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

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Inhaltsverzeichnis

0.1 1. Introduction and Motivation

0.1.1 1.1 Clinical and societal relevance of epilepsy

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 the vast range of anti-seizure medications, about 30% of patients remain drug resistant; However, patients responding to medication often suffer from severe side effects impacting quality of life (Chen et al., 2020; Kwan & Brodie, 2000).

Unpredictable seizures lead to injuries, restrictions in daily and professional life (e.g. driving bans, need for a caretaker), and reduced quality of life. (Beghi, 2016; Mahler et al., 2018).

0.1.2 1.2 Limitations of EEG-centric approaches

The standard way of diagnosis and seizure detection as well as monitoring is the electroencephalogram (EEG). And while EEGs have been proven effective through decades of research, they require stationary equipment and expert interpretation and thus far have not been made portable, and while there are attempts (ear-EEG) they have yet to show an acceptable accuracy (Villanueva et al., 2023; Wong et al., 2023). Effective seizure prediction and detection with minimal intrusion into the wearers daily life with acceptable performance remains difficult and will be the focus of this seminar paper.

0.1.3 1.3 Wearables and non-invasive sensor modalities

Wearable sensor technology (smartwatches, armbands, chest straps) 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).

Commercial wearables are already available for detecting convulsive/tonic–clonic seizures, although only a minority of devices have peer-reviewed, tested in a prospective natural-environment; Their biggest limitation remains: most are optimized for major motor seizures and *perform poorly for non-convulsive events*; Real world tests reveal increases in false alarm rates and lower sensitivities compared to controlled clinical settings (**pohWearableSeizureDetection2020**).

This indicates the current pitfalls 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).

0.2 2. Theoretical and Methodological Background

0.2.1 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). Generalized seizures present with generalized tonic-clonic seizures (GTCS) in 88% of cases (**keranenDistributionSeizureTypes1988**), while focal seizures often remain local and sometimes 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 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).

0.2.2 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).

0.2.3 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).

Newer work most often employs deep learning and explainable ML. For example, some studies identify the 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).

0.2.4 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) are currently the main sources for model training in the studies reviewed (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; popular 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).

0.3 3. Objectives and Research Questions

0.3.1 3.1 Overall objective

The 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 utilizing non-intrusive biosignals. This includes datasets, sensor types, as well as machine learning models and evaluation protocols. The work also aims to identify research gaps and potential directions for future projects. The focus will be on studies conducted in the last decade (2015-2025)

0.3.2 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, wavelets, etc.) are extracted and which ML/DL models (e.g. classical classifiers, CNN/LSTM, or deep learning models) are employed, and how interpretable as well as applicable to real world scenarios are these models? (Abtahi et al., 2025; Fujiwara et al., 2016; Ghaderi, 2025)
3. **Datasets and evaluation:** Which datasets are used for model training and evaluation and which ones offer the most complete and accurate representation of real-world scenarios? (Andrade et al., 2024; Ghaderi, 2025)
4. **Practical deployment:** Which technical and practical challenges arise for real-world deployment on wearables (e.g. battery life, performance and memory constraints, 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)

0.4 4. Planned Structure of the Seminar Paper

The seminar paper is planned as a structured literature review, planned to roughly follow this structure:

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) interconnection (Thijs et al., 2021)
    (b) Physiology of ECG, HRV and other peripheral biosignal changes in relation to seizures
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) Extracted sensor data and 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**
   (a) Summary of key findings
   (b) Future directions for further research and development

0.5 5. Literature Search Methodology

0.5.1 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.

0.5.2 5.2 Inclusion and exclusion criteria

Inclusion criteria include:

- 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 and studies with small sample sizes or incomparable evaluation protocols.

0.5.3 5.3 Data extraction and synthesis

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

0.6 6. Expected Contribution of the Seminar Paper

the work will explicitly concentrate on ECG/HRV (excluding EEG) from wearable biosignals, and the best techniques for training and deploying effective machine learning models for seizure detection and prediction in real-world scenarios.

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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