Epilepsy is a non-communicable disease that affects about 60 million people worldwide (Shoeibi et al., 2021). It is a disease that comes with sudden attacks that are caused by spikes in the brain's electrical activity that have the potential to inhibit movement, sensations, and/or awareness. There are many different types of seizures. They can range from myoclonic seizures, a seizure that lasts only a few seconds and comes with brief and sudden muscle movement, to a tonic-clonic seizure, which is a seizure affecting the person's entire body and can last up to a few minutes. Experiencing any type of seizure can cause great pain physically and emotionally along with the potential to cause irreversible damage to the brain (Ghassemi et al., 2019). Seizures are highly unpredictable events that can occur at any time without any known triggers (Ghassemi et al., 2019). A wearable device that could detect an oncoming seizure for a patient would greatly improve not only the quality of life of the patient, but also those around them, such as their caretakers.

Current machine learning models for epileptic seizure detection have demonstrated promising results, with various techniques having achieved high accuracy rates. These approaches range from traditional feature extraction methods using wavelet transforms and support vector machines (Sharma et al., 2017) to more advanced deep learning models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks (Shoeibi et al., 2021). Some studies have shown success in integrating multiple data sources, such as combining electroencephalogram (EEG) signals with electrocardiogram (ECG) data and photoplethysmography (PPG) measurements (Thakare et al. 2024), which has led to a reduction in false positives. However, several limitations persist in these models. Many rely heavily on manually designed features, which can be time-consuming and may not capture all relevant information. The predominant focus on EEG data alone, while valuable, often fails to leverage additional physiological signals that could enhance detection accuracy.

A significant challenge in current models is dealing with unwanted noise in EEG signals. Discrete Wavelet Transform (DWT) and Tunable-Q Wavelet Transform (TQWT) have been used for feature extraction and denoising to help alleviate this problem (Ghassemi et al., 2019). These methods aim to separate signal components from noise, but their effectiveness varies. Another concern is the quality and representation of data used in these models. There is an immense importance in using diverse datasets for evaluation, suggesting an awareness of the need for comprehensive and representative data in developing robust seizure detection models. However, many current approaches use snapshot data rather than leveraging temporal correlations, which limits their ability to detect seizures in real-time or predict them in advance (Shoeibi et al., 2021). This review also highlights the challenge of false alarms in seizure detection systems, which can often be triggered by noise or artifacts in the EEG signal, indicating that data quality remains a significant issue in the field.