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Non-EEG-Based Seizure Detection: A Comprehensive Review

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***Abstract*: This paper presents a review of non-electroencephalogram (EEG) modalities for seizure detection. Seizure detection is crucial for individuals with epilepsy, however traditional EEG-based methods pose limitations in terms of accessibility and usability. This study explores alternative signals, such as heart rate variability (HRV), electrocardiogram (ECG), accelerometry, and others, for robust and non-invasive seizure detection. The Paper focuses on various non-EEG-based modalities for seizure detection, including wearable devices, biosensors, smartphone applications, and machine learning algorithms. Each modality is evaluated based on its potential advantages, such as portability, continuous monitoring capabilities, and real-time alerts. This work also investigates recent advancements in non-EEG-based seizure detection, including the integration of multiple physiological signals, such as heart rate variability, skin conductance, and motion on patterns, to improve detection accuracy and reliability. Previously reported results are compared based on the technologies utilized, including wearable multimodal convulsive seizure detectors incorporating electrodermal activity, accelerometry biosensors, and heart rate variability measured using ECG. These results are evaluated on different performance metrics like sensitivity, false alarm rate (FAR), specificity and accuracy. It is found that automated HRV algorithm with matching pursuit (MP) and wigner–ville distribution (WVD) algorithm, has 100% sensitivity and 99.91% Specificity for detecting seizures, while FAR was low 0.2 events/day for wearable multimodal convulsive seizure detectors.**

Index Terms—Epileptic Seizure, EEG, Wearable Devices, Seizure alarm, Electrodermal activity, Accelerometry, Machine Learning, Deep Learning

Abbreviations:

EEG – Electroencephalogram

ECG- Electrocardiogram

ECoG – Electrocorticography

EDA - electrodermal activity

HRV- Heart Rate Variability

FAR – False Alarm Rate

WVD – Wigner Ville Distribution

MP- Matching Pursuit

SUDEP - Sudden Unexpected Death in Epilepsy

LRML - logistic regression machine learning

DL – Dual Fusion

DF - Detection Latency

I. INTRODUCTION

Epilepsy, tracing its origins back to ancient Babylonian medical texts around 3000 years ago [1], is not limited to humans but also affects animals and is prevalent worldwide [2]. This neurological disorder is characterized by recurrent seizures, abrupt and unprovoked episodes of abnormal electrical brain activity. When these seizures occur repeatedly, often accompanied by symptoms such as altered behavior, sensations, or temporary loss of consciousness, it is classified as an illness [3]. Seizure duration can vary from seconds to minutes, carrying the risk of severe injuries, burns, or even fatality. These seizures manifest diversely in presentation, duration, and severity, ranging from convulsions to altered sensations or behaviors [4], [5].

Various factors can contribute to epilepsy, including genetic predispositions, brain traumas, infections, developmental abnormalities, and structural brain irregularities. In some instances, the root cause remains unidentified despite extensive research. Nonetheless, some studies propose that disruptions in brain electrical activity, potentially triggered by events like oxygen deprivation during birth or low blood sugar levels, may be implicated [1], [2], [6].

In the treatment of epileptic seizures, medication typically serves as the initial and primary approach. However, about 30% of patients do not respond adequately to these drugs. In such instances, alternative therapies such as epileptic surgery may be recommended [7]. This procedure involves the safe removal of tissue from the affected area of the brain. Yet, achieving effective seizure control presents a considerable challenge.

Following successful surgeries for temporal lobe epilepsy, the likelihood of attaining seizure freedom stands at approximately 75% in cases where brain lesions are identifiable, and at 50% in cases without lesions. For surgeries targeting frontal lobe epilepsy, success rates hover around 60% in cases with lesions and only 35% in cases without lesions. Nevertheless, there exists a risk of surgical failure due to inaccuracies in localizing seizure foci, often attributed to the limitations of current diagnostic tools such as positron emission tomography scans and intracranial electroencephalographic (EEG) recordings. Although EEG-based seizure detection methods offer high temporal resolution and direct measurement of epileptiform activity, they may prove invasive or impractical for long-term monitoring [8], [9].

For effective initiation of epilepsy treatment, precise detection is paramount, which can be achieved through the recording and analysis of brain signals using either

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Electroencephalogram (EEG) or Non-EEG-based real-time seizure detection devices. Over time, researchers have scrutinized these brain signals, extracting insights through manual analysis or with the aid of machine learning classifiers. Due to the intricacies of these signals (EEG/ECoG), manual analysis often lacks precision in seizure detection, necessitating the utilization of various machine learning algorithms. Numerous such algorithms have been developed, posing the current challenge of selecting the most appropriate classifier and features to attain optimal accuracy [10], [11].

II. METHODOLOGY

It necessitates a thorough review of existing literature to understand the landscape of available technologies and their respective capabilities and limitations. This step serves to inform the formulation of a precise research question or objective, delineating the specific aspects of performance to be evaluated. Subsequently, a comprehensive methodology for data collection and analysis was devised. This involved designing experiments or simulations to gather relevant performance metrics, such as accuracy, sensitivity, specificity, and false alarm rate (FAR). Appropriate statistical methods employed to analyze the collected data and draw meaningful conclusions regarding the comparative performance of the technologies/devices under study. Figure 1 shows comparison of different non-EEG technologies based on their sensitivity and false alarm rate.

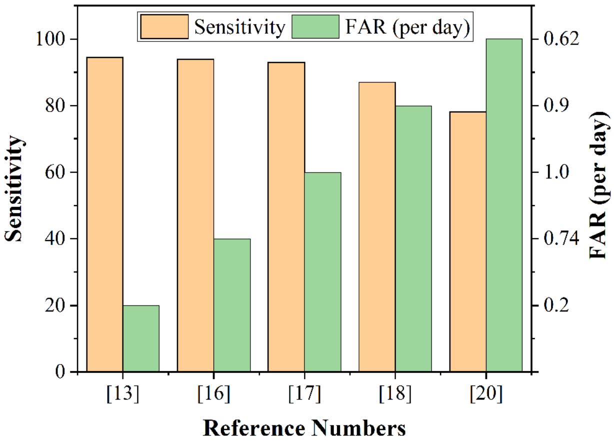

Fig. 1. Sensitivity and FAR of different non-EEG technologies

The algorithm proposed in the study by Ming-Zher Poh et al. produced only mild motor convulsions and minimal change in the electrodermal activity (EDA) signal. It's suggested that with more training examples resembling the missed seizure, the algorithm might have classified it correctly. The study's limitation includes the relatively low number of seizure examples, but extensive real-world non-seizure activity data helped estimate the false alarm rate well. Out of 80 patients, only 4 had a relatively high amount of false alarms, which were mainly triggered by forceful, rapid, and rhythmic motions during wakefulness, particularly daytime activities like dice shaking, hand flapping (some patients were on the autism spectrum), juggling, and motion-controlled gaming [13].

Soroor Behbahani et al. found that it's feasible to develop a reliable classifier based on heart rate variability (HRV) data for epileptic patients, achieving accuracies of 88.33% and 84.72% for different types of seizures. However, due to significant variations in HRV signals among individuals and over time, a classifier designed for one patient cannot be directly applied to another. Personalizing the classifier architecture and training is essential to overcome this variability. For practical use, a classifier intended to provide seizure alerts (detecting the pre-ictal state) must balance sensitivity and specificity. Relying solely on one metric undermines the usefulness of the results [14].

Two fusion systems are proposed in this study by Marwa Qaraqe et al. In the first system, decisions from EEG-based and ECG-based methods are directly combined to produce a final decision. In contrast, the second system employs an override feature, allowing seizure detection regardless of the fused decision if a sequence of EEG-based seizure decisions is observed.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT TECHNOLOGIES/DEVICES ON NON-EEG.

S. No.	Ref.	Technology/Device	Performance matrices	Performance (%)	Years	No of patients
1	[13]	Wearable multimodal convulsive seizure detectors	Sensitivity False Alarm Rate (FAR)	94.55 0.2 events/day.	2012	80
2	[14]	Heart Rate Variability (HRV)	Sensitivity Specificity Accuracy	88.66 90 88.33	2013	15
3	[15]	Heart Rate Variability (HRV) with Matching Pursuit (MP) and Wigner–Ville Distribution (WVD) algorithm	Sensitivity Detection latency Specificity	100 2.6 s 99.91	2016	10
4	[16]	Wrist-worn electrodermal activity and accelerometry biosensor	Sensitivity False Alarm Rate (FAR)	94 0.74/day	2017	69
5	[17]	Heart Rate Variability (HRV) using a wearable electrocardiography device	Sensitivity False Alarm Rate (FAR)	93.1 1.0/day	2019	100
6	[18]	Heart Rate Variability (HRV)	Sensitivity False Alarm Rate (FAR)	87 0.9/day	2020	19
7	[19]	Boosted Trees (ECG, PPG, Ear EEG)	Accuracy Sensitivity	91.5 85.4	2022	10
8	[20]	Logistic Regression Machine Learning (LRML-Classifier) based on wearable ECG-monitoring device	Sensitivity False Alarm Rate (FAR)	78.2 0.62/day	2023	62

The dual fusion (DF) system achieves 100% sensitivity, a detection latency (DL) of 17 seconds, and a false alarm (FA) rate of 0.9 per hour using EEG sub-band fusion technique. Similarly, the override system achieves 100% sensitivity with a DL of 4.2 seconds and an FA rate of 3.1 per hour using the same EEG sub-band fusion technique. Performance evaluations indicate that the DF system is beneficial for diagnostic applications, while the override system, pending further evaluation, could be suitable for medical intervention and warning systems [15].

The newly proposed convulsive seizure detectors, worn on the wrist and employing multiple modalities, offer seizure counts of higher accuracy compared to previous automated detectors and the usual patient self-reports. This enhanced accuracy is achieved while maintaining an acceptable false alarm rate (FAR) for continuous ambulatory monitoring. Additionally, the multimodal system provides an objective account of motor behaviour and autonomic dysfunction, enhancing the characterization of seizures, with potential applications in providing warnings for sudden unexpected death in epilepsy (SUDEP) [16].

The automated algorithm for heart rate variability (HRV), utilizing ECG data captured by a wearable device, exhibits high sensitivity in detecting seizures, including those that are nonconvulsive. The false alarm rate (FAR) was notably low during night-time periods. This method proves viable for patients exhibiting significant autonomic changes during seizures [17].

Jesper Jeppesen et al. suggested an algorithm which detected 20 out of the 23 seizures successfully, achieving a sensitivity of 87.0%. Specifically, it detected all but one of the 10 convulsive seizures and all 8 focal impaired awareness seizures, but missed 2 out of 4 focal aware seizures. On a per-patient basis, the median sensitivity was 100%, with all seizures detected in nine patients. The false alarm rate was low at 0.9 per 24 hours (0.22 per night). These findings indicate that HRV-based seizure detection performs well, particularly in patients with pronounced autonomic changes [18].

Through supervised machine learning techniques, various predictive models have been developed to classify the state of epileptic individuals as normal, pre-seizure, or seizure. Subsequently, David Zambrana-Vinaroz et al. proposes a simplified model using boosted trees, achieving a prediction accuracy of 91.5% and a sensitivity of 85.4%. With such high accuracy, this predictive model holds potential as a supportive tool for identifying status epilepticus and preempting seizures, thereby enhancing the quality of life for individuals affected by epilepsy [19].

The innovative LRML seizure detection algorithm by Jesper Jeppesen et al., tailored to individual patients, demonstrated superior performance compared to both generic approaches and previously published patient-specific methods. This method shows promise for integration into wearable, real-time HRV-based seizure detection systems, enabling timely alerts for patients and caregivers. Additionally, by enhancing seizure counts, this approach has the potential to optimize patient treatment strategies [20]. Figure 2 shows comparison of wearable devices and HRV on their sensitivity.

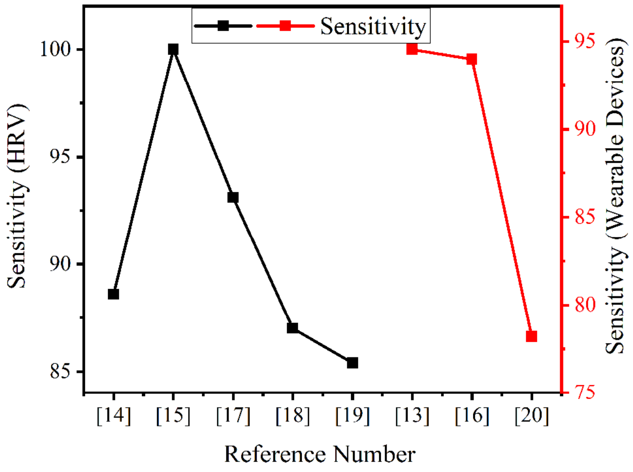

Fig. 2. Sensitivity of HRV and wearable technologies

III. CONCLUSION

Non-EEG methods provide non-invasive and wearable alternatives, offering the potential for multimodal integration and increased accessibility. However, they may have lower temporal resolution and variable sensitivity compared to EEG. On the other hand, EEG-based devices may face limitations due to their invasiveness, cost, and the requirement for trained professionals for interpretation. Non-EEG-based devices may encounter challenges related to signal accuracy, false alarms, and validation of their effectiveness in real-world settings. Despite these limitations, both EEG and non-EEG approaches contribute valuable insights to epilepsy management and monitoring, with each offering unique benefits and considerations. The decision between EEG and non-EEG methods depends on factors such as the clinical context, monitoring duration, and specific research or diagnostic objectives. Despite the rapid advancement of medications and surgical treatments, a considerable portion of individuals with epilepsy still experience seizures. To mitigate the risk of sudden unexpected death in epilepsy (SUDEP), there is a pressing need for real-time automated seizure detection using wearable devices. It's also essential to assess the level of evidence supporting these devices. Non-EEG based seizure detection is gaining traction in research, offering potential benefits such as improving the quality of life for patients and caregivers by enhancing the standard of care, providing peace of mind, and promoting independence.

Moving forward, a combination of EEG and non-EEG-based approaches may offer the most comprehensive and effective solution for epilepsy management. Integrating these technologies could provide a more holistic understanding of seizure patterns, improve detection accuracy, and offer personalized monitoring solutions tailored to individual patient needs. Additionally, ongoing research and collaboration between clinicians, engineers, and patients are essential to further advancing the development and implementation of both EEG and non-EEG-based devices for epilepsy care.

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