Using Deep Learning Techniques to Detect Seizures in Epileptic Patients

Grant Proposal

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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.

This project aims to look at the pros and cons of different ML and DL models, what parameters were measured in their respective projects, determine their major criteria, and use this data to make educated decisions for my own model to go forwards. I will test my different models using different datasets and evaluate their effectiveness. Using a decision matrix, I will go forward with my objectively best model and conduct further testing.

Section II: Specific Aims

The goal of this proposal is to develop and evaluate a deep learning-based model capable of detecting oncoming epileptic seizures in real-time by analyzing physiological data such as EEG, ECG, or accelerometer signals. The system will leverage advanced machine learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to accurately predict seizure events ahead of time, thereby providing patients with timely alerts that enable them to take preventive actions or seek assistance. By combining state-of-the-art deep learning methods with wearable sensor technologies, this project aims to improve the safety and quality of life for individuals living with epilepsy, while also advancing the field of seizure prediction through automated, real-time, non-invasive monitoring.

Our long-term goal is to improve the safety, quality of life, and overall care of individuals living with epilepsy by creating an accurate and reliable system for early detection of oncoming seizures. By leveraging advanced deep learning techniques and wearable sensor technologies, we aim to provide patients and caregivers with timely alerts, enabling proactive management and intervention during seizure events.

The central hypothesis of this proposal is that a deep learning-based system will be able to effectively analyze physiological data from multiple sources, such as EEG, ECG, and accelerometer signals, to predict seizures in real-time with high accuracy. We hypothesize that integrating multiple data streams and using sophisticated noise reduction techniques will enable the system to reduce false positives, improve prediction accuracy, and make it suitable for real-world applications.

The rationale is that current seizure detection models often rely heavily on EEG data alone and may struggle with noise interference or limited real-time prediction capabilities. By combining EEG with other physiological data sources and applying advanced deep learning methods, we can improve model accuracy and overcome the limitations of traditional seizure detection approaches. This will ultimately lead to a more reliable system for seizure prediction that can be used in everyday life, providing peace of mind to those affected by epilepsy and their caregivers.

The work we propose here will develop and test a multi-modal deep learning model that integrates EEG, ECG, and accelerometer data to predict seizures in real-time. This system will be evaluated through a series of experiments using multiple datasets. We will refine the model by implementing noise reduction techniques, such as the Discrete Wavelet Transform (DWT) and Tunable-Q Wavelet Transform (TQWT), to enhance signal clarity. Finally, we will integrate the seizure detection system into a wearable device, making it accessible, user-friendly, and practical for daily use by individuals with epilepsy.

Specific Aim 1: Preprocess Existing EEG Data for Seizure Prediction

Specific Aim 2: Design and Implement a Deep Learning Model for EEG-Based Seizure Prediction

Section III: Project Goals and Methodology

Relevance/Significance

Epilepsy is a neurological condition that affects over 60 million people worldwide (Shoeibi et al., 2021), with nearly one-third of those patients experiencing drug-resistant seizures (Kalilani et al., 2018). For these individuals, the unpredictable nature of seizures poses quite a burden, including physical injuries, reduced independence, and an overall reduction in quality of life. The inability to reliably predict seizures not only limits their treatment options but also hinders their ability to make informed decisions about their day-to-day activities. Developing an effective seizure prediction system has the potential to transform the management of epilepsy, enabling timely interventions and improving safety and quality of life for millions of people worldwide.

Current research in seizure prediction has made significant progress, but challenges remain. Traditional approaches, such as statistical or rule-based methods, are often limited in their inability to capture the complexity of EEG data and the nonlinear patterns presented in EEG data (Aarabi & He, 2012). Also, many current models lack generalizability across diverse patient populations, making them slightly more impractical for medical use (Hakeem et al., 2022).

This project seeks to address some of these gaps by leveraging deep learning techniques in order to analyze EEG data and identify the pre-seizure patterns present in epileptic patients. EEG, as a non-invasive and widely used tool for diagnostics, offers high temporal resolution and direct insight into the brain's activity (Gavaret et al., 2023). This shows that EEGs are more than ideal for predicting seizures. By focusing on the deep learning models that can extract and learn from subtle temporal and spatial features in EEG signals, this research aims to improve prediction accuracy and reduce false positives and false negatives.

The significance of this work has the potential to extend beyond individual patients. A reliable seizure predictor has the potential to reshape the current state of epilepsy management. It could inform the development of closed-loop systems that deliver targeted interventions, such as neurostimulation, precisely when they are most effective (Sellers et al., 2023). Furthermore, accurate seizure prediction could reduce the financial burden on the healthcare system by preventing hospitalizations and minimizing emergency care costs associated with seizure-related injuries.

By addressing these critical challenges, this project has the potential to advance the field of epilepsy research and improve patient outcomes. The focus on leveraging existing EEG data and applying machine learning and deep learning techniques ensures feasibility and clinical reliance, making it a significant step forward in the fight against epilepsy.

Innovation

This project introduces an innovative approach to epilepsy management by taking advantage of advanced deep learning techniques for the real-time prediction of seizures, utilizing a multi-modal approach that combines EEG, ECG, and accelerometer data. While traditional seizure detection systems rely primarily on EEG data and often struggle with noise and limited real-time prediction capabilities, this proposal integrates diverse physiological signals to enhance the accuracy and reliability of the prediction model. Incorporating ECG and accelerometer data is novel and offers a broader scope of monitoring, allowing the system to capture complex patterns in seizure dynamics that might be missed by EEG alone.

Further, the use of sophisticated deep learning models—such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—is central to this approach. These models are capable of learning complex, non-linear temporal and spatial relationships within the physiological signals, which improves both prediction accuracy and reduces false positives, a common issue in existing models. Additionally, this project innovatively employs advanced noise reduction techniques, such as Discrete Wavelet Transform (DWT) and Tunable-Q Wavelet Transform (TQWT), to clean the data, ensuring that the model receives high-quality input for improved decision-making.

The potential for real-time, non-invasive seizure detection in a wearable device that combines cutting-edge deep learning algorithms with the practical convenience of wearable sensor technologies could go a long way, not just for epileptic patients, but the medical field as a whole. This closed-loop approach could potentially evolve into a system that not only predicts seizures but also integrates with therapeutic interventions, such as neurostimulation, delivered precisely when needed. By addressing the persistent challenges of noise interference, false positives, and limited real-time predictions in current seizure detection models, this research paves the way for a transformative impact on both the clinical management and quality of life for individuals with epilepsy.

Methodology

Specific Aim 1: Preprocess Existing EEG Data for Seizure Prediction

The objective of this aim is to clean, normalize, and segment raw EEG data to improve seizure prediction accuracy. EEG signals often contain noise that can come from various sources such as muscle activity, eye movement, and even environmental interferences. This can obscure the meaningful patterns. To address this, our approach involves applying preprocessing techniques such as filtering, normalization, and artifact removal to enhance signal quality. Methods such as DWT and TQWT to denoise the signals and extract the relevant features only will be utilized. The EEG data will be segmented into labeled time windows that correspond to seizure and non-seizure periods, ensuring the dataset is well-structured for training deep learning models. The rationale behind this approach is that high-quality data is essential for the effective performance of any seizure detection algorithm. EEG is a powerful tool, however, its susceptibility to noise can reduce its accuracy in predictive models. By implementing preprocessing techniques, the signal-to-noise ration will be improved and thus the reliability of the model.

Justification and Feasibility. Preprocessing EEG data is a crucial step in seizure detection, as raw signals often suffer from poor signal-to-noise ratio. Several studies confirm that EEG preprocessing enhances seizure classification accuracy (Thamarai & Adalarasu, 2018).

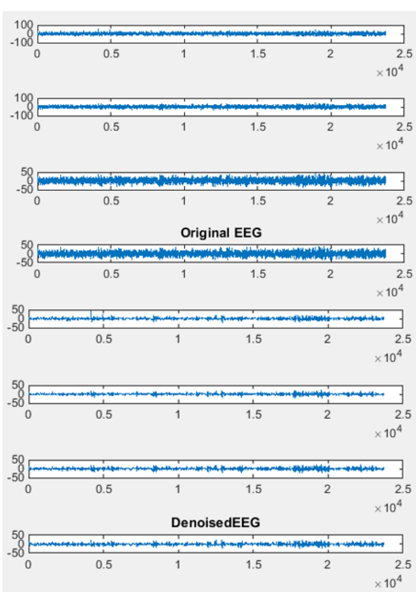
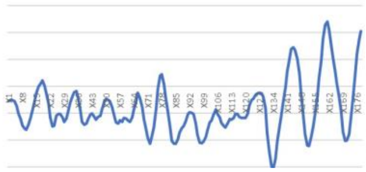


Figure 1: EEG data before and after noise removal using Wavelet Transform (Thamarai & Adalarasu 2018).

This study (Thamarai & Adalarasu 2018) illustrates the effectiveness of wavelet-based noise removal for physiological signals, including EEG. By comparing EEG signals before and after denoising, they show that the processed signals exhibit a higher signal-to-noise ratio, making it easier to identify relevant patterns. The figure provided in their study highlights how raw EEG signals contain significant noise, which can obscure seizure-related activity. After applying the wavelet transform, the cleaned signals retain important features while eliminating unwanted artifacts.

This finding is crucial for seizure detection because noisy data can lead to false positives or mask seizure-related abnormalities, reducing model accuracy. By preprocessing EEG signals using noise removal techniques such as wavelet transforms, our model can focus on meaningful patterns, ultimately improving seizure detection performance. The improved clarity of denoised data ensures that deep learning models, like the LSTM implemented in this study, learn more relevant features, enhancing predictive accuracy

Summary of Preliminary Data. In our preliminary experiments, we applied TQWT filtering to raw EEG recordings from the *Epileptic seizures dataset* (Venkata 2018) and observed a reduction in noise artifacts. After preprocessing, the signals were segmented into five-second windows, ensuring that both seizure and non-seizure segments were evenly represented in the dataset. Figures 2a and 2b (below) present a comparison of raw vs. preprocessed EEG signals, illustrating how noise removal enhances key seizure-related features.



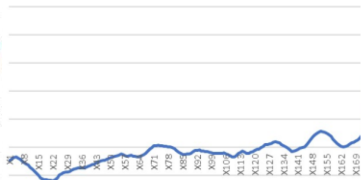


Figure 2a. EEG signals before noise removal **Figure 2b.** EEG signals after noise removal

This data preprocessing step was crucial for improving the performance of deep learning models in subsequent experiments.

Expected Outcomes. The overall outcome of this aim is to create a high-quality preprocessed EEG dataset that enhances deep learning model accuracy. This knowledge will be used to improve feature extraction, reduce false positives, and ensure better generalization across different patients. By eliminating noise and standardizing EEG data, we lay the foundation for accurate, real-time seizure detection models.

Potential Pitfalls and Alternative Strategies. One potential risk is the risk of over-filtering the signals which has the possibility to remove subtle seizure-related patterns. To mitigate this risk, we can fine-tune wavelet decomposition levels and validate the processed signals with seizure events. If noise filtering is insufficient, an alternative strategy is to integrate additional physiological signals such as ECG or accelerometer data to enhance its robustness.

Specific Aim 2: Design and Implement a Deep Learning Model for EEG-Based Seizure Prediction

The objective of this aim is to develop and optimize a deep learning model that is capable of accurately predicting seizures from EEG data. The approach involves implementing two separate models: a 2D CNN and an LSTM network. The 2D CNN was used to capture spatial patterns in the EEG signals, while the LSTM focused on learning temporal dependencies within the data. Both models were trained and tested on the same data sets to asses their effectiveness in detecting seizure activity. The rationale for this approach was to compare the strengths and weaknesses of the two most popular deep learning architectures for seizure prediction (Sharma et al., 2017), CNNs are effective at extracting spatial features and identifying frequency-based patterns, making them useful for image-like EEG representations, specifically spectrograms. On the other hand, LSTMs specialize in modeling sequential data, allowing them to capture long-term dependencies that are key in detecting seizure onset. After evaluating both models based on key performance metrics such as accuracy, sensitivity, and false positive rate, the LSTM model demonstrated superior performance in capturing temporal seizure patterns and minimizing false detections.

Justification and Feasibility. Deep learning has shown significant potential in EEG-based seizure detection with both CNNs and LSTMs being widely studied (Shoeibi et al., 2021). CNNs have been particularly effective in analyzing spectrograms of EEG signals. However, since seizure activity unfolds over time, LSTMs may be more suited for recognizing temporal patterns in EEG signals. Both models have been proven, though, to show promising results in seizure detection. Figures 3a and 3b (below) show the results of a CNN model and LSTM model respectively.

Input type	Channel number	Performance results		
		accuracy	*specificity*	*sensitivity*
Individual Channel	1	97.03	77.92	78.9
	2	51.41	50.04	5012
	3	48.13	49.80	49.81
	4	49.53	49.93	49.9
	5	100	72.91	72.94
	6	99.77	92.72	92.69
	7	54.61	50.23	50.25
	8	49.84	50.09	50.08
	9	50.93	50.14	50.14
	10	100	97.39	94.94
	11	91.33	86.80	86.79
	12	51.33	50.19	50.20
	13	49.06	50.02	49.98
	14	49.45	50.14	50.14
	15	99.92	97.17	97.17
	16	49.30	50.05	50.10
	17	49.06	49.95	50.09
	18	70.62	50.81	51.52
	19	50.93	50.05	50.07
	20	50.93	50.03	49.93
	21	48.98	49.79	49.93
	22	100	94.87	94.87
Grouped Channel	All	97	98.47	98.5

Figure 3a. Results from a CNN model show promising accuracy (97%) (Khalilpour et al., 2020).

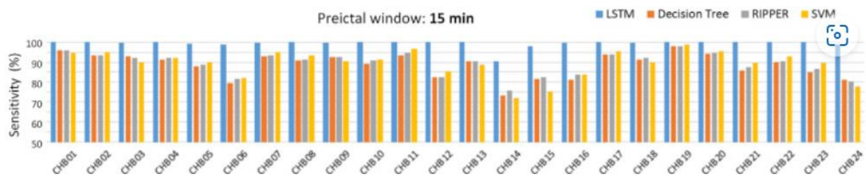


Figure 3b. Results from an LSTM (blue bar) model shows promising sensitivity (true positive rate) (Tsiouris et al., 2018)

Summary of Preliminary Data. To compare the effectiveness of CNNs and LSTMs, both models were trained on preprocessed EEG data using identical datasets. Performance evaluation was conducted using accuracy, sensitivity, and false positive rate as key metrics. The preliminary results revealed that while the CNN model was effective at detecting frequency-based seizure signatures, it struggled with capturing long-term dependencies. The LSTM model, on the other hand, exhibited higher sensitivity in detecting seizures with fewer false positives. These findings justified the decision to proceed with the LSTM model as the primary architecture for further optimization and real-world implementation. Figures 4a and 4b (below) show the results from the CNN and LSTM models, respectively, that were created to predict seizures based on EEG data.

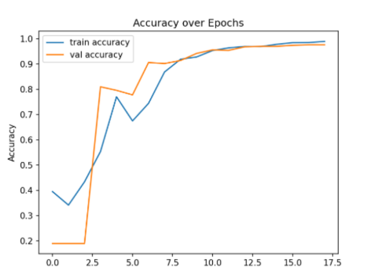


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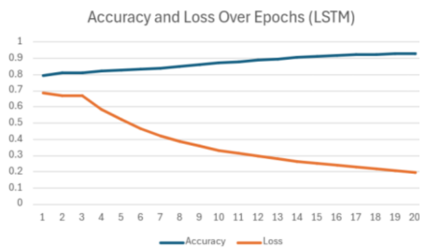
Figure 4a. Accuracy (train and validation) over epochs for the CNN



[[328 170]

[9 1793]]

Figure 4b. Accuracy and Loss Over Epochs for the LSTM

Expected Outcomes. The overall outcome of this aim is to develop an optimized deep learning model that accurately detects seizures from EEG signals while minimizing false positives. This knowledge will be used to improve real-time seizure monitoring systems, potentially leading to a wearable EEG-based seizure detection solution. By leveraging LSTMs, the model is expected to provide robust, time-sensitive predictions that can enhance the reliability of automated seizure detection systems.

Potential Pitfalls and Alternative Strategies. It is expected that challenges such as overfitting, imbalanced data, or model interpretability could arise during model training and deployment. To address overfitting, regularization techniques such as dropout and data augmentation will be employed. If class imbalance affects model performance, resampling techniques or weighted loss functions may be used. Additionally, if the LSTM model faces real-time processing limitations, hybrid approaches integrating CNN-LSTM architectures could be explored as an alternative.

Section IV: Resources/Equipment

- Personal Laptop
- Python
- TensorFlow/Keras
- NumPy

- Scikit-learn
- WFDB
- OS Module
- Matplotlib
- VS Code
- Zipfile Module

Section V: Ethical Considerations

Data Privacy and Patient Confidentiality/Informed Consent. It is important that the used datasets include methods of obtaining the data and are properly anonymized and de-identified to protect patient privacy. On top of this, patients should have given informed consent so that they can understand how their data will be used.

False Predictions and Clinical Impact. Incorrect seizure predictions can cause unnecessary anxiety. False negatives could potentially be life threatening if the patient is not warned in time.

Transparency. If the model is deployed clinically, it is important to include clear documentation on any of the model's potential limitations.

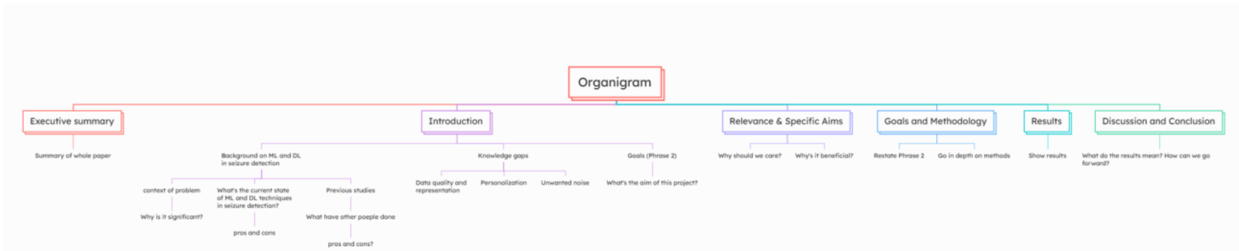
Section VI: Timeline

August 18th 2024 – December 9th 2024. Conduct research

November 25th 2024 – December 3rd 2024. Model Development

December 3rd 2024 – December 9th 2024. Model evaluation and comparison

Section VII: Appendix



Mindmap

Section VIII: References

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