1 Results

A total of 35 studies were included in this review (Table number). These studies utilized a range of devices for seizure detection, including both commercial and non-commercial options. The most frequently used commercial device was the EMPATICA E4, featured in 7 studies [studies references]. Additional studies employed either laboratory-developed devices or other commercial devices, such as: Shimmer, Samsung SM-R800 watch, Microsoft wristband, and iCalm watch.

All included studies assessed various combinations of the following physiological and movement modalities: Accelerometer (ACC), Blood Volume Pulse (BVP), Gyroscope (Gyro), Electromyography (EMG), Heart rate (HR), Oxygen Saturation (SPO2), Electrodermal activity (EDA), electrocardiography (ECG), temperature, and Heart rate variability (HRV).

1.1 Demographics

Of the studies reviewed, 25 were conducted exclusively in inpatient settings. One study didn't explicitly state the setting, but it is implied for home monitoring [1]. 2 studies included data from both inpatient and outpatient environments [2, 3]. Sample sizes varied widely, ranging from as few as 4 [4] to as many as 166 [5] participants. Five studies focused solely on adults aged 18 [6] to 64 [7] years, with one additional adult study not specifying the age range [8], and 1 providing the mean age only [9]. Ten studies were conducted exclusively in pediatric populations, including two that did not specify exact ages but stated that participants were children [10, 11]. Twelve studies included mixed-age populations, with ages spanning from 2 [12] to 75 [13] years, including three that didn't specify the age range [3, 2, 14]. Six studies did not provide any information about the participants' ages. Additionally, three studies included healthy participants to test the performance of their seizure detection methods [15, 13, 16].

1.2 Modalities

Among the 36 reviewed studies, accelerometry (ACC) was the most frequently used modality, appearing in 34 studies. This was followed by electrodermal activity (EDA) in 16, gyroscopes (GYRO) in 14, and electromyography (EMG) in 12 studies. Electrocardiography (ECG) was included in 9 papers, while temperature (TEMP) appeared in 7. Less commonly used modalities included photoplethysmography (PPG) and heart rate (HR), each in 5 studies, and SpO_2 and blood volume pulse (BVP), each in 2. Rare modalities, used only once, included audio, GSR, pulse sensor, SCR, NOWM, pitch, and roll. Many studies used multiple modalities in combination, often pairing motion and physiological signals.

1.3 Preprocessing

1.3.1 Signal Synchronization and Quality Control

To match biosignal recordings with reference data like EEG or video, many studies performed time synchronization. This included adjusting for time drift between devices using start and end timestamps or using the network time protocol (NTP) [17, 18, 19]. Some studies checked signal quality and removed invalid parts of the data. For example, segments were excluded if the temperature was too low or too high (less than 27°C or more than 45°C), which indicated the device was not worn properly [5, 19]. Other signals were removed based on quality checks, like low EDA amplitude or poor PPG quality [20, 21]. Also, the first and last 15 minutes of recordings were sometimes discarded to avoid artifacts from calibration [5].

1.3.2 Noise and Artifact Removal

Most studies used filtering to reduce unwanted signals caused by movement, other physiological activity, or environmental noise. Bandpass filters were common. For example, accelerometer and gyroscope signals were filtered between 0.2–47 Hz [10, 11], 1–24 Hz [22], or 0.5–35 Hz [23]. EMG signals were filtered between 20–90 Hz [22] or with a high-pass filter at 20 Hz [10, 11]. ECG signals used a notch filter at 60 Hz to remove electrical interference from power lines [9]. Some studies smoothed signals using moving averages, like a 10-minute average for temperature [5] or a 15-point average for EDA [15]. Median filters were also used for EDA signals [24]. A few studies used wavelet transforms to break down signals like ECG-derived respiration (EDR) to level 7 to improve entropy [25], or to clean heart rate and GSR signals [26].

1.3.3 Data Segmentation and Windowing

To analyze the signals, the data was divided into short or long windows. The window length depended on the type of seizure being studied. Short windows, between 2 and 10 seconds, were used to detect convulsive seizures. For example, one study used 2-second windows with 75% overlap for ACC and EMG data [10, 11, 27]. Longer windows, from 1 to 7 minutes, were used to detect slower changes in the body, such as with PPG, EDA [28], HRV [26], or for detecting generalized convulsive seizures (GCS) [18]. Some studies removed low-motion periods by checking if acceleration was too low, such as standard deviation below 0.2g [15, 29], or only analyzed data when acceleration was above 0.1g [13].

1.3.4 Class Imbalance Handling

Since seizures are rare compared to non-seizure events, many studies dealt with this class imbalance. One method was undersampling, where non-seizure data was randomly removed to create a more balanced dataset. For example, one study used a seizure-to-nonseizure ratio of 1:1.5 [5, 19]. Other studies used oversampling, where seizure data was repeated to make it more balanced, especially for short seizures [13]. Some used automatic filtering to remove non-seizure data based on certain signal patterns, like when the main frequency of acceleration was below 2 Hz or when the signal had a noncross ratio above 0.9 [15].

1.3.5 Features Extraction

Most studies created features from the signals to use in machine learning models. Time-domain features included basic statistics like mean, variance, and entropy [15, 29], zero-crossing rates [11], and counts of local maxima [10]. Frequency-domain features included power in certain frequency bands, like 9–22.5 Hz [10], FFT peaks [15], and heart rate variability from Lomb-Scargle analysis [28]. Some studies combined features from different sensors, such as ACC and EDA [2, 22], or used decision-level fusion [30]. To reduce the number of features and keep only the most useful ones, they used methods like minimum redundancy maximum relevance (mRMR) [15, 20], ANOVA [29], or the Wilcoxon rank-sum test [18].

1.3.6 Normalization and Baseline Correction

Normalization helped make signals more comparable between different people or recording sessions. Some studies used z-score normalization, which adjusts signals to have a mean of zero and a standard deviation of one [3]. Others used moving baselines, where the recent history of a signal (such as over 60 seconds) was used to calculate thresholds for heart rate or oxygen saturation [31]. Personalized baselines were also used, where each subject's median signal was used as a reference point [26].

1.4 Algorithms

1.4.1 Deep Learning Methods

Deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, were used in several studies and showed strong performance. For example, a CNN-LSTM fusion model was the best performer in one study [5], and a CNN was used in another [19]. LSTM was also used in [24] and [3] (with transfer learning).

1.4.2 Ensemble Methods

Tree-based ensemble methods like Random Forest and Gradient Boosting have shown good results in seizure detection tasks. For example, Random Forest has been used to detect seizures on a daily basis [15] and to monitor individual patients [25]. Gradient Boosting methods, such as XGBoost, worked well for spotting certain types of seizures, like focal to bilateral tonic-clonic seizures [6], and for tracking children's seizure patterns over time [26]. Ensemble methods combining multiple base models further enhanced accuracy. One example is the Two-Layer Ensemble Model (TLEM), which combined four tree-based models (Random Forest, Extra Trees, Gradient Boosting, and AdaBoost) with logistic regression and reached a high sensitivity of 94.57% for detecting seizures at night [29]. Bagged decision trees also performed well in real-time seizure detection systems [30].

1.4.3 Traditional Machine Learning

Traditional machine learning algorithms, especially Support Vector Machines (SVM), were frequently among the best performers. Variants such as Least Squares SVM (LS-SVM) [10], nonlinear SVM [17], and linear SVM (SVM-L) [16] were used in different contexts, often for multimodal signal analysis.

1.4.4 Rule-based and Threshold-based Methods

Rule-based and threshold-based algorithms provided interpretable and efficient solutions, particularly for combining heart rate and motion data. These included stepwise algorithms for nocturnal motor seizures [12], multi-parametric threshold-based approaches for cardiac-based detection [32], and Shewhart control charts for nocturnal seizures [23]. Fuzzy logic was also employed in an IoT-based monitoring system [1].

1.4.5 Methods with Personalization

Personalized approaches, such as transfer learning [3] and autoencoders [5], were employed to adapt detection models to individual patient physiology, improving sensitivity for specific seizure types.

2 Discussion

2.1 Modalities

Accelerometry (ACC) was the most commonly used modality and formed the basis of most systems. However, it was frequently combined with other sensors to improve detection performance, particularly for non-motor seizures. The most common combinations involved motion sensors like accelerometers (ACC) and gyroscopes, which together provided detailed information about movement intensity and orientation. These were often paired with physiological signals such as electromyography (EMG) to detect muscle activation, electrodermal activity (EDA) to monitor changes in skin conductance linked to autonomic responses, and electrocardiography (ECG) to capture heart rate and cardiac irregularities during seizures. By combining external motion data with internal physiological responses, these multimodal systems aimed to improve detection accuracy, reduce false alarms, and enable more reliable recognition of both motor and non-motor seizure events. Less frequently used modalities, including PPG, heart rate, temperature, and SpO_2, appeared mainly as supplementary inputs in broader sensor arrays. Overall, the trend favored combining motion and physiological signals to increase sensitivity and reliability across different seizure types.

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