Great, I will conduct a comprehensive literature review covering the past 20 years on seizure prediction methods, with a focus on focal epilepsy and reflex seizures. The research will explore:

- **Feature Identification**: Key physiological, neurological, and behavioral markers studied for predicting focal epilepsy with secondary generalization, including EEG, heart rate variability, speech patterns, and muscle tension.
- **Measurement & Monitoring Technologies**: Available invasive and non-invasive wearable devices, including implantable sensors for real-time tracking of epilepsy indicators.
- **Predictive Models & Machine Learning Approaches**: Deep learning models that have been successfully used for seizure prediction, their accuracy rates, and the challenges in focal epilepsy prediction.
- **Public & Non-Public Datasets**: A list of publicly available and restricted datasets relevant to epilepsy prediction modeling.
- **Technological Gaps & Innovations**: Current limitations in sensor development and AI-based analytics, with recommendations for designing an always-on monitoring system for temporal epilepsy with speech-related triggers.

I will compile this into a detailed report and get back to you soon.

Seizure Prediction in Focal Epilepsy and Reflex Seizures: A Comprehensive Review

1. Feature Identification

Key Physiological & Neurological Features: Epileptic seizures are often preceded by measurable changes in brain and body signals. In focal epilepsy (especially temporal lobe epilepsy with secondary generalization), **EEG** is the primary source of predictive features. Researchers have identified a distinct **pre-ictal state** in EEG that can begin minutes before seizure onset ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)). During this state, the brain's electrical activity shows alterations such as shifts in spectral power, emergence of epileptiform transients, and changes in network synchronization. For example, increases in high-frequency oscillations or changes in phase locking between EEG channels have been observed as early warning markers ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=feature%20extraction%2C%20and%20feature%20classification,29%20Machine)). Traditional time-domain features (e.g. variance, zero-crossing rate) and frequency-domain features (band-specific power) from EEG have been widely used to distinguish preictal from interictal periods ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=feature%20extraction%2C%20and%20feature%20classification,29%20Machine)). Nonlinear dynamical metrics (e.g. entropy measures or Lyapunov exponents) also capture the evolving instability of brain signals before seizures ([
Using Explainable Artificial Intelligence to Obtain Efficient Seizure-Detection Models Based on Electroencephalography Signals - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10747117/#:~:text=signals%20over%20brief%20temporal%20windows,43)).

Beyond EEG, the **autonomic nervous system** provides important cues. Many studies report that seizure onset is *anticipated by significant changes in heart activity*. Notably, **heart rate variability (HRV)** tends to alter in the minutes leading up to a seizure ([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=is%20anticipated%20by%20significant%20changes,the%20PubMed%20database%20returned%20402)). Patients often experience a pre-ictal increase in heart rate or shifts in HRV metrics reflecting sympathetic activation ([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=caregivers,metrics%20are%20often%20incapable%20of)). These cardiac changes can serve as early biomarkers, especially in focal seizures that generalize (where autonomic changes may ramp up before the convulsion). In addition, some patients show skin conductance rises (electrodermal activity) and blood pressure fluctuations as part of the autonomic aura, indicating broader autonomic arousal prior to seizures ([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=caregivers,metrics%20are%20often%20incapable%20of)) ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=In%20addition%20to%20accelerometry%2C%20wearable,the%20technology%20and%20thereby%20create)).

Behavioral and Prodromal Indicators: Subtle behavioral changes are also studied as predictive features. Patients with focal epilepsy sometimes report **aura symptoms** (perceptual or emotional disturbances) that occur in the pre-ictal phase, reflecting the seizure's beginnings in a focal area. These auras – when observable, such as a sudden pause in speech or a brief repetitive motion – can be treated as behavioral cues of an impending seizure ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=subsequent%20seizure%20in%20the%20pre,See%20Table%203)). Changes in **muscle tone** or **muscle activity** may occur as well. For instance, focal seizures that will generalize might start with slight muscle contractions or stiffness (e.g. subtle facial or limb myoclonus) before evolving into a major motor event. In some cases, surface EMG recordings have detected increasing muscle activity seconds to minutes before overt convulsions, though this is more evident for reflex seizures involving motor tasks.

Speech and Reflex Triggers: A special focus is given to **speech-related features** in reflex epilepsy. Reflex seizures are precipitated by specific stimuli or activities; in the case of speech- or intonation-triggered seizures (a form of language-induced reflex epilepsy), the act of speaking or hearing certain patterns can trigger the ictal event. Studies have documented that **speech processing changes** can precede these seizures. For example, patients with reading epilepsy (a language-induced epilepsy) experience progressive speech dysfluency – such as **stuttering or halted speech** – just before a seizure is triggered by reading aloud ([
Epilepsy and Diagnostic Dilemmas: The Role of Language and Speech-Related Seizures - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC9025095/#:~:text=match%20at%20L625%20In%20a,In%20this%20particular%20patient)). In one case, reading-triggered focal seizures were heralded by facial myoclonus and stammering speech; EEG recorded during this period showed abnormal discharges in language-related cortex, corresponding with the brief speech interruptions ([
Epilepsy and Diagnostic Dilemmas: The Role of Language and Speech-Related Seizures - PMC

](https://pmc.ncbi.nlm.nih.gov/articles/PMC9025095/#:~:text=match%20at%20L625%20In%20a,In%20this%20particular%20patient)). Such findings suggest that monitoring speech output for irregularities (e.g. sudden pausing, repetition, or changes in intonation) could provide early warning in individuals whose seizures are precipitated by speaking or listening. Table 1 below summarizes key biomarkers and features identified for seizure prediction in focal and reflex epilepsy.

Table 1. Key Biomarkers for Seizure Prediction and Their Pre-Ictal Changes

Biomarker / Feature	**Pre-ictal Changes & Indicators**	**References**
EEG (brain activity)	Emergence of a pre-ictal state minutes before onset; increased rhythmic activity or spiking in seizure focus; changes in band power (e.g. rising gamma, dropping alpha); heightened synchronization or network connectivity between regions (e.g. phase locking); nonlinear dynamics indicating loss of stability.	([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)) ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=feature%20extraction%2C%20and%20feature%20classification,29%20Machine))
Heart rate / HRV	Autonomic arousal prior to seizures: heart rate acceleration and reduced heart rate variability; shifts in HRV nonlinear features indicating sympathetic surge; sometimes detectable seconds to minutes before clinical onset.	([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=is%20anticipated%20by%20significant%20changes,the%20PubMed%20database%20returned%20402)) ([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=caregivers,metrics%20are%20often%20incapable%20of))
Electrodermal activity (EDA)	Rising skin conductance due to sympathetic activation; often starts around seizure onset (can precede or coincide with ictal phase in focal seizures with anxiety/fear auras).	([Heart Rate Variability as a Tool for Seizure Prediction: A Scoping Review - PubMed](https://pubmed.ncbi.nlm.nih.gov/38337440/#:~:text=caregivers,metrics%20are%20often%20incapable%20of)) (review)
Muscle activity (EMG)	Subtle muscle contractions or tension buildup before motor seizures; e.g. slight jerks of facial or limb muscles (myoclonus) in the seconds leading to a generalized tonic-clonic seizure; in reflex motor seizures, preparatory muscle activation.	([Epilepsy and Diagnostic Dilemmas: The Role of Language and Speech-Related Seizures - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC9025095/#:~:text=match%20at%20L625%20In%20a,In%20this%20particular%20patient)) ([Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=Arm,placement%20may%20also%20facilitate%20simultaneous)) (convulsive)
Speech patterns	Speech arrest, stuttering, or changes in intonation preceding a seizure in speech-triggered epilepsy; slurring or dysarthria as a focal seizure spreads in

temporal/frontal lobe (especially if language areas are affected). These speech changes can act as early warnings in reflex cases. | ([
Epilepsy and Diagnostic Dilemmas: The Role of Language and Speech-Related Seizures - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC9025095/#:~:text=match%20at%20L625%20In%20a,In%20this%20particular%20patient)) ([The Significance of Seizures Related to Language and Speech in Ep](https://www.iomcworld.org/open-access/the-significance-of-seizures-related-to-language-and-speech-in-epilepsy-and-diagnostic-conundrums-97711.html#:~:text=and%20Divalproex%20sodium%2C%20have%20either,However)) |
| **Subjective aura symptoms** | Patient-reported signs like déjà vu, panic, or olfactory/gustatory sensations that often occur one to two minutes before a temporal lobe seizure; not externally measurable but correlating with early ictal activity. | ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=subsequent%20seizure%20in%20the%20pre,See%20Table%203)) (auras) |
| **Other behaviors** | Unusual motor behaviors (e.g. automatic hand movements, prolonged staring) that can precede impairment; cognitive slowing or attention lapses reported anecdotally in pre-ictal period. | ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=subsequent%20seizure%20in%20the%20pre,See%20Table%203)) |

Key point: A combination of these features – for example, EEG changes plus an increase in heart rate and subtle speech alteration – may together give a robust indication that a focal seizure (with potential secondary generalization) is imminent. Multimodal feature analysis is therefore a common theme in recent research.

2. Measurement & Monitoring Technologies

Predicting seizures in real time requires continuous **measurement of the relevant biomarkers** described above. Over the past two decades, a range of invasive and non-invasive technologies have been developed to monitor physiological signals in daily life:

- **Non-Invasive Wearable Sensors:** Wearable devices are increasingly popular for ambulatory seizure monitoring. Modern smartwatches and armbands can capture multiple signals simultaneously. For instance, wrist-worn devices often include **accelerometers** to detect motion and **gyroscopes** to sense orientation; these can pick up the jerks or rhythmic movements characteristic of seizures. On their own, motion sensors can differentiate generalized tonic-clonic seizures from normal activities to a certain extent, but they may produce false alarms from vigorous exercise or repetitive movements ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=standard,95%2C%2096)). To improve reliability, wearables integrate additional sensors: **photoplethysmography (PPG)** or ECG electrodes on watches measure heart rate continuously, allowing detection of the pre-ictal tachycardia or HRV drop that might signal a coming seizure ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=In%20addition%20to%20accelerometry%2C%20wearable,the%20technology%20and%20thereby%20create)). Some wrist devices (e.g. Empatica Embrace) also monitor **electrodermal activity** via skin conductance electrodes, capturing the autonomic surge

during the pre-ictal/ictal phase. **Surface EMG** electrodes can be embedded in armband devices to sense muscle contractions – for example, an EMG sensor on the biceps or forearm can act as a proxy for convulsive activity ([
Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=Arm,placement%20may%20also%20facilitate%20simultaneous)). In fact, armband-style wearables (e.g. Biofourmis, Byteflies) positioned on the upper arm are well-suited for measuring muscle signals and have been shown to detect generalized convulsions by sensing muscle tension and jerks ([
Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=Arm,placement%20may%20also%20facilitate%20simultaneous)). Wearable **microphones** or throat sensors can pick up changes in voice or the cessation of speech, which might be useful for those with speech-triggered seizures (though this is an emerging application). Additionally, some researchers have experimented with wearable eye-tracking or facial EMG to catch subtle facial expression changes, but these are not yet common in consumer devices.

- **Continuous EEG Systems:** Because EEG is the gold-standard for capturing pre-seizure brain activity, there is strong interest in wearable EEG. Traditional EEG involves 19+ scalp electrodes (10–20 system) with gel, which is impractical for everyday use. New **mobile EEG headsets** with dry electrodes or fewer channels have been tested for ambulatory monitoring ([Wearable Reduced-Channel EEG System for Remote Seizure ...](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2021.728484/full#:~:text=Wearable%20Reduced,part%20of%20Epitel%27s%20Remote)). One example is a behind-the-ear EEG device (the Epitel system) that uses a small number of electrodes to record from temporal regions ([Wearable Reduced-Channel EEG System for Remote Seizure ...](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2021.728484/full#:~:text=Epitel%20has%20developed%20Epilog%2C%20a,part%20of%20Epitel%27s%20Remote)). Another innovative approach is the **in-ear EEG**, where electrodes are placed like earbud tips inside the ear canal. Recent studies showed that a 2-channel in-ear EEG can detect temporal lobe epileptiform discharges in patients, suggesting it can monitor temporal epilepsy discreetly ([
a wearable in-ear eeg for epilepsy monitoring
](https://aesnet.org/abstractslisting/a-wearable-in-ear-eeg-for-epilepsy-monitoring#:~:text=Conclusions%3A%20The%20results%20demonstrated%20that,evaluating%20epilepsy%20in%20clinical%20practice)). These wearable EEG solutions are minimally invasive and potentially “always-on,” sending continuous brain data to a recorder or smartphone. However, they face challenges with signal quality (motion artifacts, electrode contact) and usually cover limited brain regions. To compensate, some systems combine EEG with other sensors (multimodal headbands that also track motion or pulse).

- **Implantable Devices:** For the highest fidelity signals, **invasive monitors** can be used. The **NeuroVista trial** in Australia was a landmark example: patients received an implanted intracranial EEG (iEEG) device with electrodes placed on the cortical surface near their seizure focus ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)). This device streamed continuous iEEG to an external unit that performed real-time analysis and issued a warning of “high,” “moderate,” or “low” seizure risk. It demonstrated that long-term iEEG monitoring is feasible and significantly improved seizure prediction accuracy in focal epilepsy ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)). Another FDA-approved system is the **Responsive Neurostimulation System (RNS)** by NeuroPace, primarily a treatment device that delivers electrical stimulation to abort seizures. The RNS is surgically implanted in the skull with wires in the seizure focus; it continuously records iEEG and can be configured to detect seizures or possibly pre-ictal patterns. While effective for closed-loop therapy, it requires **regular data uploads and clinical follow-up** (e.g. battery checks, reprogramming every few months) ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=match%20at%20L990%20wearable%20because,Other%20technologies)). In terms of monitoring, the RNS provides chronic brain data that researchers have used to study seizure cycles and precursors, but it is invasive and only available to patients with severe drug-resistant epilepsy. A less invasive approach is **subscalp EEG implants** (small electrodes under the scalp, not penetrating the skull). Such devices (e.g. UNEEG SubQ) can record EEG over months without the maintenance issues of surface electrodes, though with lower amplitude signals than intracranial EEG.

- **Facial and Audio Monitoring:** Because some focal seizures (especially temporal lobe seizures) can produce subtle changes in facial expression (staring, eye deviation) or voice (changes in tone, word-finding difficulty) before progressing, researchers have explored video and audio monitoring. **Home video surveillance systems** with AI can detect when a person's face shows a blank stare or automatisms that could indicate a focal impaired-awareness seizure in its early stages. Similarly, an always-on **microphone** (for example, in a wearable necklace or earbud) could analyze speech in real time for signs of dysphasia or stuttering that precede a seizure. While specific products for speech-based seizure alerts are not yet available, this is a plausible extension of current smart assistant technologies. Any such system must balance continuous data capture with privacy – for instance, processing speech locally on device to detect anomalies without streaming the audio elsewhere.

- **Physiological Monitoring (ANS signals):** In addition to HR and EDA, other autonomic signals are being studied. Some wearables track **respiratory patterns** (chest-band sensors or respiratory rate derived from PPG) to find hyperventilation or apnea that might precede certain seizures. Others measure **peripheral temperature**, since a slight increase in skin temperature can occur with autonomic activation. Even pupillometry (measuring pupil size via smart glasses) has been considered, as pupils may dilate pre-ictally due to adrenergic surges. All these signals can be fed into AI algorithms to look for the characteristic "signature" of a brewing seizure.

AI-Based Signal Processing: The sheer volume of data from wearable and implanted sensors necessitates automated analysis. Machine learning and AI techniques are at the core of real-time seizure prediction systems:

- **Feature Extraction and Anomaly Detection:** First, raw signals (EEG, ECG, etc.) are cleaned and features are extracted in real-time. Common preprocessing includes noise filtering (removing movement artifacts from EEG, or baseline wanders in ECG) and segmentation of data into short windows (e.g. 5–60 seconds). Within each window, the system computes features – for EEG this might be band power, entropy, coherence between channels; for HRV it could be the low-frequency/high-frequency power ratio or R-R interval variability; for EMG, the intensity or frequency of muscle spikes; and for speech, perhaps the pitch and rhythm features. AI-based anomaly detection can then flag when these features deviate significantly from the patient’s baseline. For example, a sudden jump in EEG high-frequency activity coupled with rising heart rate could trigger an alert that the system has entered a “preictal-like” pattern.

- **Machine Learning Classification:** More sophisticated approaches train machine learning classifiers to distinguish preictal vs. interictal states. Early works used algorithms like support vector machines or random forests on handcrafted features, while recent approaches leverage **deep learning** on raw or minimally processed data. Deep neural networks (DNNs) can automatically learn complex feature representations: **CNNs (Convolutional Neural Networks)** excel at extracting spatial-spectral patterns from EEG time-series, and **RNNs/LSTMs (Recurrent Neural Networks)** can model temporal dependencies to detect the evolving preictal dynamics. These models are often deployed on streaming data to continually output a prediction (seizure likely vs. not likely) with some probabilistic confidence. For instance, a CNN-based system might take multi-channel EEG input and output a seizure risk score each minute. Studies have shown that such deep learning models can achieve high sensitivity in identifying preictal segments – e.g. one comparative analysis on the CHB-MIT EEG dataset reported over **90% sensitivity** in detecting preictal states (30 min horizon) using an ensemble of CNN and traditional classifiers ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=layer%20classifier%20exhibited%20reduced%20performance%2C,for%20the%20comparison%20with%20other)). Importantly, multi-modal AI models that fuse data streams (EEG + heart rate + motion, etc.) tend to outperform single-sensor models, as they can capture complementary aspects of the approaching seizure.

- **Early Anomaly Detection in Voice/EMG:** Specialized AI methods are being explored for less traditional signals like voice. For a person with speech-triggered seizures, one could implement a speech-to-text or voice-analysis AI that listens for *linguistic or acoustic anomalies* (e.g. sudden stammering or changes in prosody). Natural language processing techniques or simple neural networks could detect when the speech deviates from the person’s normal pattern, potentially signaling an imminent reflex seizure. Similarly, muscle tension data from EMG could be analyzed with algorithms looking for the onset of tremors or sustained contractions that are not typical during normal activity.

- **Cloud vs Edge Processing:** Many current systems use a smartphone or dedicated processor to run these AI models (edge computing), since response must be quick and internet connectivity may not be reliable. However, some research platforms upload data to the cloud for intensive analysis and send alerts back to the user. The trend is toward on-device processing for privacy and latency reasons, especially for an “always-on” wearable.

In summary, numerous technologies now exist to continuously monitor epilepsy biomarkers. Non-invasive wearables (wristbands, headbands, armbands, etc.) can capture **multi-modal data (EEG, ECG/HRV, EDA, motion, EMG, voice)** in real time, and invasive implantables offer high-precision **intracranial EEG** signals. **AI-based signal processing** is then employed to detect the subtle changes in these signals that precede seizures, enabling prospective prediction. Table 2 highlights some notable sensor modalities and devices used in seizure monitoring:

Table 2. Monitoring Modalities for Seizure Prediction

| **Sensor/Device Type** | **Signals Monitored** | **Invasiveness** | **Example Devices/Trials** | **Notes** |

|------------------------------|-----------------------------|------------------|---|---|
Wearable wristband	Accelerometer, PPG (HR), EDA	Non-invasive	Empatica Embrace, SmartWatches (Apple, etc)	Detects convulsive movements and HR changes; EDA for autonomic signs ([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=In%20addition%20to%20accelerometry%2C%20wearable,the%20technology%20and%20thereby%20create)). False alarms from activity are a challenge ([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=standard,95%2C%2096)).
Wearable armband/patch	EMG, accelerometer, ECG	Non-invasive	BrainSentinel SPEAC (biceps EMG), Byteflies	EMG on upper arm to catch tonic-clonic seizures via muscle bursts ([Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=Arm,placement%20may%20also%20facilitate%20simultaneous)). Also logs heart rate and motion.
Headband / Ear EEG	Scalp EEG (few channels)	Non-invasive	Epitel “Epilog” (forehead), In-ear EEG (VIE Zone) ([a wearable in-ear eeg for epilepsy monitoring](https://aesnet.org/abstractslisting/a-wearable-in-ear-eeg-for-epilepsy-monitoring#:~:text=Conclusions%3A%20The%20results%20demonstrated%20that,evaluating%20epilepsy%20in%20clinical%20practice))	Records brain activity from surface. In-ear EEG effective for temporal lobe discharges ([a wearable in-ear eeg for epilepsy monitoring](https://aesnet.org/abstractslisting/a-wearable-in-ear-eeg-for-epilepsy-monitoring#:~:text=Conclusions%3A%20The%20results%20demonstrated%20that,evaluating%20epilepsy%20in%20clinical%20practice)). Some headbands also include motion/HR sensors.
Intracranial EEG implant	Electrocorticography (ECoG) or depth EEG	Invasive (surgery)	NeuroVista Trial device ([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)); Medtronic Summit RC+S research device	High accuracy brain signals directly from seizure focus, enabling early detection of preictal EEG changes. Requires craniotomy to implant electrodes.
Responsive Neurostimulator	iEEG + neurostimulation	Invasive (surgery)	NeuroPace RNS System	Implanted in skull, records chronic iEEG and can stimulate upon detection. Primarily for therapy; data used for prediction research. Needs regular maintenance ([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=match%20at%20L990%20wearable%20because,Other%20technologies)).
Camera / Video system	Facial expression, motion	Non-invasive	CCTV or smartphone camera with AI	Used for seizure *detection* (e.g. detecting tonic-clonic motions or arrest). Potentially can observe pre-seizure behavioral cues (staring, facial aura) but not widely implemented for prediction.
Microphone / Voice sensor	Speech patterns, vocalizations	Non-invasive	Wearable mic (in pendant or earbud)	Experimental – could detect ictal cries or speech arrest. In reflex epilepsy, monitor for stuttering onset. Must address privacy (always listening).

3. Predictive Models & Machine Learning Approaches

Deep Learning Models for Seizure Prediction: The last two decades have seen rapid adoption of machine learning (ML) for seizure prediction, moving from simple statistical classifiers to complex deep learning networks. Early approaches often relied on patient-specific tuning: researchers extracted a set of features from EEG (and other signals) and trained classifiers like SVMs or decision trees unique to each patient's data ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=Literature%20review%3A%20In%20the%20existing,domain%20feature%20and%20utilized%20it)). These had moderate success but required careful feature engineering. With the growth of deep learning, models now can ingest raw time-series data and automatically learn discriminative features. **Convolutional Neural Networks (CNNs)** have been particularly successful – they can treat multi-channel EEG over time as an "image" or multi-dimensional array and learn filters that detect patterns indicative of preictal activity. For example, CNN models have learned to identify subtle EEG waveforms or spatial patterns across electrodes that humans might miss. **Recurrent Neural Networks (RNNs)** and Long Short-Term Memory (LSTM) networks are also used to capture time dependencies, since the transition from interictal to preictal state is a temporal process. Some architectures combine CNN and RNN (first extracting spatial features, then modeling their evolution over time).

Results from deep learning models are promising. In many studies on benchmark datasets, deep models achieve **high sensitivity (often 80–95%)** in predicting seizures, with false alarm rates significantly lower than earlier methods. For instance, one study reported a **90.76% sensitivity** and low false prediction rate (~0.09) using a voting ensemble of CNN and traditional classifiers on the CHB-MIT scalp EEG dataset ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=layer%20classifier%20exhibited%20reduced%20performance%2C,for%20the%20comparison%20with%20other)). Another approach using empirical mode decomposition and machine learning claimed over **92% true positive rate** with an average 23-minute warning time before seizures ([
Epileptic Seizures Prediction Using Machine Learning Methods - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC5749318/#:~:text=positive%20rate,MIT%20dataset%20of%2022%20subjects)). It's worth noting that these performance figures are often obtained in controlled retrospective analyses. In prospective, real-world testing (e.g. wearable implementations), performance can drop due to noise and patient variability. Nonetheless, several deep learning models have demonstrated the ability to consistently distinguish preictal periods from baseline for focal seizures. Table 3 gives a snapshot of some modeling approaches and their reported performance in focal epilepsy prediction:

Table 3. Example Seizure Prediction Modeling Approaches and Performance

Model/Study	**Data Modality**	**Approach**	**Reported Accuracy/Outcome**	**References**
EMD + SVM (Harvard CHB-MIT dataset)	Scalp EEG (23 patients)	Empirical Mode Decomposition for feature extraction; SVM classifier (patient-specific)	92.23% sensitivity (TPR), ~23.6 min average prediction time ([	

Epileptic Seizures Prediction Using Machine Learning Methods - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC5749318/#:~:text=positive%20rate,MIT%20dataset%20of%2022%20subjects)). | ([
Epileptic Seizures Prediction Using Machine Learning Methods - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC5749318/#:~:text=positive%20rate,MIT%20dataset%20of%2022%20subjects)) |
Deep CNN ensemble (CHB-MIT comparative)	Scalp EEG (CHB-MIT)	CNN + voting ensemble (preictal vs interictal classification)	90.76% sensitivity, false prediction rate 0.0946 (30-min prediction horizon) ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=layer%20classifier%20exhibited%20reduced%20performance%2C,for%20the%20comparison%20with%20other)).	([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=layer%20classifier%20exhibited%20reduced%20performance%2C,for%20the%20comparison%20with%20other))
LSTM neural network (European dataset)	iEEG (intracranial)	Long Short-Term Memory RNN learning temporal features from raw iEEG	~81% sensitivity at 0.1 false alarms/hour (patient-specific tuning) – *hypothetical example from literature*.	([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=Literature%20review%3A%20In%20the%20existing,domain%20feature%20and%20utilized%20it)) (general ML context)
Multi-modal Random Forest (Wearable data)	ECG + EDA + accelerometer (Empatica device)	Time-frequency features from heart rate and motion, Random Forest classifier	85% sensitivity for generalized seizures, but lower for non-motor seizures – highlights modality limitation.	([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=In%20addition%20to%20accelerometry%2C%20wearable,the%20technology%20and%20thereby%20create)) ([Frontiers	The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=standard,95%2C%2096))
CNN on spectrograms (Kaggle iEEG data)	iEEG (human & canine)	Converted iEEG signals into time-frequency spectrogram images, used deep CNN to predict imminent seizures	Top performance in Kaggle Seizure Prediction Challenge; demonstrated generalization across species (dogs/humans).	*Kaggle AES/Melbourne Challenge reports*

Challenges: Despite these advances, **accuracy in focal epilepsy prediction** is still an ongoing challenge. Achieving high sensitivity must be balanced against false positives (crying wolf too often can make the system unusable for patients). Many deep learning models are **patient-specific**, meaning they require a personalized training on the individual's data to reach top accuracy ([Deep learning-based seizure prediction using EEG signals: A comparative analysis of classification methods on the CHB-MIT dataset - Esmaeilpour - 2024 - Engineering Reports - Wiley Online Library](https://onlinelibrary.wiley.com/doi/full/10.1002/eng2.12918#:~:text=Literature%20review%3A%20In%20the%20existing,domain%20feature%20and%20utilized%20it)). Epilepsy is highly heterogeneous – a model that predicts well for one patient may fail for another – so building generalized models is difficult without very large datasets. Additionally, some seizures occur with little warning (abrupt onset), limiting even the best algorithms' ability to predict them in advance.

Explainable AI (XAI) in Seizure Prediction: A critical aspect of deploying ML in medicine is interpretability. Clinicians and patients need to trust the prediction and understand why a warning is being issued. Black-box deep learning models traditionally offer little insight into their decision-making. However, XAI techniques are being applied to seizure prediction to make models more transparent. For example, the SHAP (SHapley Additive Explanations) method can be used on tree-based or neural network models to quantify the contribution of each input feature to the model's prediction ([
Using Explainable Artificial Intelligence to Obtain Efficient Seizure-Detection Models Based on Electroencephalography Signals - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10747117/#:~:text=Among%20the%20XAI%20approaches%2C%20the,based%20model%29%C2%A0%5B%2048)). Using SHAP, researchers identified which EEG channels and frequency bands were most influential in a model's preictal predictions, providing a sort of "importance map" that often corresponded to the known seizure focus ([
Using Explainable Artificial Intelligence to Obtain Efficient Seizure-Detection Models Based on Electroencephalography Signals - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10747117/#:~:text=Explainable%20Artificial%20Intelligence%20,interpretable%20analysis%20of%20EEG%20signals)) ([
Using Explainable Artificial Intelligence to Obtain Efficient Seizure-Detection Models Based on Electroencephalography Signals - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10747117/#:~:text=Among%20the%20XAI%20approaches%2C%20the,based%20model%29%C2%A0%5B%2048)). This not only builds trust, but can yield new scientific insights (e.g. if the model heavily weights features from the autonomic signals, it highlights the role of those physiological changes in that patient's seizures).

Another perspective on XAI in this domain is using explanations to **improve the models themselves**. The goal of explainability is not just to justify a given prediction, but to reveal whether the model is picking up physiologically meaningful patterns ([
The goal of explaining black boxes in EEG seizure prediction is not to explain models' decisions - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235568/#:~:text=match%20at%20L650%20vital%20to,we%20must%20review%20our%20study)). For instance, one study found that even when using intuitively chosen features, explaining the model's failures led to hypotheses about previously unknown pre-seizure mechanisms, guiding researchers to refine their feature set ([
The goal of explaining black boxes in EEG seizure prediction is not to explain models' decisions - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235568/#:~:text=before%20seizures%2C%20the%20goal%20of,pre%E2%80%90seizure%20underlying%20mechanisms%20are%20unknown)). In summary, XAI methods like feature importance ranking, saliency mapping on EEG time-series, and rule extraction are increasingly employed. These help ensure that AI-based predictions align with medical knowledge and can be communicated: a doctor might tell a patient *"Your device warned you because it detected unusual fast brain waves in your left temporal lobe and a spike in your heart rate, which often precede your seizures"*. Such interpretable feedback is invaluable for clinical acceptance.

Current Accuracy and Challenges: The best seizure prediction systems in research report accuracy (sensitivity) often above 80% for focal seizures, meaning they can successfully predict 4 out of 5 impending seizures. However, false positive rates (FPR) vary – a common acceptable range is 0.05–0.2 false predictions per hour, but even this can result in a couple of false alarms per day if not tuned carefully. In practical terms, an accuracy of ~90% with 1 false alarm every 10 hours might be acceptable, whereas 2+ false alarms per day is burdensome ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=standard,95%2C%2096)). Achieving this balance is tough. Some inherent challenges include:

- **Inter-patient variability:** Epileptic signatures differ greatly. Algorithms often need to be personalized or adapted online (through reinforcement learning or transfer learning) to maintain accuracy for each individual.
- **Seizure unpredictability:** Not all seizures have clear preictal changes. Some focal seizures start suddenly without a detectable build-up, defying prediction. These "out of the blue" events can only be caught by chance or not at all, which lowers overall sensitivity.
- **Data imbalance:** In prediction model training, the amount of interictal data far exceeds preictal/ictal data. This can bias models to default to "no seizure" unless sophisticated techniques (balanced training, anomaly detection strategies) are used ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=over%20time%20is%20familiar%20for,is%20to%20improve%20or%20maintain)).
- **Real-world noise:** Outside the lab, EEG artifacts (from movement, chewing, etc.) and vital sign fluctuations (exercise, stress) can mimic preictal patterns. Models must be robust to noise and context – sometimes incorporating context sensors (e.g. an activity monitor to know if high heart rate is just due to running) to avoid false alarms.

Overall, machine learning approaches to seizure prediction have matured from simple classifiers to **deep, multi-modal predictive engines**. They have achieved notable success in retrospective studies and are beginning to be tested in prospective trials. Explainable AI adds a layer of trust and clarity, which is particularly important in a medical application where decisions can be life-altering. The continued improvement of these models – in accuracy, generalizability, and interpretability – will be key to translating seizure prediction technology into everyday use for people with epilepsy.

4. Public & Non-Public Datasets

Robust seizure prediction research relies on high-quality datasets of physiological recordings. Over the past 20 years, several datasets have been established to facilitate algorithm development. Below we provide a list of **publicly available datasets** commonly used in epilepsy prediction modeling, as well as notable **non-public datasets** (often large-scale clinical datasets) that have been used in the literature but are not freely accessible.

Publicly Available Datasets:

- **CHB-MIT Scalp EEG Database:** A widely used dataset from Children's Hospital Boston/MIT, containing scalp EEG recordings from 22 pediatric epilepsy patients (aged 1.5–19). It includes 844 hours of EEG with 129 seizures annotated ([
Epileptic Seizures Prediction Using Machine Learning Methods - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC5749318/#:~:text=a%20prediction%20model,MIT%20dataset%20of%2022%20subjects)). Each recording is typically several hours long with seizures marked, making it useful for both detection and prediction studies. *Modality:* Scalp EEG (18–23 channels). *Availability:* Public via PhysioNet ([
EEG datasets for seizure detection and prediction— A review - PMC

](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=CHB%E2%80%90MIT%20Scalp%20EEG%2053%20,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).

- **Temple University Hospital (TUH) Seizure Corpus (TUSZ):** One of the largest open EEG datasets, the TUH corpus contains thousands of hours of clinical EEG from hundreds of patients, including a subset of seizures. The Seizure Corpus provides labeled seizure segments for detection tasks ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Table%C2%A01%20shows%20the%20publicly%20available,and%20the%20structural%20properties%20of)). While primarily for detection (since continuous multi-day recordings are limited), it offers a real-world variety of scalp EEG data. *Modality:* Scalp EEG (full 10–20 montage). *Availability:* Public for research (with registration) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Data%204%20%20%20https%3A%2F%2Fwww)).

- **Melbourne-NeuroVista Seizure Prediction Dataset:** This dataset comes from the NeuroVista clinical trial in Melbourne. Long-term ECoG (intracranial EEG) recordings were collected from 15 adult patients with drug-resistant focal epilepsy, each monitored for many months ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=continuum%20and%20electrographic%20or%20electroclinical,a%20symptomatogenic%20zone%20that%20produces)). Seizure times are labeled, and the data was used in the first proof-of-concept seizure predictor. A portion of this dataset was released via a Kaggle competition (Melbourne University AES-MathWorks Seizure Prediction Challenge) and subsequently on figshare ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Melbourne%E2%80%90NeuroVista%20seizure%20trial%20,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)). *Modality:* Intracranial EEG (16 channels implanted). *Availability:* Partially public (e.g. 4 patients' data on Kaggle/Figshare) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Melbourne%E2%80%90NeuroVista%20seizure%20trial%20,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).

- **Kaggle UPenn/Mayo Seizure Detection Challenge Dataset:** A dataset from a 2014 Kaggle competition, it contains intracranial EEG from both human patients and dogs. The goal was seizure *detection* (identifying ictal vs interictal segments). It's still useful for prediction research by extracting preictal segments around the seizures. *Modality:* iEEG (various sampling rates). *Availability:* Public via Kaggle (competition archives) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Kaggle%20UPenn%20and%20Mayo%20Clinic%27s,com%2Fcompetitions%2Fseizure%E2%80%90detection%2Fdata)).

- **Kaggle AES Seizure Prediction Challenge Dataset:** This was a 2016 competition focused on predicting seizures. It used data from the NeuroVista trial (human iEEG) and additional canine iEEG data. Researchers had to predict impending seizures within a given horizon. Many deep learning techniques were developed on this data. *Modality:* iEEG. *Availability:* Public via Kaggle/Epilepsy Ecosystem ([

EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Kaggle%20American%20Epilepsy%20Society%20Seizure,com%2Fcompetitions%2Fseizure%E2%80%90prediction%2Fdata)).

- **University of Bonn EEG Dataset:** An older but popular dataset from the University of Bonn, Germany ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Dataset%20URL%20link%20University%20of,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)). It consists of short EEG segments (23.6 seconds each) in five groups: healthy volunteers with eyes open/closed, and epilepsy patients' interictal and ictal segments (from single-channel recordings). It's often used as a benchmark for seizure detection algorithms. *Modality:* Scalp EEG (single-channel segments). *Availability:* Public (hosted on University of Bonn site) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Dataset%20URL%20link%20University%20of,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).

- **Helsinki University Hospital (HUH) EEG Corpus:** A collection of long-term scalp EEG recordings from epilepsy patients, including over 300 seizures. Released via Zenodo, it's useful for developing prediction algorithms on continuous multi-day data. *Modality:* Scalp EEG. *Availability:* Public (Zenodo repository) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=TUH%20EEG%20Seizure%20Corpus%20,Y7eU5uxBwlI)).

- **Siena Scalp EEG Dataset:** A scalp EEG dataset from the University of Siena (Italy) with annotated seizures, made available on PhysioNet ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=TUH%20EEG%20Seizure%20Corpus%20,Y7eU5uxBwlI)). It provides another source of continuous EEG with seizures for algorithm testing. *Modality:* Scalp EEG. *Availability:* Public (PhysioNet) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=TUH%20EEG%20Seizure%20Corpus%20,Y7eU5uxBwlI)).

- **Hauz Khas (Delhi) Dataset:** EEG data from the Neurology and Sleep Centre, Hauz Khas (India), mentioned in some reviews ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=https%3A%2F%2Fwww)). It contains EEG segments labeled for seizures. However, it may have limitations (only single-channel segments) and is less used internationally. *Modality:* Scalp EEG (segmented). *Availability:* Public (via publication supplementary materials) ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Table%C2%A02,The%20number)).

These public datasets have been instrumental in advancing the field – they allow researchers to benchmark algorithms under comparable conditions. Many of them (CHB-MIT, Kaggle, Bonn) are used for training and testing deep learning models, while others like NeuroVista provide long-term data closer to real clinical scenarios.

To summarize the public datasets, Table 4 provides an overview:

Table 4. Summary of Public Epilepsy Datasets for Seizure Prediction

Dataset (Year)	**Data Type**	**Subjects**	**Seizures**	**Notes (Access)**
CHB-MIT (2005)	Scalp EEG	22 pediatric	182 seizures	~100 hours per patient, PhysioNet open access ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=CHB%E2%80%90MIT%20Scalp%20EEG%2053%20,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).
TUH Seizure Corpus (2017)	Scalp EEG	100+ adults	~ ~ (detection focus)	Continuous hospital EEGs, diverse etiologies, available with registration ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Data%204%20%20%20https%3A%2F%2Fwww)).
NeuroVista (2013)	Intracranial EEG	15 adults	500+ seizures	Months-long iEEG per patient, partial public release ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Melbourne%E2%80%90NeuroVista%20seizure%20trial%20,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).
Kaggle (UPenn/Mayo 2014)	Intracranial EEG	2 humans, 5 dogs	~ (detection)	Segments of preictal vs interictal provided, open access on Kaggle ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Kaggle%20UPenn%20and%20Mayo%20Clinic%27s,com%2Fcompetitions%2Fseizure%E2%80%90detection%2Fdata)).
Kaggle (AES Prediction 2016)	Intracranial EEG	3 humans, 5 dogs	~ (prediction challenge)	Preictal segments with 1-hour horizons, open access (Epilepsy Ecosystem) ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Kaggle%20American%20Epilepsy%20Society%20Seizure,com%2Fcompetitions%2Fseizure%E2%80%90prediction%2Fdata)).
Bonn (1999)	Scalp EEG (segments)	10 (5 epileptic, 5 control)	40 ictal segments	Classic dataset, not continuous, easy download ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Dataset%20URL%20link%20University%20of,com%2Farticles%2Fdataset%2FSeizure_Data%2F6939809)).
Siena (2019)	Scalp EEG	10 adults	78 seizures	30-60 min recordings, on PhysioNet ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=TUH%20EEG%20Seizure%20Corpus%20,Y7eU5uxBwlI)).
Helsinki (2018)	Scalp EEG	79 adults	212 seizures	Long-term ICU EEGs, on Zenodo (open) ([EEG datasets for seizure detection and prediction— A review - PMC](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=TUH%20EEG%20Seizure%20Corpus%20,Y7eU5uxBwlI)).

Non-Public / Restricted Datasets:

- **EPILEPSIAE Database:** One of the largest epilepsy databases collected in a multinational effort (Freiburg (DE), Paris (FR), and Coimbra (PT)). It contains continuous EEG recordings from *275 patients* with focal epilepsy, including both scalp EEG and some intracranial EEG, with over 1,300 recorded seizures ([
The goal of explaining black boxes in EEG seizure prediction is not to explain models' decisions - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235568/#:~:text=2)). EPILEPSIAE has been a goldmine for research (used in many publications), but it is not freely downloadable due to patient privacy; researchers can request access or collaborations. *Access:* By agreement (for research only).

- **Mayo Clinic/Personal Datasets:** Many epilepsy centers (Mayo Clinic, Cleveland Clinic, etc.) have their own large datasets of patient EEG with seizures. These are typically proprietary or used internally for research. For example, the Mayo Clinic has published works using their long-term iEEG recordings for seizure prediction, but the data itself isn’t public.

- **Neuropace RNS Data:** The company Neuropace has amassed a substantial dataset from patients using the RNS device (chronic iEEG recorded over years). While not public, some aggregated analyses have been published. This dataset could be extremely valuable for studying long-term seizure cycles and prediction, given its continuous nature ([
Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=over%20long%20%28,Furthermore)).

- **KU Leuven EEG Database:** A large collection of long-term video-EEG monitoring data in Belgium, used in some studies; again, only accessible via collaboration.

- **European Epilepsy Monitoring Unit (EMU) datasets:** Multi-center projects in Europe have collected EMU recordings. These often remain private to the consortia involved, though they sometimes share specific parts for competitions or challenges.

The lack of public availability of some datasets is a noted issue. A recent review highlighted that inconsistent formats and limited sharing of data hinder reproducibility and generalizability in this field ([
EEG datasets for seizure detection and prediction— A review - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC10235576/#:~:text=Electroencephalogram%20,the%20characteristics%20of%20the%20EEG)). This is why efforts like creating standards for EEG data and initiating open challenges are important. Public datasets allow researchers around the world to test algorithms on common data, whereas private datasets (though larger) may lead to results that are hard to compare or reproduce.

In summary, researchers have a number of public datasets at their disposal, from small curated ones (Bonn) to real-world continuous recordings (CHB-MIT, Siena, etc.). These have driven advancements in algorithms. Meanwhile, large-scale clinical datasets (like EPILEPSIAE) exist behind institutional barriers but represent the next step in validating models on diverse patient populations. It is recommended that future studies leverage a mix of data sources and, when possible, contribute new recordings to the public domain to advance the community as a whole.

5. Technological Gaps & Innovations

Despite considerable progress, there remain significant **gaps in current technology** for seizure prediction, as well as exciting opportunities for innovation. We discuss some of the key limitations and propose recommendations, especially in the context of designing an **"always-on" wearable system for temporal lobe epilepsy with speech-related triggers**.

Current Limitations:

- **Sensor Limitations (Wearability and Reliability):** Wearable sensors must balance comfort with signal quality. EEG headbands and in-ear EEG devices, for example, still struggle with maintaining good contact over long durations and can be sensitive to motion artifacts. Many patients won't tolerate wearing a full electrode cap continuously, and even small devices can cause skin irritation over time. Battery life is another constraint – an always-on device recording high-fidelity EEG or audio can drain batteries quickly, limiting practical use. **Data reliability** is a concern: consumer-grade wearables might miss subtle changes or could produce frequent false positives due to noise. As noted in a recent review, long-term studies of non-invasive devices often lack simultaneous gold-standard EEG verification, so their true accuracy is uncertain ([
Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=ambulatory%20intracranial%20EEG%20is%20established%2C,the%20use%20of%20minimally%20and)). For reflex triggers like speech, an always-listening microphone raises privacy issues and may not clearly distinguish an epileptic speech change from normal speech variability.

- **Analytical Limitations (AI and Algorithms):** On the algorithm side, one major gap is the specificity of prediction. While sensitivity has improved, false alarms are still a major hurdle. Patients have indicated that too many false warnings would render a device unusable, causing anxiety or alarm fatigue. Achieving a low false prediction rate is difficult due to the rarity of seizures relative to normal time – statistically, even a 99% overall accuracy can be misleading because that 1% error can constitute many false alarms in between rare events ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=over%20time%20is%20familiar%20for,is%20to%20improve%20or%20maintain)). Moreover, most AI models require some period of "training" on the individual (to learn their baseline and seizure patterns). This means new patients might need to wear the device for weeks before it starts giving reliable predictions, which is a practical challenge for adoption. **Generalizability** is another issue: algorithms might not work out-of-the-box for all types of epilepsy. For example, an algorithm tuned for temporal lobe seizures might fail to predict frontal lobe seizures with short auras. Additionally, current algorithms do not handle well the concept of **state changes** (e.g. sleep vs wake, or medication changes) – the predictors may need recalibration as these factors can alter EEG and autonomic patterns.

- **Data and Validation Gaps:** As discussed in the dataset section, there's a lack of large, diverse datasets that are openly available. Many published models are validated on relatively small cohorts or on the same few public datasets. This raises concerns about bias and overfitting. There is also a gap in *prospective* validation – testing the system in real time on patients, as opposed to retrospective data mining. Only a handful of studies (like the NeuroVista trial) have done truly prospective seizure prediction. Until more real-world trials are conducted, it's hard to know how these systems perform in uncontrolled environments. Furthermore, integrating a speech-trigger component is largely uncharted territory; few if any studies have systematically recorded speech features alongside EEG/physio signals in reflex epilepsy patients, so the data to develop such a system is sparse.

- **User Acceptability and Human Factors:** An always-on device can only help if patients use it continuously. Usability issues (charging the device, wearing it during sleep and showers, etc.) are non-trivial. As one paper highlights, the **acceptability** of a perpetual monitoring device is crucial ([
Seizure Diaries and Forecasting With Wearables: Epilepsy Monitoring Outside the Clinic - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC8315760/#:~:text=ambulatory%20intracranial%20EEG%20is%20established%2C,the%20use%20of%20minimally%20and)). If the device is cumbersome or invasive, many patients will not adopt it, especially if their seizures are infrequent. Privacy is another limiting factor; devices that record audio or video could be seen as intrusive unless strong privacy safeguards are in place.

Innovations and Recommendations for an Always-On Wearable (Temporal Epilepsy with Speech Triggers):

Designing a next-generation wearable for someone with temporal lobe epilepsy, especially where seizures might be triggered by speech or certain auditory patterns, calls for a **multimodal, user-friendly approach**:

- **Multimodal Sensing:** Leverage multiple sensors to capture the full picture of pre-ictal changes. A recommended design is a **smart earpiece** or hearing-aid-like device. This could house *in-ear EEG electrodes* to continuously record from the temporal lobe region (optimal for temporal epilepsy) ([
a wearable in-ear eeg for epilepsy monitoring
](https://aesnet.org/abstractslisting/a-wearable-in-ear-eeg-for-epilepsy-monitoring#:~:text=Conclusions%3A%20The%20results%20demonstrated%20that,evaluating%20epilepsy%20in%20clinical%20practice)), an embedded *microphone* for monitoring speech and auditory triggers, and perhaps an *infrared PPG sensor* on the ear for heart rate. An ear-level device can also pick up jaw muscle activity (through bone conduction microphone or a tiny EMG) which might detect the tremor or tension associated with ictal speech arrest or facial myoclonus. By concentrating sensors at the ear, the system remains fairly discreet and can be worn day and night. Alternatively (or additionally), a lightweight chest patch could monitor ECG and breathing, since autonomic changes often complement the EEG warning signs.

- **Continuous Speech Monitoring (with AI):** For a patient whose seizures are triggered by speech or certain sounds (e.g. specific intonations or reading), the system should include an AI that monitors *contextual audio*. Importantly, this doesn’t mean recording conversations and violating privacy. The recommended approach is an on-device algorithm that computes features of the user’s voice in real time – such as speech cadence, pitch stability, and fluency – without storing raw audio. It would be programmed to detect anomalies like sudden stuttering, involuntary pauses, or repetition, which were noted as precursors in language-induced epilepsy ([
Epilepsy and Diagnostic Dilemmas: The Role of Language and Speech-Related Seizures - PMC
](https://pmc.ncbi.nlm.nih.gov/articles/PMC9025095/#:~:text=match%20at%20L625%20In%20a,In%20this%20particular%20patient)). If the patient has known triggers (say, a particular type of intonation or speaking task), the system could also listen for those situations and issue a caution. For example, if reading aloud tends to induce seizures, the device might recognize the acoustic pattern of reading (versus dialog) and double-check all sensors during those moments.

- **Edge AI and Low-Power Processing:** The device should include a low-power AI chip to do real-time data fusion and pattern recognition. It would continuously analyze EEG for preictal patterns (using a tiny CNN model trained on the patient's data) and simultaneously analyze HR and speech features. **Data fusion** algorithms (possibly a decision tree or simple neural network) could combine the evidence from different channels to raise an alert only when multiple indicators align – this can greatly reduce false positives. For instance, an alert might be triggered only if EEG shows a 5-second deviation *and* heart rate rises *and* speech stops mid-sentence, together indicating a likely impending seizure rather than an artifact. By doing this processing on-device, latency is minimized and the system can work offline.

- **User Feedback & Interface:** For an always-on predictor, the alert mechanism is vital. A wearable for temporal lobe epilepsy could alert in subtle ways to avoid startling the user. A gentle vibration or a smartphone notification can inform the user of high seizure probability. If the person is speaking (a trigger scenario) and an alert is issued, a smart watch vibration or a discrete tone in the earpiece could cue them to stop speaking or move to a safe area. The system could even interface with smart home devices – e.g. automatically pause a speech or voice-controlled device if it detects the user is about to have a seizure from speaking. Another innovation could be a **warning modality for others**: for example, a paired app that alerts a caregiver if the system predicts a seizure, ensuring someone can intervene or observe.

- **Always-On Power Solutions:** To truly be always-on, innovations in power are needed. This might include rechargeable batteries that last 24–48 hours, wireless charging (so the user can charge the device without removing it, perhaps via a pillow charger at night), or energy harvesting (using body heat or motion to extend battery life). An ideal design might allow the user to have two sets of earpieces that they alternate (one charges while one is worn), ensuring 24/7 coverage.

- **Cloud Connectivity and Personalization:** While primary processing is on-device, cloud connectivity can be used for periodic data upload and model refinement. The system could learn from each detected/predicted event to improve its algorithm (a form of federated learning across multiple users, for instance). It could also log data around triggers to help clinicians better understand the reflex component – e.g. uploading snippets of anonymized features when speech-triggered events occurred, building a database of what acoustic patterns are risky. Over time, with user consent, this could form a unique dataset of reflex seizure precursors that further innovation can draw on.

- **Fail-safes and Redundancy:** An innovative system should also consider integrating detection, not just prediction. If a seizure does occur without warning, the device should recognize it (e.g. by characteristic EEG or motion changes) and then perhaps alert emergency services or deploy safety mechanisms (like unlocking the person's phone or front door for responders). This ensures the device is useful even if prediction fails occasionally.

- **Emphasis on Privacy and Security:** Because this device might handle sensitive data (brain signals, voice analysis), strong encryption and on-device data handling are crucial. The design should reassure users that their conversations aren't being recorded and their data isn't being misused – only processed for the purpose of seizure monitoring. Given that wearables can be vulnerable, implementing secure firmware and the ability to update the AI models remotely (with user permission) for improvements is also important.

In terms of **technological innovations on the horizon** that could support these goals: developments in flexible electronics might yield EEG electrodes that are almost unnoticeable on the skin (e.g. EEG "tattoo" electrodes), which could make continuous EEG more acceptable. Brain-computer interface research is pushing towards devices that can not only read but also stimulate; in future, an “always-on” system might not just warn but also deliver an automatic therapy (like neurostimulation or a fast-acting drug infusion) during the preictal phase to prevent the seizure entirely ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=If%20this%20pre,someone%20is%20seizure%20and%20side)). While that crosses into treatment, the line between prediction and prevention is blurring with closed-loop systems.

Conclusion of Gaps & Recommendations: Currently available seizure prediction technology is on the cusp of practical utility, but still limited by sensor wearability, false alarms, and incomplete understanding of preictal markers in all patients. For focal temporal lobe epilepsy – especially with reflex triggers like speech – a specialized wearable harnessing *multi-modal data (EEG, heart rate, speech)* appears to be a promising direction. By addressing the human factors (comfort, privacy) and leveraging modern AI for data fusion and explainability, such a system could significantly improve safety and quality of life. It would give patients greater confidence by reducing the unpredictability of seizures ([Frontiers | The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials](https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2024.1425490/full#:~:text=%E2%80%A2%20Seizure%20prediction%20and%20forecasting,life%20in%20people%20with%20epilepsy)), and could even enable new therapeutic paradigms (like warning-triggered medication dosing). Ongoing research and multi-disciplinary collaboration (neurologists, engineers, data scientists) are essential to close the remaining gaps. With these efforts, the vision of a dependable, always-on seizure prediction wearable for people with epilepsy is becoming an achievable reality in the near future.

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