EAI Endorsed Transactions
on Collaborative Computing
Research Article EAI.EU

Seizure Classification Using Person-Specific Triggers

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Abstract

Introduction: With advancements in personalised medicine, healthcare delivery systems have moved away from the one-size-fits-all approach, towards tailored treatments that meet the needs of individuals and specific subgroups. As nearly one-third of those diagnosed with epilepsy are classed as refractory and are resistant to antiepileptic medication, there is need for a personalised method of detecting epileptic seizures. Epidemiological studies show that up to 91% of those diagnosed identify one or more epilepsy related trigger as the causation behind their seizure onset. These triggers are person-specific and affect those diagnosed in different ways dependent on their idiosyncratic tolerance and threshold levels. Whilst these triggers are known to induce seizure onset, only a few studies have even considered their use as a preventive component, and whether they could be used as an additional sensing modality for non-EEG detection mechanisms. **Objectives**: 1. To record person-specific triggers (PST) from participants using IoT-enabled sensors and smart devices. 2. To train and test several dedicated machine learning models using a single participants data, 3. To conduct a comparative analysis and evaluate the performance of each model, 4. Formulate a conclusion as to whether PST could be used to improve on current methods of non-EEG seizure detection. **Methodology**: This study uses a precision approach combined with machine learning, to train and test several dedicated algorithms that can predict epileptic seizures. Each model is designed for a single participant, enabling a personalised method of classification unseen in non-EEG detection research. **Results**: Our results show accuracy, sensitivity, and specificity scores of 94.73%, 96.90% and 93.33% for participant 1 and 96.87%, 96.96% and 96.77% for participant 2, respectively. **Conclusion**: To conclude, this preliminary study has observed a noticeable correlation between the documented triggers and each participants seizure onset, indicating that PST have the potential to be used as an additional non-EEG sensing modality when classifying epileptic seizures.

Keywords: Multi-modal · Seizure Detection · Person-specific · Classification · Epilepsy

Received on 20 November 2020, accepted on 18 December 2020, published on 04 February 2021

doi: 10.4108/_______________

1. Introduction

Epilepsy is a prevalent neurological condition that affects an estimated 70 million people worldwide [1]. An overload of electrical activity between communicating neurons causes a temporal imbalance of neurological activity, culminating in the occurrence of an unprovoked seizure, often leaving an individual with a loss of anatomical motor functions and clarity of memory [2]. An estimated 30% of those diagnosed are classed as refractory and are resistant to anti-epileptic drugs (AEDs) [3]. Those who are resistant have no form of defence and are at a higher risk of triggering a convulsive seizure which can lead to an acute cardiac and respiratory dysfunction [4].

A sudden unexpected death in epilepsy (SUDEP) is the most frequent direct cause of epilepsy-related deaths, predominately affecting those who are resistant or have poorly controlled chronic epilepsy. A study by Lambert *et al.* [5] identified 58% of SUDEP cases are nocturnal and occur once an individual has been asleep and experienced a generalised tonic-clonic (GTC) seizure. As the underlying cause of SUDEP remains unknown and without treatment at

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