A Smart Device for the Prediction of Epileptic Seizures using Machine Learning Algorithms

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Abstract: More than 65 million people live with epilepsy. The unpredictable nature of epileptic seizures drastically increases the risk of injury, especially in daily activities such as walking or driving. The purpose of this project is to develop an accurate prediction device that utilizes raw EEG data for the prediction of epileptic seizures to alert patients of an oncoming seizure beforehand to escape dangerous situations. Using the raw EEG data, features were extracted by computing the average power spectral density of different brain waves after applying the Fast Fourier Transform. These features were used as the input dataset to the machine learning algorithms. Each model is tested with new unseen data using various metrics such as accuracy, precision, recall, and F1 score. The highest performing algorithm, Random Forest (RF) produced a prediction accuracy of 99.0% and a precision of 99.3%. Channel importance is calculated for the RF algorithm. This analysis helped to reduce the number of channels from 22 before feature importance to only 7 channels without significant hits to performance metrics. Using the RF algorithm, an embedded program is developed to run on a portable, low-power hardware device to predict the onset of a seizure. The hardware includes BeagleBone Black microcontroller running open-source software and a Bluetooth transmitter-receiver to transmit the prediction to smartphone devices. By reducing the number of EEG channels to 7 channels, the system is more convenient for a future wearable device. Hardware with the ability to predict epileptic seizures can save many patients from potentially dangerous situations such as driving or swimming. It can help many patients in their daily lives by removing the uncertainty and improving their quality of life.

Keywords: Channel importance, Feature extraction, Machine learning algorithms, Seizures, Spectral density

I. INTRODUCTION

Epilepsy is one of the most common neurological conditions that results in unexpected seizures. About 1% of the world's population is affected with this condition. Because the occurrence of these seizures is always unknown, it puts patients at risk of serious injuries. The uncertainty affects the quality of life of many individuals.

The question that immediately arises is whether it is possible to predict seizures accurately and provide a warning for the individuals and others around them. Such a model could inform patients ahead of time helping them to avoid dangerous situations. A seizure prediction system must be able to predict the onset of seizures well in advance. All seizure prediction algorithms involve two main steps. First, appropriate quantitative values or features, such as Electroencephalograms (EEG) features, movements, or other biomarkers, must be computed from the data. The second step, called classification, might be as simple as thresholding a value or might require models derived from machine learning algorithms to accurately predict the onset of seizures. Generation of relevant features for seizure detection depends on the physiological data that are recorded. It is helpful to keep in mind that the training or supervised learning phase involves various steps that are carried out separately on previously recorded data from a large population. During this step, model parameters that decide criteria for the occurrence or lack of seizures are computed. These criteria will then apply to predict seizures in other patients [1].

Machine learning techniques and computational methods are used for predicting epileptic seizures from EEG signals. Epileptic seizures have four different states: preictal, ictal, postictal, and interictal states. Preictal state occurs before the seizure begins followed by the ictal state that begins with the onset of the seizure and ends with an attack. After the seizure, a patient usually experiences a postictal state followed by an interictal state that represents the return to normal neural patterns. Seizures can be predicted by detecting the beginning of the preictal state [2].

A sequence of data from EEG signals that tracks interictal and preictal data from epileptic seizures can be abstracted as a general time series problem. In a sense, this time series problem represents an anomaly detection style problem in which the anomaly that an algorithm should try to identify is the start of the preictal phase of the seizure. Machine learning models have shown great success in the field of anomaly detection which is a subset of classification problems. Consequently, machine learning models may successfully predict epileptic seizures. With the use of publicly available seizure datasets, it is possible to experiment and find out what machine learning models work particularly well for this problem. Finding a model that can identify the inception of preictal stages in epileptic seizures may aid the lives of many of these patients.

The classification scheme in machine learning is suitable for the prediction of epileptic seizures. There are a number of classification models. Classification models include Logistic Regression (LR), Linear Discriminant Analysis (LDA), k-Nearest Neighbor (KNN), decision tree algorithm like Classification and Regression Trees (CART), Gaussian Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting (GB).

The preictal state - which begins several minutes before the onset of a seizure, and ends with the start of ictal state. Although lot of research has been done [3]–[7] to detect the beginning of the preictal state by using EEG signals, only a few could reliably detect the preictal state of epilepsy.

Combining many linear univariate features in one feature space and classifying it using machine learning algorithms could predict epileptic seizures. Rasekhi et al. in [4] have extracted 22 univariate linear properties by using only six EEG channels, thereby creating a 132-dimensional feature space. The preictal time was chosen as 10, 20, 30, and 40 min. Applying machine learning methods on a multidimensional feature space of 22 univariate features predicted seizure onsets with reasonably high accuracy. The authors used Support Vector Machine as a classifier to classify the preictal and ictal states of EEG signals. On average, the seizures were predicted correctly in 73.9% of the cases.

Bandarabadi et al. have proposed an algorithm [5] which combines spectral powers of EEG across channel pairs to track gradual changes preceding seizures. After suitable selection of features, Support Vector Machine algorithm is used for classification. They have observed sensitivity of 75.8% (66 out of 87 seizures). They have suggested that, seizure prediction performance can be improved by applying these methods, after reducing proposed features subset. In another study, the authors have proposed a method to separate preictal and interictal states based on the analysis of the high frequency activity of intracerebral EEGs (iEEG) in epileptic patients [6]. Wavelet energy and entropy were computed from preictal and interictal states. On a dataset of six patients, two or three channels have been selected for testing purposes. The results are promising with a sensitivity of 88% and an average anticipation time of 22 minutes.

Dadgar-Kiani et al [3] have suggested to use both statistical and deep learning methods to classify iEEG signals as preictal or interictal for the prediction of seizures. The extracted features represent both the frequency and temporal properties of the raw data. Neural networks, Logistic Regression and Support Vector Machine models are used for classification. All of the classifiers have an area under receiver operating characteristics (AUROC) curve values higher than 0.9 even though the majority of samples representing non-seizure data. On the other hand, Support Vector Machine outperforms the other classifiers in terms of recall value.

The engineering goals of this project are to develop a software model that would help predict the occurrence of seizures in advance using machine learning algorithms and using the best performing algorithm, develop a prototype capable of predicting seizures with minimum number of EEG channels. This prototype could be later extended to use in a wearable device.

II. MATERIALS AND METHODS

A. Patient Dataset (Epilepsy) - Raw EEG Data

The patient database is collected from 22 subjects at the Children's Hospital Boston which comprises of EEG recordings from pediatric subjects with seizures. Each case (Filename chb01, chb02, etc.) contains between 9 and 42 continuous .edf files. All signals were sampled at 256 samples per second with 16-bit resolution [8]. The .edf files contain one hour of digitized EEG signals in most cases. EEG data from 22 channels are used for this research.

B. Feature Extraction from Raw EEG Data

The size of the EEG data is very large; therefore, using raw time-series data as input to the machine learning algorithms might not produce high accuracy. This emphasizes the need for feature extraction from raw EEG data. More recently, a variety of methods have been used to extract the features from EEG signals. A few of these methods are time frequency distributions, Fast Fourier Transform (FFT), Wavelet Transform (WT) etc.

FFT is an algorithm used to decompose a signal in the time domain into its frequency components. It is a numerically efficient method to calculate the Discrete Fourier Transform (DFT). The DFT of a signal is computed as

$$X_k = \sum_{n=0}^{N} x_n e^{-i2\pi kn/N} \quad k = 0, \ldots, N-1$$

where N is the number of time samples, n represents the current sample being considered, while k represents the current frequency being considered. X_k is the amount of frequency k in the signal and x_n is the value of the signal at time n [9].

C. Brain Waves

There are 4 types of brain waves [10]. The normal, pre-ictal and epileptic activities are concentrated within these four waves.

• Delta waves (.5 to 3 Hz): Delta brainwaves have the lowest frequency. They are typically generated in deep meditation or while sleeping with no dreams.

• Theta waves (3 to 8 HZ): Theta brainwaves occur most often in sleep and states of reduced consciousness. Theta waves dominate when our body falls asleep.

• Alpha waves (8 to 12 Hz): Alpha brainwaves are dominant when we are quietly thinking and resting.

• Beta waves (12 to 38 Hz): Beta brainwaves dominate our normal state of consciousness when attention is engaged towards cognitive tasks and the outside world.

D. Performance Evaluation of Classification Models

A binary classification model classifies each data sample into one of two classes: a true and a false class. This gives rise to four possible classification of each data sample; a true positive, a true negative, a false positive, and a false negative [11].

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1. True positive (TP): the patient is susceptible to an epileptic seizure and the prediction is positive.

2. False positive (FP): the patient is not susceptible to an epileptic seizure but the prediction is positive.

3. True negative (TN): the patient is not susceptible to an epileptic seizure and the prediction is negative.

4. False negative (FN): the patient is susceptible to an epileptic seizure but the prediction is negative.

The accuracy of a model refers to the ability of the model to correctly identify patients that are susceptible to an epileptic seizure and those that are not.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

The precision of a diagnosis model refers to the ratio of correctly predicted positive observations (disease) to the total predicted positive observations.

$$Precision = \frac{TP}{TP + FP}$$

The recall (sensitivity) of a model refers to the ability of the test to correctly identify patients that are susceptible to an epileptic seizure.

$$Recall = \frac{TP}{TP + FN}$$

The F1 score of a model is the harmonic mean of precision and recall.

$$F1\ Score = 2 \times \frac{precision \cdot recall}{precision + recall}$$

III. EXPERIMENTAL SETUP

A. Software Configuration

The time-series EEG data from each of the 22 channels is split into multiple 2-second epochs of data for normal and preictal activities of each patient. The FFT is calculated for each of these 2-second data for normal and preictal activities. The power spectral values are calculated for delta, theta, alpha, and beta waves. The average power for each of the four brain waves is calculated using Welch's periodogram which consists in averaging consecutive Fourier transform of small windows of the signal without overlapping [12]. The average power of the four brain waves (delta, theta, alpha and beta) for normal activity and preictal activity are calculated for each epoch for each EEG channel. This is done for all of the 22 channels. The result is stored into a csv file (extracted features). The preictal time is chosen as 15-minutes. The output 'y' of each row in the csv file is updated to '0' if it corresponds to a normal activity and '1' if it is a preictal activity.

The brain wave features thus extracted from the raw EEG data is used as the training and testing datasets of the various classification models: LR, LDA, KNN, CART, NB, SVM, RF, and GB. 70% of this data is randomly selected (which contains normal and preictal cases) to train the classification models and the remaining 30% data is used as test dataset. 10-fold cross validation is used to train the classification models. The methodology used is shown Fig. 1.

The best performing algorithm is selected for the hardware implementation. The EEG channels that have the most importance in the prediction of seizures are identified. Using the brain wave features extracted only from the channels of importance, the model is trained again to use in the device.
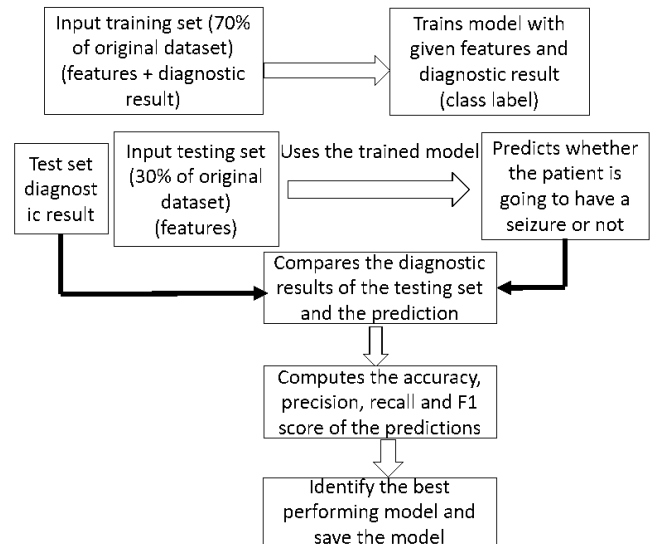
The software is developed in Python 3.6.

Fig. 1: Methodology

B. Hardware Configuration

The prototype is designed and tested with the raw dataset from the epileptic patients.

1. The central processing unit will process the EEG data to extract the features and run the machine learning algorithm to predict any oncoming seizures.

2. Based on the prediction result, the buzzer will generate an alarm.

3. Broadcast the prediction result to iPhone/Android devices.

IV. RESULTS

A. Software Results with the Patient Datasets

The predictions of each model are compared with the actual diagnostic information whether a patient is going to have epileptic seizure or not. The accuracy, precision, recall, and F1 score of each model in validating the test dataset are computed and given in Table- I. The confusion matrix for each classification model is also generated as the program output.
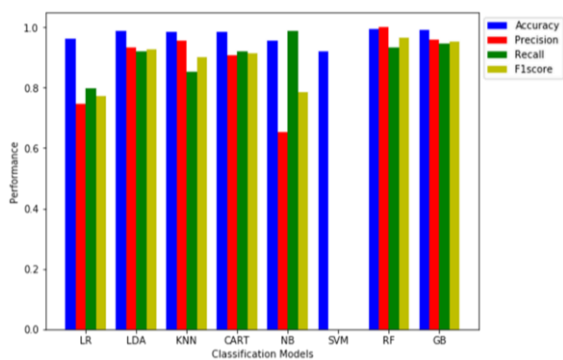
A bar graph for the performance of the classification models in terms of accuracy, precision, recall and F1 score is given in Fig. 2. The model RF showed the highest prediction accuracy (99%) and precision (99.3%). RF produced a recall of 91.4% and F1 score of 93.9%. GB also showed good performance (accuracy: 98.8%, precision: 93%, recall: 92.4%, F1 score: 92.9%). This means that both of these models have a high ability to predict whether the patient is going to have a seizure or not. LDA also has a high ability to predict epileptic seizures with an accuracy, precision and recall of 98.6%, 92% and 87.6%, respectively. The worst performing model was SVM with the prediction accuracy of 92.3% and precision, recall, and F1 score are all zero.

Table- I: Performance of the Classification Models

| Classifier	Average values of			
	Accuracy	Precision	Recall	F1 score
LR	0.957	0.717	0.727	0.722
LDA	0.986	0.920	0.876	0.905
KNN	0.980	0.948	0.784	0.857
CART	0.982	0.880	0.881	0.880
NB	0.957	0.645	0.989	0.779
SVM	0.923	0	0	0
RF	**0.990**	**0.993**	**0.914**	**0.939**
GB	0.988	0.930	0.924	0.929

Fig. 2: Performance of the Classification Models

Receiver operating characteristic (ROC) graphs are constructed by plotting the true positive rate against the false positive rate [13]. The area under the curve (AUC) can have any value between 0 and 1. When the AUC is higher, the model is better. The ROC/AUC of each classification model is given in Fig. 3. The models RF, GB, and LDA showed the highest value of AUC (1.0). The model NB has an AUC of 0.99. KNN, CART, and LR have an AUC of 0.98, 0.95, and 0.94 respectively. The model SVM has the least value of AUC (0.52). The confusion matrix is generated for each model using Python package scikit-learn.
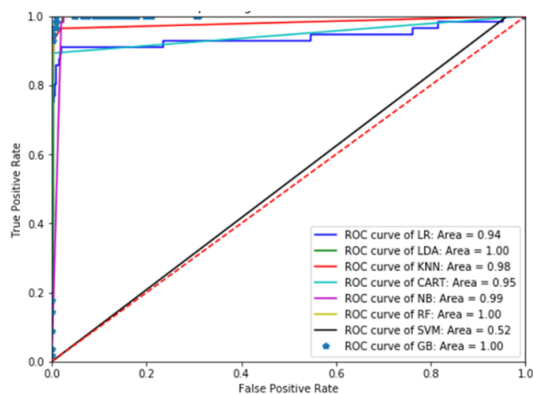

Fig. 3: ROC/AUC Curve

Channel importance is calculated for the highest performing algorithm (RF) and is plotted in Fig.4. From the graph, it is evident that the top 7 channels significantly outweigh all other channels in terms of their predictive power.
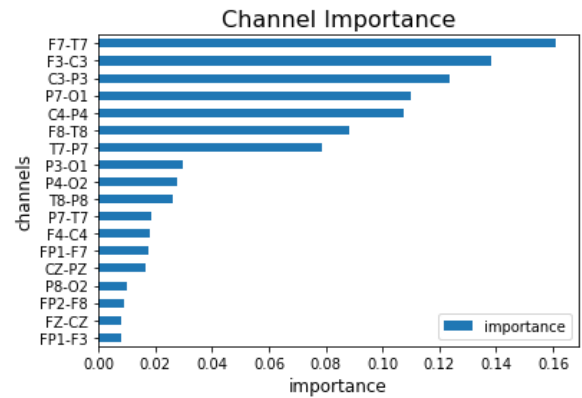
Fig. 4: Channel Importance for RF Algorithm

B. System Hardware Implementation

The overview of hardware architecture is given in Fig. 5. Based on the channel importance analysis, seven of the EEG channels are selected. The portable, low power hardware device consists of nRF52832 chip [14] (which could be later extended to use as the real-time EEG data acquisition unit in a wearable device) and ARM Cortex-A8 1GHz processor (BeagleBone Black) to process the EEG data [15]. In addition, it runs the best performing machine learning algorithm (RF) to predict any onset of seizures. The BeagleBone Black (BBB) is the host in this architecture.
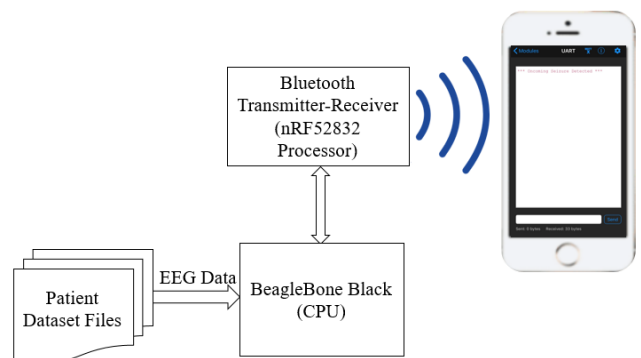
Fig. 5: Overview of Architecture

C. System Software Implementation

The program flowchart is given in Fig. 6. There are two blocks, BBB and nRF52832. BBB block consists of the host processor which reads the EEG data. The host processor has Linux Operating system. The main program is developed in Python.

The program starts with initializing GPIO. After the initialization, the processor reads the dataset file saved in csv format. This data file is then processed to extract the features and is stored. The processed dataset is given to the RF algorithm running on BBB. The prediction result is sent to a buzzer for alerting any onset of seizures. The prediction result is also sent to the Bluetooth radio in nRF52832 for sending the alert message to iPhone/Android devices.
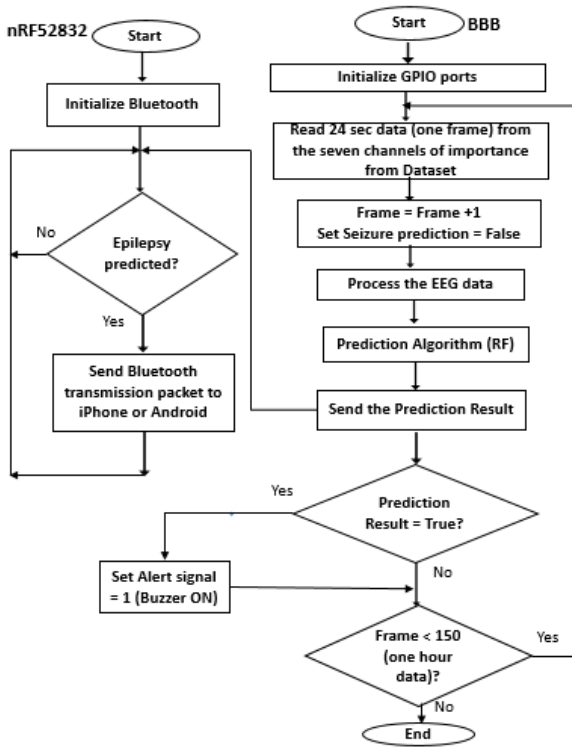
Figure 6: System Software Flowchart

Fig. 7: Test Results of the Device with Patients' Datasets

In the nRF52832 block, the software is developed in the Arduino Development Environment (IDE) and uploaded to the data acquisition unit [16]. The program flow starts with initializing a Bluetooth transmitter. The system then enters into a program loop. When the prediction result is received from the BBB block, if there is an onset of seizure, this block sends the alert message to iPhone/Android device through Bluetooth radio.

The hardware device is capable of predicting seizures using the RF model running on BBB. The device is tested with epileptic/normal patient datasets from patients, chb01, chb02 and chb03. When tested with a preictal dataset, the buzzer makes a beeping noise when the software model predicted that a seizure is going to happen. A warning message is sent to the iPhone that an onset of seizure is detected. The device is tested with multiple test datasets and the results of seizure datasets are given in Table- II.

Using the patients' EEG dataset, the hardware device is tested with a total of 38 EEG data files from 3 patients. In these 38 files, 17 files are with epileptic seizures and 21 are normal cases. The device could predict 12 cases of seizure successfully and generated the warning by making the buzzer ON and sending an alert message to the phone. The prediction times were in the range of 37 seconds to 12.3 minutes before the onset of seizure. The device identified 19 normal cases as normal and generated false alarm in 2 cases. Overall test results of the hardware device with patients' datasets are given in Fig. 7.

The model is able to predict a seizure when it encounters the preictal state in the dataset and generates a warning. This will give enough time for the patient to get out of any activity that could be potentially dangerous at the time of seizure.

V. CONCLUSION

Epileptic seizures occur when parts of the brain receive a burst of abnormal electrical signals that temporarily interrupt normal electrical brain function. Epileptic patients do not have any knowledge whether a seizure will occur when they are driving, swimming, or doing any other activity that would make a seizure particularly dangerous. Early prediction of epileptic seizures is very useful because the patient could avoid a potentially dangerous situation. The goals of this study were to develop a software model that would help predict the occurrence of seizures in advance using machine learning algorithms and also to develop a prototype capable of predicting seizures using the best performing algorithm.

A raw EEG dataset which contains both normal and epileptic activities is used to find out the best performing model for epileptic prediction. With the test dataset,

Table- II: Testing the Hardware Device with Epileptic Patients' Datasets

Patient#	Number of seizure cases	Data File Name	Buzzer Status	Message send to iPhone	Seizure Prediction Time	Actual Seizure Start Time
		chb01_03.edf	ON	Yes	2257 seconds	2996 seconds
		chb01_04.edf	ON	Yes	937 seconds	1467 seconds
		chb01_15.edf	ON	Yes	1009 seconds	1732 seconds
1	7	chb01_16.edf	ON	Yes	601 seconds	1015 seconds
		chb01_18.edf	ON	Yes	1633 seconds	1720 seconds
		chb01_21.edf	OFF	No	No Prediction	327 seconds
		chb01_26.edf	ON	Yes	1249 seconds	1862 seconds
		chb02_16.edf	ON	Yes	73 seconds	130 seconds
2	3	chb02_16+.edf	ON	Yes	2593 seconds	2972 seconds
		chb02_19.edf	ON	Yes	2833 seconds	3369 seconds
		chb03_01.edf	OFF	NO	No Prediction	362 seconds
		chb03_02.edf	OFF	NO	No Prediction	731 seconds
		chb03_03.edf	OFF	NO	No Prediction	432 seconds
3	7	chb03_04.edf	OFF	NO	No Prediction	2162 seconds
		chb03_34.edf	ON	YES	1945 seconds	1982 seconds
		chb03_35.edf	ON	YES	2185 seconds	2592 seconds
		chb03_36.edf	ON	YES	1561 seconds	1725 seconds

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generated by extracting the features from raw EEG data, the model RF showed the highest prediction accuracy (99%) and precision (99.3%). It produced a recall of 91.4% and F1 score of 93.9%. GB also showed a good performance (accuracy: 98.8%, precision: 93%, recall: 92.4%, F1 score: 92.9%). This means that both of these models have a high ability to predict whether the patient is going to have a seizure or not. LDA also has a high ability to predict epileptic seizures with an accuracy, precision and recall of 98.6%, 92% and 87.6%, respectively.

Overall, based on the performance metrics from all machine learning algorithms, the RF algorithm is the best performing with the highest prediction accuracy and precision. Therefore, the software model is developed with the RF algorithm and is used in the embedded program. This program runs on a portable, low power hardware device to provide a warning (buzzer alert and an alert message to iPhone/Android devices) about the onset of a seizure. With the channel importance analysis, the number of EEG channels required for data has been reduced from 22 to 7 channels, making it much more convenient for a future wearable device.

The hardware device is tested with three patient datasets with normal/epileptic activities and achieved excellent results in the case of patient #1 and patient #2. The proposed architecture is a portable, low power, and low cost system. Overall results are promising for the implementation of a wearable device to predict seizures. The nRF52832 chip could be later extended to use as the real-time EEG data acquisition unit in a wearable device.

With the consistent results seen using the hardware device, this system is certainly promising for an accurate prediction device for epileptic seizures. The device's ability to predict oncoming seizures minutes before its occurrence can save many patients from any potentially dangerous situations such as driving or swimming. This hardware would, therefore, help numerous epileptic patients in their daily lives as it would significantly reduce the uncertain nature of these seizures, improving their quality of life. In the future, the hardware can be extended to a wearable device that will acquire EEG data in real-time, which will require testing of this device in real-time by acquiring the data from epileptic patients.

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