Exposé: Machine Learning for Prediction and Detection of Epileptic Seizures Using ECG and Other Non-Invasive Sensor Data

Paulin Saher

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1 Introduction

Epilepsy is one of the most common chronic diseases of the central nervous system, affecting around 7.6 per 1,000 people (Beghi, 2019). Despite this, epilepsy remains poorly understood, resulting in 30% of patients being drug resistant and patients responding to the drugs report severe side effects and subsequent impacts on quality of life. (Chen et al., 2020; Kwan & Brodie, 2000). The prediction and detection of epileptic seizures can be helpful by enabling timely drug administration, the anticipation and inhibition of seizure-related accidents as well as prompt first aid responses.

When treatment fails patients are at risk for sudden death of epilepsy (SUDEP), as well as physical injuries related to muscle spasms and falls during seizures. (Hesdorffer et al., 2011).

This highlights the need for reliable and acessible seizure detection and prediction methods. In clinical settings reliable detection and prediction has alerady been achived

using EEG, however there is a lack of solutions for ambulatory monitoring since EEG requires bulky and obtrusive equipment (Chen et al., 2020).

The rapid introduction of wearable technology specifically regarding health monitoring, paired with improvements in the machine learning sector has opened up the possibility of dependable, accessible and affordable seizure detection and prediction in ambulatory settings.

This literature review aims to consolidate the current state of research regarding seizure detection and prediction using wearable technology and machine learning methods to identify the most promising methods and modalities, give a concise overview and and highlight future directions for research in this area. (Miron et al., 2025; Seth et al., 2023; Shum & Friedman, 2021)

2 Technical Background

2.1 Epileptic Seizures

Epileptic seizures are classified by their onset as focal (starting in a specific area of the brain) or generalized (affecting both hemispheres from the onset).

1. **Focal Seizures**: Seizures are further split up into focal aware and focal impaired awareness seizures, depending on whether the patient is aware during the seizure or not and by the onset features (motor vs non-motor). Focal seizures may evolve to bilateral tonic–clonic seizures.

2. **Generalized Seizures**: Generalized seizures begin in both cerebral hemispheres and include motor (e.g. tonic–clonic, myoclonic, atonic) and non-motor (absence) types.

(Fisher et al., 2017). **Note:** Tonic-clonic seizures describe a type of seizure starting with a brief tonic phase of sustained muscle contraction followed by a clonic phase of followed by a clonic phase of rhythmic jerking. They commonly cause loss of consciousness and carry increased risk of injury and SUDEP (Hesdorffer et al., 2011).

2.2 Autonomic Nervous System

The autonomic nervous system (ANS) comprises the sympathetic (arousal) and parasympathetic/vagal (rest) branches. Heart-rate variability (HRV) reflects how these two balance each other: HF power and RMSSD mainly indicate parasympathetic (calming) activity. LF includes a mix of both branches. The LF/HF ratio is only a rough summary of this balance. Electrodermal activity (EDA) is a direct sympathetic output with a tonic skin conductance level (SCL) and phasic skin conductance responses (SCRs). Photoplethysmography (PPG) yields pulse-rate variability analogous to HRV from ECG (Miron et al., 2025).

2.3 Non-tonic–clonic seizures and autonomic markers

Non-convulsive/focal seizures typically elicit subtle autonomic signatures rather than large motor patterns. Sympathetic activation manifests as:

1. ictal (during a seizure) tachycardia and preictal HR rise with reduced HRV (lower RMSSD/HF, higher LF/HF) measurable from ECG or PPG-derived pulse rate variability;

2. increased electrodermal activity (tonic SCL, phasic SCRs);

3. limited accelerometry changes mainly useful for artifact rejection and context (e.g. sports).

Patient-specific thresholds or fine-tuning are often needed due to differences in autonomic reactivity and medication effects between patients. (Mason et al., 2024; Miron et al., 2025; Seth et al., 2023).

2.4 Wearable Technology

Wearable technology refers to electronic devices (armbands, watches, chest straps) that are worn on the body, often equipped with sensors to monitor heart rate, acceleration, respiration, skin conductance and blood pressure. Detection performance of wearables for generalized tonic-clonic seizures(GTCS) is already quite high, due to the fact that these seizures produce large stereotyped motor patterns as well as heart-rate and EDA changes. Several of these devices have regulatory clearances for GTCS detection (Miron et al., 2025; Seth et al., 2023).

2.5 Machine Learning

Machine learning on wearable biosignals (ECG/HRV, EDA, ACC, PPG) typically frames seizure detection and prediction as standard classification. Classical models (e.g., SVM, RF, kNN) on HRV/EDA/ACC features achieve solid detection and some prediction, but often in retrospective designs (Mason et al., 2024; Seth et al., 2023).

Deep architectures (1D-CNN, LSTM) and multimodal fusion remain the most promising improving robustness and phase classification, especially when combining ECG/EDA/ACC with attention/fusion layers (Pordoy et al., 2025; Yang et al., 2022).

ECG-focused studies add interpretable features and out-of-distribution evaluation but emphasize non-stationarity, class imbalance, and scarce prospective validation as key limitations (Abtahi et al., 2025; Kalousios et al., 2024).

2.6 Patient-Specific Fine-Tuning

Inter-patient variability in autonomic responses and preictal dynamics is substantial; the most informative features often differ by patient, which degrades population-trained models. Patient-specific fine-tuning typically improves sensitivity and lowers false alarms in ambulatory, alarm-based settings (Andrade et al., 2024).

2.7 Datasets and Synthetic Data

Public datasets for seizure detection/prediction are largely EEG-centric with auxiliary ECG (TUH, EPILEPSIAE, RPAH, CHB-MIT), while truly wearable multimodal corpora are scarce; one of the few open non-EEG sources is the Open Seizure Database (ACC+HR) (Pordoy et al., 2025; Yang et al., 2022). Cross-dataset and pseudo-prospective evaluation across TUH→RPAH/EPILEPSIAE and across EPILEPSIAE/CHB-MIT/AES/Epilepsy

Ecosystem exposes domain shift and favors alarm-based over sample-based metrics (Andrade et al., 2024; Yang et al., 2022). Given rare events, imbalance, and noisy labels, studies use augmentation (time-warping, jitter, scaling) and synthetic data to balance preictal/ictal segments, with patient-preserving splits and external validation to avoid device/site overfitting (Kalousios et al., 2024; Seth et al., 2023).

3 Methodology

1. **Scope:** human studies in journals (2015–2025) on non-EEG wearable/autonomic biosignals (ECG/HRV, PPG, EDA, ACC) for seizure detection or prediction.
2. **Search:** Google Scholar (scoping), IEEE Xplore (all queries), PubMed and Scopus (targeted) using predefined query strings and result deduplication.
3. **Screening:** title/abstract screen, then full-text eligibility. backward/forward citation chasing on key papers.
4. **Extraction:** dataset type (wearable vs clinical), name, availability, task (detection vs prediction), metrics (sensitivity, FAR/h, AUC), personalization, cohort size/class balance.
5. **Quality flags:** sample- vs alarm-based evaluation; patient-preserving splits; cross-dataset/external validation.
6. **Synthesis:** narrative grouping by modality and task with emphasis on ambulatory feasibility and edge constraints.

4 Key Research Questions

1. Which wearable biosignals (ECG/HRV, EDA, ACC, PPG) yield the best detection and prediction performance across seizure types and settings?
2. Which model classes (feature-based vs deep multimodal) generalize across datasets and maintain performance under pseudo-/prospective, alarm-based evaluation?
3. What is the performance gain from patient-specific fine-tuning, and how can adaptation be implemented under edge compute and energy constraints?
4. How can false alarms be minimized while preserving high sensitivity in ambulatory use?
5. What dataset gaps exist for non-EEG wearables, and how can augmentation and synthetic data mitigate imbalance without inducing bias?

5 Overview of literature Review

1. **Modalities:** ECG/HRV, EDA, ACC, PPG; brief physiology, sensor placement, and artifact handling relevant to wearables.

2. **Tasks:** seizure detection vs prediction windowing and labeling conventions; alarm-based metrics (sensitivity, FAR/h, AUC-ROC/PR).

3. **Models:** classical feature-based pipelines vs deep 1D-CNN/LSTM attention and interpretability considerations.

4. **Multimodal fusion:** feature-, decision-, and representation-level fusion strategies and benefits.

5. **Personalization:** patient-specific calibration/fine-tuning, online adaptation, drift management, and thresholding.

6. **Datasets and evaluation:** key datasets and availability patient-preserving splits; cross-dataset transfer retrospective vs pseudo-/prospective designs.

7. **Edge and deployment:** latency/energy constraints, on-device inference strategies, robustness in ambulatory settings.

8. **Gaps and future directions:** dataset scarcity (non-EEG wearables), focal seizure detection, prospective validation, standardization, and clinical integration.

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