

# The Open Seizure Database

## Facilitating Research Into Non-EEG Seizure Detection

J. Pordoy, G. Jones, N. Matoorian, N. Dadashiserej and M. Zolgharni

**Abstract**— This research introduces the Open Seizure Database and Toolkit as a novel, publicly accessible resource designed to advance non-electroencephalogram seizure detection research. This paper highlights the scarcity of resources in the non-electroencephalogram domain and establishes the Open Seizure Database as the first openly accessible database containing multimodal sensor data from 49 participants in real-world, in-home environments. The database is comprised of 494 events, encompassing 146 epileptic seizures, collected over a duration of 453 days, presenting the most extensive publicly available non-electroencephalogram seizure data to date. Additionally, the database has 348 labelled false alarms, including 302 common human movements and activities. The Open Seizure Toolkit is designed to facilitate machine and deep learning practices by streamlining data from the Open Seizure Database. Utilising these resources, researchers can rapidly develop and train seizure detection models before deploying them to the Open Seizure Detector Android Application. Access to these resources is expected to foster collaborative efforts, ultimately contributing to the establishment of a non-electroencephalogram gold standard and advancing the field of seizure detection.

**Index Terms**— Seizure Detection, Epilepsy, Multimodal, Open Seizure Detector, Deep Learning, Accelerometer, PPG

### I. INTRODUCTION

Epilepsy is a chronic neurological disorder that affects an estimated 65 million people worldwide, characterised by recurring unprovoked seizures due to an abnormal, hypersynchronous discharge between communicating neurons [1]. Epidemiological studies suggest that approximately 30% of patients with epilepsy (PWE) are refractory to common therapeutic treatments, which increases the risk of a sudden unexpected death in epilepsy (SUDEP). SUDEP is the leading cause of premature death observed in patients diagnosed with refractory epilepsy and is defined as a death in epilepsy that is not attributable to trauma, drowning or status epilepticus [2].

Although the underlying etiology behind SUDEP remains unknown, studies show that in 67% of cases, there were indications of a generalised seizure preceding the terminal event [3] [4]. Additionally, there is evidence to indicate that seizure-induced perturbations in respiratory, cardiac, and electrocerebral functions, along with several potential predisposing risk factors, could contribute to SUDEP [5]. Lamberts *et al* found that 58% of SUDEP cases were associated with sleep, and that 86% of instances occurred when the PWE was alone and unsupervised [6]. Sveinsson *et al*'s analysis of 321 SUDEP cases yielded similar findings, with most instances occurring at night in the patient's home whilst living alone (71%) [6]. While similar

J. Pordoy, Department of Computing, University of West London, St Mary's Rd, London W5 5RF, (e-mail:jamie.pordoy@uwl.ac.uk).

G. Jones, Open Seizure Detector, Hartlepool, UK, TS26 (e-mail:graham@openseizuredetector.org.uk).

N. Matoorian, Dept of Computing, University of West London, St Mary's Rd, London W5 5RF, (e-mail:Nasser.matoorian@uwl.ac.uk).

N. Dadashiserej, Dept of Computing, University of West London, St Mary's Rd, London W5 5RF (e-mail:nassim.dadashiserej@uwl.ac.uk).

M. Zolgharni, Dept of Computing, University of West London, St Mary's Rd, London W5 5RF (e-mail:massoud.Zolgharni@uwl.ac.uk).

findings can be found in broader literature, closer examination reveals that predisposed factors for SUDEP are primarily triggered when the individual with epilepsy is at home. These findings indicate that such factors significantly increase the likelihood of SUDEP, with studies concluding that up to 69% of cases could have been prevented if patients were not left unattended at night. Despite an increase in clinical studies, little progress has been made in characterising SUDEP risk factors and the underlying mechanisms leading to premature death in epilepsy [7] [8]. This has led numerous studies to postulate that seizure detection could serve as a means to deter terminal seizures pre-ictal, and reduce the incidence of SUDEP cases through early intervention and prevention.

### II. RELATED WORK

The electroencephalogram (EEG) represents the diagnostic gold standard modality for capturing seizures within hospital settings, employing continuous electrical brain wave monitoring over an extended period. However, the EEG's utility as an assistive diagnostic tool is unsuitable outside of a hospital or epilepsy monitoring unit (EMU) due to the need for a PWE to remain in a stationary position with multiple scalp-based electrodes attached, and a full-time neurodiagnostic technician to interpret real-time neurological activity. To overcome the limitations associated with EEG, a new sub-field of research has emerged known as non-EEG detection. This approach utilises non-invasive methods to detect seizures in real-world environments. These methods include wearable devices that measure physiological signals such as heart rate, movement and electrodermal activity.

The accelerometer (ACM) has emerged as the most promising non-EEG sensing modality, having been extensively explored in non-EEG research for capturing changes in motion and velocity displayed by PWE. Notably, these investigations have showcased the ACMs potential for detecting rhythmic movements, particularly those associated with a generalised tonic-clonic (GTC) seizures. By leveraging ACM data, sophisticated algorithms have been developed to identify the convulsive movements characteristic of a seizure's clonic phase. Seminal studies conducted by Conradsen *et al.* and Lockman *et al.* serve as notable examples, demonstrating the practical application of ACM-based detection with remarkable accuracies of 90% and 91% respectively [9] [10].

However, it is important to note that the ACM data utilised in these studies did not originate from patients diagnosed with epilepsy; rather, it was simulated by healthy participants in controlled short-term studies. This prevailing trend is widespread in the field of non-EEG seizure detection, as a significant portion of studies have relied on small-scale, simulated, or synthetic datasets [16]. Two predominate factors contribute to this observation. Firstly, the field of research in non-EEG detection is relatively new, and as such, there are no established, publicly available datasets, which are more common in other domains of healthcare research. Secondly, epileptic seizures are infrequent, rare events, which makes it challenging to record an extensive dataset of generalised seizure recordings from multiple PWE.

**TABLE I:** Summary of the publicly available datasets used for non- electroencephalogram seizure detection where the # symbol represents the “number of”, Ref = Reference, Prt = Participants, Sz = Seizure, Ps = Per Sample, SR = Sample Rate and p/e = per event

Ref	Dataset	Sensors	Type	#Prt	#Sz	Dur	SR
[11]	MyNeuroHealth	Smartphone tri-axial accelerometer	Real	23	3	30s p/e	15Hz
[12]	Epilepsy Convulsion Recognition	Tri-axial accelerometer	Simulated	6	10	30s p/e	16Hz
[13]	Patient-Specific Dataset	Electrocardiogram & electroencephalogram	Real	15	38	-	512Hz
[14]	Post-Ictal Heart Rate Oscillations	Single-lead ECG	Simulated	5	11	15-110s p/e	200 Hz
[15]	Gestures: MICCAI 2021	Video Capture & Image Capture	Real	68	183	approx 0.5s p/e	-
Total	5	7		2	210		

Table I provides a comprehensive overview of the non-EEG datasets currently accessible in the public domain, intended to drive progress in the field. However, upon closer examination, it becomes evident that a significant portion of the data is either simulated or recorded using sub-optimal sensing modalities, such as smartphones with embedded MEMS. Additionally, the existing data lacks the necessary depth to capture the complexities inherent in different types of epilepsy. To address this, non-EEG data should be recorded from real-world, in-home environments, as this is where most seizures and SUDEP cases occur. By utilising real-world data, non-EEG detection systems can be modelled to accurately reflect the real-world complexities encountered by PWE in their day to day lives.

While publicly available non-EEG data remains limited, commercial organisations and international consortiums have conducted studies using several non-EEG detection techniques. Empatica’s Embrace has been used in several studies to detect convulsive seizures, demonstrating an average sensitivity of 92-100% and a false alarm rate (FAR) between 0.2-1 per day [17] [18] [19] [20]. Another commercially available device, Seer Medical’s smartwatch has yielded a mean area under curve (AUC), a sensitivity, and a FAR per day of 0.98, 0.93, and 2.3, respectively for 19 motor seizures from 10 in-hospital patients [21]. However, it should be noted that the data used in these studies is not accessible to the wider academic community, limiting the ability to replicate these findings. Additionally, consideration should be given to the fact that the data used in these commercial studies predominantly originates from clinical trials conducted in EMUs, where the environmental dynamics are closely regulated [22].

The progress in non-EEG research is currently hindered by the lack of publicly available data, impeding scientific advancements and leading to slower progress compared to other fields utilising Machine Learning/Deep Learning techniques in clinical practice [23]. Additionally, non-EEG literature often demonstrates high accuracy scores but is accompanied by a significant occurrence of false positives. The presence of false alarms poses challenges in real-world seizure detection applications, as it can result in unnecessary alerts, incorrectly indicating the presence of a seizure [24]. Reducing false alarms is crucial to enhancing the reliability and effectiveness of seizure detection models. The use of multimodal sensors shows promise in achieving this goal. By combining data from different sensors, a more accurate and robust dataset can be constructed for the development of intelligent detection models. Several studies have suggested that multimodal sensing could decrease the false positive rate observed in literature and improve the accuracy and performance of existing seizure detection models. To achieve these goals there is a pressing need for a large-scale in-home study to record multimodal sensor data. By recording individuals with epilepsy in their real-world home environments using multiple sensors, a comprehensive dataset could be created, offering sufficient depth and breadth to tackle the current challenges in non-EEG seizure detection research.

Large-scale data repositories and collaborative data sharing have become integral to clinical progress. In epilepsy research, the European Epilepsy Database (EED) is the largest and most comprehensive database for human surface and intracranial EEG recordings. It contains clinically annotated pre-ictal, ictal, and post-ictal EEG data from 278 patients suffering from pharmaco-resistant partial epilepsy [25] [26]. Through collaborative sharing and centralised data access, the EED has been cited in over 138 publications, facilitating research progress in the field of EEG detection [25]. However, the EED stores data strictly for neurological research and does not store any non-EEG resources.

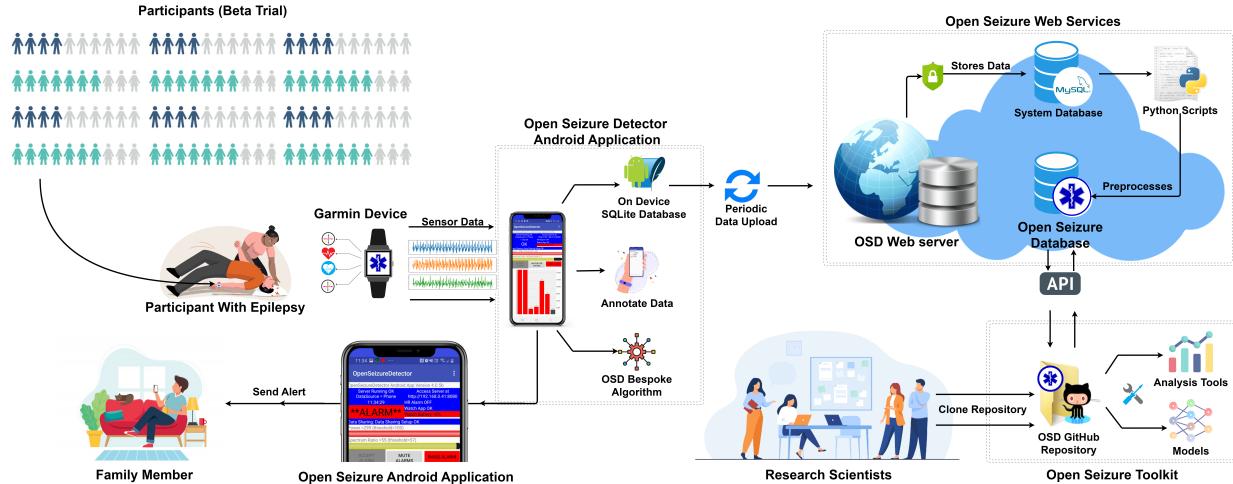
A publicly available non-EEG database dedicated to storing sensor data from patients with epilepsy in real-world conditions holds great potential for transforming the field of seizure detection research. This approach would enable benchmark testing and comparative analysis under reproducible conditions, facilitating the evaluation and advancement of novel seizure detection techniques. Moreover, such a database could advance epilepsy research through data sharing and collaboration [27], enabling researchers to investigate innovative concepts such as patient-specific and seizure-specific detection.

This paper is organised into the following sections: Section III details the development of the Open Seizure Database. Section IV outlines the Open Seizure Toolkit, highlighting its capacity to rapidly develop algorithms compatible with Open Seizure Detector. Section V presents the experimental results achieved using the the Open Seizure Database and Toolkit. In Section VI, a comprehensive discussion of this paper’s findings and finally, Section VII concludes by highlighting the studies impact on the field of non-EEG seizure detection.

### III. METHODOLOGY

This study introduces the Open Seizure Database (OSDB) and Open Seizure Toolkit (OSTK) as novel contributions to the field of non-EEG seizure detection [28]. Developed in collaboration between Open Seizure Detector (OSD) [29] and the University of West London [30], the OSDB serves as the first publicly accessible database containing non-EEG epileptic seizure recordings from real-world, in-home environments. OSD, established in 2013, is the largest open-source seizure detection software package, distributed under the open-source, GNU General Public License (GPL), boasting over 5000 downloads [31], and an estimated 300 daily users [29].

A comprehensive beta trial was conducted, utilising non-invasive wearable sensing devices to capture non-EEG data from a diverse cohort of participants diagnosed with various forms of epilepsy. This beta trial, closely supervised by OSD, spanned from January to June 2022. In adherence to ethical standards, all participants provided informed consent [33], and voluntarily enrolled in the beta trial through the Google Play Services Public Beta Program [32]. Furthermore, this research study obtained approval from the ethics committee at the University of West London.



**Fig. 1:** An illustration of the Open Seizure Detector architecture used to record participant data. The architecture consists of four main components, Open Seizure Detector Android Application, Open Seizure Web Server, Open Seizure Database and the Open Seizure Toolkit

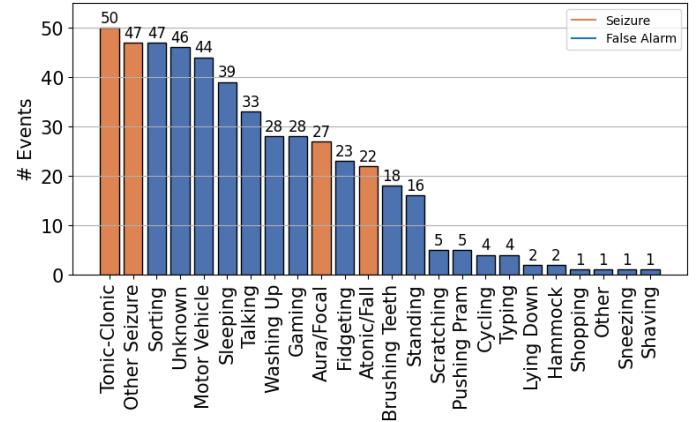
To uphold strict confidentiality during the data collection process, stringent measures were implemented, encompassing the removal of personal identifiers to ensure anonymity. Subsequent to the beta trial period, the opportunity to contribute data to the database was extended to all OSD users who consented to the data safety statement. Notably, data collection remains ongoing to the present day.

For the beta trial, individuals with partial-onset epilepsy, particularly those susceptible to absence or complex focal seizures, were intentionally excluded during the initial phase of data collection. This decision was predicated on the absence of tonic, atonic, myoclonic, or clonic movements typically associated with generalised epilepsy. Consequently, among the participants who signed up to the beta trial, 49 individuals met the required criteria concerning both technological aspects, such as device and sensor compatibility, as well as physiological requirements pertaining to the type of epilepsy.

Participants were instructed to install the OSD Android application [31] and continually wear a wrist-worn sensor device (Fig. 3), except when charging was required. Several Garmin devices (TABLE III) were employed for data collection, in which sensor data was transmitted to the participants Android device using a Bluetooth connection. Sensor data is then stored temporally on the end users device where it is analysed to detect seizure-like movement as described in Section III-F. When seizure-like movement is detected, the associated data is stored long term using the OSD web server (Fig. 1).

### A. Dataset

During the 453 day data collection period, a total of 494 events were recorded from 49 participants. 146 events were recorded as epileptic seizures, while the remaining 348 were classified as false alarms. Among the false alarms, 302 were associated with human/physical activities and were appropriately labelled as such (Fig. 2). The remaining 46 events were categorised as false alarms where the activity is unknown. Epileptic seizures were recorded from 18 participants, amounting to a cumulative duration of 5 hours and 51 minutes (TABLE II). A diverse range of epileptic seizures were recorded with 50 GTC seizures, 27 aura/focal seizures, 22 atonic seizures/falls and 47 seizures labelled as "Other Seizure". It is important to note that, for the purposes of this study, "Other seizure" are defined as seizures that were labelled only by type (e.g. seizure or false alarm). Participants did not provide further categorisation of the events specific sub-types (e.g. atonic, aura, tonic-clonic).



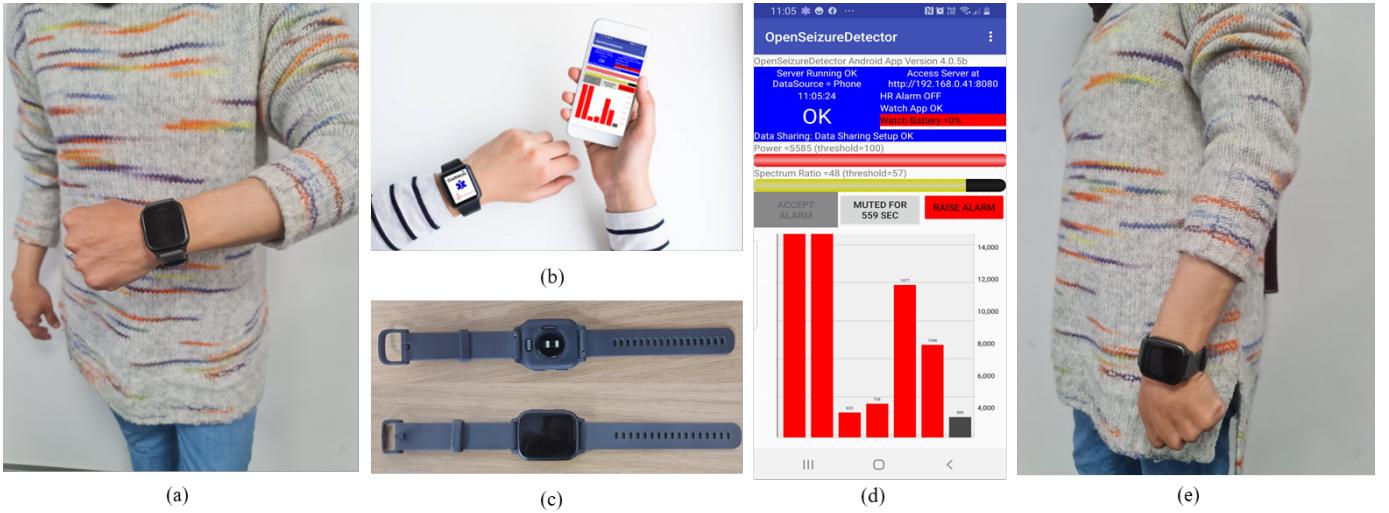
**Fig. 2:** Summary of the different events recorded. Epileptic-related events are highlighted in orange, while common human activities responsible for triggering false alarms are indicated in blue.

### B. Sensing Modalities

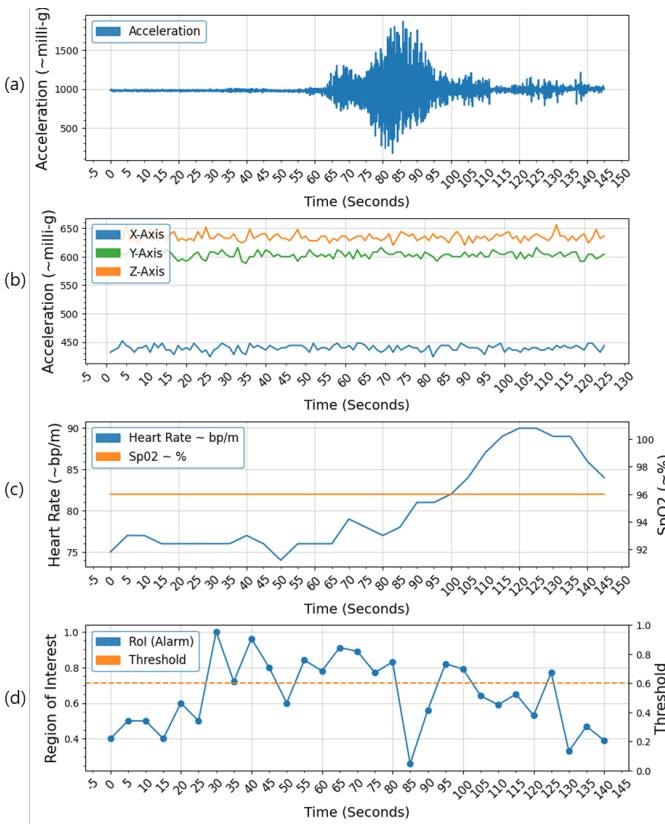
Recording epileptic seizures from a large group of participants using multiple sensors is a significant challenge. To overcome this, we employed Garmin wearable devices, capable of measuring accelerometry, photoplethysmography (PPG), and pulse-oximetry (SpO<sub>2</sub>) signals. The use of Garmin devices proved to be a cost-effective and easily accessible solution to record sensor data (Fig. 4) from a large cohort of participants with epilepsy in their real-world, home environments. This section details the sensors used during the study.

Garmin wrist-worn devices are equipped with tri-axis ACM and have a sensing range of  $\pm 2\text{ g}$  up to  $\pm 16\text{ g}$ , where 'g' quantifies the gravitational forces along different device axes [34]. This range signifies the maximum acceleration value accurately measurable by a Garmin device. The  $\pm 2\text{ g}$  range accommodates the broad spectrum of human movements and activities, while the  $\pm 16\text{ g}$  range can facilitate the detection of high intensity movements.

For heart rate monitoring, Garmin devices are equipped with an embedded optical PPG sensor, located on the back, which utilises a green light-emitting diode to emit light onto the skin, thereby measuring volumetric variations in blood circulation [35]. The reflected light from the red blood cells in the skin facilitates the measurement of the participant's heart rate in beats per minute (bpm).



**Fig. 3:** The architecture of Open Seizure Detector, detailing the components utilised by each participant. (a) and (e) depict a participant wearing a Garmin device on their dominant hand from front and side angles. (b) illustrates the Bluetooth inter-connectivity between the Garmin wearable device and the participant’s Android device. (c) is an example of a Garmin (Garmin Venu SQ) device used during the trial and (d) illustrates the Open Seizure Detector application Interface.



**Fig. 4:** Graphical plots detailing sensor data recorded for events in the Open Seizure Database. In plot (a), acceleration is measured as vector magnitude. Plot (b) visualises the acceleration data for the event along the  $x$ ,  $y$ ,  $z$  axis. Plot (c) visualises heart rate and oxygen saturation levels obtained from the photoplethysmography sensor and oxygen saturation sensors. Plot (d) depicts the  $R_{roi}$  and sensitivity threshold measurements that represents the sequence in which the event was detected by Open Seizure Detector algorithm.

**TABLE II:** Summary of the seizure events that were recorded during the beta trial where data is distributed by participant Id, seizure type and duration. Epileptic seizures were recorded from 18/49 participants in which TC = Tonic-clonic and Oth Sz = Other Seizure

Participant Id	#TC	#Aura	#Atonic/ Fall	#Oth Sz	Recorded Duration
P45	25	22	0	10	02:21:35
P39	11	0	0	33	01:48:20
P53	0	0	16	0	00:41:45
P83	5	0	0	1	00:16:05
P8	3	3	0	0	00:05:00
P421	2	0	0	0	00:04:40
P236	0	2	0	0	00:04:20
P55	0	0	0	2	00:04:15
P470	0	0	2	0	00:02:45
P62	0	0	0	1	00:02:45
P389	1	0	0	0	00:02:30
P157	1	0	0	0	00:02:30
P465	1	0	0	0	00:02:30
P483	1	0	0	0	00:02:15
P80	0	0	1	0	00:02:35
P59	0	0	1	0	00:02:25
P132	0	0	1	0	00:02:20
P138	0	0	1	0	00:02:35
	18	50	27	22	05:51:00

Newer Garmin devices are equipped with oxygen saturation sensors (SpO<sub>2</sub>) to non-invasively measure blood oxygen levels. These devices utilise two wavelengths of light, red and infrared, with red light being absorbed by oxygenated blood and infrared light by deoxygenated blood. By analysing the absorption ratio of these wavelengths, oxygen saturation levels can be calculated [36].

### C. Data Storage

To address the long-term data storage requirements, a mobile-client, client-server architecture was implemented. Short-term data

storage utilised an SQLite database on each participants Android device, leveraging local storage capabilities. Mobile Sync ensured efficient and reliable data synchronisation between the mobile client and the OSD web server.

Sensor data was transmitted using Bluetooth in 5 second timesteps (intervals) to the on-device database, striking a balance between capturing sufficient information for seizure detection and minimising energy consumption. Furthermore, the periodic transmission of locally stored data to the OSD Web Server was designed to prevent potential bottlenecks during the upload.

The OSDB was designed to be flexible and maintain backward compatibility. Initially, it stored one-dimensional ACM data in the form of vector magnitude and heart rate data. However, during the beta trial, adjustments were made to accommodate the storage of SpO<sub>2</sub> and three-dimensional ACM data. By utilising an SQLite database on the Android platform and integrating additional features and sensors, the OSD project achieved scalability and ensured compatibility. Design choices were driven by the goal of optimising data storage, capturing relevant sensor data, and improving overall performance.

#### D. Database Schema

The database schema for the OSDB was carefully anonymized and preprocessed, and the data was converted into a series of JSON scripts. The utilisation of JSON provided a structured representation of the data, ensuring accessibility across different platforms and programming languages. Version 1 of the OSDB is available upon request through the OSDB GitHub repository. It can be accessed either as a single JSON script containing data for all labelled events or as a subset focusing on specific event types such as tonic-clonic or false alarms. The datasets are organised hierarchically using a one-to-many relationship, where each event has multiple sub-events. Each sub-event corresponds to a 5-second timestep, and sensor data for that timestep is stored as a JSON array called "Datapoints." The complete JSON schema of the OSDB, including accurate attribute names, arrays, and data types, is provided in Fig. 5 and TABLE IV.

#### E. Annotating Event Labels

As the beta trial had a diverse cohort of participants spread across the globe, a self-annotation system was developed where participants were able to label an event as it occurred using the OSD Android application. When an event was detected, participants were instructed to label the event by type (e.g., Seizure, false alarm) and then sub-type (e.g., aura, tonic-clonic). Participants had the flexibility to add custom class labels for more accurate annotation or choose from a predefined set of labels commonly associated with false alarms. Additionally, participants had the option to manually trigger an alarm and label an event in cases where the algorithm failed to detect a seizure.

**TABLE III:** Summary of the different Garmin devices and sensor configurations employed for this study. Grouped by Device

Device	Code	Sensors	Participants
Venu	006-B3226-00	ACM, PPG, Sp02	16
Venu SQ	010-02427-10	ACM, PPG, Sp02	10
Venu 2	010-02430-11	ACM, PPG, Sp02	13
Forerunner	010-02120-11	ACM, PPG	5
Vivoactive 4	006-B3225-00	ACM, PPG, Sp02	6
Vivoactive HR	006-B2337-00	ACM, PPG	7

OSD performed a second stage of annotation, involving expert labelling the start and end of each seizures convulsive or seizure-like movement. The duration of each seizure is stored as an array labelled "seizureTimes", denoting the start and end time of the seizure-like movement. By leveraging self-annotation during the trial and expert labelling afterwards, the resulting OSDB presents the most accurate, publicly available set of fully annotated non-EEG recordings.

```
{
  "eventId": 47000,
  "type": "Seizure",
  "subType": "Other",
  "desc": "partial. arm flapping",
  "userId": 39,
  "dataSourceName": "Garmin",
  "alarmFreqMax": 8,
  "alarmFreqMin": 3,
  "datapoints": [
    {
      "alarmPhrase": "OK",
      "alarmState": 0,
      "dataTime": "2023-05-15T06:45:56Z",
      "hr": 87,
      "o2Sat": 0,
      "rawData": [x1, x2, x2, ..., x125],
      "rawData3D": [x1, y1, z1, ..., z375],
      "roiPower": 4,
      "roiRatio": 40,
      "simpleSpec": [s1, s2, ..., s10],
      "specPower": 1
    },
    {...}, {...}],
    "seizureTimes": [-20, 60],
    "has3dData": true,
    "hasHrData": true,
    "hasO2SatData": false,
    "hrThreshMax": 150,
    "hrThreshMin": 40,
    "hrAlarmActive": false,
    "phoneAppVersion": "4.1.2",
    "sampleFreq": 25,
    "watchFwVersion": "2.4.9",
    "watchPartNo": "006-B2337-00",
    "watchSdName": "GarminSD"
  }
}
```

**Fig. 5:** Open Seizure Database JSON schema. Events are stored by eventID and sensor data is stored using the "datapoints" array

**TABLE IV:** Summary of datapoints array. Datapoints are recorded for each timestep and can be accessed using the following attributes

Id	Attribute	#DP	Description
1	RawData	125	1D Vector magnitude signal in milli-g
2	3dRawData	375	3D (xyz) accelerometer signal in milli-g
3	Hr	1	Heart rate signal in bpm
4	O2Sat	1	Oxygen Saturation (Sp02 %)
5	SimpleSpec	10	Spectral power in 1 second wide frequency bins (0-10 Hz)
6	RoiRatio	1	Region of Interest Ratio for OSD algorithm
7	RoiPower	1	Region of Interest power
8	SpecPower	1	Power of Frequency Spectrum

### F. Open Seizure Detector Algorithm

For seizure detection during the beta trial, participants were instructed to use the OSD Android application which runs a deterministic detection algorithm. Sensor data was transmitted from the participants' Garmin device to the OSD application in five second timesteps at a sample frequency of 25 Hz, resulting in 125 measurements per timestep. To optimise the battery capacity of participants' Android devices, acceleration was measured as a unit of vector magnitude instead of measuring three separate spatial dimensions ( $x, y, z$ ), thus reducing the computational requirements by a factor of  $\frac{2}{3}$ . This decision was made to increase the data collection duration without the need for frequent battery replacement or recharging. Vector magnitude for the current timestep can be calculated as

$$A_t = \sqrt{(a_{x-t}^2 + a_{y-t}^2 + a_{z-t}^2)} \quad (1)$$

Where  $a_{x-t}$ ,  $a_{y-t}$  and  $a_{z-t}$  represent the moving acceleration of each orthogonal axis for timestep ( $t$ ). The algorithm then transforms the vector magnitude signal from the time domain to the frequency domain by utilising a Fast Fourier Transform ( $FFT$ ) to compute the power in each frequency range.

As stated by the Nyquist Theorem, the maximum frequency that can faithfully represent the original signal is half of the sample frequency [37]. Consequently, the OSD algorithm running on a Garmin device is capable of precisely reconstructing signals with frequencies up to 12.5 Hz without experiencing aliasing. If the algorithm detects a participant moving at a frequency exceeding 12.5 Hz, the resulting observation will manifest as an alias feature in the spectrum. However previous studies have reported that common human movement predominantly occur within a frequency range between 0-12.5 Hz [38]. Given this observation, we posit that any high-frequency movement beyond the 12.5 Hz threshold will exert minimal influence on algorithmic performance, as it lies outside the typical range of human movement. Furthermore, studies have shown that during the clonic phase the body's major muscle groups exhibit repetitive convulsions at a frequency range between 3-8 Hz, which is inside the algorithms detectable frequency range [39] [40].

The frequency resolution of the spectrum is then determined by dividing the sample frequency (25 Hz) by the number of measurements (125) per timestep, resulting in a resolution of 0.2 Hz. This resolution allows for effective detection and differentiation of frequency components with a precision of 0.2 Hz. These calculations indicate that the algorithm can accurately identify frequency components that are spaced at intervals of 0.2 Hz, however any frequency differences smaller than this value may not be distinguishable [41].

To detect a 'seizure-like' movement, the algorithm calculates the average power for the whole spectrum ( $P_s$ ) and then the average power of the 3-8 Hz Region of Interest ( $P_{roi}$ ) for each timestep. To reduce the FAR, ( $P_s$ ) is checked against a threshold to ensure that there is a sufficient level of movement, thus avoiding spurious alarms caused by measurement noise when there is minimal movement. If the movement detected exceeds the movement threshold, then  $R_{roi}$  is calculated as the ratio between ( $P_{roi}$ ) and ( $P_s$ ) which can be expressed as

$$R_{roi} = \frac{P_{roi}}{P_s} \quad (2)$$

A seizure is then detected if  $R_{roi} \geq$  the algorithms sensitivity threshold. If the sensitivity threshold is exceeded for three consecutive timesteps, an alarm state is raised, and the data saved to the database. Three consecutive timesteps (15 seconds) were utilised to give balance between reducing false alarms and ensuring prompt generation of an alarm when a genuine seizure was detected. The above process is detailed in Algorithm 1.

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**Algorithm 1** Pseudo code for the OSD algorithm where  $A_t$  = acceleration (vector magnitude) at timestep  $t$ ,  $P_s$  = spectrum power,  $P_{roi}$  = Region of Interest power,  $R_{roi}$  = ROI Ratio,  $Th$  = threshold. DoAnalysis takes  $A_t$  as an input parameter on a repeating loop every 5 seconds. The acceleration values are passed to a  $FFT$  to convert values into the frequency domain. For each timestep  $t$  the average of  $P_s$  and  $P_{roi}$  are calculated to find the ratio of  $R_{roi}$ . If  $R_{roi} \geq Th$ , 'seizure-like' movement is detected where  $SD$  = Seizure Detected and  $AS$  = Alarm State. Variables  $SD$  and  $AS$  are initialised at 0

$A_t = [x_1, x_2, x_3, \dots, x_{125}]$

$Th$ = Threshold

**function:** DoAnalysis( $A_t$ )

1.  $FFT \leftarrow$  FastFourierTransform( $A_t$ )
2.  $P_s \leftarrow$  CalculateAveragePower(0 – 12.5Hz)
3.  $P_{roi} \leftarrow$  CalculateAveragePower(3 – 8Hz)
4.  $R_{roi} \leftarrow \frac{P_{roi}}{P_s}$

**Input:** DoAnalysis( $A_t$ )

**Output:** Alarm 'Seizure Detected'

**if**  $A_t = True$  **then**

**for** each 5-second timestep where  $SD = True$  **do**

**if**  $SD = True$  &  $AS = 0$  **then**

            update  $AS = 1$

            DoAnalysis( $A_t$ )

**else if**  $SD = True$  &  $AS = 1$  **then**

            update  $AS = 2$

            DoAnalysis( $A_t$ )

**else if**  $SD = True$  &  $AS = 2$  **then**

            update  $AS = 3$

            Alert 'Seizure Detected'

            DoAnalysis( $A_t$ )

**else if**  $SD = True$  &  $AS = 3$  **then**

$AS == AS$

            DoAnalysis( $A_t$ )

**end**

**for** each 5-second timestep where  $SD = False$  **do**

**if**  $SD = False$  &  $AS = 0$  **then**

$AS == AS$

            DoAnalysis( $A_t$ )

**else if**  $SD = False$  &  $AS = 1$  **then**

            update  $AS = 0$

            DoAnalysis( $A_t$ )

**else if**  $SD = False$  &  $AS = 2$  **then**

            update  $AS = 1$

            Alert 'Seizure Detected'

            DoAnalysis( $A_t$ )

**else if**  $SD = False$  &  $AS = 3$  **then**

            update  $AS = 2$

            DoAnalysis( $A_t$ )

**end**

**else**

$AS == AS$

    Alert 'Input not received'

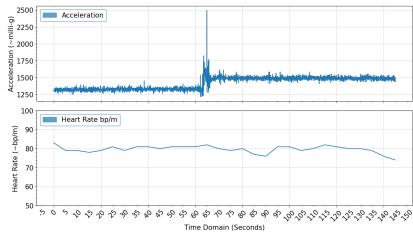
    DoAnalysis( $A_t$ )

**end**

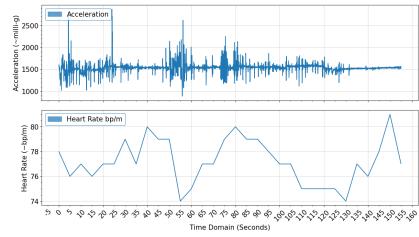
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**TABLE V:** Summary of the events recorded during the beta trial. Events are categorised by type and sub-type and ordered by frequency of event. The average duration is a calculation of the average duration of events (145s) \* number of events for each sub type.

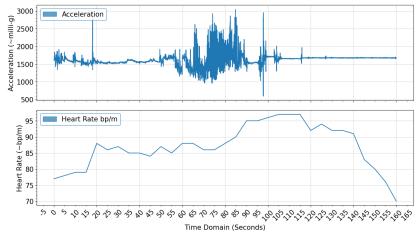
Class ID	Type	Sub Type	Participants	Events	Sub Events	Average Duration (hh:mm:ss)
c21	Seizure	Tonic-Clonic	9	50	1450	02:01:50
c4	Seizure	Other Seizure	5	47	1363	01:53:35
c18	False Alarm	Sorting	5	47	1363	01:53:35
c23	False Alarm	Unknown	18	46	1334	01:51:10
c10	False Alarm	Motor Vehicle	8	44	1276	01:46:20
c16	False Alarm	Sleeping	7	39	1092	01:31:00
c20	False Alarm	Talking	9	33	957	01:20:30
c24	False Alarm	Washing Up	4	28	812	01:07:40
c7	False Alarm	Gaming	8	28	784	01:05:35
c2	Seizure	Aura/Focal	3	27	899	01:15:55
c6	False Alarm	Fidgeting	3	23	667	00:55:35
c1	Seizure	Atonic/Fall	6	22	464	00:39:40
c3	False Alarm	Brushing Teeth	8	18	504	00:42:00
c19	False Alarm	Standing	3	16	464	00:37:20
c13	False Alarm	Scratching	3	5	145	00:12:05
c12	False Alarm	Pushing Pram	1	5	116	00:09:40
c5	False Alarm	Cycling	1	4	116	00:09:40
c22	False Alarm	Typing	1	4	116	00:09:40
c9	False Alarm	Lying Down	2	2	58	00:05:50
c8	False Alarm	Hammock	1	2	48	00:04:50
c15	False Alarm	Shopping	1	1	29	00:02:25
c11	False Alarm	Other	1	1	28	00:02:20
c17	False Alarm	Sneezing	1	1	28	00:02:20
c14	False Alarm	Shaving	1	1	24	00:02:00
#	2	24	49	494	-	19:42:35



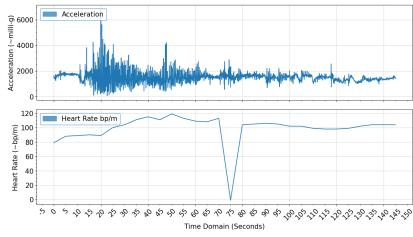
(a) Event:5382 - Atonic/Fall



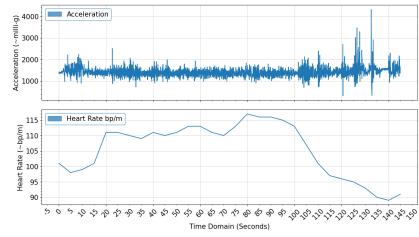
(b) Event:6884 - Aura/Focal



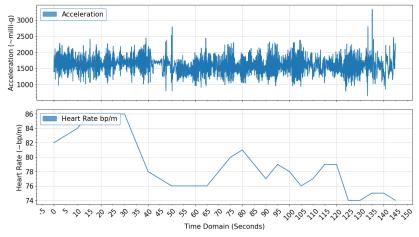
(c) Event:8875 - Tonic-Clonic



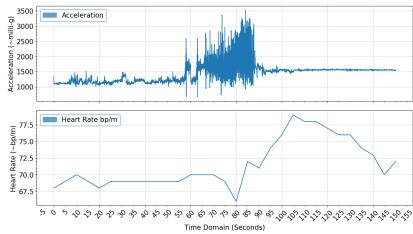
(d) Event:5610 - Other Seizure



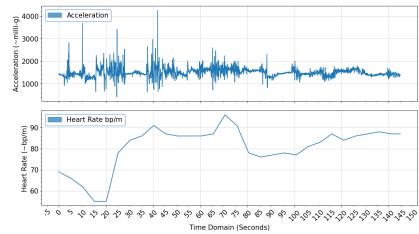
(e) Event:5221 - Cycling



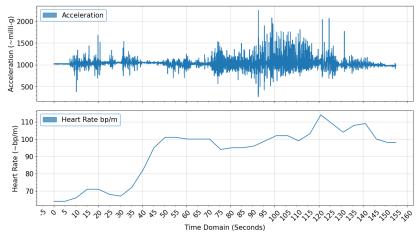
(f) Event:5470 - Brushing Teeth



(g) Event:8737 - Tonic-Clonic

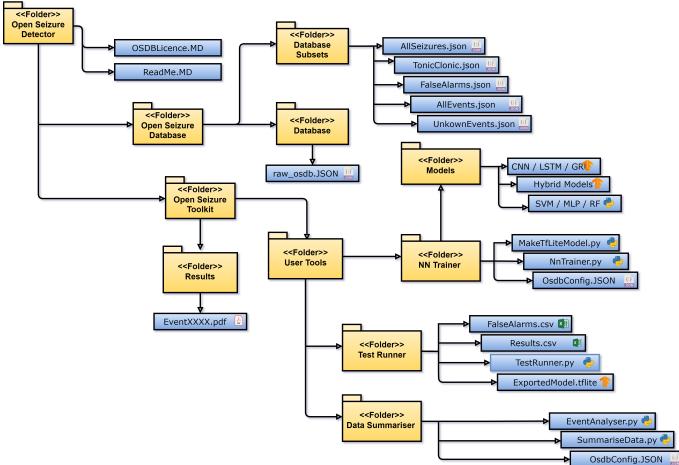


(h) Event:5218 - Scratching



(i) Event:8800 - Other Seizure

**Fig. 6:** A representative subset from the Open Seizure Database that visualises acceleration and heart rate signals for different types of event



**Fig. 7:** A hierarchical overview of the file structure and core components of the Open Seizure Database and Open Seizure Toolkit

#### IV. THE OPEN SEIZURE TOOLKIT

The Open Seizure Toolkit is a software package developed by OSD, serving to facilitate data access to the OSDB, enabling the analysis and development of seizure detection models compatible with the OSD Android application. Fig.7 depicts the hierarchical structure of the OSTK, which encompasses three primary components (NN Trainer, Test Runner, and Data Summariser) located in the User Tools directory. To access the OSDB, users are required to clone the OSTK repository from the official OSD GitHub Repository. Additionally, data access requires user registration with OSD and compliance with the guidelines specified in the OSDB licence [43]. The following section illustrates the functionality of the OSTK by conducting a series of experiments to developing a basic seizure detection model compatible with the OSD Android application. For this experiment a subset of 190 events were selected from 16 participants diagnosed with different epilepsy types.

##### A. Preprocessing and Data Engineering

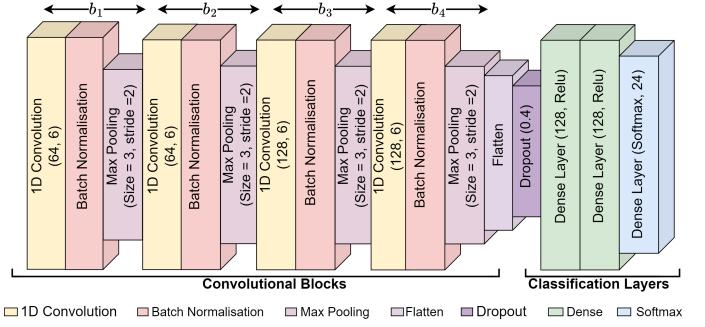
By utilising the OSTK WebApi connector, data was extracted as a JSON string and subsequently transformed by flattening the hierarchical structure of the data's nested objects and loaded as a dataframe for manipulation. Data cleaning, analysis, and feature engineering were conducted to prepare the data for classification. To address the issue of imbalanced data, random oversampling was applied to the minority class. In order to mitigate the effects of data duplication resulting from oversampling, Gaussian noise was introduced to the ACM data as a form of data augmentation, thereby enhancing the variability among samples.

##### B. Class Relabelling and One Hot Encoding

In this experiment, one-hot encoding was used to convert 24 class categorical class labels into a binary vector representation. The resulting binary vectors contain all zero values except for the index corresponding to the class label, which is set to 1. The `nNTrainer.py` and `processing_pipeline.py` scripts were then used to partition the subset into a 75:25 split for the training and test sets, respectively.

##### C. Neural Network Trainer

In this experiment, a 1-dimensional Convolutional Neural Network (1D CNN) was developed, featuring four convolutional blocks labelled as  $b_1, b_2, b_3, b_4$ , each with an associated filter size of 64,

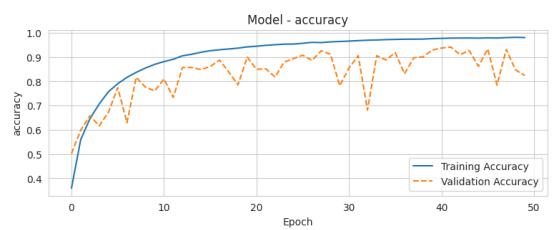


**Fig. 8:** Architectural schematic of 1D Convolutional Neural Network

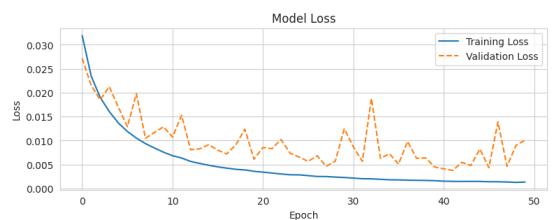
128, 128, and 256, respectively, providing varying levels of receptive field. Each block contains a convolutional layer with ReLU activation and batch normalisation to capture spatial dependencies. Furthermore, a max pooling layer was added to each block to reduce spatial dimensionality. The output vector from  $b_4$  is flattened and fed into the models classification block which has three dense layers. The first two dense layers contain 128 fully connected neurons with ReLU activation units, while the third layer incorporates a softmax activation function to produce an output vector of multiple probabilities. Categorical cross-entropy loss was used to optimise the learning process in conjunction with the Adam optimisation technique. To enhance numerical stability, the optimiser's epsilon score and learning rate were reduced to 1e-05 and 0.0001, respectively. The toolkit can be used to visualise the models learning rate by plotting accuracy and loss scores for training and validation sets (Fig.9-10).

**TABLE VI:** Hyper parameter configuration used for 1D CNN model

Id	Hyper Parameter	Optimisation Metric
1	Train/Test split	75:25
2	Validation Set	0.1
3	Training Epochs	50
5	Batch Size	24



**Fig. 9:** A visual representation of accuracy and validation accuracy plotted by the Open Seizure Toolkit



**Fig. 10:** A visual representation of loss and validation loss plotted by the Open Seizure Toolkit

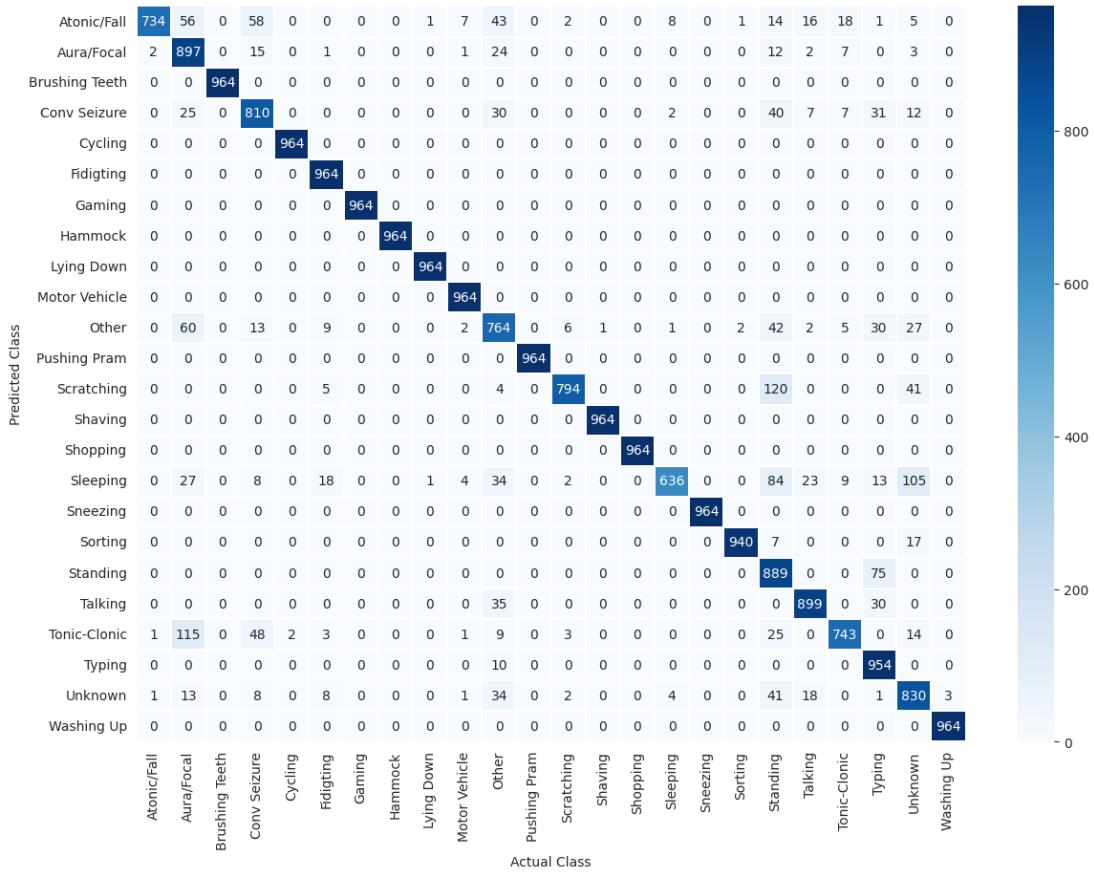


Fig. 11: Multi-class Confusion Matrix: Evaluating the models ground truth and predicted class labels.

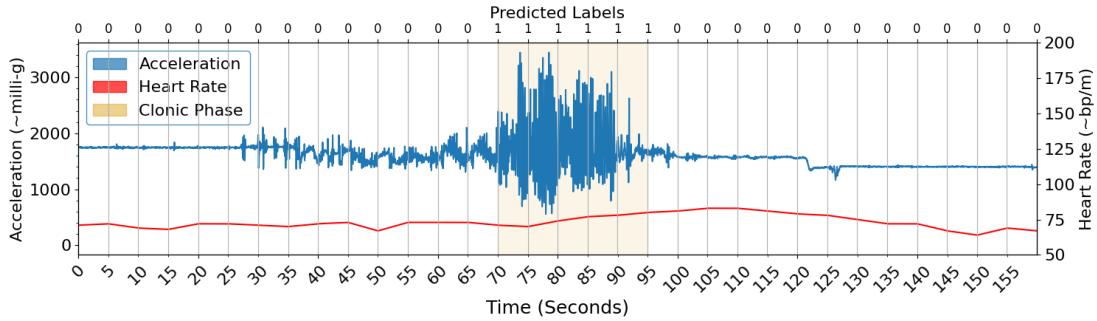


Fig. 12: 1D Convolutional Neural Network detecting a "tonic-clonic" event: A visualisation plot illustrating how the model classifies a tonic-clonic seizure. The upper x-axis plots the models predicted labels for each timestep where 0 = no seizure and 1 = tonic clonic seizure.

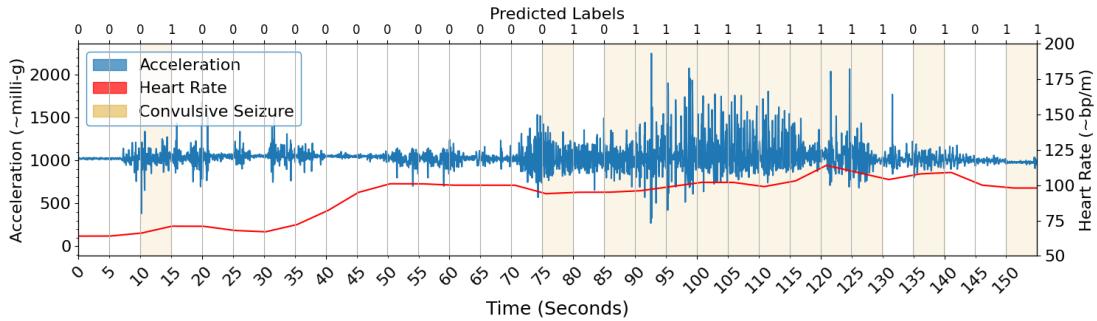


Fig. 13: 1D Convolutional Neural Network detecting an "Other Seizure" event: A visualisation plot showcasing the model's accurate classification of convulsive movement. The upper x-axis plots the models predicted labels for each 5 second timestep

**TABLE VII:** Summary of the overall classification results detailing the performance of the 1D Convolutional Neural Network

Id	Classification Metric	Abbreviation	Classification Result
1	True Positive Rate	TPR	0.998
2	False Positive Rate	FPR	0.071
3	Positive Predictive Value	PPV	0.941
4	Matthews Correlation Coefficient	MCC	0.933
5	False Negative Rate	FNR	0.002
6	True Negative Rate	TNR	0.929
7	False Discovery Rate	FDR	0.059
8	Accuracy	ACC	0.966
9	Specificity	SPC	0.929
10	Prevalence	PREV	0.532
11	F1-Score	F1	0.969
12	False Omission Rate	FOR	0.003
14	Informedness	BM	0.927

## V. EXPERIMENTS & RESULTS

This section presents the experiments conducted using the OSTK and the results achieved. The 1D CNN was trained for 50 epochs, and recorded accuracy and loss scores of 0.959 and 0.1412 receptivity. The model was then evaluated on an unseen test set, and recorded an accuracy score of 92.75% with 0.298 loss. A full breakdown of the models overall performance is detailed in TABLE VII.

The OSTK Data Summariser was utilised to plot a multi-class confusion matrix, visualising the model's predicted and ground truth labels for the 24 classes used in these experiments. An analysis of the confusion matrix demonstrated how well the model distinguishes between the different classes.

For the "O Seizure" class, 810 true positives (TP) were accurately detected, however, 48 instances of "Tonic-Clonic," 15 "Aura/focal," and 58 "Atonic/fall" were misclassified. Additionally, 8 instances were labelled as "Sleeping" and 13 as "Other".

Further analysis of the "Tonic-Clonic" class classified 743 TP instances. However, 7 instances were misclassified as "Other Seizure," 7 as "Aura/focal" and 18 as "Atonic/fall". Furthermore, 14 instances were incorrectly labelled as common human movements, with 9 instances labelled as "Sleeping" and 5 as "Other".

An analysis of the "Atonic/fall" class revealed 734 TP instances, with only 2 instances inaccurately classified as "Aura/focal". Moreover, a single instance each of "Tonic-Clonic" and "Unknown" were misclassified, whilst there were no incorrect classifications associated with the "Other Seizure" class. These results demonstrate the model's ability to differentiate between "Atonic/fall" and "Other Seizure" classes.

For the "Aura/focal" class, the model accurately identified 897 TP instances. However, 56 instances were incorrectly labelled as "Atonic/focal", 25 as "Other Seizure" and 115 as "Tonic-Clonic". A further 13 labels were incorrectly classified as "Unknown", 27 as "sleeping" and 60 as "Other". However, these findings were expected, as a considerable proportion of GTC seizures exhibit an aura (preictal) phase. A further analysis shows that GTC seizures have an average clonic phase lasting 25 to 35 seconds after generalisation. Therefore a degree of similarity between these classes is to be expected and highlights the importance of considering the dynamics of each sub-event. Overall the model has demonstrated a clear ability to differentiate between the "Other Seizure" and "Atonic/fall" classes, as well as "Aura/focal" and "Atonic/fall". However, there were challenges distinguishing between the "Tonic-Clonic" and "Aura/focal" classes.

**TABLE VIII:** Summary of 1D Convolutional Neural Network classification results, measuring precision, recall and f1-scores for each class

Class ID	Type	Sub Type	Precision	Recall	F1 Score
c <sub>1</sub>	Seizure	Atonic/Fall	0.84	0.83	0.83
c <sub>2</sub>	Seizure	Aura	0.61	0.83	0.71
c <sub>3</sub>	False Alarm	Brush Teeth	1.00	0.97	0.98
c <sub>4</sub>	Seizure	Other Seizure	0.85	0.88	0.87
c <sub>5</sub>	False Alarm	Cycling	0.55	0.84	0.67
c <sub>6</sub>	False Alarm	Fidgeting	1.00	0.96	0.98
c <sub>7</sub>	False Alarm	Gaming	0.98	0.83	0.90
c <sub>8</sub>	False Alarm	Hammock	1.00	0.78	0.87
c <sub>9</sub>	False Alarm	Lying Down	1.00	0.81	0.89
c <sub>10</sub>	False Alarm	Motor Vehicle	0.96	0.94	0.95
c <sub>11</sub>	False Alarm	Other	0.96	0.97	0.97
c <sub>12</sub>	False Alarm	Pushing Pram	0.48	0.71	0.58
c <sub>13</sub>	False Alarm	Scratching	0.98	1.00	0.99
c <sub>14</sub>	False Alarm	Shaving	1.00	1.00	1.00
c <sub>15</sub>	False Alarm	Shopping	1.00	1.00	1.00
c <sub>16</sub>	False Alarm	Sleeping	0.76	0.61	0.68
c <sub>17</sub>	False Alarm	Sneezing	1.00	1.00	1.00
c <sub>18</sub>	False Alarm	Sorting	0.90	0.95	0.92
c <sub>19</sub>	False Alarm	Standing	0.85	0.81	0.83
c <sub>20</sub>	False Alarm	Talking	0.95	0.46	0.62
c <sub>21</sub>	Seizure	Tonic-Clonic	0.86	0.71	0.78
c <sub>22</sub>	False Alarm	Typing	0.82	0.93	0.88
c <sub>23</sub>	False Alarm	Unknown	0.76	0.72	0.74
c <sub>24</sub>	False Alarm	Washing Up	0.98	1.00	0.99

Table VIII summarises the classification results for each class. For the purpose of these experiments, the results will be focused on the four classes of seizure. For the "Tonic-Clonic" class denoted in the results as c<sub>21</sub>, the model achieved a precision score of 0.94 and a recall of 0.77. These metrics signify that 86% of positive predictions were correct, while the recall indicates that 23% of true instances of c<sub>21</sub> were incorrectly classified. For c<sub>2</sub> (Aura), the model demonstrated a precision of 0.75, indicating that 75% of the instances predicted were correct. However the recall score of 0.93 highlights the model's ability to correctly identify 93% of actual instances of c<sub>2</sub>. An analysis of c<sub>1</sub> (Atonic/fall) recorded a precision score of 0.99, signifying that 99% of the instances predicted as c<sub>1</sub> were true instances. Nonetheless, a recall score of 0.76 suggests that the model is overcompensating and classifying to many instances of c<sub>1</sub>, which has lead to a trade-off between the precision and recall scores. For c<sub>4</sub> (Other Seizure), the model displayed a balanced performance, recording a precision, recall, and F1-score of 0.84. A precision score of 84% indicates a relatively low false positive rate and demonstrates a high level of accuracy when classifying TP instances of c<sub>4</sub>. Furthermore, a recall score of 84% demonstrated the number of true instances correctly classified by c<sub>4</sub>.

To provide a comprehensive assessment, an F1-score was computed for each class type, resulting in values of 0.86, 0.83, 0.84, and 0.85 for c<sub>1</sub>, c<sub>2</sub>, c<sub>4</sub> and c<sub>21</sub>, respectively. F1-score results indicate a realistic trade-off between correctly identifying positive instances (recall) and minimising false positives (precision) for each class. In summary, the model's performance demonstrates a clear ability to accurately classify seizure-related classes while maintaining a balance between precision and recall.

## VI. DISCUSSION

This study introduces the Open Seizure Database and Toolkit, a publicly available resource designed to facilitate scientific investigation into non-EEG seizure detection. The primary objective of this research is to address the scarcity of resources in the field of non-EEG seizure detection by establishing the OSDB as the first openly accessible database encompassing non-EEG sensor data from multiple sensing modalities.

This study distinguishes itself by utilising real-world data, providing an accurate depiction of everyday life compared to controlled EMU-based datasets. The beta trial's success led to an indefinite extension of the data collection period, showcasing our commitment to continually enriching the OSDB and contributing to non-EEG seizure detection research.

The initial version of the OSDB is comprised of 494 events collected over 453 days, with each event labelled and optimised for machine/deep learning. Among these events, 146 epileptic seizures were recorded; 50 GTC seizures, 47 Other seizures, 27 aura/focal, and 22 atonic/falls. The cumulative duration of recorded epileptic events amounts to 5 hours, 51 minutes, making it the most extensive publicly available cohort of non-EEG seizure data to date.

Additionally, 302 common human movements that triggered false alarms during the data collection period were recorded and labelled. A further 46 events were classified as false alarms, where the triggering activity remains unidentified. The inclusion of labelled false alarms in the dataset offers a valuable resource to address the challenge of false positives in non-EEG seizure detection.

### A. Future Research

The introduction of the OSDB sets forth several possibilities for future research. As the data collection process is extended indefinitely, individuals with epilepsy can continue to participate and contribute data. As more data is collected, the exploration of novel techniques such as patient-specific and seizure-specific detection becomes a possibility. However, due to the dataset's current size, dedicated classification models cannot be trained for these concepts yet. Nevertheless, as more data accumulates over time, these concepts will become feasible.

## VII. CONCLUSION

In conclusion, the introduction of the OSDB and OSTK represents a significant milestone in non-EEG seizure detection research, providing a valuable resource to overcome existing scarcity in this domain. With real-world data collected from in-home environments, researchers can explore diverse multimodal approaches for seizure detection. The OSDBs extensive data on epileptic seizures and labelled false alarms presents a unique opportunity to advance the field. With continued data collection and exploration of novel techniques, the OSDB and OSTK has the promise of establishing a non-EEG gold standard and ultimately improving seizure detection techniques. Researchers investigating non-EEG detection can access the dataset, code, and models through the official OSDB GitHub repository.

**Acknowledgements:** A heartfelt thank you to all the participants. Your invaluable contributions have been instrumental in advancing non-EEG seizure detection research. Your commitment has paved the way for exploring new possibilities and making a positive impact on the lives of those affected by epilepsy. We are deeply grateful for your support and dedication.

**Open Seizure Database (OSDB):** See <https://github.com/OpenSeizureDetector/OpenSeizureDatabase> for instructions on how to access the Open Seizure Database.

**Open Seizure Database Licence:** A summary of the licence under which the Open Seizure Database is released can be accessed at <https://github.com/OpenSeizureDetector/OpenSeizureDatabase/blob/main/documentation/LICENCE.md>

**Informed Consent Statement:** The users gave their consent to publish the developed database by agreeing to the Privacy Policy at [https://github.com/OpenSeizureDetector/OpenSeizureDatabase/blob/main/documentation/Privacy\\_Policy.pdf](https://github.com/OpenSeizureDetector/OpenSeizureDatabase/blob/main/documentation/Privacy_Policy.pdf)

**Data Collection and Data Sharing:** Details of the beta trial, data collection and data sharing can be viewed at [https://www.openseizuredetector.org.uk/?page\\_id=1818](https://www.openseizuredetector.org.uk/?page_id=1818)

**Conflicts of Interest:** The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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