
Pediatric Seizure Detection System: A Data-Driven Approach with Predictive and Generative AI Integration

Tanisha Sood
Monta Vista High School

Abstract

The gravity of seizures in pediatric populations cannot be overstated. From the youngest infants to adolescents on the brink of adulthood, seizures disrupt not only neurological functions but also the fabric of daily life. According to the Centers for Disease Control and Prevention [1], about 470,000 children in the United States have epilepsy, which is a neurological disorder characterized by recurrent seizures. Drawing from personal encounters with seizures, I recognize the critical need for effective seizure detection mechanisms. This study addresses the challenge of detecting seizures in children, especially in environments where constant supervision may not be feasible. Utilizing CAD, 3D design, and machine learning algorithms, this prototype predicts a seizure onset by analyzing bio data from a simulation of possible data sets carefully overviewed by my pediatrician Sara MachMan. The prototype integrates insights from a literature search, including the CDC publication on seizure detection, highlighting brain activity, fever, and body movements as triggers. Based on these triggers and thorough data analysis with a pediatrician, I was able to discover a breakthrough. Despite encountering a 15% error rate from my simulated data analysis, the prototype effectively alerts parents and medical professionals, demonstrating its potential to reduce the unpredictability of seizures and positively impact lives.

1. Introduction

1.1 Problem Overview

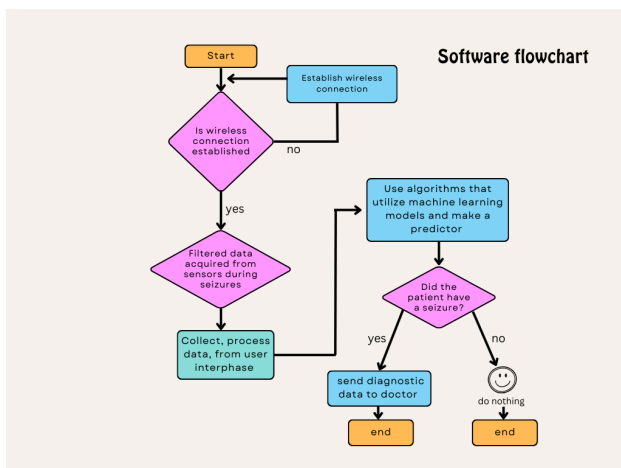
Seizures in pediatric patients pose a significant challenge due to their sudden and unpredictable nature, causing distress for both children and caregivers. For children, seizures can be frightening and disorienting experiences. They may not understand what is happening to them or why it is happening, which can lead to feelings of fear and confusion. Parents,

conversely, carry heightened anxiety and stress, especially in situations where continuous supervision is impractical [2]. Continuous vigilance becomes challenging when caregivers must attend to other responsibilities or when children are in environments where constant supervision is not feasible, such as school or daycare. The unpredictability inherent in this situation induces chronic stress, a factor associated with an array of adverse health ramifications such as depression, anxiety disorders, and diminished quality of life [3].

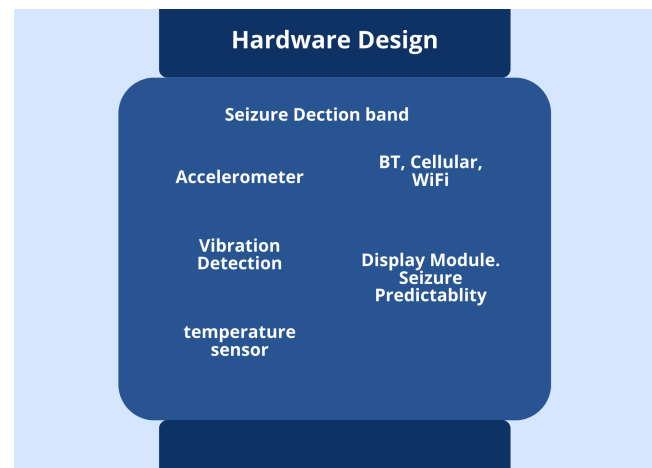
1.2 Current Research Advancements and Objective

Recent advances in technology have opened doors for innovative solutions to combat such medical challenges with seizures. From Vagus Nerve Stimulation (VNS) Therapy to Intracranial Electroencephalography (iEEG), these monitoring units show promise to treat and manage epilepsy in adolescents. Further research by Kim et al. [4] supports these findings. However no significant advancement has been made in integrating generative AI to initiate initial actions when specific parameters indicate high risk. To address this pressing need, this research aims to introduce a cost effective pioneering method for seizure detection by harnessing technological advancements, machine learning algorithms, and biomedical engineering. By leveraging interdisciplinary approaches, this comprehensive system not only detects seizures but also proactively takes action to mitigate risks and improve patient outcomes.

Img 1 Software Flowchart:



Img 2 Hardware Flowchart:



2. Materials and Methods

2.1 Data Collection and Processing

Utilized system selection to conduct a simulated analysis using literature search and data processing algorithms.

Simulated Data Analysis

Based on CDC's *seizures in children and Adolescents Aged 6–17 Years* weekly report [5], I researched prior symptoms and narrowed it down to 4 main parameters that affect seizures: heart rate, temperature, bodily movements, and electrical impulses. Based on this research I modeled a spreadsheet of simulated data analysis with different predictions on when a seizure is at high risk/low risk/potential risk of occurring. This was done using the metrics and parameters that were researched prior to formatting this spreadsheet from CDC.

Figure 1:

AI Data Model & Table for Seizure Measurement Device

Body Movements (measured on wrist)		Temporal and brain activity			Seizure Risk
Accelerometer (linear speed)	Gyroscope (Orientation and rotational)	Heart Rate (60-100bpm)	Temperature (98 - 105F)	Electrical impulse (Low - High)	
na	na	na	104	na	
na	na	na	105	na	
na	na	na	na	High	
na	na	95	na	na	
Very High	Very High	na	na	na	
na	na	90	103	Medium	
Very High	Very High	90	103	na	
Very High	Very High	na	na	Medium	

Figure 2:

AI Data Model & Table for Seizure Measurement Device

Body Movements (measured on wrist)		Temporal and brain activity			Seizure Risk
Accelerometer (linear speed)	Gyroscope (Orientation and rotational)	Heart Rate (60-100bpm)	Temperature (98 - 105F)	Electrical impulse (Low - High)	
na	na	na	103	na	
na	na	na	102	na	
na	na	na	101	Medium	
na	na	90	na	na	
High	High	85	101	na	
na	na	90	102	Medium	
High	High	90	102	na	
High	High	na	na	Medium	

Figure 3:

AI Data Model & Table for Seizure Measurement Device					
Body Movements (measured on wrist)		Heart Rate (60-100bpm)	Temporal and brain activiaty		Seizure Risk
Accelerometer (linear speed)	Gyroscope (Orientation and rotational)		Temperature (98 - 105F)	Electrical impulse (Low - High)	
Low	Low	75	98	Medium	
Low	Low	75	99	Medium	
Low	Low	75	100	Medium	
Low	Low	75	101	Medium	
Low	Low	80	98	Medium	
Low	Low	80	99	Medium	
Low	Low	80	100	Medium	
Low	Low	80	101	Medium	
Medium	Medium	75	98	Medium	
Medium	Medium	75	99	Medium	
Medium	Medium	75	100	Medium	
Medium	Medium	75	101	Medium	
Medium	Medium	80	98	Medium	
Medium	Medium	80	99	Medium	
Medium	Medium	80	100	Medium	
Medium	Medium	80	101	Medium	
Low	Low	75	98	Low	
Low	Low	75	99	Low	
Low	Low	75	100	Low	
Low	Low	75	101	Low	
Low	Low	80	98	Low	
Low	Low	80	99	Low	
Low	Low	80	100	Low	
Low	Low	80	101	Low	
Medium	Medium	75	98	Low	
Medium	Medium	75	99	Low	
Medium	Medium	75	100	Low	
Medium	Medium	75	101	Low	
Medium	Medium	80	98	Low	
Medium	Medium	80	99	Low	
Medium	Medium	80	100	Low	
Medium	Medium	80	101	Low	

Data Processing

Machine learning algorithms were implemented to analyze and interpret data acquired from the sensors, enabling the extraction of valuable insights and patterns. A significant challenge was validating the simulated data to ensure it closely mirrored real-world conditions. This involved addressing numerous variables and potential anomalies. To enhance the accuracy of the simulated data, I collaborated with my pediatrician, who reviewed and provided feedback on the data. To address this challenge, I employed a 85-15 training-testing split, where 85% of the data (considered to be most accurate with small margin for error) was used

to train the machine learning algorithms and the remaining 15% was reserved for testing (margin where parameters could vary for multiple reasons). This approach allowed for a comprehensive training phase, ensuring the algorithms could learn and identify seizure patterns effectively, while still maintaining a substantial testing set to validate the system's performance and accuracy under varied conditions. Balancing these technical and validation challenges was critical to developing a reliable seizure detection system.

2.2 Prototype design

Used CAD and 3D design to facilitate prototype design and functionality during my engineering process.

Sensor and System Selection

During the CAD design phase, two distinct sensor types were created: a hearing aid-based temporal sensor and a wristband sensor. The hearing aid-based temporal sensor was chosen due to its capability to monitor temperature and brain electrical activity using the temporal artery across the frontal and auricular region. This device was designed to be fitted around the ear and paired wirelessly with the wristband. The wristband sensor was selected to track heart rate, spatial, and accelerated body movements via an integrated accelerometer and gyroscope. Both sensors were outfitted with audio and LED alarm indicators, facilitating immediate alert notifications. CAD facilitated the development of the physical prototype, ensuring compatibility with the selected sensors and data processing algorithms.

Figure 1:

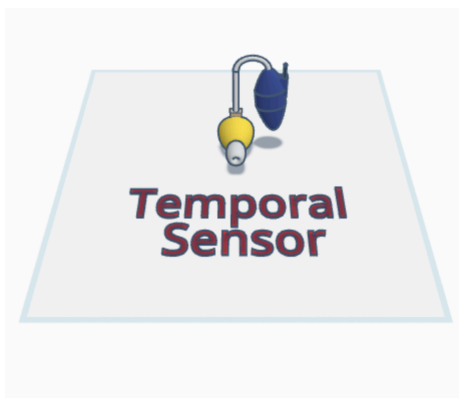


Figure 2:



3D modeling:

Using the Tina2S 3D Printer, was the next step to prototype design after my system

selection. I learned about specific filament types, model preparation, and printer specifications that truly enhanced my design showcase. This not only boosted my creativity and taught me a new skill in design, but it is cost effective and better for families who can't afford treatment using large machines like the VNS.

Algorithm Development

In response to the need for a proactive and autonomous seizure detection system, algorithm development played a pivotal role in the advancement of this research project. Leveraging machine learning techniques and predictive data analysis, the algorithm processed the simulated sensor data to identify patterns indicative of impending seizures. Through iterative refinement and optimization, the algorithm was fine-tuned to enhance its sensitivity and specificity in detecting seizure events. One of the key innovations of this research project lies in the incorporation of generative AI capabilities within the algorithm. This groundbreaking feature enabled the algorithm to take proactive measures in the event of a seizure onset. Specifically, the algorithm was programmed to compose and send email or message notifications to a designated group of medical professionals or caregivers when seizure symptoms were detected. Significantly distinguishing this research from existing sensor technologies is its capacity to undertake these proactive measures, notifying medical professionals preemptively prior to the onset of a critical emergency event. This capability represents a substantial advancement in seizure detection systems, setting this research apart from conventional sensor solutions available in the current landscape.

2.3 Testing

The primary objective of testing the Pediatric Seizure Detection System was to rigorously evaluate the system's accuracy, reliability, and responsiveness. Specifically, the testing aimed to validate the simulation was as close to accurate as possible by monitoring the key vitals in the predictive data analysis model and looking at the efficiency in the alert mechanisms. To test the system, a series of simulations were conducted using the synthesized data sets reviewed by the pediatrician. These simulations included various scenarios to mimic real-world conditions, ensuring the system's reliability under different physiological states. Each parameter—heart rate, temperature, bodily movements, and electrical impulses—was tested individually to verify the sensor's precision with my doctor. The wristband sensor's accuracy was compared to standard medical heart rate monitors, with discrepancies noted and

adjustments made to improve precision. The temporal sensor was tested against clinical thermometers to ensure reliable temperature readings. Accelerometers and gyroscopes in the wristband were validated against controlled movements to ensure accurate detection of bodily movements indicative of seizures. The ability of the temporal sensor to accurately capture brain electrical activity was verified using EEG simulators.

3. Discussion

3.1 Results

As I tested my results, it showed an 85% success rate, with a 15% error rate through my simulation. This error occurred because some symptoms were present, but the patient did not experience a seizure. For example, if the device detects a sudden spike in temperature, it may interpret it as the onset of a seizure, even if the individual is experiencing a fever due to an unrelated illness. The error rate highlights a common challenge in medical device accuracy—differentiating between symptoms caused by different conditions. For instance, Mac Ewen in 2008 [4] discusses the physiological impacts of stress, which can cause symptoms such as increased heart rate and elevated body temperature, potentially leading to false positives in seizure detection systems. Additionally, the study by Halford et al. in 2010 [6] emphasizes that the unpredictable nature of seizures and the varied presentation of symptoms can complicate accurate detection, underscoring the need for continuous refinement and calibration of the detection algorithms. Even with that error, the message can always be canceled from the wristband if one feels the call for action is unnecessary. This feature provides an additional layer of user control and can help mitigate the impact of false positives. Despite this, the 85% success rate is promising, demonstrating the potential efficacy of the Pediatric Seizure Detection System in real-world applications. This also acts as a cost effective method for families who cannot afford expensive purchases of surgical implications or hospital treatment 24/7.

3.2 Future Action

Further validation and refinement of the Pediatric Seizure Detection System are essential to improving its accuracy and reliability. Conducting extensive testing with actual pediatric patients will provide real-world data to refine the system. This phase is critical to understanding how the device performs in diverse, uncontrolled environments and to identify any additional variables that need to be accounted for in the algorithm. Current testing focuses on three primary symptoms—heart rate, temperature, and bodily movements. Future research should explore additional physiological and neurological indicators of seizures, such as oxygen saturation levels, electrodermal activity, and more detailed EEG patterns, to capture a broader spectrum of seizure manifestations.

By addressing these future actions, the Pediatric Seizure Detection System can be refined and validated to provide a robust and reliable tool for early seizure detection and intervention. The ultimate goal is to enhance the quality of life for pediatric patients with epilepsy and their caregivers by offering a proactive, affordable, and efficient solution.

References

- [1] www.cdc.gov. (11AD). *Seizures in Children and Adolescents Aged 6–17 Years — United States, 2010–2014*. <https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6443a2.htm>.
- [2] Kwan, P. (2004). The natural history of epilepsy: an epidemiological view. *Journal of Neurology, Neurosurgery & Psychiatry*, [online] 75(10), pp.1376–1381.
doi:<https://doi.org/10.1136/jnnp.2004.045690>.
- [3] Mac Ewen, Garg, R., Aggarwal, S., Chawla, S. P. S., & Pal, R. (2018). *Adult onset seizures: Clinical, etiological, and Radiological Profile*. *Journal of family medicine and primary care*.
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5958567/#:~:text=Overall%2C%20the%20most%20common%20etiology%20of%20seizure%20was%20stroke%2>

- [4] Kim, D., Kim, T., Hwang, Y., Lee, C.Y., Joo, E.Y., Seo, D.-W., Hong, S.B. and Shon, Y.-M. (2022). Prediction of the Responsiveness to Vagus-Nerve Stimulation in Patients with Drug-Resistant Epilepsy via Directed-Transfer-Function Analysis of Their Perioperative Scalp EEGs. *Journal of Clinical Medicine*, [online] 11(13), p.3695. doi:<https://doi.org/10.3390/jcm11133695>.
- [5] CDC. "Seizures in Children and Adolescents Aged 6-17 Years — United States, 2010-2014." Wwww.cdc.gov, 2010, www.cdc.gov/mmwr/preview/mmwrhtml/mm6443a2.htm.
- [6] Halford, J. J., Shiau, D.-S., Kern, R. T., Stroman, C. A., Kelly, K. M., & Sackellares, J. C. (2010). *Seizure detection software used to complement the visual screening process for long-term EEG monitoring*. American journal of electroneurodiagnostic technology. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4674077/>