Seizure Detection System Based on EEG Data Analysis and Machine Learning

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Abstract

As the average age of individuals across the globe grows due to increased medical research and advancements, so do age dependent neurological disorders or deficiency such as memory loss, Alzheimer's Disease, Parkinson's disease, and epilepsy. With growing advancements in machine learning, the ability to detect and classify these disorders is becoming more possible and thus vital to improving health. For epilepsy in particular, the ability to detect and classify seizures of epileptics can lead to improved treatments and understanding of the neurological disorder such as biomarker detection. In our project, we tested various models and achieved an accuracy of 90.50% by applying binary classification to electroencephalogram (EEG) recordings from participants who either suffered from or did not suffer from epileptic seizures. Also, we have successfully developed a prototype Graphic User Interface (GUI) application to demonstrate the potential of real-time seizure detection and alarm systems. As we move into the future, we believe that this project could contribute to the ubiquity and simplicity of neurological devices, empowered by Brain-Computer Interface (BCI) and neurotechnology. This technology has the potential to help countless patients by providing more accessible and accurate tools for detecting, monitoring, predicting, and managing neurological conditions.

Background and Dataset

Source and Recording

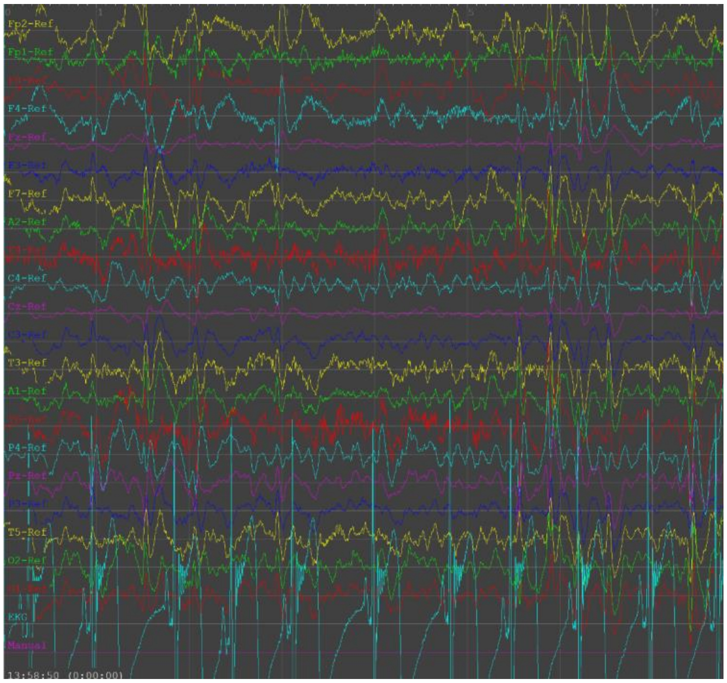
Our chosen dataset for this research project is taken from the American University of Beirut Medical Center, where in January 2014 - July 2015, EEG data from 6 epileptic patients was collected using 21 scalp electrodes with the 10-20 electrode system.

The data was obtained from patients diagnosed with focal epilepsy and undergoing presurgical evaluation with long-term video-EEG monitoring for possible epilepsy surgery. During this evaluation, the anti-seizure medications are stopped in an attempt to record the patient's habitual seizures. There are 6 patients with a total of 20 recordings. Each EEG recording includes a period without seizures (interictal phase), and at least one period where a seizure occurred, (ictal phases). For each recording, information regarding seizure type, the specific brain region where the seizure begins (ictal onset zone), and the duration of each seizure is included in the data.

The dataset also captures three types of seizures: complex partial seizures, electrographic seizures, and video-detected seizures. A complex partial seizure, also called focal impaired awareness seizures, are the most common form of seizures for adult epilepsy patients and can be observed both clinically and in EEG data. Electrographic seizures are seizures that can only be observed in EEG data and often do not have clinical manifestations. They are marked by itcal patterns and abnormal rhythms. A video-detected seizure is observed clinically without noticeable changes in EEG data.

Sampling & Filtering

The sampling frequency for each data point is 500Hz and the data was already provided with abandpass filter between 1/1.6Hz and 70Hz, in order to obtain the desired frequency range for various brain waves, along with a 50Hz notch filter to attenuate electrical artifacts from standard international power supplies. The raw data is stored in the European Data Format (EDF) which divides the EEG records into header information and data information.



[Figure A] Visualization of Patient 1 data of 19 channel EEG data using EDF application

Formatting

It is necessary to then label EEG data recordings as normal or lesional/abnormal as it is crucial for developing our binary classification models. Therefore, the available EEG datasets have been processed, separated and labeled as normal or lesional data.

The classified data is categorized as matrices of size 19x500 where 19 is the number of electrode channels on the EEG cap used to record the participants and 500 is a one second recording with sampling rate is 500Hz.

Previously, originally dataset had the labeling as follows:

1: Complex Partial Seizures, 3034 matrices of size 19x500 corresponding to 3034 seconds of complex partial seizures

2: Electrographic Seizures, 705 matrices of size 19x500 corresponding to 750 seconds of electrographic seizures

3: Video-detected Seizures with no visual change over EEG, 111 matrices of size 19x500 corresponding to 111 seconds of Video-detected Seizures with no visual change over EEG

0: Normal data, 3895 matrices of size 19x500 corresponding to 3895 seconds of normal data,. 3895 is the total duration of all available seizures to create the balance between normal and lesional data

The total labeled data will therefore have a total size of 7790x19x500 where 7790 is the summation of the above seconds, normal and seizures. The data will be split into train and test data, 7011 (90%) and 779 (10%) respectively. The data was available in both numpy (.npy) and Matlab (.mat) format, saved as shown below:

x_train, size 7011 x 19 x 500 with its respective labels y_train

x_test, size 779 x 19 x 500 with its respective labels y_test

Data Visualization and Preprocessing

During the preprocessing phase, we took the initial raw and slightly filtered data and prepared the data using reshaping in order to get our desired format of data ensuring that the data was in the correct format for subsequent analysis with MNE-Python and analyzed the data using visualization to detect possibilities for feature engineering and correlation amongst features.

Data Transformation & Labeling

Firstly, in order to do binary classification between seizure and non seizure instead of distinguishing between different forms of seizures, we grouped

labels 1, 2, and 3 into a single class (1). Which represented an active seizure while class 0 represented the normal (non seizure) state. For training, we split the data into training and testing sets with a 90-10 ratio.
The original EEG data, X_train, was in the shape of (samples, channels, time), specifically (7011, 19, 500). Which corresponds to 7011 samples, 19 EEG channels, and 500 points per sample.

We transposed and reshaped the data using eeg_data = eeg_data.transpose(1, 2, 0) to (19, 500, 7011), which aligns the data in terms of channels, time, and samples.

Further, the data was flattened using eeg_data_2d = eeg_data.reshape(19, -1), creating a 2D array with the shape (19, sampletime), where 19 corresponds to the number of EEG channels, and sample time corresponds to the total time samples for all epochs. This transformation is necessary for the MNE library, which expects data in this format for creating RawArray objects.

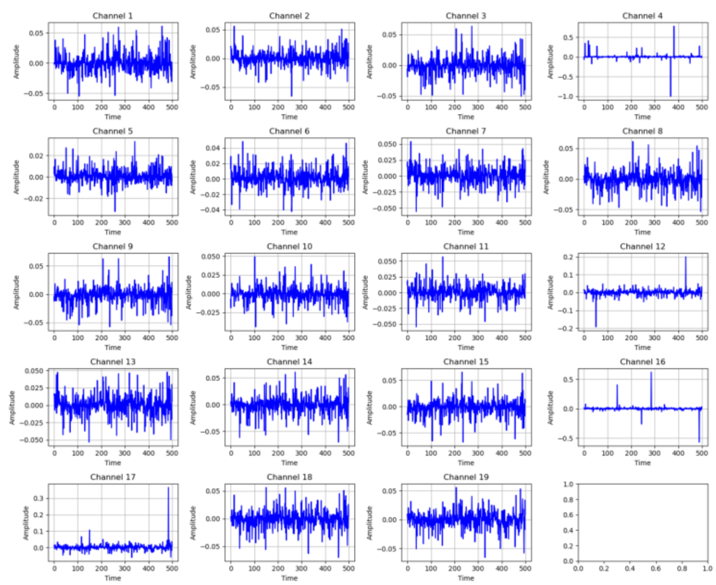
The EEG signals were recorded with a sampling frequency of 500 Hz (samples per second). This parameter was specified when creating the info object for MNE, ensuring that the time resolution is accurately represented in further analyses.

Each of the 19 EEG channels was respectively assigned a label EEG 1 to EEG 19. These labels are important for identifying the channels during both visualization and analysis by allowing us to identify relationships between channels and modify weights of certain channels due to locality importance.

The info object was created using mne.create_info. It was here where channel names, sampling frequency, and channel type (EEG) were specified. This object encapsulates essential metadata about the EEG recording, such as channel information and sampling rate that will be later used in the building of the model.

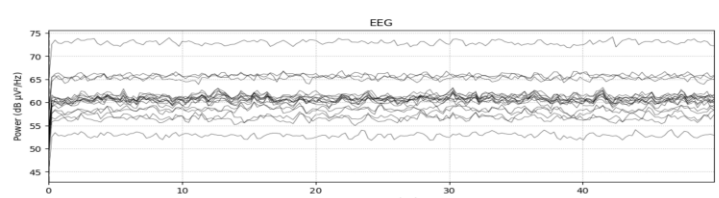
Visualization

Time-Series Plot:
To start out visualization of the data, we created a time series plot corresponding to each of the 19 channels. In these plots, we plotted the first 500 data points of each channel, which corresponded to one second of recording, against the channel's amplitude **[Figure B]**. These plots allow us to observe raw temporal characteristics of each EEG channel, such as oscillations and potential artifacts.



[Figure B] Time series plot per channel : Total 19 EEG

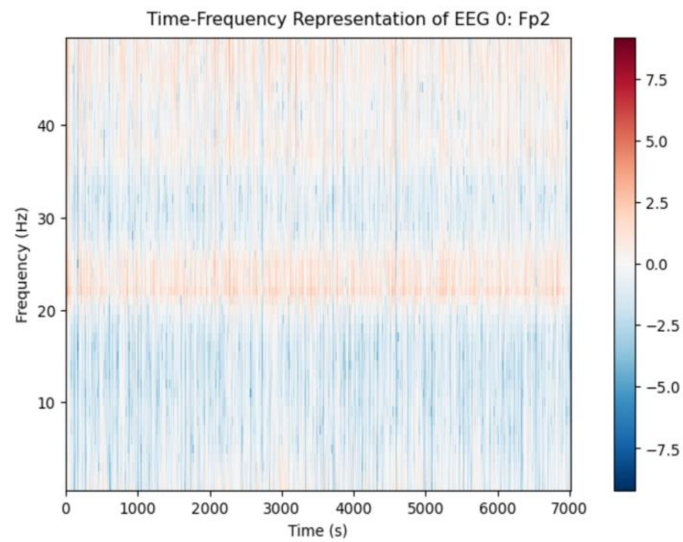
Power Spectrum Density:
Next, we plotted the power spectrum density (PSD) for each of the channels. This allows us to see how the power of each of the channels changes with respect to the frequency the signal is operating at [Figure C].



[Figure C] Power Spectrum Density

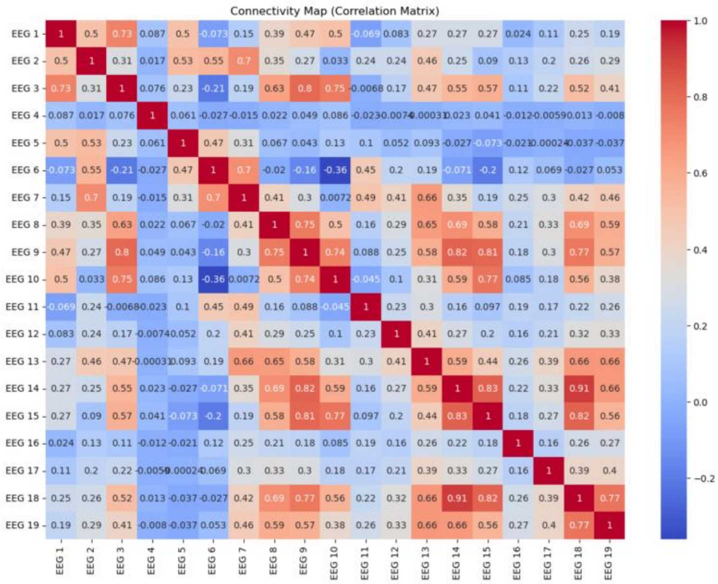
Time-Frequency Representation:
After this we analyzed the time-frequency representation (TFR) which was used to analyze the changes in frequency content over time of the EEG channels. This step is important for detecting oscillatory activity, which can be associated with various cognitive or neurological processes. Here are the steps for TFR that we used:

Epoch Extraction:
A single channel, channel zero in this demonstration, was selected for time-frequency analysis to demonstrate the process. The data was reshaped into epochs using mne.EpochsArray to segment the data.
Morlet Wavelet Transform:
We computed the time-frequency representation using Morlet wavelets, which are well-suited for EEG signal analysis due to their balance between time and frequency localization. The frequency range of interest was chosen from 1 Hz to 50 Hz, covering both low and high-frequency oscillations of the brain such as delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-50 Hz) bands. The n_cycles parameter was set as the frequency divided by 2, which defines the duration of each cycle for the wavelet transformation.
TFR Plotting:
The computed TFR visualization was constructed using data from the first channel, EEG 0, showing how power in different frequency bands changes over time [Figure D]. This time-frequency plot is useful for detecting event-related oscillations or rhythms in specific frequency bands, which can be linked to cognitive tasks or brain states.



[Figure D] The computed TFR was visualized for the first channel (EEG 0).

Correlation Map:
The next visualization technique that we did in an attempt to better understand the association between various channels was plotting a correlation map [Figure E]. A correlation matrix was computed using np.corrcoef, which captures the pairwise correlation between all 19 channels. This analysis provides insights into the functional connectivity of the brain regions represented by the EEG channels. The matrix was visualized using a heatmap generated by seaborn, with color intensities indicating the strength of the correlations between channels. Positive correlations indicate synchronized activity between channels, while negative correlations suggest inverse relationships. The correlation map helps in understanding which brain regions, which are represented by the EEG channels, are co-activating, which is useful for studying brain networks or detecting abnormal connectivity patterns in EEG data.



[Figure E] Correlation Map

Preprocessing Techniques

Noise Removal:
Like previously stated, the original raw information was filtered using first a bandpass filter between 1/1.6Hz and 70Hz in order to obtain the desired frequency range, which was mostly attenuated high frequency noise. The second filtering technique was to apply a notch filter to 50Hz. In addition, after data visualization we found that some of the channels were highly contaminated with noise and thus were omitted from the model.

Normalization:
Because the amplitude of our EEG signals were extremely concentrated, we applied logarithmic normalization in order to properly disperse and spread out our data so that our model can better detect features.

Models and Results

For deciding what models to use, we narrowed it down to testing with 3 different models: LSTM, CNN, and XGBoost. Then we trained and tested on each of these models separately and compared the log loss and testing accuracy results in order to determine how to proceed and which model to choose.

LSTM

We chose to try the LSTM model because it is known to be ideal for time-series data because it utilizes memory cells which allows it to retain information over long sequences, and because our EEG recordings are sequential, this lends itself to be a good model choice. Also because LSTM is a type of RNN, and thus a neural network, it can learn complex features directly from the raw data instead of having to identify features manually. After constructing and hyper parameterizing the model, our test accuracy turned out to be 89.98% which was satisfactory, but we wanted to see better results.

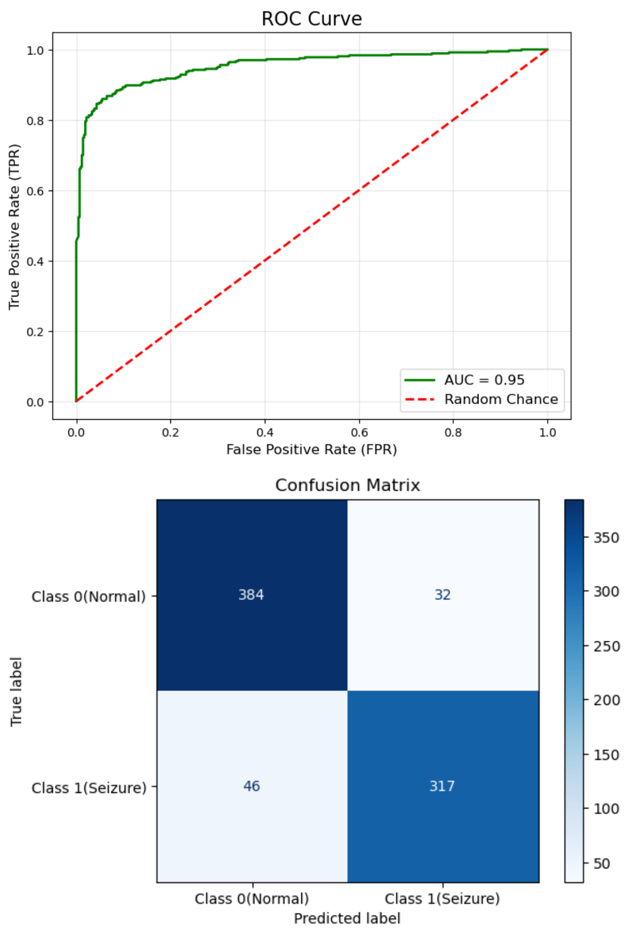
The hyperparameters in Table 1 below were determined through a process of manual tuning, where we adjusted each parameter iteratively and evaluated its impact on model performance. After testing various configurations, these hyperparameters limited overfitting and converged the loss quickly. For selecting optimizers during training, we first experimented with stochastic gradient descent. With the chosen hyperparameters, log loss results remained the same at 0.693 which for binary classification is nearly random guessing which wasn't good. After that, we tested out Adam which yielded much better results by converging much faster to 0 loss. The loss is binary cross entropy because we were doing binary classification.

Hyperparameters of LSTM

Hyperparameter	LSTM
Batch size	64
Optimizer	Adam
Learning rate	0.005
Epochs	100
Loss function	Binary Cross Entropy
Hidden size	64
Number of layers	2

[Table 1]

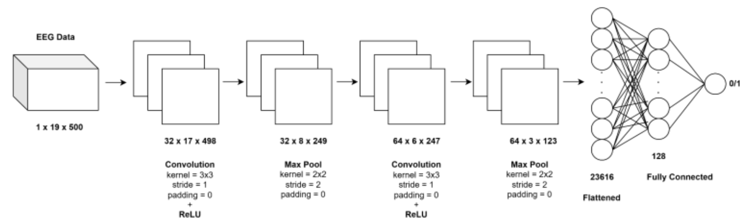
The AUC for the LSTM model is 0.95 which indicates that the model has a good ability to predict when someone is having a seizure. This prediction is significantly better than random chance as seen in the graph. The ROC curve is initially steep, which shows that the model has a high true positive rate (TPR) even for relatively small false positive rate (FPR).



[Figure F] ROC curve of LSTM, Confusion Matrix

CNN

Although CNNs are used primarily for image processing, we decided to test it out as an alternative to LSTM as CNN has spatial detection advantages, which is helpful with electrodes placed at different spots around the scalp. Just like the LSTM, CNN is also a neural network and thus can identify and learn complex features without manual feature engineering. After constructing and hyper parameterizing the model, the test accuracy was 90.50%, which was better than the LSTM model.



[Figure G] Best CNN model structure

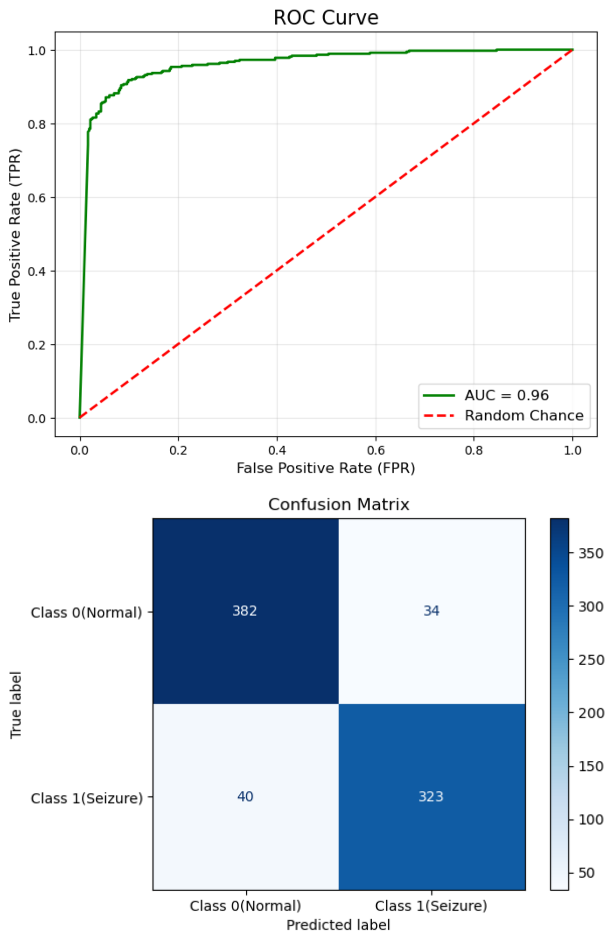
Like the hyperparameters for the LSTM, the hyperparameters in Table 2 below were manually tuned to achieve best performance. Again for the optimizer, Adam converged much faster than stochastic gradient descent. We chose ReLU as the activation function since it is the most commonly used for CNN models.

Hyperparameters of CNN

Hyperparameter	CNN
Batch size	32
Optimizer	Adam
Learning rate	0.001
Epochs	100
Loss function	Binary Cross Entropy
Activation	ReLU

[Table 2]

Improving upon the previous model, the AUC for our CNN model is 0.96 which reveals the model's improved ability to distinguish between seizure and nonseizure data. With this improved detection, the CNN proved to be our top model of choice.



[Figure H] ROC curve of CNN, Confusion matrix

XGBoost

After obtaining high test results with the CNN model, we wanted to try a non NN model to compare results. XGBoost has great success with binary classification as it builds its model by assembling a collection of decision trees that distinguish between various features. Also, XGBoost models are extremely versatile, as you can manually tune them to optimize training and testing accuracy. Another benefit of an XGBoost model in the context of our problem is that it is a simpler and computationally cheaper model to construct, which is important for real-time detection, which is the end goal for training seizure detection models.

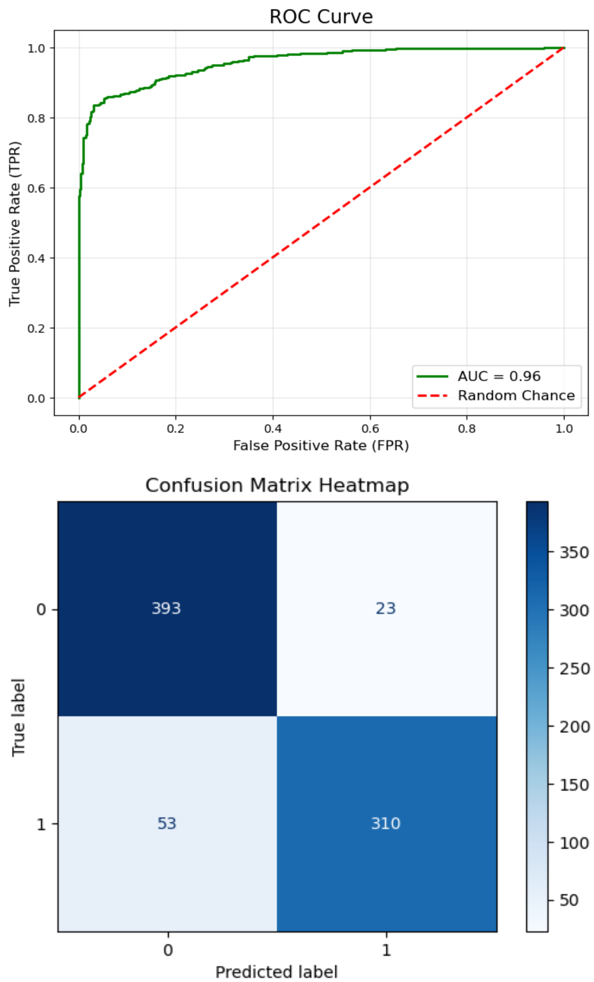
The EEG data was three-dimensional, so in order to use XGBoost, we had to make the data two-dimensional. This resulted in the training data having 9500 features which was too large; thus dimensionality reduction was required. We used principal component analysis (PCA) to select the best 100 features. Then, we tuned XGBoost using the optuna library because of the library's ease of use and quick setup. optuna uses Bayesian optimization to automatically find the most optimal hyperparameters which should do better than manual tuning. After 100 studies, the best hyperparameters were the ones in Table 3 below.

Hyperparameters of XGBoost

Hyperparameter	XGBoost
max_depth	16
min_child_weight	5
subsample	0.745
colsample_bytree	0.683
learning_rate	0.044
n_estimators	503

[Table 3]

Similarly to our CNN model, the AUC for the XGBoost model appears to also be 0.95. However, due to increased accuracy in the CNN model (90.50%) compared to the XGBoost one (90.24%), we conclude that the CNN model had the highest performance out of the three models we tested and thus chose to be our model for this project. However, is it important to note XGBoost's high performance for its low computational complexity which may be useful in the future for real-time applications.



[Figure I] ROC curve of XGBoost, Confusion matrix

Final Result

After testing and comparing the performance of three models—LSTM, CNN, and XGBoost—we determined that the CNN model yielded the best results in terms of both accuracy and AUC. The CNN achieved a test accuracy of 90.50% and an AUC of 0.96, indicating strong performance in detecting seizures. While the LSTM and XGBoost models also performed well, with accuracies of 89.98% and 90.24% respectively, CNN outperformed the others in our tests. These results suggest that CNN is the most suitable model for seizure detection in EEG data within the scope of this project.

Accuracy and AUC of LSTM, CNN, and XGBoost

Model	Accuracy (%)	AUC
LSTM	89.98	0.95
CNN	90.50	0.96
XGBoost	90.24	0.96

[Table 4] Final Result

LSTM Results

Result	precision	recall	f1-score	support
Class 0	0.89	0.92	0.91	416
Class 1	0.91	0.87	0.89	363
accuracy			0.90	779
macro avg	0.90	0.90	0.90	779
weighted avg	0.90	0.90	0.90	779

[Table 5] Result of LSTM Model

CNN Results

Result	precision	recall	f1-score	support
Class 0	0.91	0.92	0.91	416
Class 1	0.90	0.89	0.90	363
accuracy			0.91	779
macro avg	0.90	0.90	0.90	779
weighted avg	0.91	0.91	0.90	779

[Table 6] Result of CNN Model

XGBoost Results

Result	precision	recall	f1-score	support
Class 0	0.88	0.94	0.91	416
Class 1	0.93	0.85	0.89	363
accuracy			0.90	779
macro avg	0.91	0.90	0.90	779
weighted avg	0.90	0.90	0.90	779

[Table 7] Result of XGboost Model

Discussion

Based on the results of testing accuracy, the best model out of those tried in our project for detecting seizures is a convolutional neural network. CNNs are good models for classifying time-series and signal data, making it a strong baseline mode for future iterations. Additionally, neural networks outperform non neural network models in detecting seizure activity, likely due to the nature of EEG data. Because EEG data measures what are often small changes in electrical activity in the brain, amplitude peaks and wave patterns are better captured and recognized by deep learning models. Additionally, because seizure EEG patterns may differ between patients, a neural network is more adaptive and better suited for medical applications, especially if the model were to be individually trained on each patient.

When looking at the results of our project within the context of the medical problem we are tackling, it is important to balance the significance of detecting seizures and not wasting the time and resources of medical staff responding to a false incident. Choosing a lower threshold may detect more seizures, but lead to more false positives, while a higher threshold may not detect some seizures but will not have as many false positives. Considering how serious seizures can be, it could be more beneficial to choose a lower threshold to detect more seizures, even if it results in more false positive occurrences.

Using a simple model, we have accomplished high accuracy and demonstrated the validity and potential of future BCI applications for ubiquitous medical device use. However, there is still room for improvement in accuracy when compared to existing literature. Specifically, looking at a 2023 study by Princess Nourah bint Abdulrahman University Researchers[1], researchers using a Deep Neural Network and the Binary Dragon Algorithm (BDFA) for feature selection were able to effectively distinguish normal, interictal, and ictal signals with 100% accuracy, sensitivity, and specificity. This model is lean, using only 13% of available features to make predictions, which indicates that our model may be improved with better machine learning methods, data pre-processing and feature selection.

On that note, several limitations exist for our model. As mentioned above, individual differences exist between patients and EEG data, which our model is unable to fully capture. Additionally, our data is relatively scarce and heavily pre-processed. EEGs are subject to environmental noise due to the nature in which data is collected. We passed our data through two separate filters to remove high-frequency noise and select a desired frequency noise. We also eliminated channels we deemed noisy and contaminated, which were arbitrary selections made by us and prone to human error. In this trade-off, we could have lost details that would have been useful in making classifications. Our dataset also only contained data from six epileptic patients. A more robust model would have been trained on more patients as well as controls (non-

[1] Additional techniques, such as Wavelet transform, were used for efficient feature extraction. Based on preliminary searches, this hybrid DNN-BDFA model is the best performing model for seizure detection currently.

epileptic patients) to better capture individual differences in how seizures manifest.

Now, collecting mass amounts of EEG data from epilepsy patients and non-epileptic patients would be time-consuming and costly, so an alternative solution to having more data is to utilize transfer learning, which would increase our model's flexibility to match individual differences and reduce the data requirement. A 2021 study by Zitong Wan et Al provides an overview of the four main methods of transfer learning and practical applications for EEG signal analysis and illuminates how future research can improve CNN model performance in detecting seizures from EEG data[2].

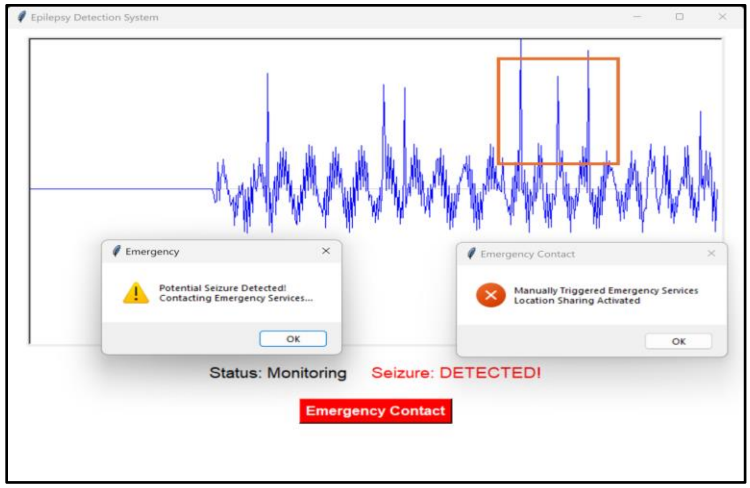
Application and Web App Demonstration

Additionally, we developed a prototype GUI application using Tkinter to demonstrate the potential of real-time seizure detection systems. Although our implementation did not utilize actual patient EEG data, the application successfully simulated a real-time signal monitoring and detection mechanism, and alarm system to local hospitals showcasing the potential for ubiquitous medical monitoring technologies.

The prototype includes critical features such as continuous signal visualization and an emergency notification system designed to alert medical professionals immediately upon detecting potential seizure events [Figure J].

However, significant limitations currently constrain the development of portable, real-time seizure detection devices. Development is currently hindered by several existing EEG technological limitations, including the need for more bio-adhesive and comfortable electrodes, improved signal-to-noise ratio, higher spatial resolution, and the integration of a closed-loop adaptive system for practical, everyday use.

While our current implementation is a simplified demonstration, it represents an important step towards developing more advanced, user-friendly medical monitoring technologies.



[Figure J] Web app demonstration

Conclusion

While detecting epileptic seizures is helpful for diagnosing and treating patients, it does not reach the threshold of providing real-time benefits, as our project focused more on seizure detection rather than prediction. Seizure detection research has existed for years, but with the progression of deep learning and higher computational power, the next frontier in EEG signal analysis is seizure prediction. While detection is useful, it only allows for treatment after-the-fact, meaning patients still have to suffer through epileptic seizures, risking adverse health effects, brain damage, and death. Additionally, even with treatment from antiepileptic drugs (AEDs), 35% of patients become resistant to medication[3]. This necessitates further investigation

[2] This study conducted a comprehensive overview of existing literature on transfer learning in EEG signal analysis. It found that CNNs were the most explored deep NN model type, validating our findings, but also identified a number of limitations in the development of transfer learning-based DNNs.

[3] From a 2014 study by Negin Moghim and David W. Corne on seizure prediction. See works cited for more information.

into how we can predict seizures before onset to provide timely and preventative care. A 2023 study suggested that there may be up to a 30 minute window before seizure onset during which proictal brain activity (increased or erratic brain activity before seizure activity) can be detected[4].

However, through the demonstration of our GUI application, we have shown that our design can be adapted for real-time epilepsy detection. This could prove extremely beneficial, especially as brain-computer interface (BCI) technology continues to advance. With such progress, there will be the potential for individuals suffering from epileptic seizures to seek urgent medical attention before an episode begins. The projected growth of the BCI market, estimated to reach $400 billion by 2024 according to Morgan Stanley, highlights the immense potential for improvements in sensing, diagnosis, detection, and intervention technologies. As BCI technology advances, real-time systems like ours could significantly reduce the risks associated with epilepsy, enabling timely treatments that predict seizures before they occur based on biomarkers. Through the use of CNN, feature engineering, and preprocessing with filters, our improved system offers hope for more efficient and effective management of epilepsy.

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[4] Based on research from the University of Alabama at Birmingham, published in *NEJM Evidence*. This study took a novel approach to EEG measurements by measuring thalamus activity specifically. It’s findings were limited to patients with temporal lobe epilepsy.