Platzhalter titel

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

1. Introduction and Motivation

1.1 Clinical and societal relevance of epilepsy

Epilepsy is one of the most common chronic diseases of the central nervous system, affecting approximately 7.6 per 1,000 people (Beghi, 2019).

Despite the availability of anti-seizure medications, about 30% of patients remain drug resistant; even patients without drug resistance suffer from side effects (Chen et al., 2020; Kwan & Brodie, 2000).

Unpredictable seizures lead to injuries, restrictions in daily and professional life, fear of the next event and reduced quality of life as well as a heightened risk of accidents (Beghi, 2016; Mahler et al., 2018).

1.2 Limitations of EEG-centric approaches

The current gold standard for diagnosis and seizure monitoring is the electroencephalogram (EEG). However, EEG-based approaches are often resource-intensive and tied to clinical environments. They can be intrusive and are therefore difficult to deploy in everyday life (Wong et al., 2023). Long-term recordings with high user comfort and minimal intrusion remain challenging.

1.3 Wearables and non-invasive sensor modalities

Wearable sensor technology (smartwatches, armbands, chest straps, patches) can continuously capture ECG or PPG-based HR/HRV, accelerometry and respiration in daily life (Beniczky et al., 2020; Bonato, 2010; Villanueva et al., 2023; Wu et al., 2024).

Commercially available wearables have demonstrated clear success for detecting convulsive/tonic–clonic seizures in several studies, with some devices reporting sensitivities often above 85–90% in controlled or selected cohorts. Multimodal systems (motion + autonomic sensors, or EMG + motion) tend to improve detection and reduce false alarms compared with unimodal approaches (Shum & Friedman, 2021).

Important limitations remain: only a minority of devices have peer-reviewed, prospective natural-environment evaluations or regulatory approval; most are optimized for major motor seizures and *perform poorly for non-convulsive events*; ambulatory use increases false alarms and depends on correct placement, smartphone connectivity and user compliance; cost, comfort and caregiver availability constrain real-world utility (Shum & Friedman, 2021).

This motivates investigation of seizure detection and prediction based on non-invasive, ambulatory biosignals particularly for non-convulsive seizures (Alshehri & Muhammad, 2021).

Against this background, the planned seminar paper systematically investigates machine-learning (ML) approaches for seizure detection for *non-convulsive seizures* and prediction that do *not* primarily rely on EEG, but on ECG and other non-invasive sensor data (e.g. PPG, accelerometer, respiration).

2. Theoretical and Methodological Background

2.1 Epilepsy, seizure types and autonomic manifestations

Epileptic seizures are classified by onset as focal (starting in a localized brain region) or generalized (involving both hemispheres from onset). Primary generalized epilepsies commonly present with generalized tonic-clonic seizures (GTCS), while focal seizures can remain local or propagate to produce focal-to-bilateral tonic-clonic seizures (FBTCS/SGTCS). GTCS/FBTCS are associated with higher risk of injury and pronounced autonomic/cardiovascular disturbances, which motivates monitoring peripheral cardiac signals alongside EEG (**fisherILAEOfficialReport2017**; Beniczky et al., 2020; Thijs et al., 2021).

Seizures commonly produce autonomic responses—most notably changes in heart rate, rhythm and HRV—that are visible in ECG/HR signals and can, in some cases, precede clinical or electrographic onset (Thijs et al., 2021; Zijlmans et al., 2002). Peri-ictal tachycardia, arrhythmias and altered HRV are therefore relevant for monitoring and risk stratification, but resting ECG alone shows limited value for reliable seizure forecasting (Drake et al., 1993; Nei et al., 2000).

2.2 Non-invasive sensor systems and wearables

In addition to single or multi-lead ECG, recent studies increasingly use wearable devices with PPG, accelerometers and respiratory channels (Beniczky et al., 2020; Villanueva et al., 2023; Wu et al., 2024).

Multimodal armband or patch systems enable continuous monitoring in everyday life, but require energy-efficient and robust algorithms, as well as reliable data transmission and security (Bonato, 2010; Forooghifar et al., 2019).

2.3 Machine learning for detection and prediction

Early ECG/HRV-based approaches mainly rely on statistical HRV features and classical machine-learning models (Fujiwara et al., 2016; Leal et al., 2017; Pavei et al., 2017).

More recent work increasingly employs deep learning and explainable ML. For example, some studies identify the most relevant ECG features using SHAP (Abtahi et al., 2025). Other works compare model classes or provide feasibility evidence and sensor- and feature-level separability analyses in small inpatient samples (Ghaderi, 2025; Hamlin et al., 2021).

Targeted reviews exist on HRV-based prediction and on multimodal non-EEG biosignals (Mason et al., 2024; Miron et al., 2025; Pordoy et al., 2025; Seth et al., 2023).

2.4 Datasets, study designs and evaluation

Clinical ECG/HRV datasets (e.g. EPILEPSIAE, Siena, proprietary long-term recordings) and wearable/multimodal datasets (e.g. Empatica, patient-specific armband/patch systems) form the empirical basis for model training and evaluation (Beniczky et al., 2020; Fujiwara et al., 2016; Villanueva et al., 2023).

Validation protocols vary (patient-specific vs. cross-patient, prospective, pseudo-prospective) and substantially affect reported performance; commonly used metrics include sensitivity, false-alarm rate per hour (FPR/h), AUC and time-in-warning (Andrade et al., 2024).

Methodological pitfalls to watch for include small sample sizes, data leakage, unrealistic warning horizons and lack of prospective evaluation (Andrade et al., 2024; Kalousios et al., 2024).

3. Objectives and Research Questions

3.1 Overall objective

The overall objective of the seminar paper is to analyse the current state of the art in machine-learning (ML) approaches for detecting and predicting epileptic seizures through non-intrusive biosignals. This includes datasets, sensor types as well as machine learning models and evaluation protocols. The work will identify research gaps and potential directions for future projects.

The focus is on human studies from roughly the last ten years that use ECG/HR/HRV or multimodal wearable data.

3.2 Specific research questions

The following research questions guide the work:

1. **Signals and modalities:** Which non-invasive biosignals (ECG, HRV, PPG, accelerometer, respiration, etc.) are used for seizure detection and prediction? (Beniczky et al., 2020; Miron et al., 2025; Seth et al., 2023)

2. **Features and models:** Which feature families (time, frequency and non-linear HRV measures, Lorenz features, multifractal descriptors, etc.) and which ML/DL models (e.g. classical classifiers, CNN/LSTM, ensembles) are employed, and how interpretable are these models? (Abtahi et al., 2025; Fujiwara et al., 2016; Ghaderi, 2025)

3. **Datasets and evaluation:** Which datasets are used for (ML) model training and evaluation and which ones have the potential for real-world application? (Andrade et al., 2024; Ghaderi, 2025)

4. **Practical deployment:** Which technical and practical challenges arise for real-world deployment on wearables (e.g. energy, performance and memory constraints,

robustness, user acceptance)? (Donati et al., 2025; Hashash et al., 2021; Najafi et al., 2024; Sivathamboo et al., 2022)

5. **Research gaps:** Where are the main research gaps and what are the implications for future academic work, especially on ECG-based warning systems and multimodal wearable solutions? (AbuAlrob et al., 2025; Hixson & Braverman, 2020)

4. Planned Structure of the Seminar Paper

The seminar paper is planned as a structured literature review, aligned with the search and review strategy drafted in the project documents. A preliminary outline is:

1. **Introduction**
   (a) Motivation: burden of disease, limitations of EEG-based approaches (Beghi, 2016; Wong et al., 2023)
   (b) Aim and scope (ECG/HRV and other non-EEG sensors only)
   (c) Research questions

2. **Background**
   (a) Epilepsy, seizure types and autonomic nervous system (ANS) manifestations (Thijs et al., 2021)
   (b) Physiology of ECG, HRV and other peripheral biosignals in relation to seizures
   (c) Wearable technologies in healthcare (Alshehri & Muhammad, 2021; Bonato, 2010; Donati et al., 2025)

3. **Problem Formulation and Evaluation Criteria**
   (a) Definition of detection vs. prediction, pre-ictal windows
   (b) Clinically meaningful metrics (sensitivity, FPR/h, time-in-warning, PPV) (Andrade et al., 2024)

4. **Datasets and Study Designs**
   (a) Clinical ECG/HRV datasets (e.g. EPILEPSIAE, Siena, proprietary long-term recordings) (Fujiwara et al., 2016; Ghaderi, 2025; Leal et al., 2017)
   (b) Wearable and multimodal datasets (e.g. Empatica, patient-specific armband/patch systems) (Beniczky et al., 2020; Villanueva et al., 2023; Wu et al., 2024)
   (c) Validation protocols (patient-specific vs. cross-patient, prospective, pseudo-prospective) (Andrade et al., 2024)

5. **Feature Engineering and Modelling**
   (a) HRV, Lorenz and multifractal features (Abtahi et al., 2025; Fujiwara et al., 2016)
   (b) Classical ML models (e.g. SVM, Random Forest, ensembles) (Dong et al., 2022)
   (c) Deep learning and explainable ML approaches (Abtahi et al., 2025; Ghaderi, 2025)

6. **Results and Comparison of Studies**
   (a) Performance summary by task type (detection vs. prediction)
   (b) Influence of sensor setup, features and models
   (c) Usability and accuracy of everyday wearables
7. **Discussion**
   (a) Methodological limitations (small sample sizes, data leakage, unrealistic evaluation protocols) (Andrade et al., 2024; Kalousios et al., 2024)
   (b) Technical and regulatory challenges (Hashash et al., 2021; Hixson & Braverman, 2020)
   (c) Implications for clinical practice and future research (**abuAlrobUnlockingNewFrontiers2**
8. **Conclusion and Outlook**

5. Literature Search Methodology

5.1 Databases and search strategy

The main databases searched are IEEE Xplore, PubMed, Scopus and Google Scholar.

Search terms combine the dimensions „seizure prediction/detection", „ECG/HRV/heart rate", „wearable", „PPG/EDA/accelerometer" and explicitly exclude EEG-only studies.

5.2 Inclusion and exclusion criteria

Inclusion criteria include, among others:

- Peer-reviewed original research articles or systematic reviews (approx. 2015–2025)
- Use of ECG, HR/HRV or other non-invasive peripheral biosignals for seizure detection or prediction
- Reporting of quantitative performance metrics (e.g. sensitivity, specificity, FPR/h, AUC)

Excluded are EEG-only studies and purely conceptual papers without empirical evaluation.

5.3 Data extraction and synthesis

Data extraction will be based on a predefined table with fields for dataset, sensors, preprocessing, features/models, validation protocol and metrics.

The extracted information will be synthesised narratively and, where appropriate, presented in comparative tables and graphs.

6. Expected Contribution of the Seminar Paper

The seminar paper will provide a consolidated overview of ML-based approaches to seizure detection and prediction using non-invasive cardiovascular and other peripheral sensor signals.

In contrast to EEG-focused reviews, the work explicitly concentrates on ECG/HRV and wearable biosignals and links methodological aspects (feature engineering, model choice, evaluation design) with practical questions regarding deployment on wearables and edge devices.

More specifically, the paper aims to highlight

- the maturity of current methods for everyday, real-world application scenarios,
- key methodological pitfalls (e.g. data leakage, unrealistic warning horizons, lack of prospective evaluation),
- and open research questions for future Bachelor, Master and seminar projects on ECG-based warning systems and multimodal wearable approaches

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