motor seizures, seizure-like movements performed by healthy volunteers | Discrete wavelet transformation/wavelet packet transform techniques used to extract features. SVM classification system | Evaluated healthy subjects simulating seizures. SEN of 91–100% and SPEC of 100% |