Platzhalter titel

Paulin Saher

24. November 2025

Inhaltsverzeichnis

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

1. Background 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 ($\approx$ 0.76% lifetime prevalence), with prevalence and incidence varying by region and study methodology (Beghi, 2019). Despite the availability of anti-seizure medications, about 30% of patients remain drug resistant (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 (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, tied to clinical environments, sometimes invasive, and therefore difficult to deploy in everyday life (Wong et al., 2023). In addition, long-term recordings with high user comfort and minimal intrusion remain challenging.

1.3 Autonomic and cardiovascular changes in seizures

A large body of work shows that epileptic seizures are accompanied by characteristic autonomic changes, particularly in the cardiovascular system. These manifest in the electrocardiogram (ECG), heart rate (HR) and heart rate variability (HRV) (Thijs et al., 2021; Zijlmans et al., 2002). For example, Zijlmans et al. (2002) report an ictal heart-rate increase of >=10 beats/min in about 73% of seizures (seen in 93% of patients) and ECG abnormalities in roughly 26% of seizures; in approximately 23% of seizures (49% of patients) the heart-rate change preceded both the electrographic and the clinical onset (Zijlmans et al., 2002).

Resting ECG studies such as Drake et al. (1993) observed higher resting ventricular rates and modest prolongation of the QT interval in some patient groups (for example, complex partial seizures), but concluded that resting ECG has low diagnostic yield for seizure prediction (Drake et al., 1993).

Ictal heart rate increases, arrhythmias and altered HRV patterns occur peri-ictally and are discussed as potential predictive markers. Zijlmans and Thijs report that heart-rate changes preceded electrographic or clinical onset in a subset of seizures (Thijs et al., 2021; Zijlmans et al., 2002).

Other studies document a high prevalence of peri-ictal ECG abnormalities and an increased prevalence of ECG risk markers in refractory epilepsy, supporting the relevance of cardiac signals for risk stratification although they do not by themselves demonstrate consistent pre-ictal predictive signals (Lamberts et al., 2015; Mason et al., 2024; Nei et al., 2000).

1.4 Wearables and non-invasive sensor modalities

In parallel, wearable sensor technology has become widely available (smartwatches, armbands, chest straps, patches). These devices can continuously capture ECG or PPG-based HR/HRV, accelerometry, electrodermal activity (EDA) and respiration in daily life (Beniczky et al., 2020; Bonato, 2010; Villanueva et al., 2023; Wu et al., 2024). This opens the possibility of seizure detection and prediction based on non-invasive, ambulatory biosignals (Alshehri & Muhammad, 2021).

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

2. Objectives and Research Questions

2.1 Overall objective

The overall objective of the seminar paper is to structure and critically review the state of the art in ML-based methods for seizure prediction and detection using cardiac and other peripheral biosignals, and to identify research gaps for future work. The focus is on human studies from roughly the last ten years that use ECG/HR/HRV or multimodal wearable data.

2.2 Specific research questions

The following research questions guide the work:

1. **Signals and modalities:** Which non-invasive biosignals (ECG, HRV, PPG, accelerometer, EDA, respiration, etc.) are used for seizure detection and prediction, and in which combinations (unimodal vs. multimodal)? (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:** How are datasets, study designs and validation protocols set up (e.g. patient-specific vs. cross-patient, pseudo-prospective evaluation, definition of pre-ictal windows) and which metrics are reported (e.g. sensitivity, FPR/h, AUC, time-in-warning)? (Andrade et al., 2024; Ghaderi, 2025)

4. **Practical deployment:** Which technical and practical challenges arise for real-world deployment on wearables and edge devices (e.g. energy and memory constraints, latency, robustness, data quality, 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)

3. Theoretical and Methodological Background

3.1 Epilepsy and autonomic dysfunction

Epileptic seizures frequently go along with characteristic changes in heart rate and rhythm, such as tachycardia, arrhythmias and altered HRV levels (Drake et al., 1993; Lamberts et al., 2015; Nei et al., 2000). Several works suggest that HR and HRV changes can precede clinical seizure onset and thus could serve as predictive markers (Amengual-Gual et al., 2019; Mason et al., 2024; Zijlmans et al., 2002).

3.2 Non-invasive sensor systems and wearables

In addition to 1- or multi-lead ECG, recent studies increasingly use wearable devices with PPG, EDA, 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).

3.3 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 to identify the most relevant ECG features using SHAP (Abtahi et al., 2025) or to compare model classes and to provide feasibility evidence and sensor- and feature-level separability analyses in small inpatient samples (Ghaderi, 2025; Hamlin et al., 2021). In parallel, there are targeted reviews on HRV-based prediction (Mason et al., 2024; Seth et al., 2023) and on multimodal non-EEG biosignals (Miron et al., 2025; Pordoy et al., 2025).

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 manifestations (Thijs et al., 2021)
   (b) Physiology of ECG, HRV and other peripheral biosignals
   (c) Wearable technologies and edge computing 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, SPH/SOP
   (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) Transferability to 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 literature search will follow a pre-defined search and screening scheme (see project documents in `Organization/`). The main databases 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 (see project documents in `Organization/`).

5.2 Inclusion and exclusion criteria

Inclusion criteria include, among others:

- Peer-reviewed original research articles or systematic reviews (approx. 2015–2025)
- Human participants with epilepsy
- 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, animal experiments and purely conceptual papers without empirical evaluation.

5.3 Data extraction and synthesis

Data extraction will be based on a predefined table (see `extraction-template.csv`) with fields for dataset, sensors, preprocessing, features/models, validation protocol and metrics (see project documents in `Organization/`). The extracted information will be synthesised narratively and, where appropriate, presented in comparative tables.

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

using the already collected organisational notes and intermediate results (see `Organization/`) we will highlight key methodological pitfalls and open research questions (Ghaderi, 2025; Miron et al., 2025).

Literatur

Abtahi, A., Ryvlin, P., & Aminifar, A. (2025). Identification of Relevant ECG Features for Epileptic Seizure Prediction Using Interpretable Machine Learning. *IEEE Access*, *13*, 111293–111303. DOI: 10.1109/ACCESS.2025.3583461 (siehe S. 3, 4).

AbuAlrob, M. A., Itbaisha, A., & Mesraoua, B. (2025). Unlocking New Frontiers in Epilepsy through AI: From Seizure Prediction to Personalized Medicine. *Epilepsy & Behavior*, *166*, 110327. Verfügbar 21. November 2025 unter URL: https://www.sciencedirect.com/science/article/pii/S1525505025000666 (siehe S. 3).

Alshehri, F., & Muhammad, G. (2021). A Comprehensive Survey of the Internet of Things (IoT) and AI-Based Smart Healthcare. *IEEE Access*, *9*, 3660–3678. DOI: 10.1109/ACCESS.2020.3047960 (siehe S. 2, 4).

Amengual-Gual, M., Sánchez Fernández, I., & Loddenkemper, T. (2019). Patterns of epileptic seizure occurrence. *Brain Research*, *1703*, 3–12. DOI: 10.1016/j.brainres.2018.02.032 (siehe S. 3).

Andrade, I., Teixeira, C., & Pinto, M. (2024). On the performance of seizure prediction machine learning methods across different databases: The sample and alarm-based perspectives. *Frontiers in Neuroscience*, *18*. DOI: 10.3389/fnins.2024.1417748 (siehe S. 3, 4).

Beghi, E. (2016). Addressing the Burden of Epilepsy: Many Unmet Needs. *Pharmacological research*, *107*, 79–84. Verfügbar 21. November 2025 unter URL: https://www.sciencedirect.com/science/article/pii/S1043661816301633 (siehe S. 1, 4).

Beghi, E. (2019). The Epidemiology of Epilepsy. *Neuroepidemiology*, *54*(2), 185–191. DOI: 10.1159/000503831 (siehe S. 1).

Beniczky, S., Arbune, A. A., Jeppesen, J., & Ryvlin, P. (2020). Biomarkers of seizure severity derived from wearable devices. *Epilepsia*, *61 Suppl 1*, S61–S66. DOI: 10.1111/epi.16492 (siehe S. 2–4).

Bonato, P. (2010). Wearable Sensors and Systems. *IEEE Engineering in Medicine and Biology Magazine*, *29*(3), 25–36. DOI: 10.1109/MEMB.2010.936554 (siehe S. 2–4).

Chen, Z., Rollo, B., Antonic-Baker, A., Anderson, A., Ma, Y., O'Brien, T. J., Ge, Z., Wang, X., & Kwan, P. (2020). New Era of Personalised Epilepsy Management. *bmj*, *371*. Verfügbar 21. November 2025 unter URL: https://www.bmj.com/content/371/bmj.m3658.long (siehe S. 1).

Donati, E., Zhao, B., Benatti, S., & Cossettini, A. (2025). Guest Editorial: Ultralow-Power Technologies for Edge Computing in Human-Machine Interface Applications. *IEEE Transactions on Biomedical Circuits and Systems*, *19*(1), 2–4. DOI: 10.1109/TBCAS.2025.3533805 (siehe S. 3, 4).

Dong, C., Ye, T., Long, X., Aarts, R. M., van Dijk, J. P., Shang, C., Liao, X., Chen, W., Lai, W., Chen, L., & Wang, Y. (2022). A Two-Layer Ensemble Method for Detecting Epileptic Seizures Using a Self-Annotation Bracelet With Motor Sensors. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1–13. DOI: 10.1109/TIM.2022.3173270 (siehe S. 4).

Drake, M. E., Reider, C. R., & Kay, A. (1993). Electrocardiography in Epilepsy Patients without Cardiac Symptoms. *Seizure*, *2*(1), 63–65. Verfügbar 19. November 2025 unter URL: https://www.sciencedirect.com/science/article/pii/S1059131105801049 (siehe S. 2, 3).

Forooghifar, F., Aminifar, A., & Atienza, D. (2019). Resource-Aware Distributed Epilepsy Monitoring Using Self-Awareness From Edge to Cloud. *IEEE Transactions on*

Biomedical Circuits and Systems, *13*(6), 1338–1350. DOI: 10.1109/TBCAS.2019.2951222 (siehe S. 3).

Fujiwara, K., Miyajima, M., Yamakawa, T., Abe, E., Suzuki, Y., Sawada, Y., Kano, M., Maehara, T., Ohta, K., Sasai-Sakuma, T., Sasano, T., Matsuura, M., & Matsushima, E. (2016). Epileptic Seizure Prediction Based on Multivariate Statistical Process Control of Heart Rate Variability Features. *IEEE Transactions on Biomedical Engineering*, *63*(6), 1321–1332. DOI: 10.1109/TBME.2015.2512276 (siehe S. 3, 4).

Ghaderi, F. (2025, 11. April). *Advances in Machine Learning for Epileptic Seizure Prediction: A Review of ECG-Based Approaches*. 2025040942. DOI: 10.20944/preprints202504.0942.v1. (Siehe S. 3–5).

Hamlin, A., Kobylarz, E., Lever, J. H., Taylor, S., & Ray, L. (2021). Assessing the Feasibility of Detecting Epileptic Seizures Using Non-Cerebral Sensor Data. *Computers in Biology and Medicine*, *130*, 104232. DOI: 10.1016/j.compbiomed.2021.104232 (siehe S. 3).

Hashash, O., Sharafeddine, S., Dawy, Z., Mohamed, A., & Yaacoub, E. (2021). Energy-Aware Distributed Edge ML for mHealth Applications With Strict Latency Requirements. *IEEE Wireless Communications Letters*, *10*(12), 2791–2794. DOI: 10.1109/LWC.2021.3117876 (siehe S. 3, 4).

Hixson, J. D., & Braverman, L. (2020). Digital tools for epilepsy: Opportunities and barriers. *Epilepsy Research*, *162*, 106233. DOI: 10.1016/j.eplepsyres.2019.106233 (siehe S. 3, 4).

Kalousios, S., Müller, J., Yang, H., Eberlein, M., Uckermann, O., Schackert, G., Polanski, W. H., & Leonhardt, G. (2024). ECG-based Epileptic Seizure Prediction: Challenges of Current Data-driven Models. *Epilepsia Open*, *10*(1), 143–154. DOI: 10.1002/epi4.13073 (siehe S. 4).

Kwan, P., & Brodie, M. J. (2000). Early Identification of Refractory Epilepsy. *New England Journal of Medicine*, *342*(5), 314–319. DOI: 10.1056/NEJM200002033420503 (siehe S. 1).

Lamberts, R. J., Blom, M. T., Novy, J., Belluzzo, M., Seldenrijk, A., Penninx, B. W., Sander, J. W., Tan, H. L., & Thijs, R. D. (2015). Increased Prevalence of ECG Markers for Sudden Cardiac Arrest in Refractory Epilepsy. *Journal of Neurology, Neurosurgery & Psychiatry*, *86*(3), 309–313. Verfügbar 19. November 2025 unter URL: https://jnnp.bmj.com/content/86/3/309.short (siehe S. 2, 3).

Leal, A., da Graça Ruano, M., Henriques, J., de Carvalho, P., & Teixeira, C. (2017). On the Viability of ECG Features for Seizure Anticipation on Long-Term Data. *2017 IEEE 3rd International Forum on Research and Technologies for Society and Industry (RTSI)*, 1–5. DOI: 10.1109/RTSI.2017.8065951 (siehe S. 3, 4).

Mahler, B., Carlsson, S., Andersson, T., & Tomson, T. (2018). Risk for injuries and accidents in epilepsy. *Neurology*, *90*(9), e779–e789. DOI: 10.1212/WNL.0000000000005035 (siehe S. 1).

Mason, F., Scarabello, A., Taruffi, L., Pasini, E., Calandra-Buonaura, G., Vignatelli, L., & Bisulli, F. (2024). Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review. *Journal of Clinical Medicine*, *13*(3), 747. DOI: 10.3390/jcm13030747 (siehe S. 2, 3).

Miron, G., Halimeh, M., Jeppesen, J., Loddenkemper, T., & Meisel, C. (2025). Autonomic biosignals, seizure detection, and forecasting. *Epilepsia*, *66 Suppl 3*, 25–38. DOI: 10.1111/epi.18034 (siehe S. 2, 3, 5).

Najafi, T. A., Calero, J. A. M., Thevenot, J., Duc, B., Albini, S., Amirshahi, A., Taji, H., Beneyto, M. J. B., Affanni, A., & Atienza, D. (2024). VersaSens: An Extendable Multimodal Platform for Next-Generation Edge-AI Wearables. *IEEE Transactions on Circuits and Systems for Artificial Intelligence*, *1*(1), 83–96. DOI: 10.1109/TCASAI.2024.3453809 (siehe S. 3).

Nei, M., Ho, R. T., & Sperling, M. R. (2000). EKG Abnormalities During Partial Seizures in Refractory Epilepsy. *Epilepsia*, *41*(5), 542–548. DOI: 10.1111/j.1528-1157.2000.tb00207.x (siehe S. 2, 3).

Pavei, J., Heinzen, R. G., Novakova, B., Walz, R., Serra, A. J., Reuber, M., Ponnusamy, A., & Marques, J. L. B. (2017). Early Seizure Detection Based on Cardiac Autonomic Regulation Dynamics. *Frontiers in Physiology*, *8*. DOI: 10.3389/fphys.2017.00765 (siehe S. 3).

Pordoy, J., Jones, G., Matoorian, N., Evans, M., Dadashiserej, N., & Zolgharni, M. (2025). Enhanced Non-EEG Multimodal Seizure Detection: A Real-World Model for Identifying Generalised Seizures Across the Ictal State. *IEEE Journal of Biomedical and Health Informatics*, *29*(5), 3329–3342. DOI: 10.1109/JBHI.2025.3532223 (siehe S. 3).

Seth, E. A., Watterson, J., Xie, J., Arulsamy, A., Md Yusof, H. H., Ngadimon, I. W., Khoo, C. S., Kadirvelu, A., & Shaikh, M. F. (2023). Feasibility of Cardiac-based Seizure Detection and Prediction: A Systematic Review of Non-invasive Wearable Sensor-based Studies. *Epilepsia Open*, *9*(1), 41–59. DOI: 10.1002/epi4.12854 (siehe S. 2, 3).

Sivathamboo, S., Nhu, D., Piccenna, L., Yang, A., Antonic-Baker, A., Vishwanath, S., Todaro, M., Yap, L. W., Kuhlmann, L., Cheng, W., O'Brien, T. J., Lannin, N. A., & Kwan, P. (2022). Preferences and User Experiences of Wearable Devices in Epilepsy: A Systematic Review and Mixed-Methods Synthesis. *Neurology*, *99*(13), e1380–e1392. DOI: 10.1212/WNL.0000000000200794 (siehe S. 3).

Thijs, R. D., Ryvlin, P., & Surges, R. (2021). Autonomic manifestations of epilepsy: Emerging pathways to sudden death? *Nature Reviews. Neurology*, *17*(12), 774–788. DOI: 10.1038/s41582-021-00574-w (siehe S. 1, 2, 4).

Villanueva, G. M. B., Lopez-Iturri, P., Esteban, M. A., Granda, J. A. G., Trigo, J. D., Serrano-Arriezu, L., Falcone, F., & Ustarroz, M. V. (2023). Multimodal Minimally Invasive Wearable Technology for Epilepsy Monitoring: A Feasibility Study of the Periauricular Area. *IEEE Sensors Journal*, *23*(21), 26620–26635. DOI: 10.1109/JSEN.2023.3314190 (siehe S. 2–4).

Wong, S., Simmons, A., Rivera-Villicana, J., Barnett, S., Sivathamboo, S., Perucca, P., Ge, Z., Kwan, P., Kuhlmann, L., Vasa, R., Mouzakis, K., & O'Brien, T. J. (2023). EEG Datasets for Seizure Detection and Prediction— A Review. *Epilepsia Open*, *8*(2), 252–267. DOI: 10.1002/epi4.12704 (siehe S. 1, 4).

Wu, D., Wei, J., Vidal, P.-P., Wang, D., Yuan, Y., Cao, J., & Jiang, T. (2024). A Novel Seizure Detection Method Based on the Feature Fusion of Multimodal Physiological Signals. *IEEE Internet of Things Journal*, *11*(16), 27545–27556. DOI: 10.1109/JIOT.2024.3398418 (siehe S. 2–4).

Zijlmans, M., Flanagan, D., & Gotman, J. (2002). Heart Rate Changes and ECG Abnormalities During Epileptic Seizures: Prevalence and Definition of an Objective Clinical Sign. *Epilepsia*, *43*(8), 847–854. DOI: 10.1046/j.1528-1157.2002.37801.x (siehe S. 1–3).