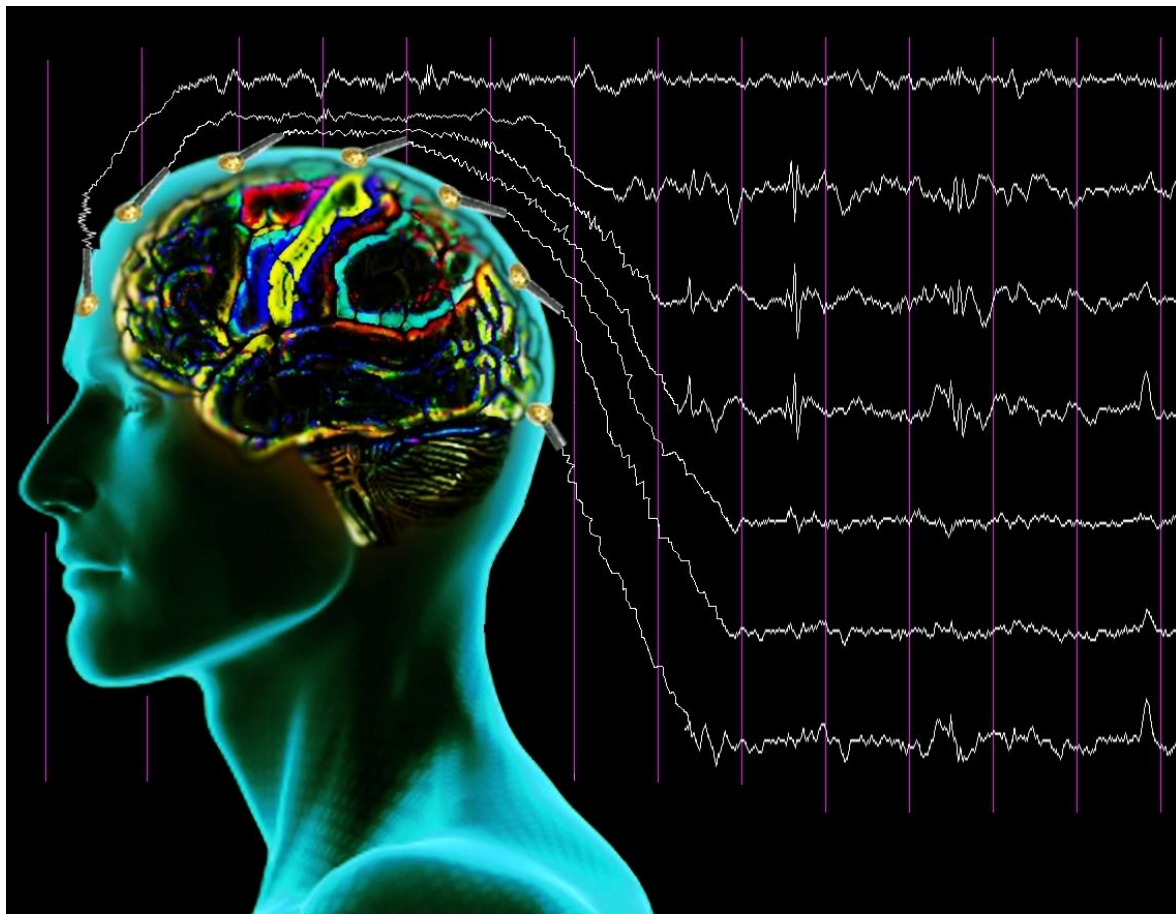


Project 1

Monitoring and diagnosing
Epileptic electroencephalography
(EEG) signals.



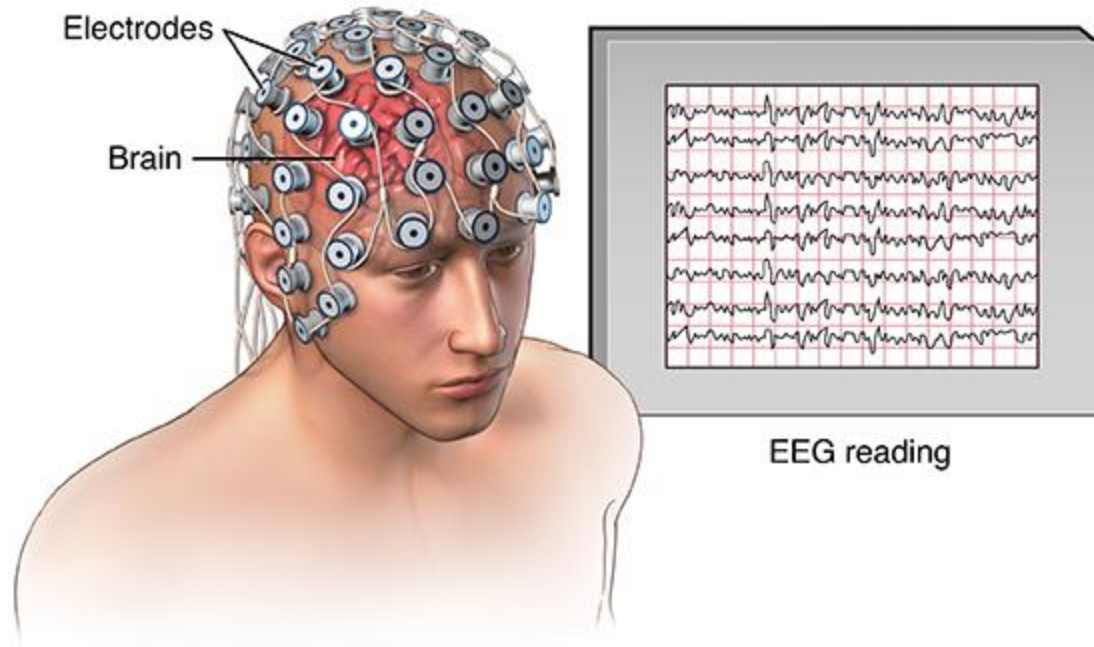
Karim Mohamed Farahat	201801904
Abdullah Muhammad	201801271
Mohamed Ahmed	201800760

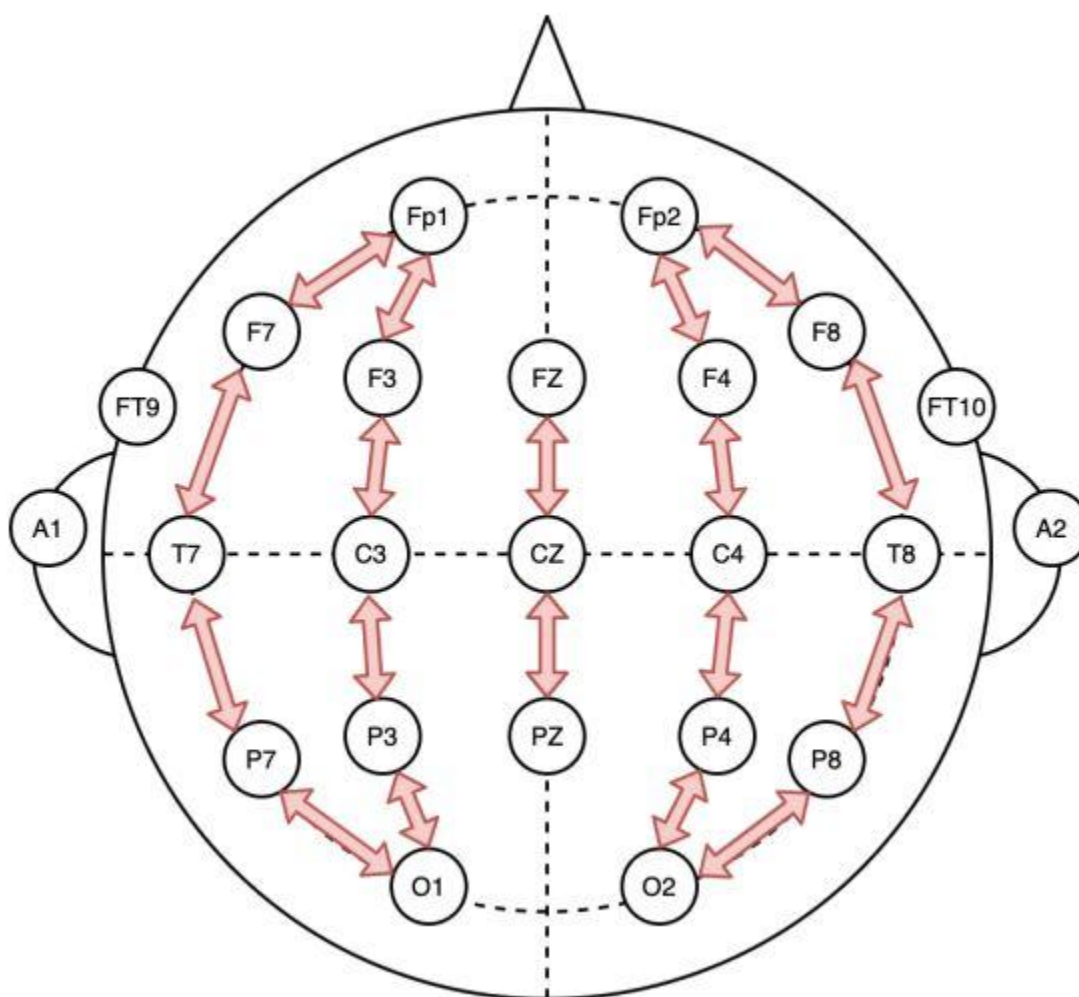
Introduction

Epilepsy is a condition of the central nervous system that can strike people of any race, gender, or age. Multiple seizures occurring on different occasions help doctors diagnose an epileptic patient. Data from the Centers for Disease Control show that Disease Prevention (CDC), 1.2% of Americans in 2015 have active epilepsy . According to the present research, an electrical disturbance in the brain that may result in uncontrollable behavior and unconsciousness is what causes epilepsy. When patients engage in daily activities like diving or swimming, the risk may increase. More urgently, Sudden Unexpected Death in Epilepsy, the primary cause of epilepsy-related death (SUDEP), is a potentially fatal risk that may arise in people who have persistent, frequent, and intractable seizures. Despite the fact that the majority of seizures end on their own without any risk, preventing injury with a system warning within a considerable lead Time is still possible. Epileptic seizures, however, have been classified as an "unpredictable" disorder for a long time because there are no reliable tools for predicting when a seizure would start. A seizure is an abrupt, uncontrollable aberrant brain activity that can manifest as abnormal entire or partial bodily movements, among other symptoms. Electroencephalography (EEG) is the gold standard for diagnosing epilepsy by identifying unique brain wave patterns. By keeping an eye on patients' electrophysiological condition, various long-term brain activity of seizure patients have recently been recorded. In therapeutic settings, scalp EEG and stereoelectroencephalography are two EEG variants that are frequently used (SEEG). While scalp EEG places the electrodes on the surface of the brain and SEEG inserts the electrodes deep inside the brain, EEG captures voltage variations brought on by ionic current within the brain's neurons [3]. Each EEG electrode in an EEG recording system, which typically consists of tens of electrodes, represents a persistent voltage signal at a particular spot in the brain. According to a common international technique, the location

determines the name of each electrode.

Electroencephalogram (EEG)





Data set

The CHB-MIT(Children's Hospital Boston-Massachusetts Institute of Technology) dataset, is a dataset of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. The dataset contains 23 patients divided among 24 cases (a patient has 2 recordings, 1.5 years apart). The dataset consists of 969 Hours of scalp EEG recordings with 173 seizures. There exist various types of seizures in the dataset (clonic, atonic, tonic). The diversity of patients (Male, Female, 10-22 years old) and different types of seizures contained in the datasets are ideal for assessing the performance of automatic seizure detection methods in realistic settings.

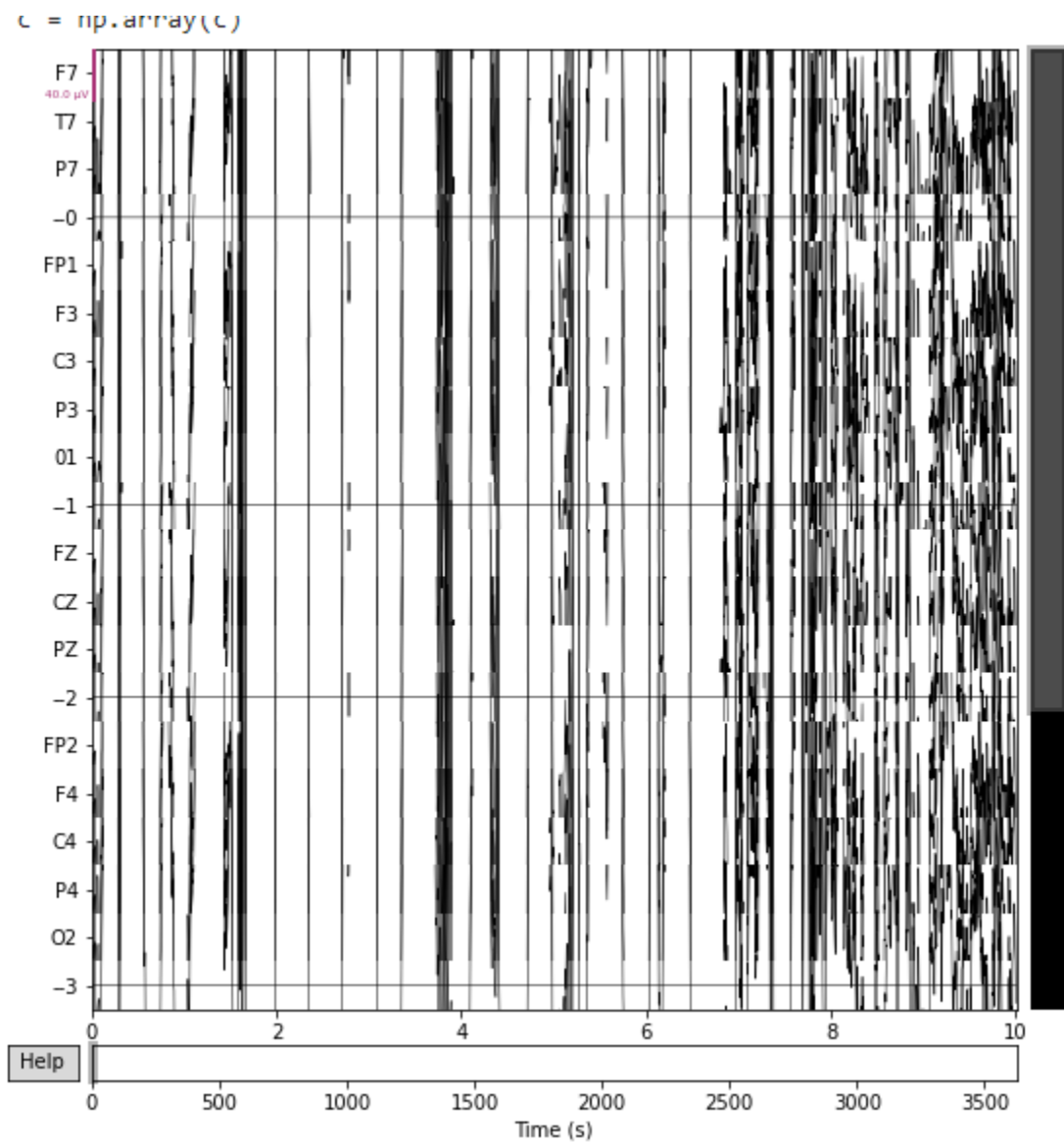
Pre-processing

Within the time domain, there is a clear difference between seizure and free cases.

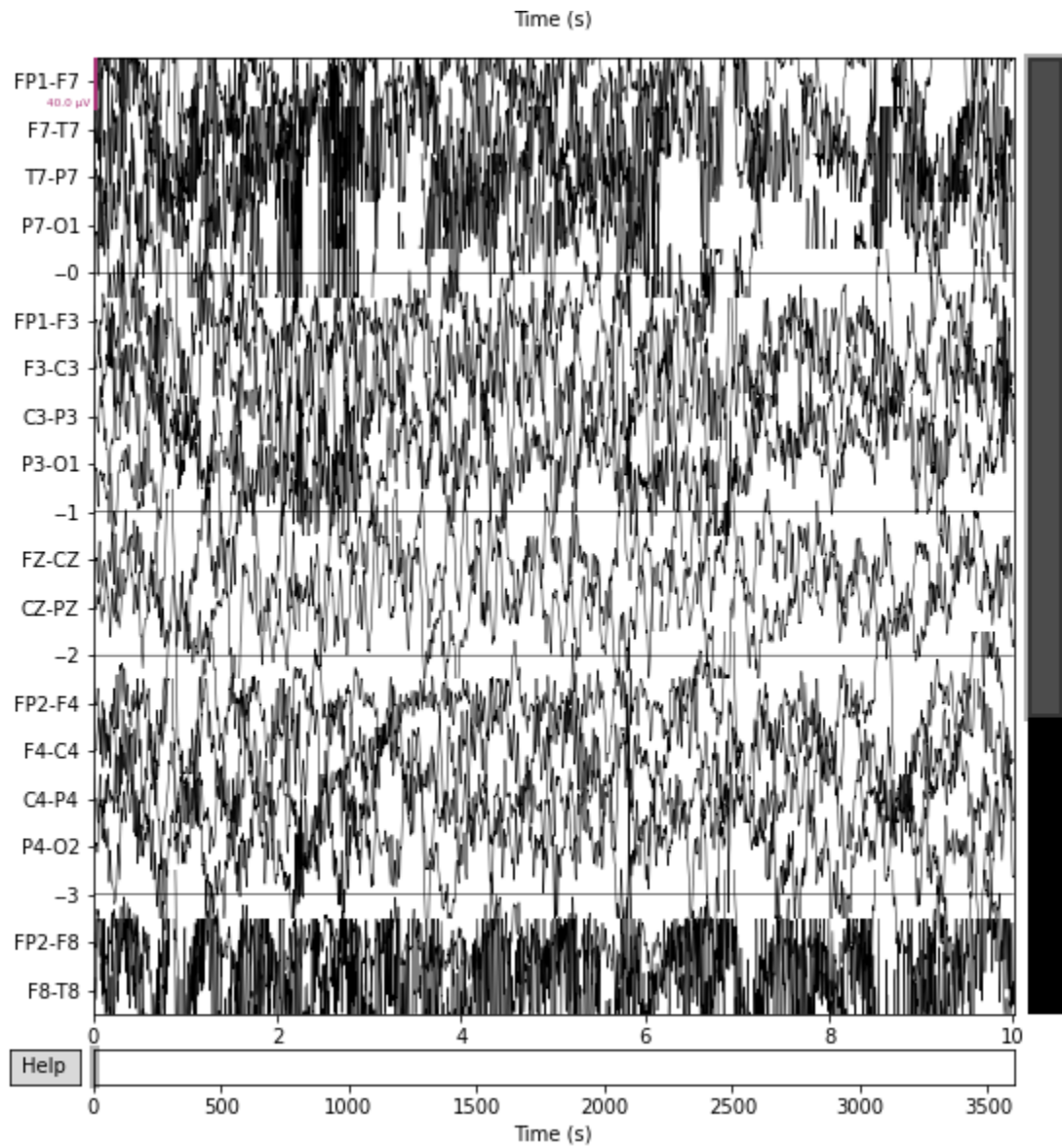
As seizure free records, the signal has the same pattern over the whole the time interval

On the other hand, the seizure cases contain compression waves with existing samples within an interval and there is no sample within other intervals.

The Seizure Patient:



The normal human behavior



- **Data Frame**

Showing some samples from the dataframe to take a look within the time domain

	F7	T7	P7	-	FP1	F3	C3	P3	Ø1	- ...	T8	P8	EKG1-CHIN	C2	C6	CP2	CP4	CP6	seizure	
0	-810.158730	-837.118437	-827.741148	0.0	-775.775336	-749.987790	-769.133089	-832.039072	-827.741148	0.0	...	-807.814408	-833.601954	-718.730159	-718.730159	-767.179487	-784.371184	-594.871795	-797.655678	0.0
1	0.195360	0.195360	0.195360	0.0	0.195360	0.195360	0.195360	0.195360	0.195360	0.0	...	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.0
2	0.586081	0.586081	0.586081	0.0	0.586081	0.586081	0.586081	0.586081	0.586081	0.0	...	0.586081	0.586081	0.195360	0.586081	0.586081	0.586081	0.586081	0.586081	0.0
3	2.539683	2.539683	2.148962	0.0	2.539683	2.148962	2.148962	2.148962	2.148962	0.0	...	2.539683	2.539683	0.195360	2.148962	2.539683	2.539683	3.321123	2.539683	0.0
4	-2.148962	-2.148962	-1.758242	0.0	-2.148962	-1.758242	-1.758242	-1.758242	-1.758242	0.0	...	-1.758242	-1.758242	0.195360	-1.758242	-2.148962	-1.758242	-0.586081	-2.148962	0.0

- **The intervals of the ictal samples:**

```

: [28355: 38691])
: [141824: 151553])
: [297728: 306945])
: [358656: 470433])
: [482304: 491777])
: [910592: 917505])

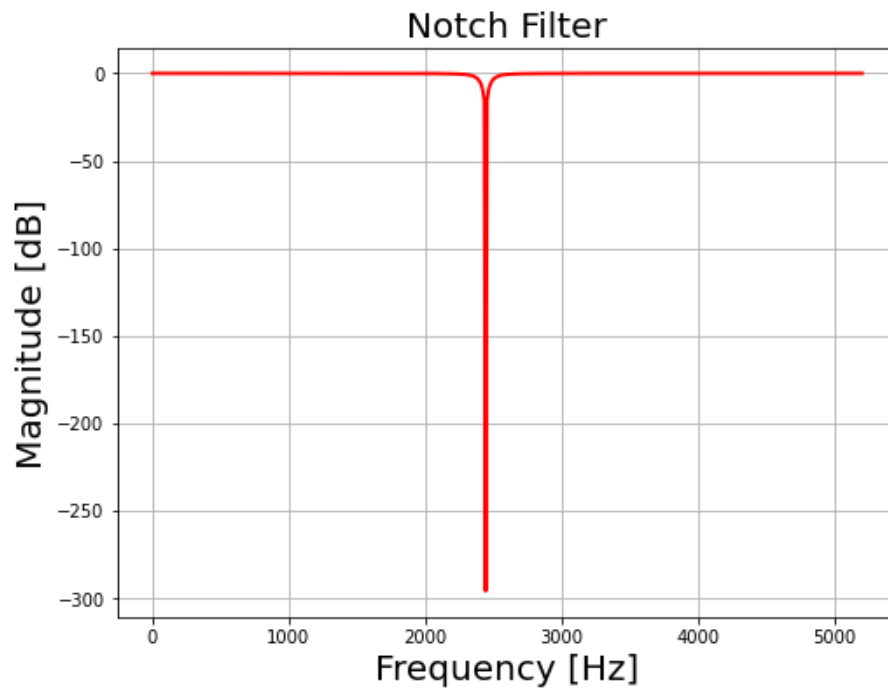
```


- collecting of all ictal intervals within only one dataframe:

```
seizure_record_df.sample(10)
```

	F7	T7	P7	-	FP1	F3	C3	P3	O1	-	...	T8	P8	EKG1-CHIN	C2	C6	CP2	CP4	CP6	seizure	index
384235	60.366300	117.802198	90.451770	0.0	88.498168	34.578755	22.857143	4.493284	74.822955	0.0	...	34.188034	83.809524	-15.824176	-32.625153	51.379731	-55.286935	-88.498168	-17.777778	0.0	384236
405196	214.700855	173.284493	192.039072	0.0	198.290598	179.926740	156.092796	166.251526	170.158730	0.0	...	204.932845	197.509158	282.686203	150.231990	252.600733	169.377289	174.847375	233.455433	0.0	405197
369012	49.035409	73.260073	66.617827	0.0	56.459096	128.351648	112.332112	119.365079	125.616606	0.0	...	-143.980464	171.721612	176.019536	212.356532	211.184371	235.799756	232.283272	245.567766	0.0	369013
487292	256.89657	150.231990	84.200244	0.0	354.969475	180.708181	163.907204	163.907204	116.630037	0.0	...	183.833944	176.410256	164.297924	181.098901	242.832723	198.681319	227.594628	220.561661	0.0	487293
382021	-904.713065	-871.501832	-803.516484	0.0	-907.448107	-914.481074	-855.482295	-808.205128	-825.396825	0.0	...	-848.840049	-879.706960	-842.588523	-863.296703	-860.952381	-861.733822	-826.568987	-880.879121	0.0	382022
445893	13.089133	43.956044	52.551893	0.0	-45.909646	33.797314	9.572650	30.671551	11.526252	0.0	...	29.499389	83.028083	9.572650	16.214896	14.261294	12.307692	-39.267399	42.783883	0.0	445894
383115	38.876679	23.247963	41.611722	0.0	49.426129	30.280630	17.777778	77.948718	74.041514	0.0	...	33.015873	49.816850	70.134310	22.075702	20.903941	45.518926	20.512821	27.155067	0.0	383116
448679	127.960928	112.332112	105.689866	0.0	145.934066	151.013431	123.663004	77.948718	68.571429	0.0	...	142.026862	97.094017	117.802198	154.139194	168.205128	123.272283	101.001221	158.437118	0.0	448680
424300	-123.272283	-113.504274	-115.067155	0.0	-88.888889	-105.689866	-118.192918	-86.935287	-114.285714	0.0	...	-25.201465	-90.061050	-93.968254	-100.219780	-61.538462	-89.670330	-77.948718	-68.571429	0.0	424301
463751	-10.744811	0.976801	22.075702	0.0	-21.684982	-39.267399	-4.102564	11.135531	54.505495	0.0	...	-0.195360	25.592186	-52.551893	-37.704518	-9.572650	-21.294261	-7.228327	0.976801	0.0	463752

Notch filter is working as a bandpass filter to remove the frequency component at 60 Hz for a signal that is sampled with $f_s = 256$. it returns the filter parameters and plot its response:



The function Filter signal takes selected channels and takes the data frame of the records and the filter parameter b, a. It applies the notch filter on the signal to remove the 60 Hz band frequency and then it plots the filtered signal.

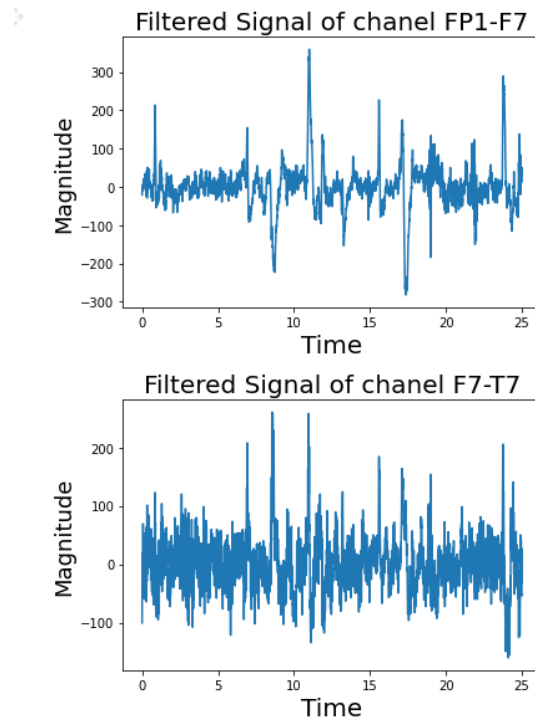
The user can edit it if he want to choose different channels to work with

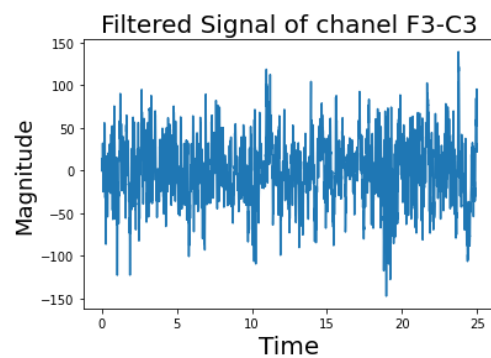
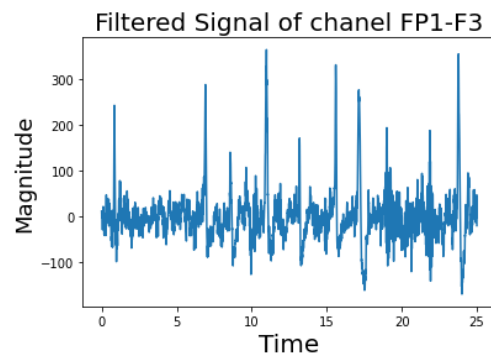
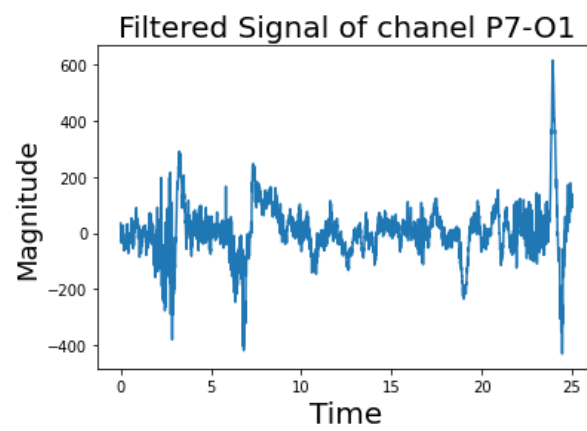
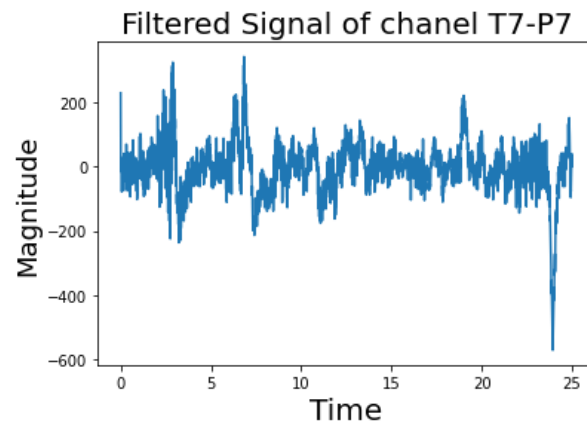
We need to find the average of the selected channels to work with it as a new feature that represents the performance of the selected channels:

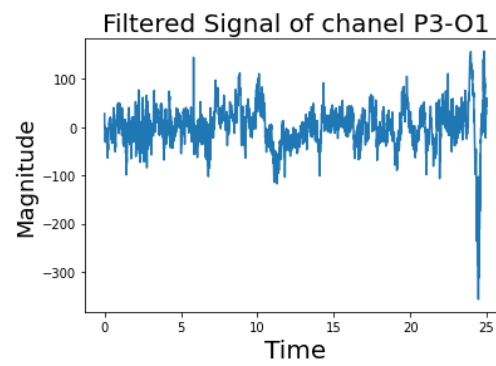
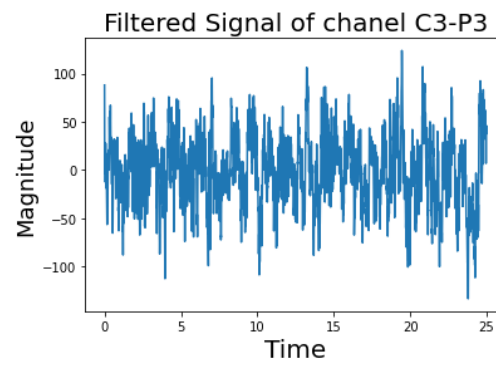
```
seizure_free_record_df['avgsignal'] = seizure_free_record_df[selected_chanel_free].mean(axis=1)
seizure_record_df['avgsignal'] = seizure_record_df[seizure_selected_chanel].mean(axis=1)
```

Filtering the seizure free records:

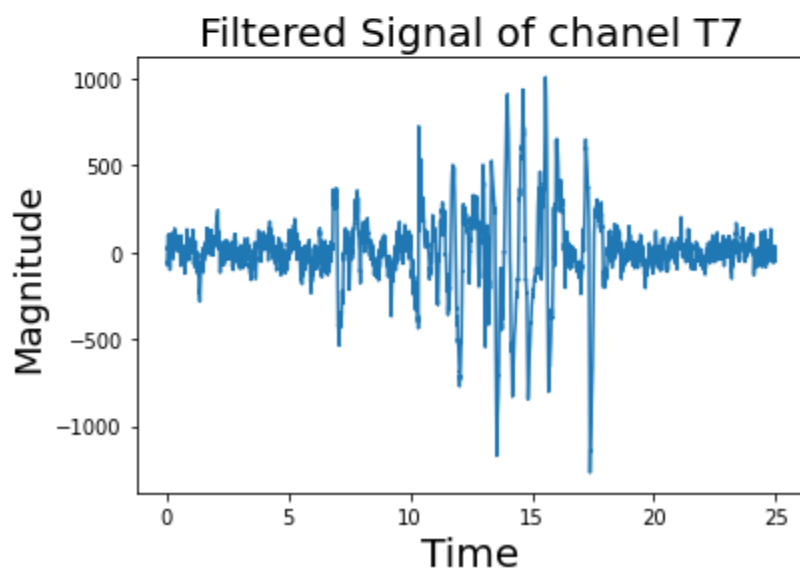
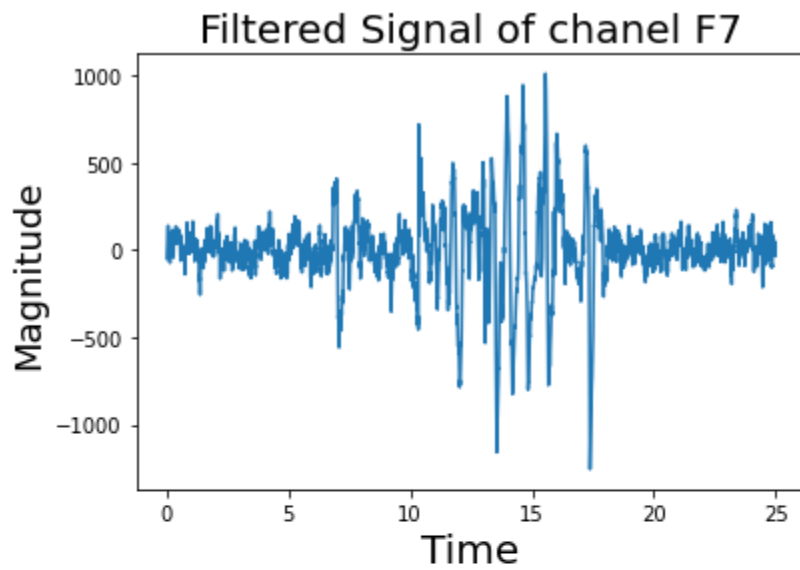
Without averaging, it works on the selected channel



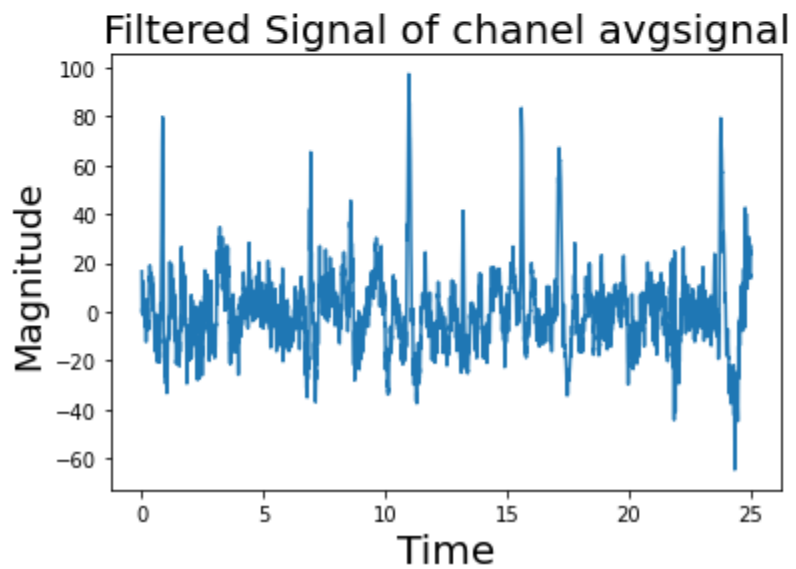
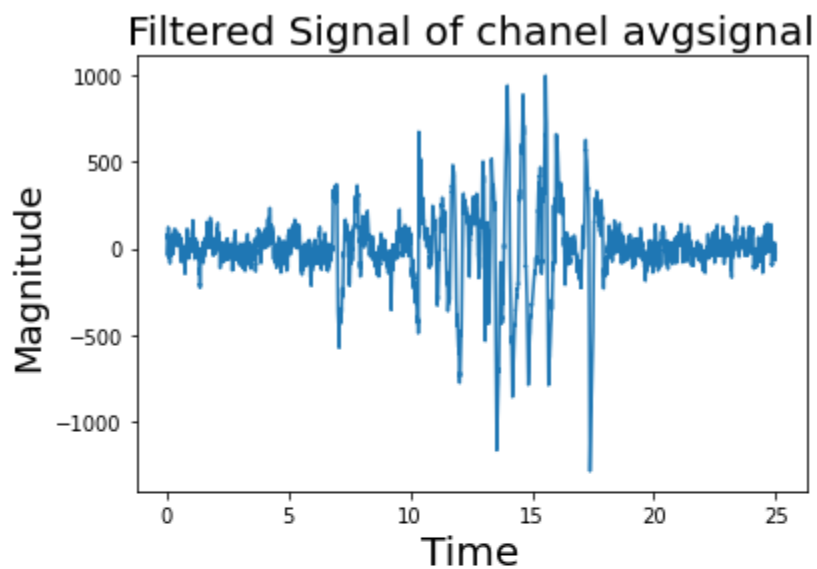




For the Seizure cases graphs:



working on the average new channel that represents the selected channels:



We notice that within the seizure samples a sudden change in the samples on the other hand, with free seizure has the same pattern over the whole time interval.

Spectrogram

calcSTFT evaluate the STFT of each signal with input parameters

such as, the signal itself, fs, the window type, the window length, the number of points to overlap:

inputSignal: numpy array for the signal (it also works for Pandas.Series);

samplingFreq: the sampling frequency;

window : str or tuple or array_like, optional

Desired window to use. If `window` is a string or tuple, it is

passed to `get_window` to generate the window values, which are

DFT-even by default. See `get_window` for a list of windows and

required parameters. If `window` is array_like it will be used

directly as the window and its length must be nperseg. Defaults

to a Hann window.

nperseg : int, optional

Length of each segment. Defaults to 256.

figsize: the plot size, set as (6,3) by default;

cmap: the color map, set as the divergence Red-Yellow-Green by default;

ylim_max: the max frequency to be shown. By default it's the half sampling frequency;

output: 'False', as default. If 'True', returns the STFT values.

Outputs (if TRUE):

f: the frequency values

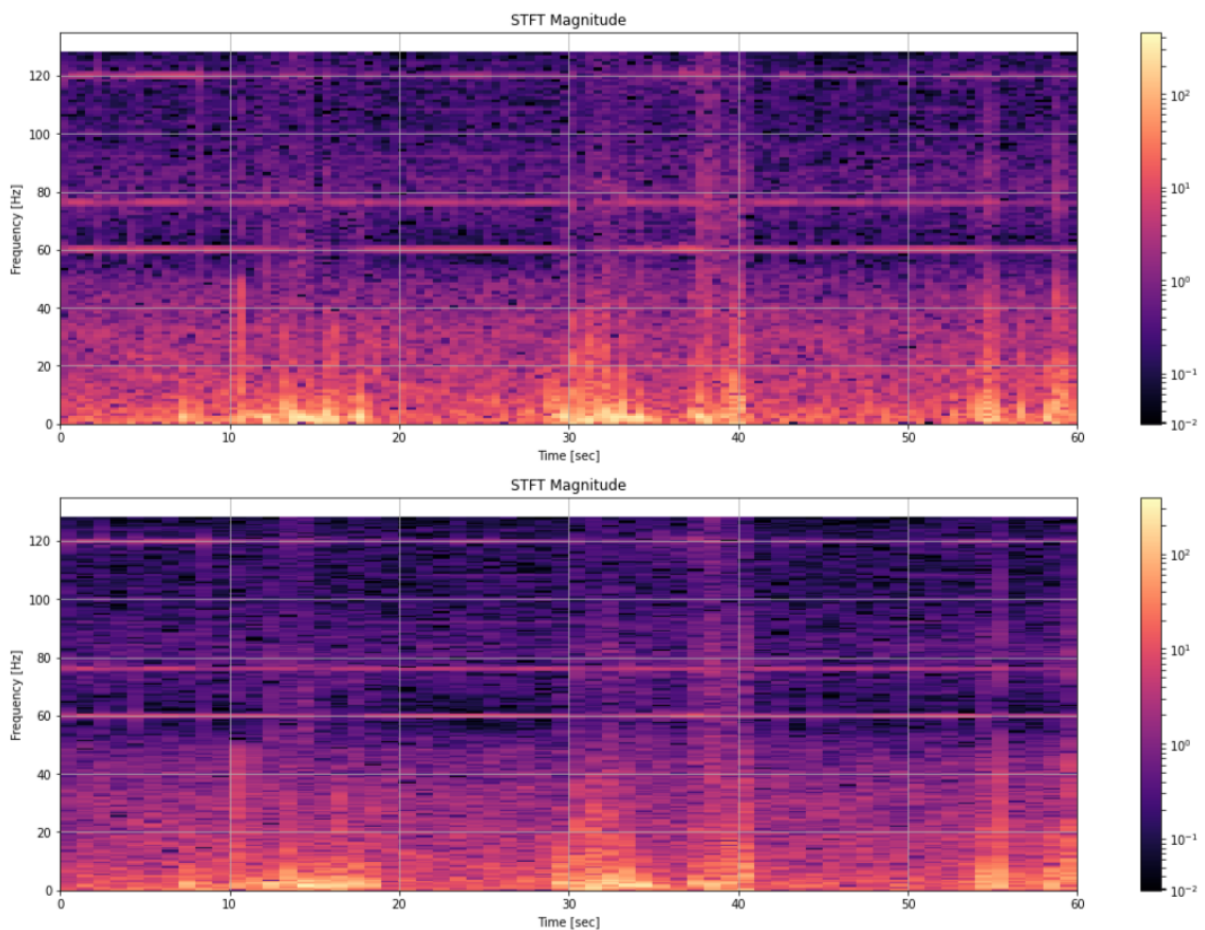
t: the time values

Zxx: the STFT values""

Changing Window Parameters:

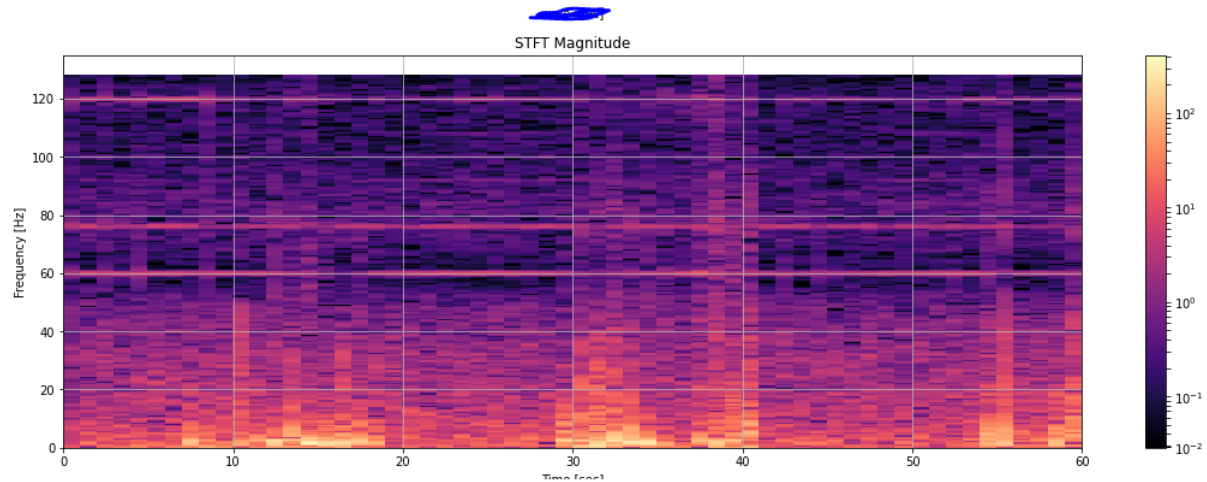
Different window size

we let the type fixed here with different window size and for the upcoming cells, we will use different window types but with different window sizes

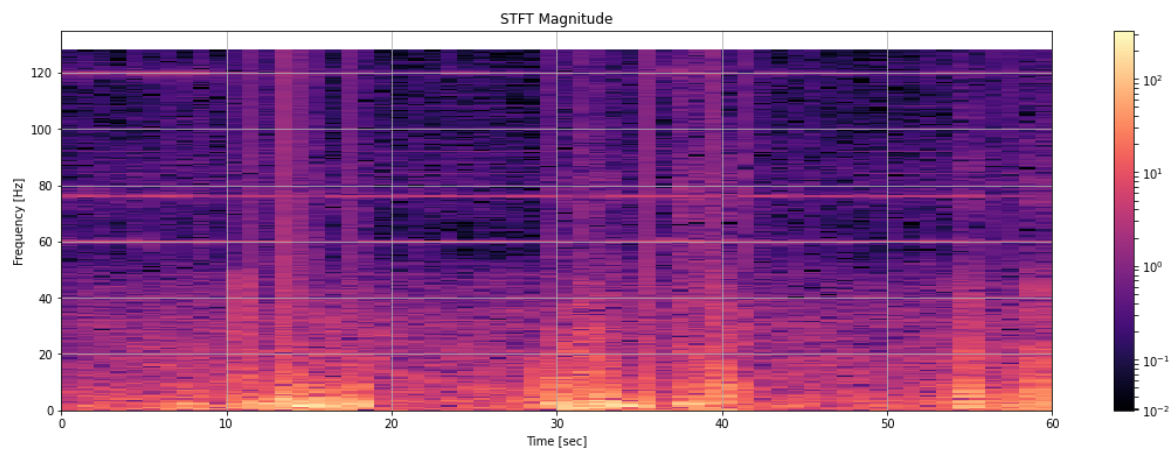


Changing the window type parameter:

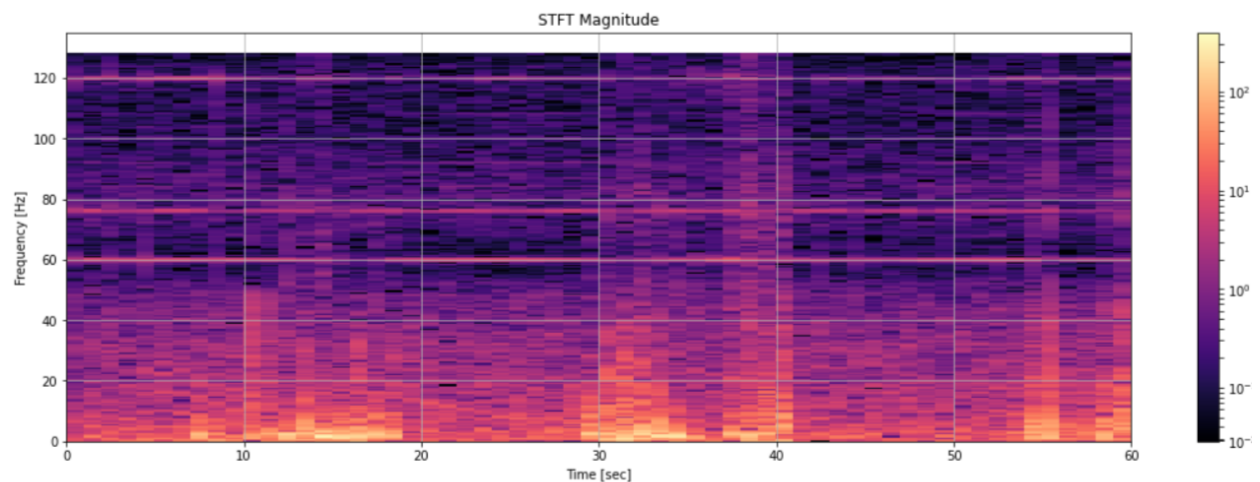
window of balckman:



Boxcar window -Rectangular Window-:



Triang window :



Comment:

till now, we have performed different window sizes with different window types. We have noticed a tradeoff of using a window size over another size and different window types which each one has a specific target we use it when we need to achieve.

- **Window Size:**

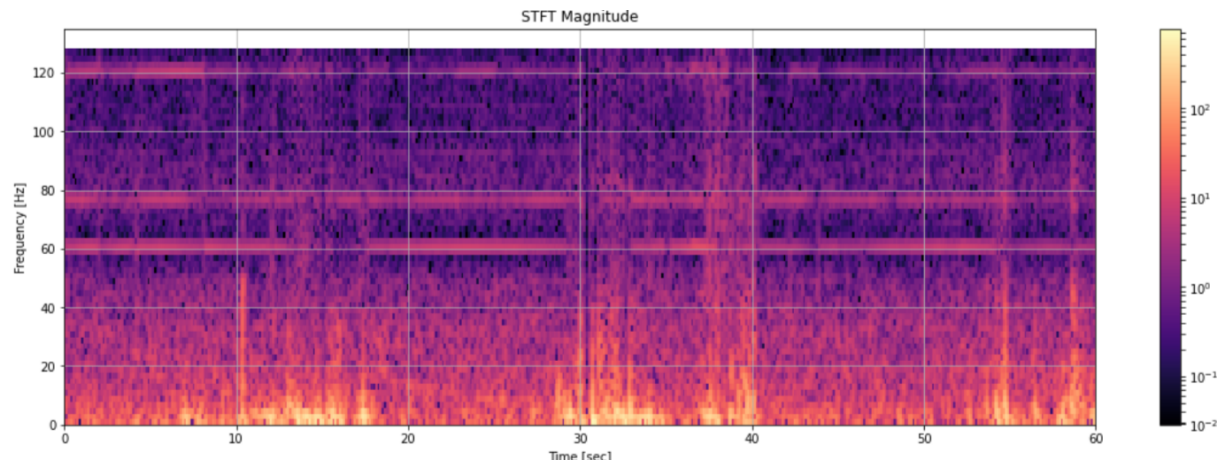
We have noticed that for larger window sizes, we get high frequency resolution but a bad Time resolution and more DFT points

for smaller window sizes, we get a bad Frequency resolution and a high Time resolution with fewer DFT points.

- **Window Type:**

for the dataset we are working on, isolated frequencies that are far from each other, but there were noises around the main signals. We have noticed that the most suitable window for that task is the Hamming window which has a wider main component to clarify the main signals and very small side components that help us to ignore the noises effect.

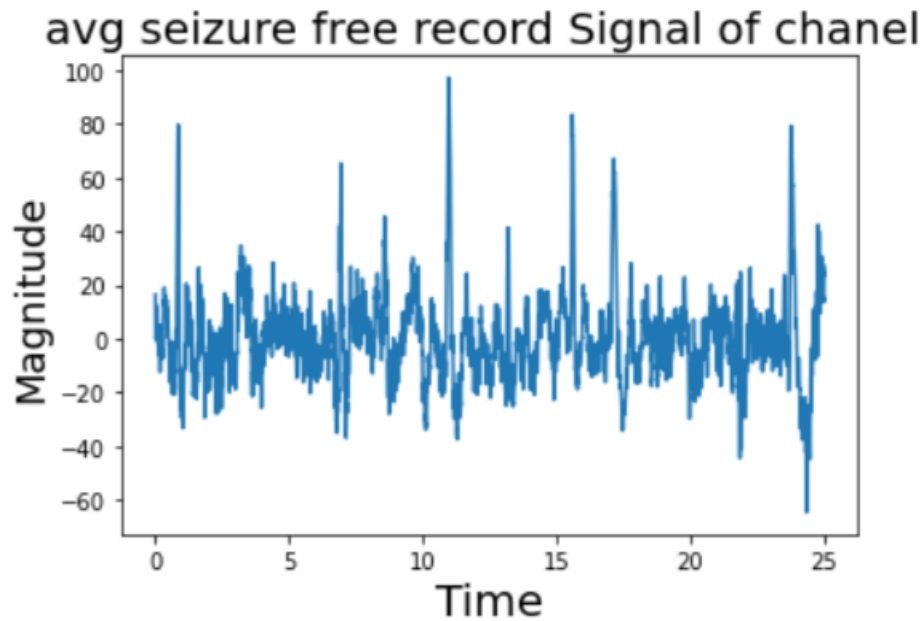
- **Changing Overlapping number of points parameter:**



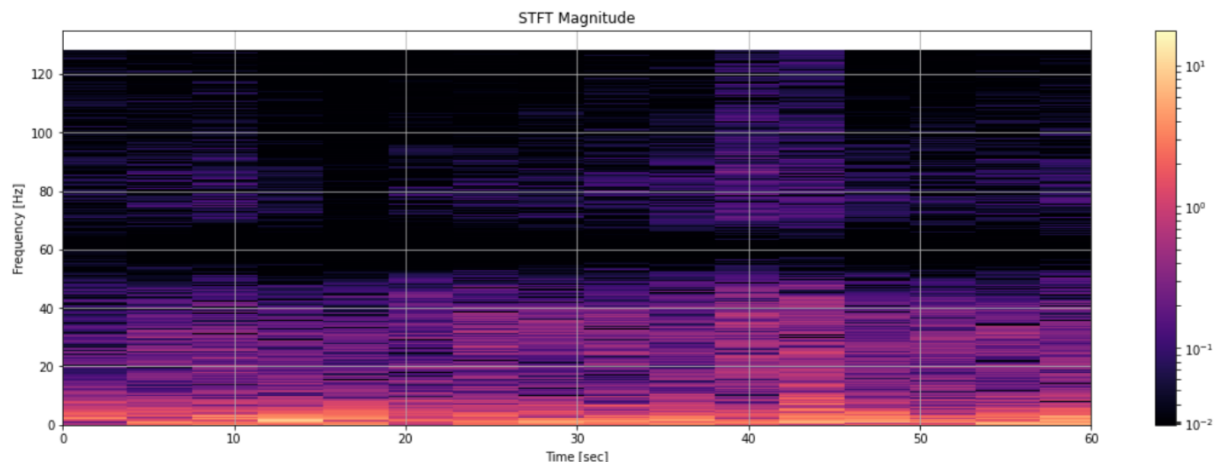
Using different overlapping samples according to the length of the window or the number of points in each segment. We have noticed that for smaller overlapping ratios, we get high frequency resolution but a bad time resolution. For larger overlapping ratios, we get a bad frequency resolution and a high time resolution. For the filtered seizure cases, we can notice the existence of the frequency component in the spectrogram graph at different frequencies in addition to the 60 Hz band component.

for the filtered free, there is no 60 Hz band component

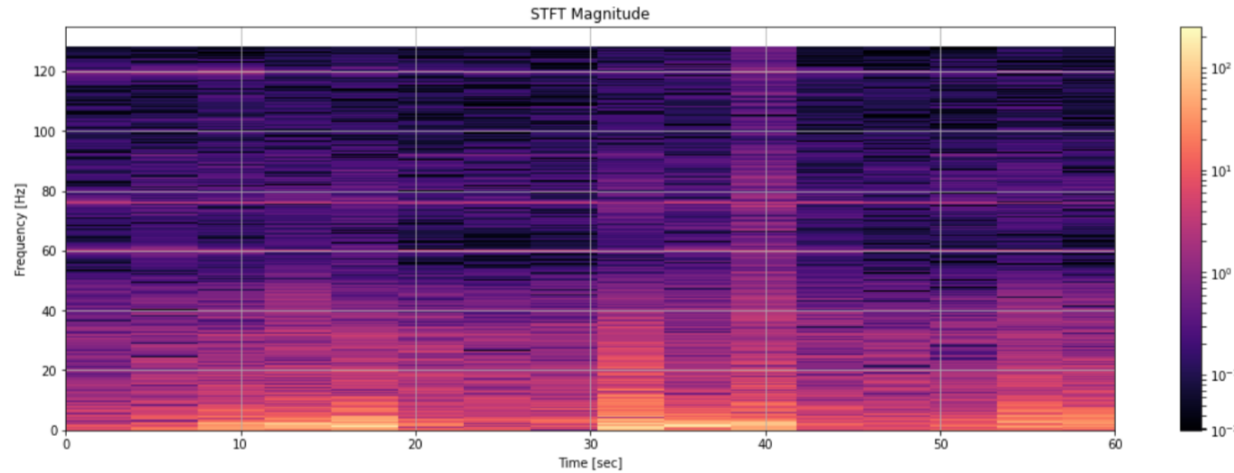
there is no band larger than 100



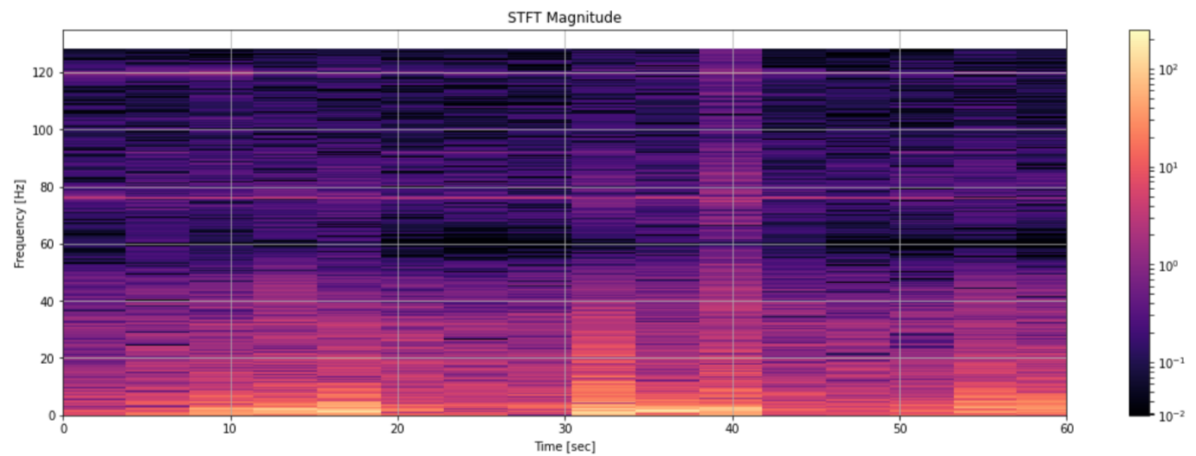
- free filtered:



The next spectro. is for the avg seizure records which contain different frequency components in addition to the band 60 Hz one.



The same signal but now it is filtered:



For the filtered Seizure records, it is clear that the filter removed the band 60 Hz component frequency from the frequencies components.