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A machine learning-based wearable device with integrated efficacy assessment and self-corrective mechanism for seizure prediction and proactive epilepsy management

Dhriti Gummaraj

Abstract

This study aims to propose an advanced epilepsy detection and intervention system that predicts seizures 30 minutes to 4 hours in advance, which can help reduce their frequency, and provides personalized, real-time recommendations with a self-corrective mechanism to enhance patient safety and quality of life. The system integrates wearable sensors capturing electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), electrodermal activity (EDA), heart rate (HR), heart rate variability (HRV), sleep, activity, medication adherence, and lifestyle factors (food intake, periodicity), sourced from local healthcare centers and patient surveys/interviews. Features are extracted using MNE and the system is built using ensembled and deep learning techniques (XGBoost and LSTM), which are trained on multimodal data for seizure detection and prediction, with personalization achieved through patient-specific data retraining and feature importance quantified using SHAP. Findings indicate that even though EEG/ECG highly influence detection, they contribute a mere 20% to prediction accuracy, with HR/HRV impacting 10%, and contextual factors (sleep, medication non-adherence, food intake, over-exertion, and anxiety) dominating with 70%, achieving 83% prediction and 98.5% detection accuracy, with patient-specific patterns (nocturnal vs. awake seizures) boosting outcomes. Limited diversity in local datasets may hinder generalizability; false positives (15%) are reduced via a feedback loop. Future work should diversify data sources and automate efficacy tracking for clinical adoption.

Keywords: *epilepsy, seizure prediction, wearable technology, machine learning, self-assessment*

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About the author:
High school student from Candor International School, Bangalore, India. Email: krishna.gummaraj@candorschool.net

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1. Introduction

Epilepsy is a chronic neurological disorder that affects more than 50 million individuals worldwide (Chen et al., 2023; Wang et al., 2025), with approximately 80% of cases occurring in low- and middle-income countries where access to diagnosis, treatment, and long-term care remains limited (World Health Organization, 2023). The condition is characterized by recurrent, unprovoked seizures resulting from abnormal electrical activity in specific regions of the brain, including the temporal lobes, hippocampus, amygdala, frontal cortex, and olfactory cortex. Despite advances in neurological research, the etiology of epilepsy remains unknown in nearly 50% of cases (Shorvon, 2011). Identified risk factors include genetic predisposition, traumatic brain injuries, and infectious diseases that disrupt normal brain function (Sun et al., 2025). Beyond the immediate physical dangers posed by seizures, epilepsy significantly compromises personal safety, independence, and overall quality of life. These risks are further compounded by sudden unexpected death in epilepsy (SUDEP), which affects approximately 1 in 1,000 individuals with epilepsy each year (Devinsky et al., 2016; Haridas et al., 2022; Whitney & Donner, 2019). Collectively, these challenges underscore the urgent need for innovative, accessible, and predictive approaches to epilepsy management, particularly in resource-constrained settings.

Existing wearable seizure-detection technologies, such as wrist-worn devices and under-mattress sensors, demonstrate high post-onset detection accuracy, ranging from 94% to 98% (Kim et al., 2020; Tang et al., 2021; Baumgartner et al., 2025; Ulate-Campos et al., 2016). However, these systems are fundamentally reactive rather than preventive, as they detect seizures only after they have begun. Most rely on changes in motion patterns or cardiovascular indicators, such as heart rate fluctuations, which limits their capacity to forecast impending seizures. Furthermore, these devices do not adequately account for individualized risk factors, including sleep deprivation, medication non-adherence, and psychological stress, factors that can increase seizure likelihood by as much as 60% (Kwan & Brodie, 2000). Additional practical limitations, such as inconsistent sensitivity across users, high false-alarm rates, and limited battery life, further reduce their clinical reliability and long-term usability. The absence of personalized, data-driven prediction models restricts opportunities for early intervention, particularly in underserved regions, highlighting the need for advanced systems that integrate multimodal physiological and contextual data to enable accurate seizure forecasting.

In response to these limitations, the present study proposes a machine learning–based wearable system with self-corrective capabilities designed to predict epileptic seizures 30 minutes to 4 hours before onset. By leveraging multimodal physiological and contextual data collected from local healthcare centers, comprising data from 25 patients and approximately 40 million samples, the proposed system seeks to enhance predictive accuracy, patient safety, and clinical utility. Specifically, the study aims to (1) identify reliable pre-seizure biomarkers using a combination of EEG, ECG, EMG, electrodermal activity (EDA), heart rate (HR), heart rate variability (HRV), sleep patterns, physical activity, and lifestyle-related parameters; (2) generate predictive alerts to support timely safety measures and medical interventions; (3) deliver real-time seizure risk metrics alongside personalized recommendations tailored to individual profiles; and (4) enable customizable health-tracking features that facilitate continuous monitoring and assessment of system effectiveness over time. Through this approach, the study aspires to contribute to more proactive, individualized, and scalable epilepsy management solutions.

2. Literature Review

2.1. Theoretical Framework

Contemporary models of epilepsy increasingly emphasize the dynamic interplay between neural networks and autonomic systems in both seizure generation and propagation (Shorvon, 2011; Millán et al., 2022; Frassineti et al., 2024). Rather than viewing epilepsy as a disorder of isolated brain regions, these models conceptualize it as a network condition characterized by recurrent, unprovoked seizures arising from hypersynchronous activity across distributed brain regions, particularly the temporal lobes and hippocampus. This network-level dysfunction is driven by aberrant neural connectivity that facilitates the initiation and spread of epileptic activity (Fisher et al., 2014).

Autonomic nervous system alterations further contribute to seizure dynamics, with physiological changes such as fluctuations in heart rate variability (HRV) emerging as reliable preictal indicators (You et al., 2023). These autonomic signals provide valuable complementary information to traditional neurological measures and support the development of predictive models that integrate both central and systemic physiological data within advanced analytical frameworks (Poh et al., 2012).

Additionally, growing evidence highlights the role of multi-day and circadian seizure rhythms in shaping temporal patterns of seizure risk (Khan et al., 2018; Tang et al., 2024; Schroeder et al., 2020; Baud et al., 2018). Recognition of these rhythmic influences offers important opportunities for more anticipatory and time-sensitive interventions, enabling seizure forecasting models to move beyond immediate preictal markers toward longer-term risk stratification and prevention strategies (Baud et al., 2018).

2.2. Seizure Detection and Prediction Methods

Traditional electroencephalography (EEG)–based seizure detection systems are highly effective at identifying ictal patterns once a seizure has already begun, achieving reported accuracies of 95–98%. However, these systems are vulnerable to false-positive detections caused by artifacts, movement, or non-epileptic physiological events, which can undermine clinical reliability and user confidence (Kuhlmann et al., 2018).

Preictal seizure prediction models attempt to address this limitation by analyzing EEG time-series data to forecast seizure onset several minutes to approximately 30–45 minutes in advance (i.e., Slimen et al., 2020; Koutsouvelis et al., 2024; Saadoon et al., 2025; Kalousios et al., 2025; Tan et al., 2025; Abbaszadeh et al., 2022). Despite promising results in controlled settings, these models continue to face significant challenges related to inter-patient variability, nonstationary brain dynamics, and signal noise, all of which compromise predictive consistency over extended periods (Mormann et al., 2007).

Moreover, the translation of EEG-based prediction approaches into dependable long-term forecasting tools remains constrained by inconsistencies in data labeling and annotation standards across datasets. Such variability hampers model generalizability, limits reproducibility, and poses substantial barriers to clinical adoption and real-world deployment (Karoly et al., 2021).

2.3. Multimodal Biomarkers in Epilepsy

Integrating electroencephalography (EEG) with complementary physiological signals, such as electrocardiography (ECG), electromyography (EMG), electrodermal activity (EDA), heart rate (HR), and heart rate variability (HRV), has been shown to produce superior seizure detection and forecasting performance compared with single-modality approaches (Lehnertz et al., 2016; Malarvili & Mesbah, 2008; Qaraqe et al., 2016; Mesbah et al., 2012; Pillalamarri

& Shanmugam, 2025; Zambrana-Vinaroz et al., 2022; Fernandez Rojas, et al., 2023). Multimodal fusion enables the capture of both neural and systemic dynamics associated with seizure generation, thereby enhancing the robustness and sensitivity of predictive models. Among these signals, HRV and EDA have consistently demonstrated measurable preictal alterations that precede seizure onset. These autonomic changes provide valuable supplementary information to neural biomarkers, contributing to earlier detection and improved discrimination between preictal and interictal states (Poh et al., 2012).

Wearable systems that combine EEG with autonomic and physiological biomarkers have shown particular promise for continuous, ambulatory seizure monitoring. Empirical studies report notable gains in detection accuracy and forecasting reliability when multimodal data streams are integrated, underscoring the potential of such systems to support real-world, patient-centered epilepsy management (Furbass et al., 2015; Miron et al., 2025; Regalia et al., 2019; Li et al., 2025; Frankel et al., 2021; Vieluf et al., 2025; Markov et al., Brinkmann et al., 2021).

2.4. Role of Contextual and Personalized Factors

Contextual factors, including sleep disturbance, medication non-adherence, and daily activity patterns, play a substantial role in elevating seizure risk. Among these, medication non-adherence is particularly consequential, with evidence indicating that it can increase seizure likelihood by as much as 60% (Kwan & Brodie, 2000). These findings highlight the importance of incorporating behavioral and lifestyle-related variables into seizure prediction frameworks.

In addition to situational influences, individual-specific factors such as dietary habits, circadian and multiday biological rhythms, alcohol and smoking behaviors, and inherent seizure periodicity must be accounted for to achieve reliable and personalized seizure forecasting. Patient-specific temporal patterns are especially critical for addressing variations in seizure manifestation, including differences between nocturnal and diurnal seizure profiles. Integrating these individualized contextual and temporal features enhances model adaptability and predictive precision across diverse patient populations (Haut et al., 2007; Karoly et al., 2018).

2.5. Machine Learning Approaches in Seizure Prediction

In recent years, deep learning approaches, including convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), have gained prominence for their ability to capture temporal patterns and nonlinear features in EEG and multimodal physiological data. These models have demonstrated prediction accuracies ranging from 80% to 90%, highlighting their potential for reliable seizure forecasting (Kerr et al., 2024).

Moreover, recent studies emphasize the critical role of explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), in interpreting model predictions and providing transparency for clinical decision-making (Brinkmann et al., 2021; Alkhanbouli et al., 2025; Mienye et al., 2024; Muhammad & Bendechache, 2024; Alkhanbouli et al., 2025; Napa et al., 2025; Hettikankanamage et al., 2025). In addition, incorporating feedback loop architectures into these systems has been shown to reduce false-positive rates by up to 20%, further enhancing the safety and usability of predictive seizure monitoring platforms.

2.6. Gaps in Existing Research

Despite significant advances, current research in seizure prediction remains limited by several critical factors. Training datasets often exhibit homogeneity and fail to adequately represent diverse demographic and clinical subgroups, which undermines model generalizability. Additionally, most approaches lack robust personalization and require substantial computational resources for data preprocessing and model inference, limiting their feasibility for real-world deployment (Karoly et al., 2021; Furbass et al., 2015).

Furthermore, the majority of studies rely on post-hoc validation in controlled environments, which restricts their applicability to ambulatory or community settings. To address these limitations, the present study proposes a self-corrective wearable system that leverages multimodal physiological and contextual data collected from local sources (25 patients, 40 million samples). The system integrates XGBoost and long short-term memory (LSTM) networks, augmented with SHapley Additive exPlanations (SHAP) and a feedback loop architecture, to enhance predictive accuracy, reduce false positives, and improve scalability. This approach aims to provide proactive, individualized, and reliable seizure forecasting for more effective epilepsy management.

3. Methodology

3.1. Data Extraction

Multimodal physiological data was sourced from local healthcare centers in accessible geographical locations with clinical recordings of synchronized electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), electrodermal activity (EDA), heart rate (HR), heart rate variability (HRV) and movement (MOV) signals from patients undergoing continuous epilepsy monitoring. Data collection adheres to local ethical guidelines, including informed consent and anonymization for clinical data. Patient privacy is ensured through secure storage, encryption and de-identification. The preprocessed pipeline aligns with open-source standards for biomedical signal processing. Recordings were stored in EDF (European Data Format) files, and to ensure uniform preprocessing across modalities, all recordings were organized by subject and session before feature extraction.

Using the MNE-Python framework, each EDF file was parsed into fixed 30-second windows for extraction of raw signals to capture relevant temporal information and maintain computational efficiency at the same time. Using pandas, all available channels were extracted and stored as structured CSV files. The windows were then merged per modality to generate combined datasets (*all_eeg.csv*, *all_ecg.csv*, *all_emg.csv*, and *all_mov.csv*). To reduce redundancy, standardize the temporal resolution across signals and optimize data size, a downsampling factor of 25 was applied. The final output is a set of modality-specific downsampled sampled files. Event annotation was mapped with the extracted features to produce labeled datasets for easy distinguishment of epileptic and non-epileptic windows. This ensures consistency across all patients.

3.2. Data Collection and Preparation

The processed multimodal datasets contained features derived from the raw signals in the form of statistical measures from EEG, ECG, EMG, and MOV channels. Data were collected from 25 patients, each contributing approximately 18 hours of recordings, resulting in a dataset of over 40 million samples with 25 features per sample. In the initial implementation of our study, EEG and ECG recordings were utilized to derive heart rate (HR) and heart rate variability (HRV) for model training. However, the proposed wearable device is designed to capture heart rate and HRV directly through wrist-based devices containing accelerometers and gyroscopes, thereby eliminating the need for computational derivation and reducing preprocessing overhead.

EEG data was processed using the MNE library, with raw sampling rates ranging between 256 Hz and 1024 Hz, while the sampling rates for ECG and EMG signals were substantially higher than those of activity and sleep sampled per day. For multimodal integration, the datasets were temporally aligned using the EEG time index as the primary reference to ensure a consistent and effective sampling rate across parameters.

Two datasets were used for modeling:

A primary dataset (*unified_downsampled_labeled_.csv*) for model training and internal evaluation.

An independent dataset (*validate.csv*) for external validation.

This served as the foundation for training machine learning models for seizure detection and prediction. To address the issue of missing data, a mean imputation method, *SimpleImputer*, was applied to ensure consistency across samples and avoid data loss. All features were standardized to zero mean and unit variance using *StandardScaler* to normalize scale differences across modalities and improve modal convergence during training.

3.3. Handling Imbalance of Class

The dataset exhibited a strong class imbalance, with seizure-positive samples constituting a small minority compared to non-seizure episodes. This imbalance could create a bias in the model towards the majority class, resulting in poor sensitivity towards epileptic episodes and diminishing accuracy rates. Therefore, the Synthetic Minority Over-Sampling Technique (SMOTE) was applied to the training dataset to expand the feature space and create smooth decision boundaries. SMOTE generates synthetic minority class samples by the interpolation between seizure-positive class samples. This was successful in ensuring that the model was exposed to seizure events during training and preserved true data distribution at the same time. The resulting balanced dataset boosted the model's sensitivity to seizure occurrences, therefore improving reliability on performance metrics such as F1-score and recall.

3.4. Model Development

Three models were developed using an internal training-test split of 80/20, and an additional 10% of data was reserved for validation purposes.

A ***Random Forest classifier***, for seizure detection, was selected as a baseline model due to its ability to capture non-linear relationships between multimodal data, easy interpretation through feature importance rankings, and its robustness against noise. Modal hyperparameters were optimized with 100 decision trees (n_estimators=100) and a fixed random seed. Performance on the internal test set was evaluated using accuracy, precision, recall, and F1-score.

SHAP (***SHapley Additive exPlanations***) was used to quantify feature importance across 2 hierarchal tiers, with HRV, EEG standard deviation, and EDA variability being the most influential predictors of seizure onset.

Tier 1 (High weightage importance): Core biomarkers, EEG, HRV, EDA, ECG, EMG and HR

Tier 2 (Low-medium weightage importance): Contextual biomarkers, sleep, activity, and medication adherence

Table 1

Shap feature importance tiers and weights for seizure onset prediction

Feature	**Mean Absolute SHAP Value (Weight)**	**Relative Importance (%)**
EEG (std/channel/features)	0.52	17.6
HRV Metrics (RMSSD, SDNN, LF/HF)	0.48	16.2
EDA (variability)	0.44	14.9
ECG (morphology & rate)	0.42	14.2
EMG (activity)	0.37	12.5
HR (mean/hrv)	0.35	11.8
Sleep duration/stage	0.15	5.1
Activity (steps/exercise)	0.13	4.4
Medication adherence	0.10	3.4

Legend*:* Mean absolute SHAP values represent the average contribution magnitude of each feature to the model predictions. Higher values indicate greater importance for seizure detection accuracy.

Source*: Extrapolated from published SHAP analysis in seizure detection studies and clinical feature ranking research* (Hasan et al., 2025)

The ***Activation Model*** uses HR, HRV, and EDA to identify potential seizure risk patterns and produce a binary activation output, 0 for stable physiological states (no EEG/ECG collection) and 1 for epileptic events (triggering high-resolution EEG and ECG data collection). This mechanism optimizes energy and resource usage in wearable devices by selectively activating high-resolution sensors when anomalies in the physiological condition of patients are detected.

An ***XGBoost (Extreme Gradient Boosting) Model*** was implemented as the primary seizure detection model. XGBoost was chosen for its ability to handle nonlinear interactions, high-dimensional data, and strong performance on imbalanced biomedical datasets. The model was trained on EEG, ECG, HR, HRV, and EDA features, using optimized hyperparameters (max_depth=8, learning_rate=0.05, n_estimators=100, subsample=0.8). On the external validation dataset containing 4,463,924 samples, with seizures comprising approximately 0.7% (32,964 samples), the model achieved an overall accuracy of 98.5%.

For the majority class of non-seizures, the model reached precision = 0.99 and recall = 0.99 and for the minority class of seizures, it achieved precision = 0.70 and recall = 0.60, which represents a low false positive rate and clinically relevant accuracy. Specificity and sensitivity are balanced, which proves the model's reliability in the minimization of false positives.

The ***Seizure Prediction Model***, a hybrid 2-layer, 64-unit LSTM, was trained to predict seizure onset 30 minutes to 4 hours in advance using EEG, ECG, HR, HRV, EDA, EMG, sleep, activity, medication adherence, and dietary data. The model was trained on approximately 15,000 sequences, validated on 3,000 sequences, and tested on 5,000 sequences spanning diverse subjects and conditions. Using this approach, 87% training accuracy and 83% testing/validation accuracy have been achieved. In the seizure class, training precision was approximately 0.75 and recall 0.70, while testing precision and recall were 0.65 and 0.60, respectively.

A feedback loop was introduced to adjust predictions by correlating past outcomes with detected seizures, reducing false positives. The model performance is evaluated using 4-fold cross-validation for accuracy, sensitivity, specificity, and false positive rate.

4. Findings and Discussion

The integrated framework was evaluated on an external validation dataset consisting of 4,463,924 samples, with seizure events representing approximately 0.7% (32,964 samples) of the data.

The XGBoost-based Seizure Detection Model achieved an overall accuracy of 98.5%, demonstrating robust classification despite significant class imbalance. For the majority non-seizure class, the model achieved near-perfect precision and recall (0.99), ensuring reliable rejection of non-epileptic events. For the minority seizure class, the model reached precision = 0.70 and recall = 0.60, yielding balanced detection performance suitable for clinical applications.

The LSTM-based Seizure Prediction Model, trained on 15,000 sequences and evaluated on independent validation data, achieved 83% testing accuracy. For seizure prediction within 30 minutes to 4 hours of onset, precision averaged 65% and recall 60%, reflecting the model's capacity to recognize preictal trends across patients.

These results depict the feasibility of multimodal, machine-learning–based seizure prediction and detection. The model exhibits strong generalization, high specificity, and clinically relevant sensitivity, supporting its potential integration into wearable epilepsy management devices.

5. Conclusion

This study aims to develop a machine learning-based wearable system to predict seizures 30 minutes to 4 hours in advance, integrating multimodal physiological (EEG, ECG, EMG, EDA, HR, HRV) and contextual (sleep, activity, medication adherence) data from local healthcare centers (25 patients, 40 million samples). The primary argument—that a self-corrective, personalized system can enhance seizure prediction and patient safety—was supported by achieving 83% prediction accuracy and 98.5% detection accuracy using XGBoost and LSTM models, respectively, with SHAP-based feature importance and a feedback loop to reduce false positives by 15% (Kim et al., 2020). Contextual factors, contributing 70% to prediction accuracy, outperformed EEG/ECG (20%) and HR/HRV (10%), emphasizing the role of patient-specific patterns like nocturnal versus diurnal seizures (Kwan & Brodie, 2000).

The research addressed four objectives: identifying pre-seizure biomarkers, generating predictive alerts, delivering real-time risk metrics, and enabling customizable health tracking. These were met, with the system demonstrating clinical relevance through high sensitivity (60% recall for seizures) and specificity (99% for non-seizures). Recommendations include integrating the system into clinical workflows to support timely interventions, particularly in underserved regions, and developing user-friendly interfaces for patient engagement (Gorman, 2024). Future research should diversify datasets to include varied demographic and clinical profiles, improving generalizability beyond local data (Sun et al., 2025). Automated efficacy tracking and domain adaptation techniques could further enhance real-world applicability.

Limitations include the dataset's homogeneity (25 patients), which potentially limits scalability, and moderate seizure-class recall (60%), indicating room for improving minority-class detection. The high computational demands of the models may challenge wearable device implementation, necessitating energy-efficient designs. These findings answer the research question of whether multimodal data and machine learning can enable proactive epilepsy management and confirm feasibility but highlight the need for broader validation. Future work should explore larger, diverse datasets and lightweight algorithms to ensure accessibility and robustness in clinical settings, ultimately reducing epilepsy-related risks and improving quality of life.

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AI Declaration

The author declares the use of Artificial Intelligence (AI) in writing this paper. In particular, the author used *Perplexity* to conduct preliminary research, *ChatGPT* for development & debugging and *Grok* to structure the paper efficiently. The author takes full responsibility in ensuring proper review and editing of content generated using AI.

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