# Signal Processing Techniques to Improve Feature Space for EEG-based Epileptic Seizure Detection

Project Presentation

BME 1473: Acquisition and Processing of Bioelectrical Signals

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M.A.Sc. in Electrical and Computer Engineering

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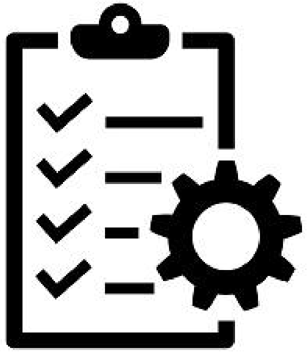
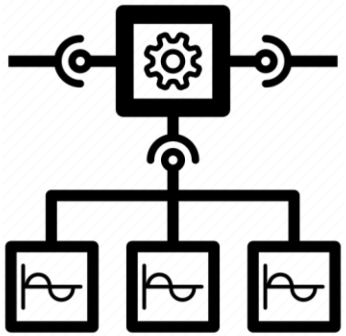
# Content

Problem Statement



Background



Analysis Results

Conclusions

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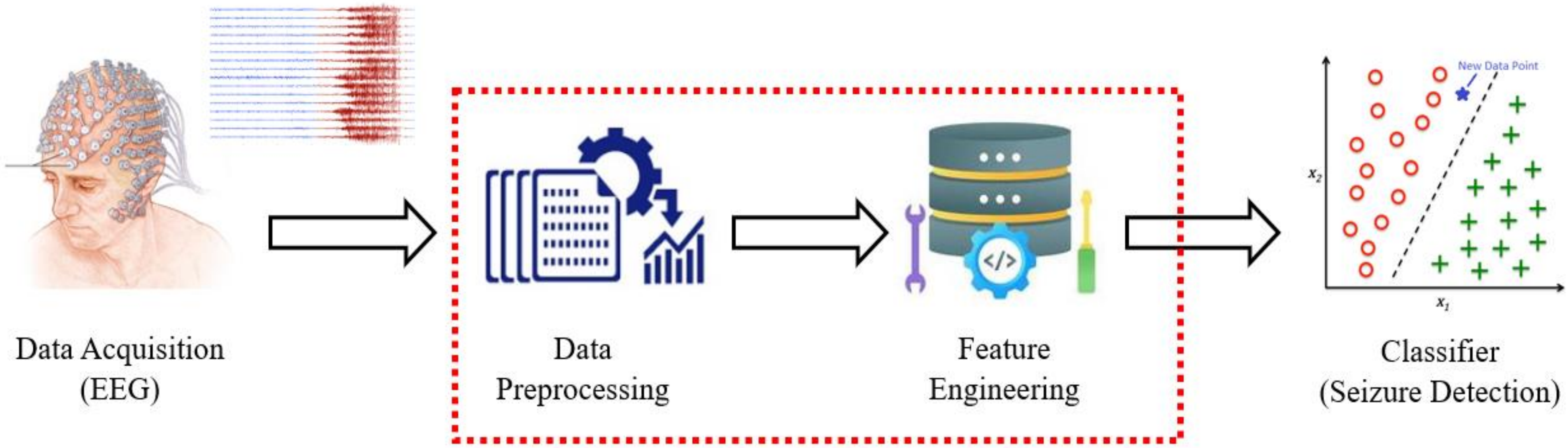

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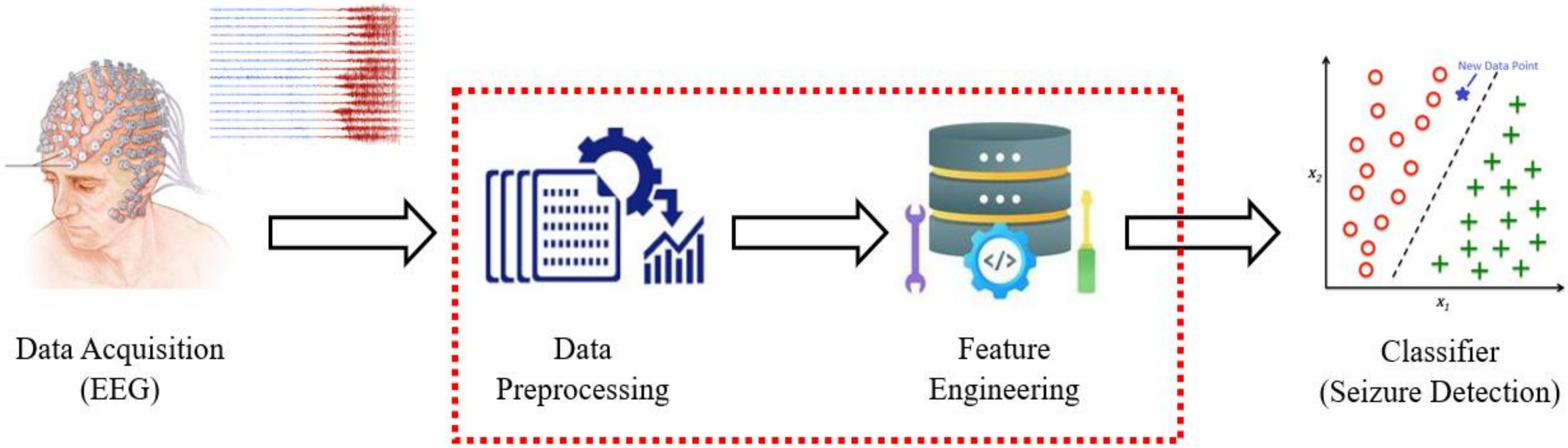


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- Analyze the impact of signal processing techniques on <u>Epilepsy Detection Accuracy.</u>
  i. Data Preprocessing (EEG Sphering + EEG Denoising)
  ii. Feature Engineering

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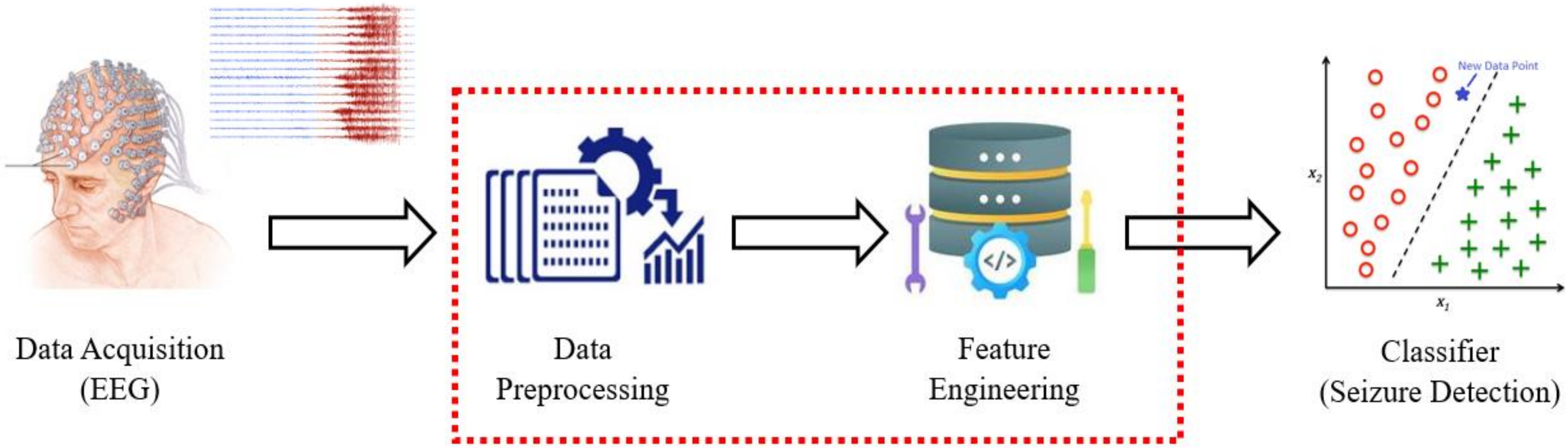


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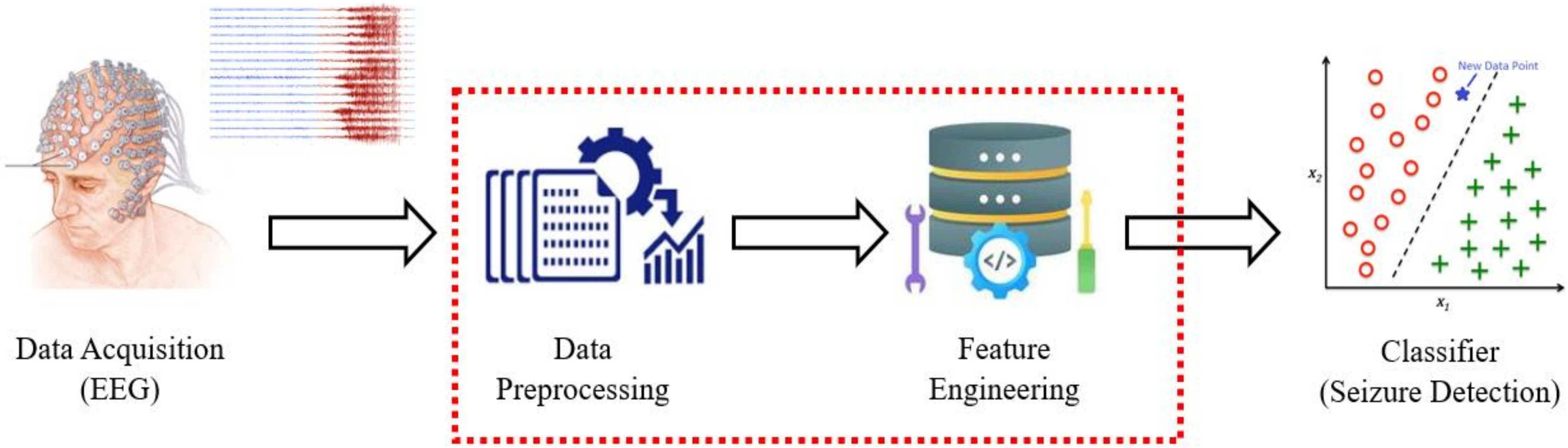


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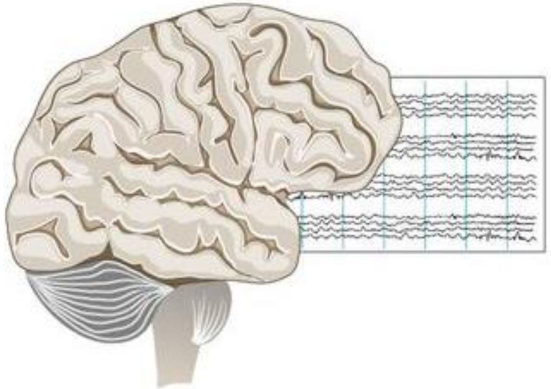
## Epilepsy

- A central nervous system (neurological) disorder
- Brain activity becomes abnormal
- Causes seizures or periods of unusual behavior, sensations and sometimes loss of awareness.



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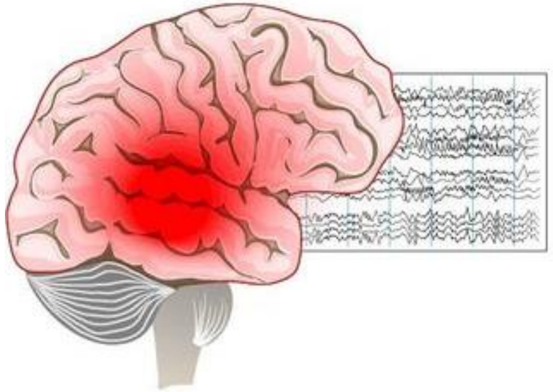

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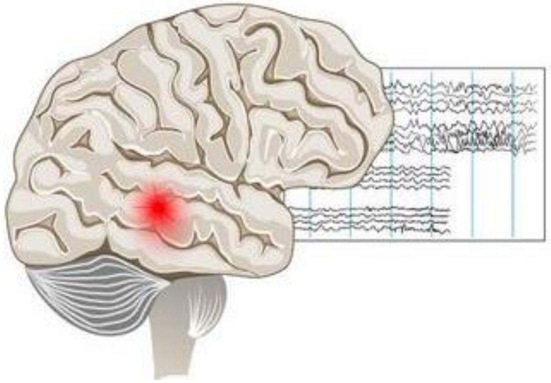

Focal Seizure

Source: [Epilepsy - Symptoms and causes - Mayo Clinic]

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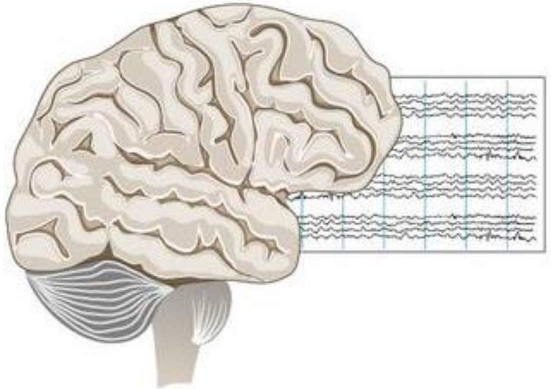

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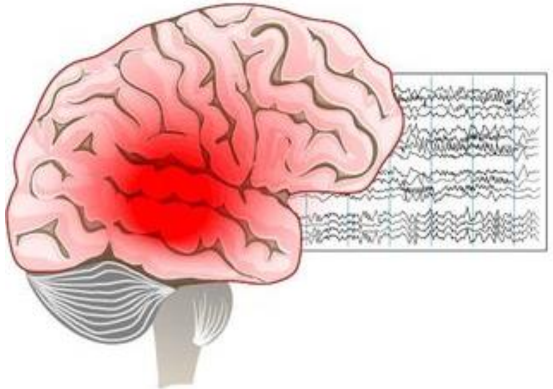

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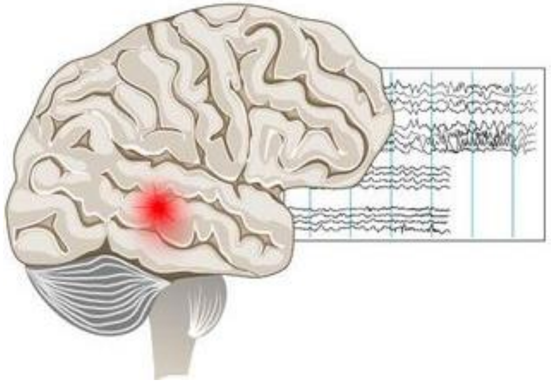

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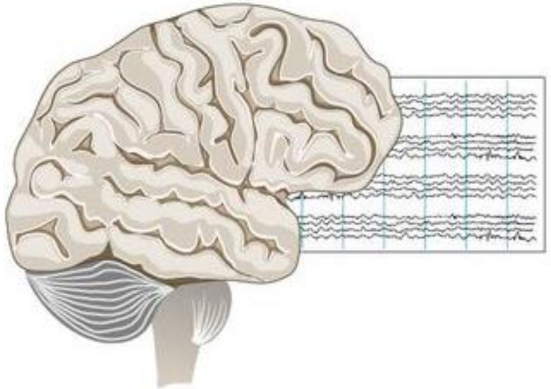

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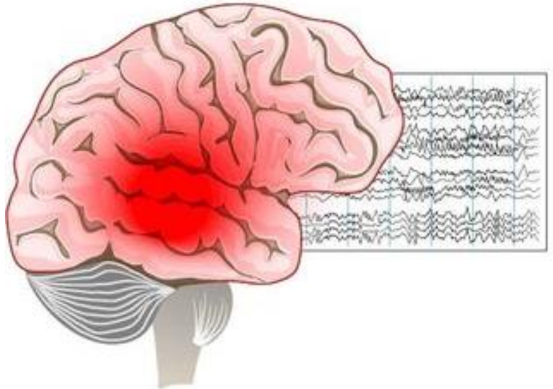

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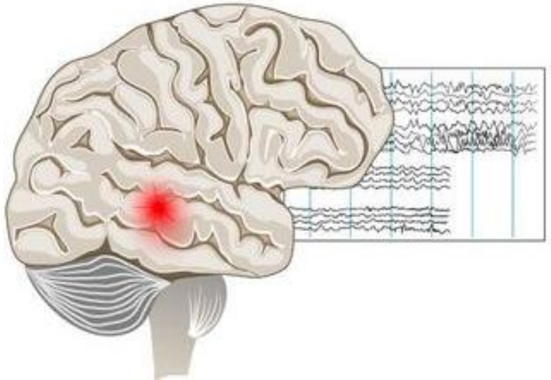

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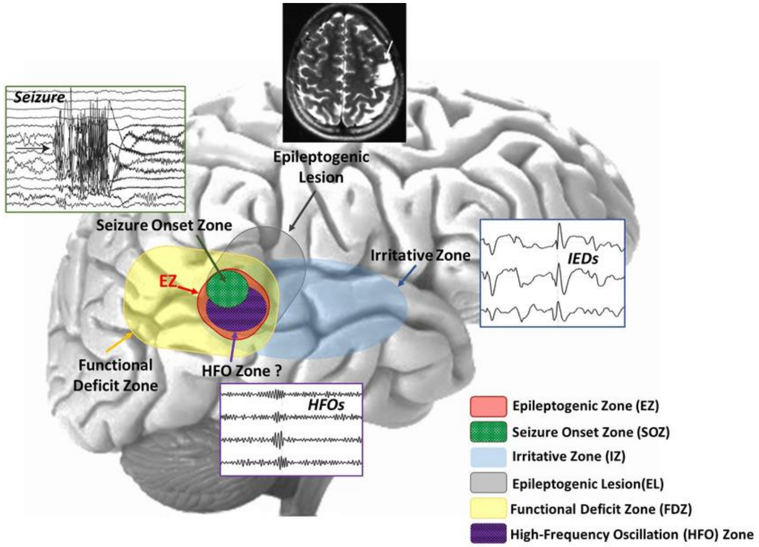
Epileptogenic Zone




Source: Tamilia, Eleonora, et al.[1]

# Background

## Dataset: Epileptogie EEG Data[2, 3]

A publicly available dataset with 5 data directories

A. Surface EEG from 5 volunteers in a relaxed state with eyes open
B. Surface EEG from 5 volunteers in a relaxed state with eyes closed
C. Intracranial EEG from 5 patients from the hippocampal formation of the opposite hemisphere of the brain – Inter-Ictal EEG Signals
D. Intracranial EEG taken from 5 patients from within the epileptogenic zone - Inter-Ictal EEG Signals
E. Intracranial EEG taken from 5 patients from within the epileptogenic zone – Ictal EEG Signals

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FIG. 2. Scheme of intracranial electrodes implanted for presurgical evaluation of epilepsy patients. Depth electrodes were implanted symmetrically into the hippocampal formations (top). Segments of sets C and D were taken from all contacts of the respective depth electrode. Strip electrodes were implanted onto the lateral and basal regions (middle and bottom) of the neocortex. Segments of set E were taken from contacts of all depicted electrodes.

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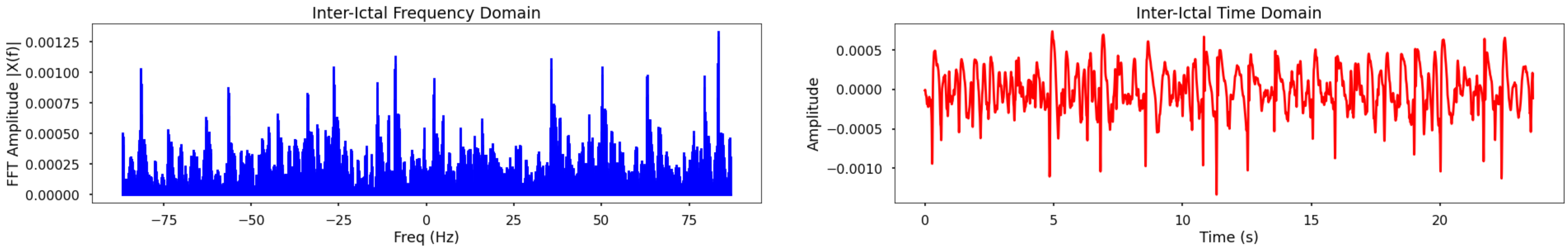


Figure: Inter-Ictal EEG Signal Sample

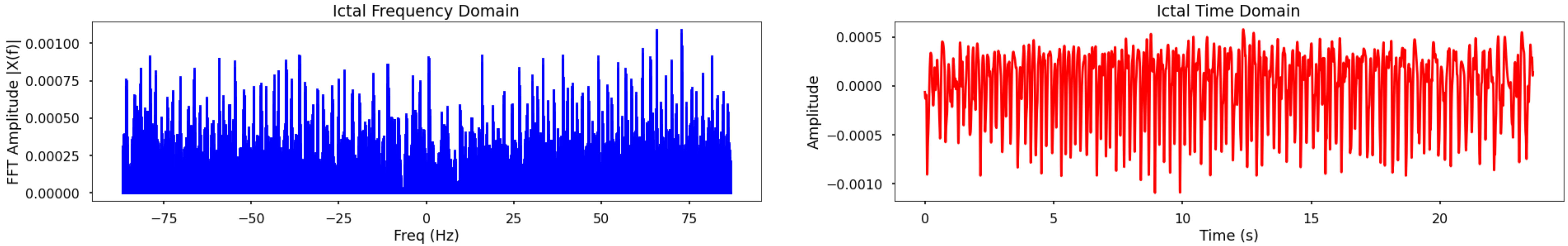


Figure: Ictal EEG Signal Sample

# Background

## Dataset: Epileptogie EEG Data[2, 3]

Table: Summary of Dataset Used

| | |
|---|---|
| **Sampling Frequency** | **173.63 Hz** |
| **Inter-Ictal EEG Signal dataset (D)** | 100 segments |
| **Ictal EEG Signal dataset (E)** | 100 segments |
| **Recording Site** | Hippocampus Formation |
| **Reference** | Average Common Regerence |
| **Type of Data** | Intracranial EEG |
| **Segment Length** | 23.6s (4097 samples) |

# Background

## Applications of Signal Processing

Data Preprocessing

Data
Detrending
Data
Whitening
PCA, ZCA

Data
Denoising
FIR Filtering
DWT Denoising

Data Engineering

Time-
Frequency
Features
Wavelet
Transformation

Temporal/
Spectral
Features
Spectral/Tempor
al Entropy etc.

Step 01

Data Detrending

$$\tilde{x} = x - \bar{x} \in \mathbb{R}^{N \times M}$$

$$\bar{x} = \frac{1}{M}\sum_{i=1}^{M} x_i$$

To obtain Weak Stationarity

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Step 02

**Data Whitening**

$$x_w = W\tilde{x}$$

$$\Sigma_{Original} = \mathbb{E}[\tilde{x}\tilde{x}^T]$$

$$\Sigma_{Original} = Q\Lambda Q^T \in \mathbb{R}^{N \times N}$$

$$W^{PCA} = \Lambda^{-\frac{1}{2}}Q^T \qquad W^{ZCA} = Q\Lambda^{-\frac{1}{2}}Q^T$$

To decorrelate the EEG signals in the dataset

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- Attenuate possible artifacts and noise components that result from different sources including the brain rhythms that are caused by other neural activities
- Use *attenuating frequencies of interest*
- Spectral components above 40 Hz that corresponds to $\gamma$ brain rhythms are usually irrelevant for seizure

# Background

## Applications of Signal Processing


**FIR Filtering**

Finite length and maintain a linear phase response within the passband

Two parameters are critical

- *Filter Window Type:*

  (1) rectangular window

  (2) Hamming window

  (3) Blackman-Harris window.

- *Filter Order (or window length):* $n = \{16, 32, 64, 128\}$.

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**DWT Denoising**

Decompose the signal into multiple bands and attenuate the spectral components in the higher resolutions if the noise operates at the higher resolutions

Two parameters are critical

- *Wavelet Function:*
  - (1) Daubechies with 2 taps (db2)
  - (2) Daubechies with 6 taps (db6)
  - (3) Daubechies with 8 taps (db8)
  - (4) Haar
- *Filter bank levels:* $n = 6$

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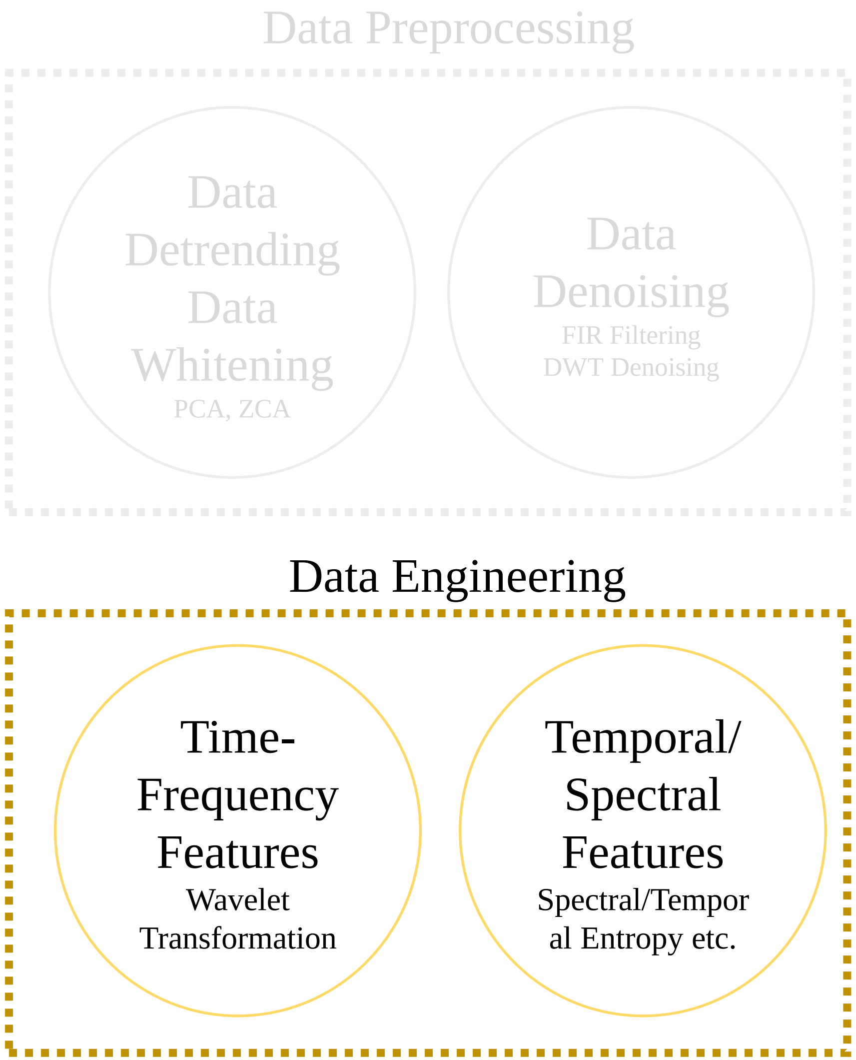


**Wavelet Transformation-based Features**

Uses discrete wavelet coefficients

Three critical parameters that need further analysis

- *Wavelet Transformation:*

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**Wavelet Transformation-based Features**

Features Extracted

| Feature | Description |
| --- | --- |
| **Log-Sum Energy** | Log-transformed wavelet coefficients to achieve robustness to noise |
| **Mean of Absolute Value** | Average of absolute wavelet coefficients for each sub-band |
| **Average Power** | Average of wavelet coefficients for each sub-band |
| **Standard Deviation** | Standard deviation (variance) of wavelet coefficients |
| **Ratio of the Absolute Mean values** | Ratios of mean absolute features of adjacent sub-bands |

# Background

## Evaluation Metrics

| Metric | Definition |
|---|---|
| **Signal Distortion (dB)** | $10\log\left(P^2_{filtered,0-40}/P^2_{unfiltered,0-40}\right)\ dB$ |
| **Noise Reduction (dB)** | $10\log\left(P^2_{filtered,>40}/P^2_{unfiltered,>40}\right)\ dB$ |
| **Accuracy** | $(TP+TN)/(TP+TN+FP+FN)\,\%$ |
| **Precision** | $TP/(TP+FP)\,\%$ |
| **Sensitivity/Recall** | $TP/(TP+FN)\,\%$ |
| **Specificity** | $TN/(TN+FP)\,\%$ |
| **F1 Score** | $(2\times TP)/(2TP+FP+FN)\,\%$ |
| **Area Under the Curve (AUC)** | Area of the Receiver Operating Characteristic (ROC) curve |

$P^2_{\mathrm{i},0-40}$ = Signal Power of interest (within 0 – 40 Hz),

$P^2_{\mathrm{i},>40}$ = Noise Power of interest (above 40 Hz),

i $\in \{unfiltered, filtered\}$

TP = # true positive predictions

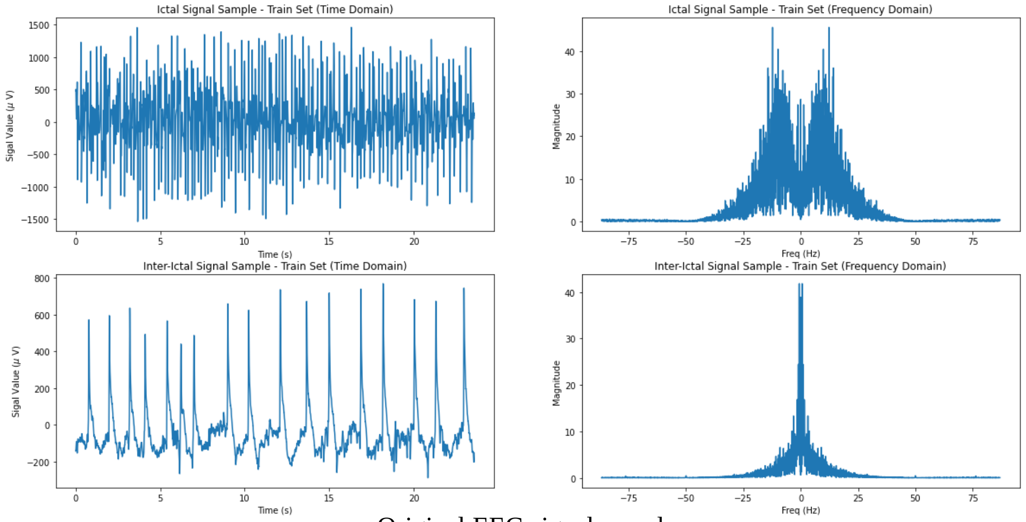
FP = # false positive predictions

TN = # true negative predictions

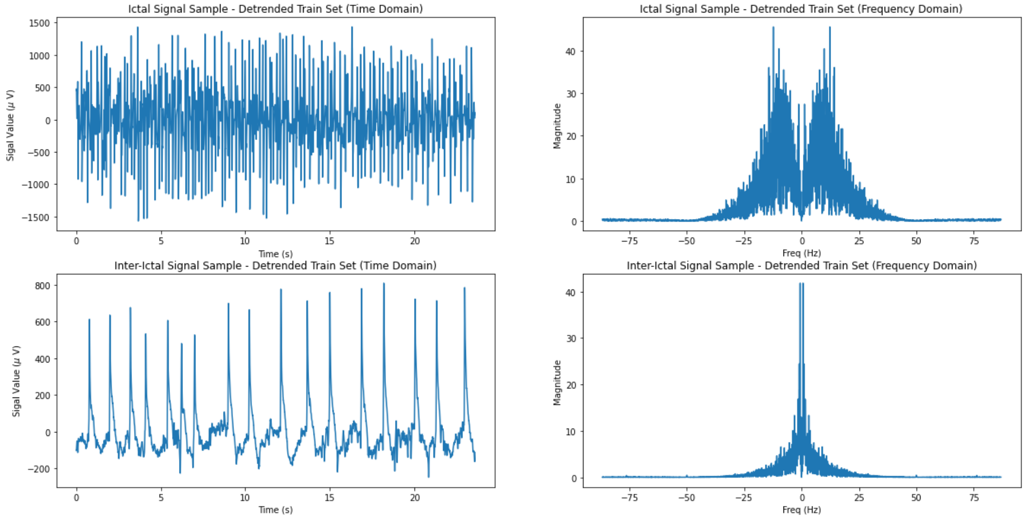
FN = # false negatives predictions

# Analysis

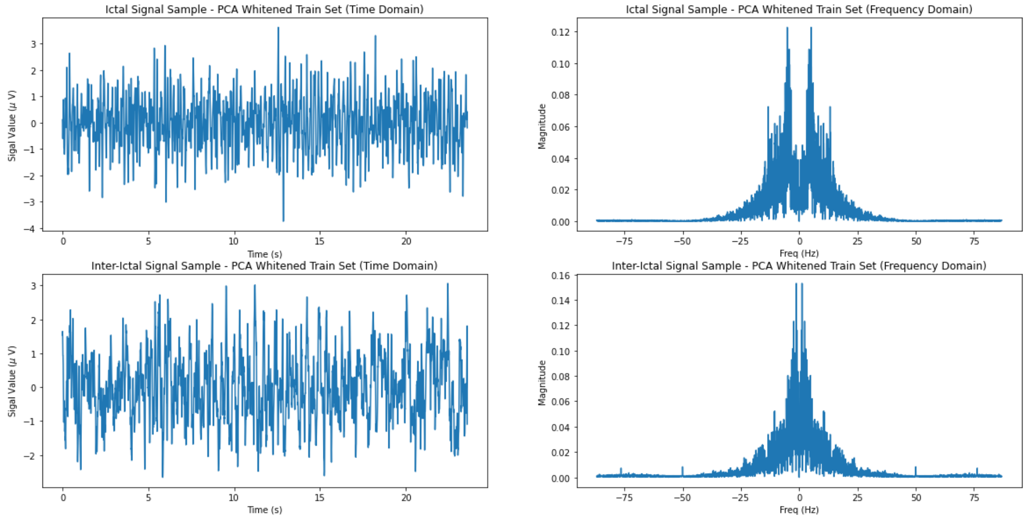
## Data Preprocessing – Data Detrending and Whitening



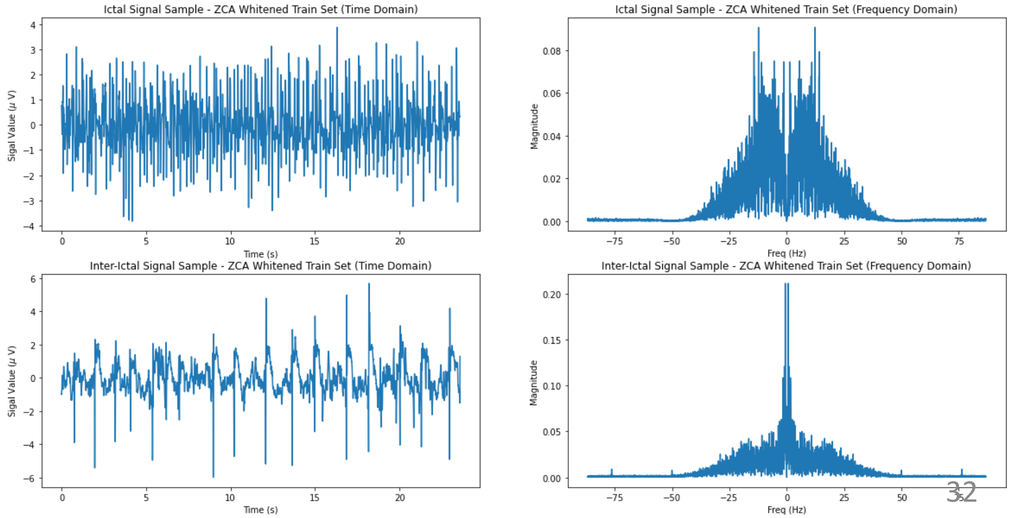

Original EEG signal sample




Detrended original signal sample




PCA-whitened original signal sample






ZCA whitened original signal sample

# Analysis

## Data Preprocessing – Data Detrending and Whitening

Observations:

- Detrending has little effect – Dataset has already made weak stationarity
- PCA-whitened signals – most of the oscillations within $\pm 1$ from its mean.
- Changed the spectrum of the original signal.

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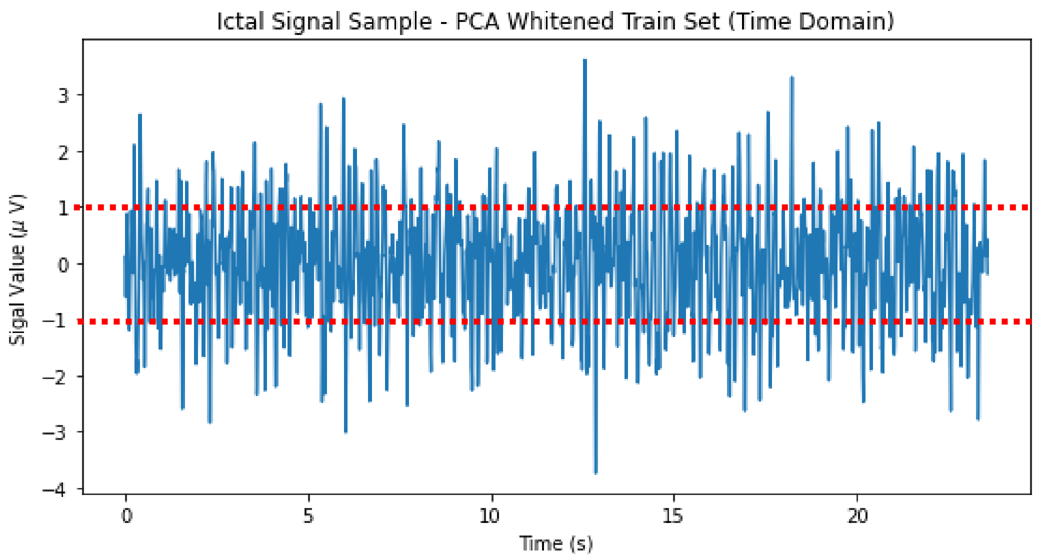


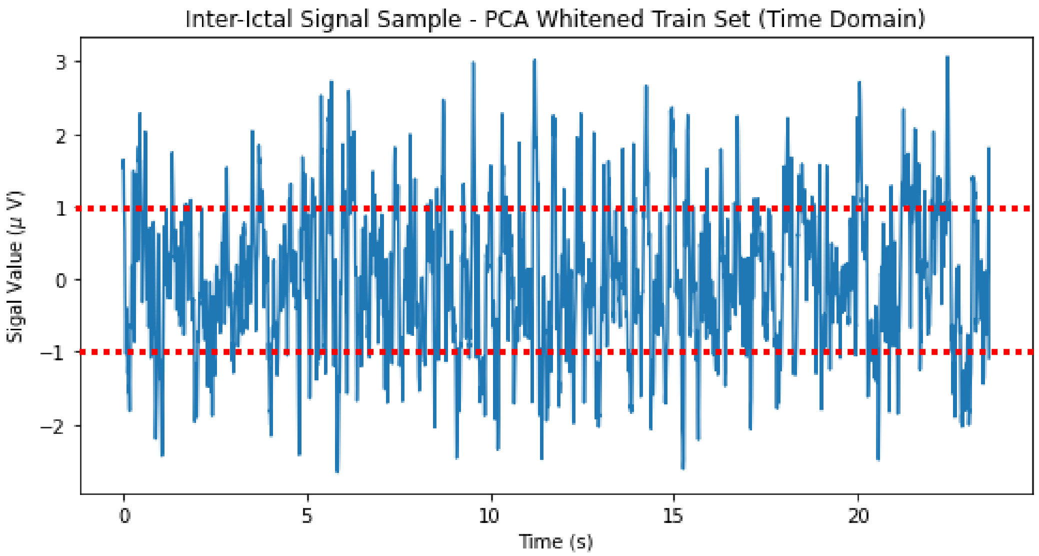

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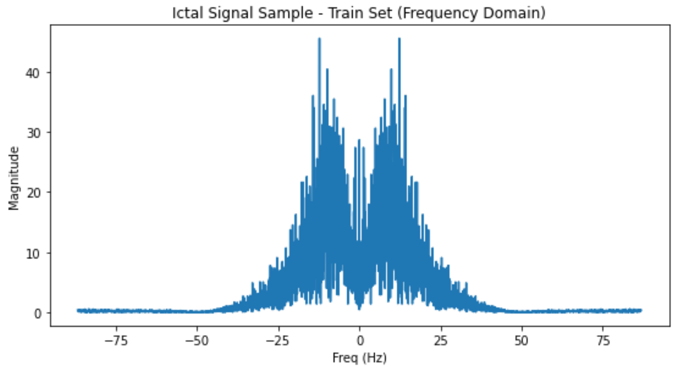


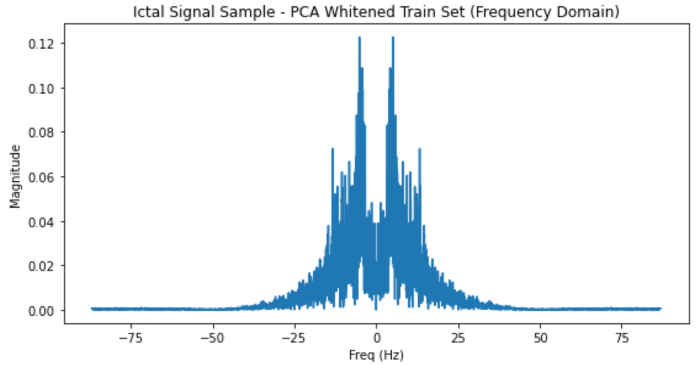


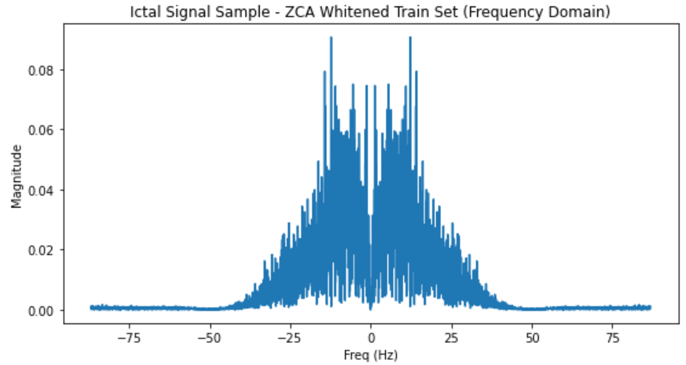


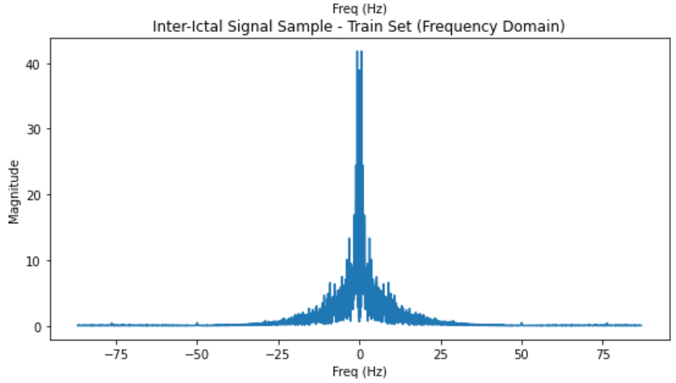


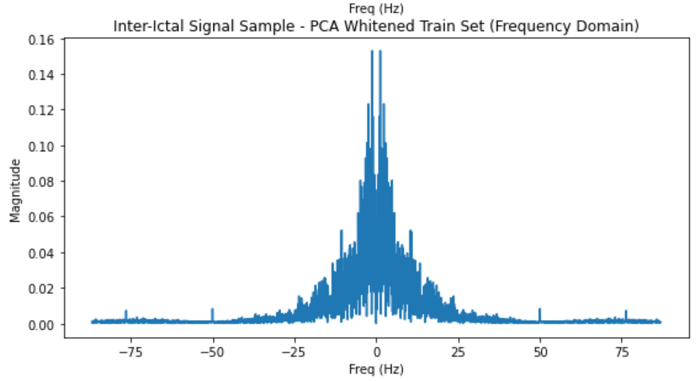


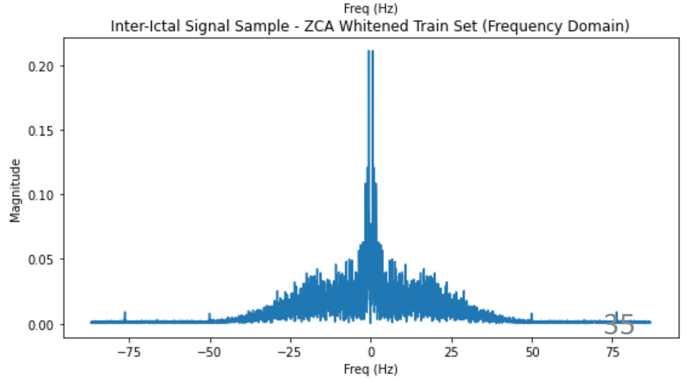

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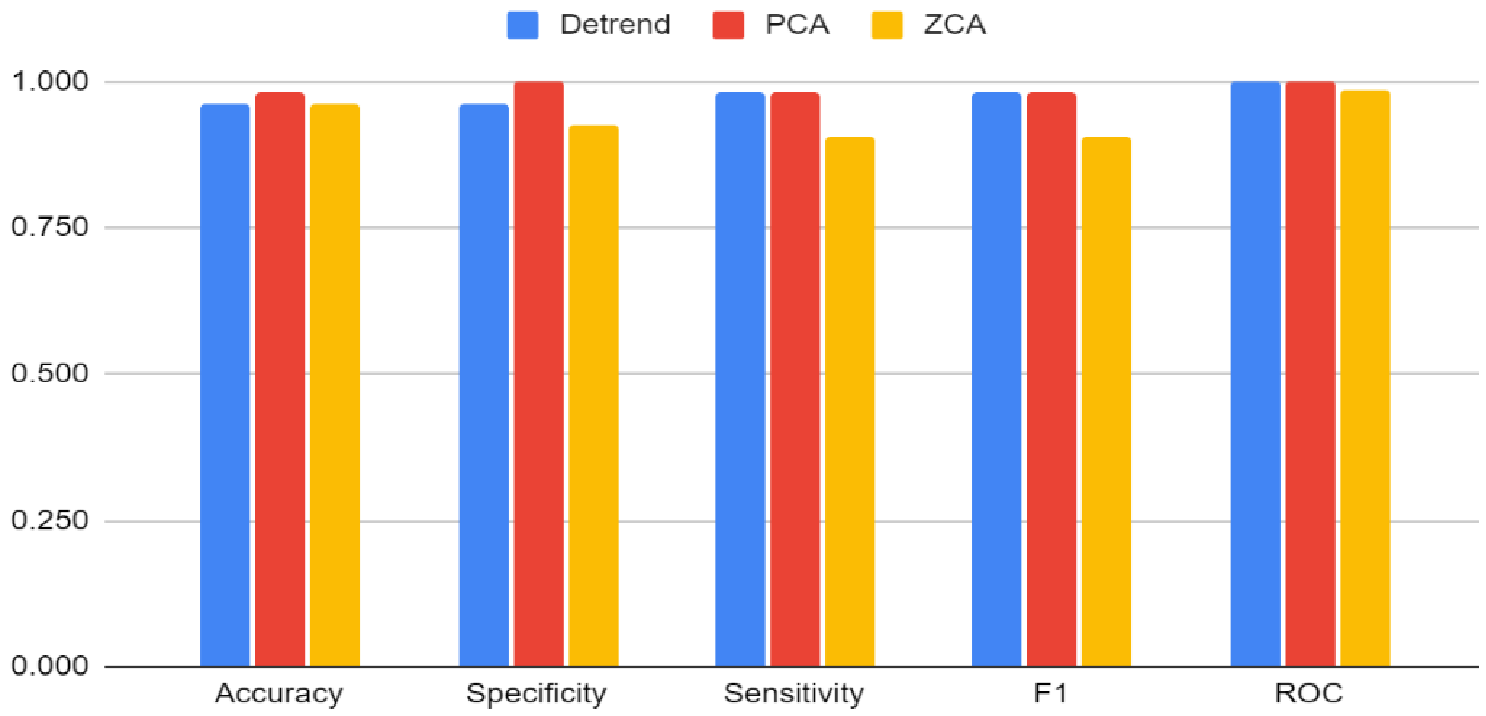
Using DWT features obtained by db6



Quantitative performance comparison between different data preprocessing techniques

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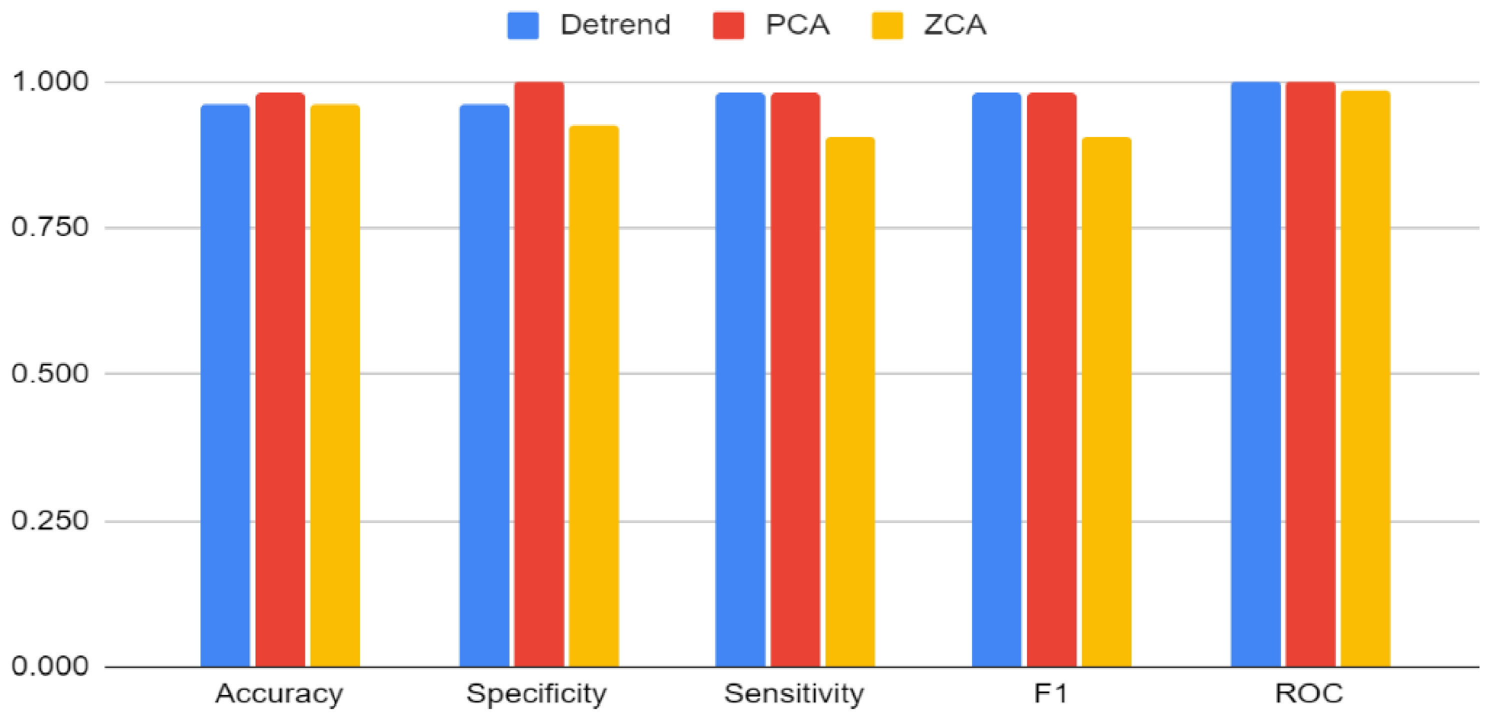
Using DWT features obtained by db6

Observations:

- ZCA has the lowest performance
- PCA has marginally improved over detrended EEG signal classification



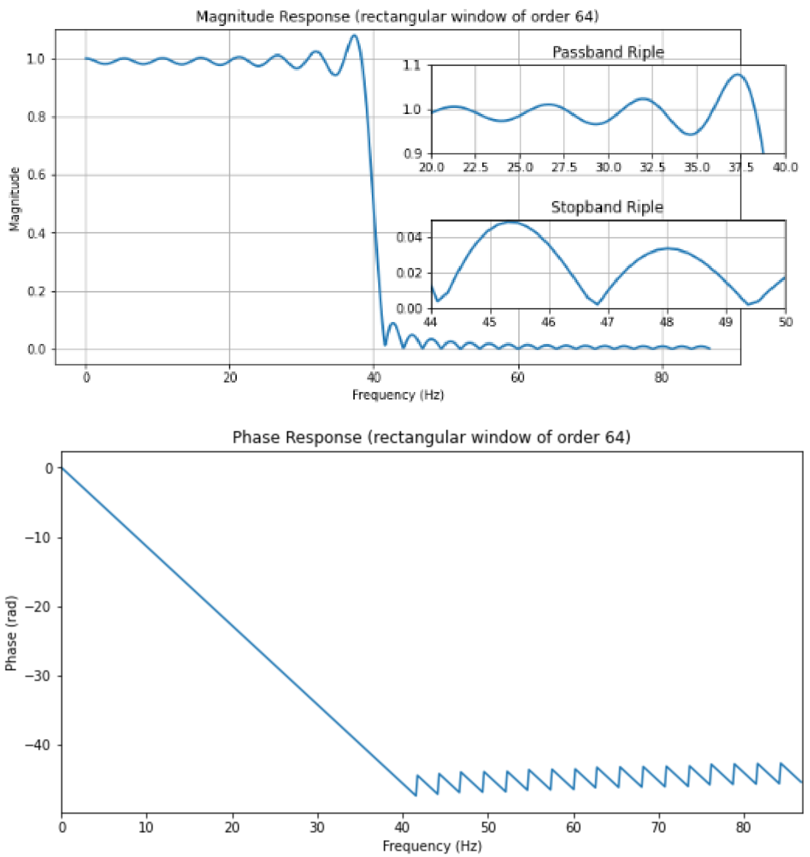

Quantitative performance comparison between different data preprocessing techniques

# Analysis

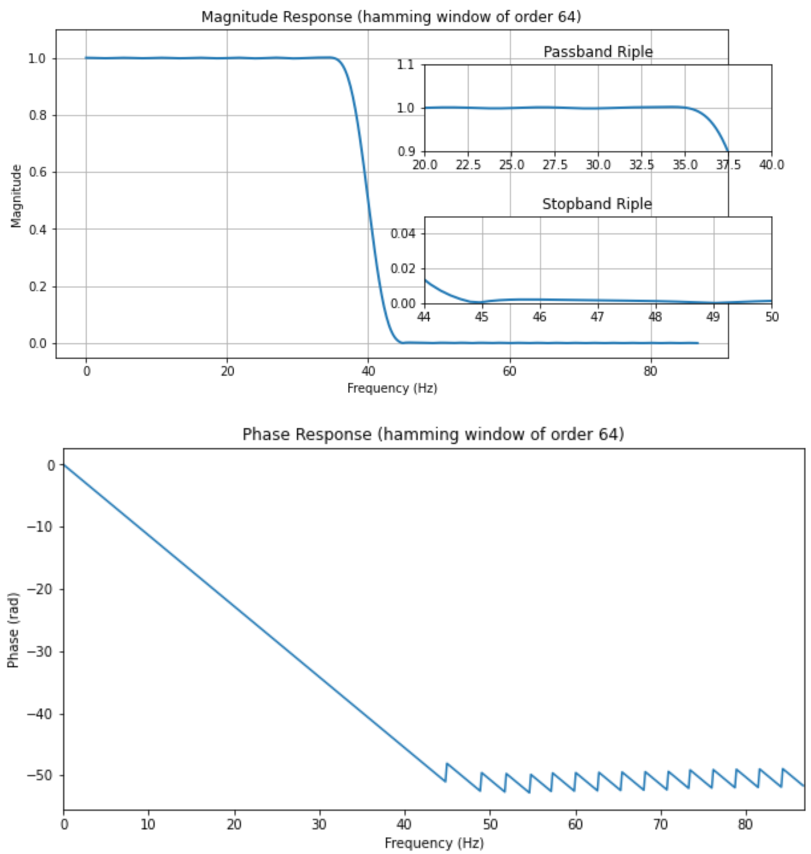
## Data Preprocessing – Data Denoising

### FIR Filtering – Comparing Filter Type

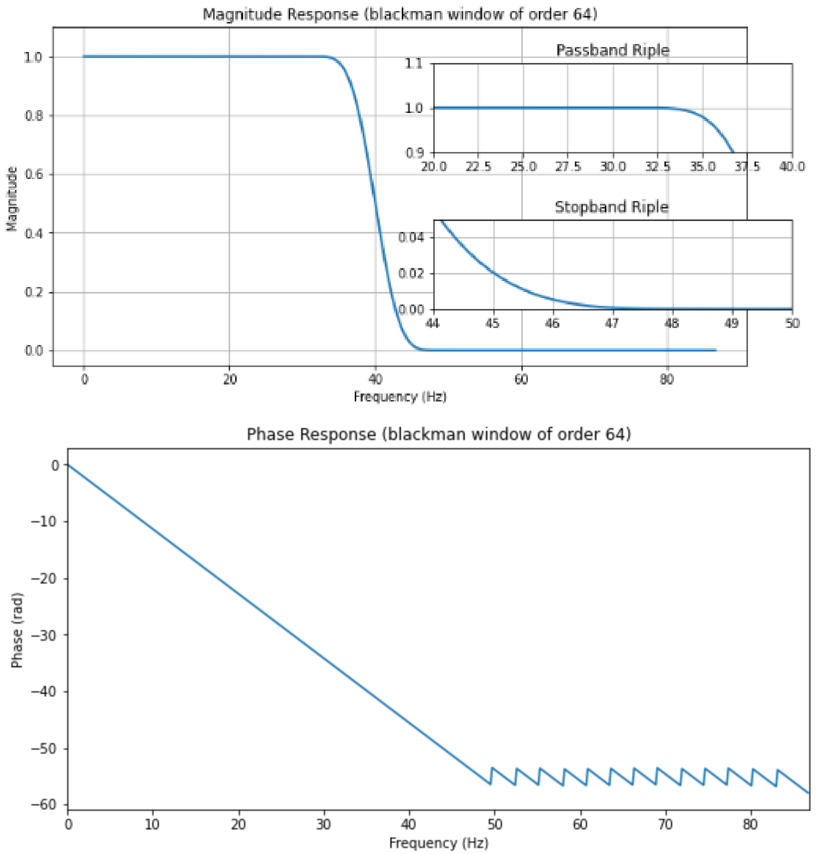
Comparison of different window types at n = 64 and cut-off frequency = 40 Hz




Rectangular window




Hamming window

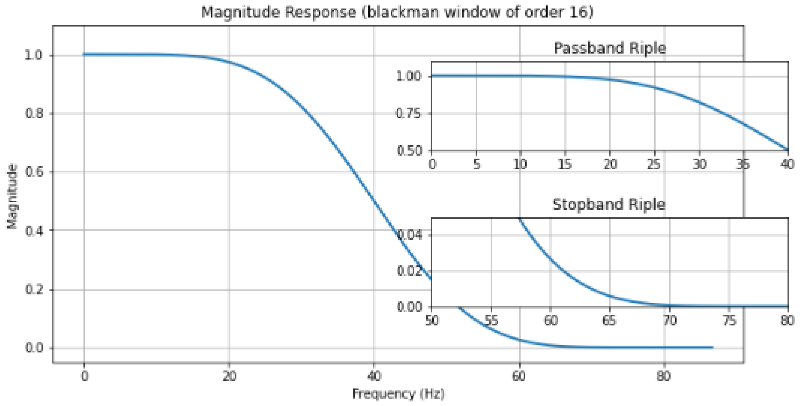



Blackman window

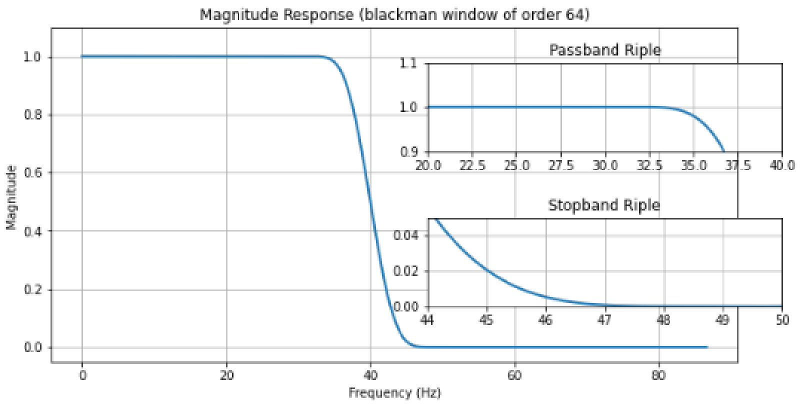
# Analysis

## Data Preprocessing – Data Denoising

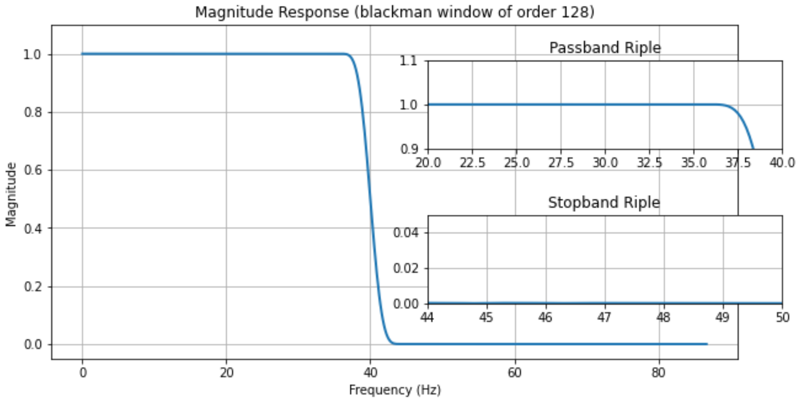
### FIR Filtering – Comparing Filter Order for Blackman – Harris Window




Order = 16




Order = 64




Order = 128

Comparing different filter orders (n) with Blackman window-based FIR filters

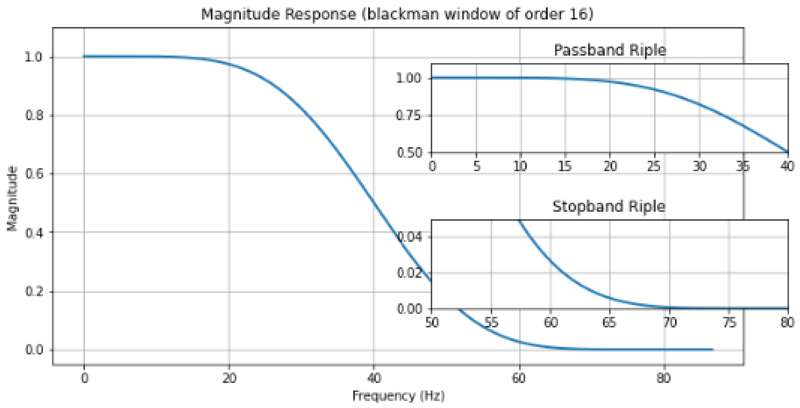
Observations:

- With *n=16* – the transition band is much wider and causes significant spectral leakage + significant spectral information loss happens in the useful signal band (0 – 40 Hz).
- Higher the filter order, sharper the transition band.

# Analysis

## Data Preprocessing – Data Denoising

### FIR Filtering – Comparing Filter Order for Blackman – Harris Window

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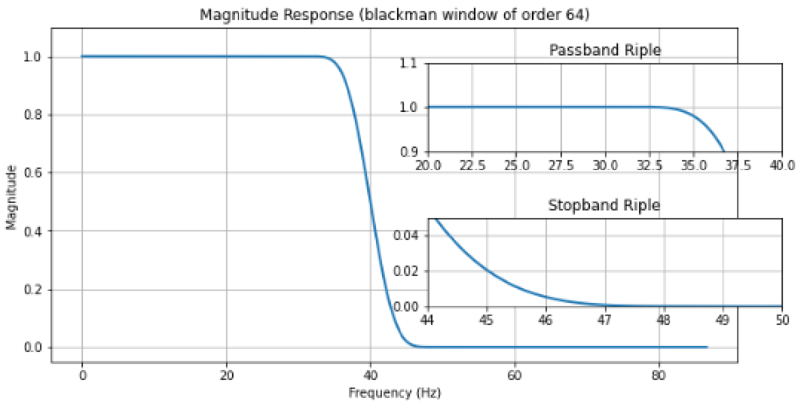


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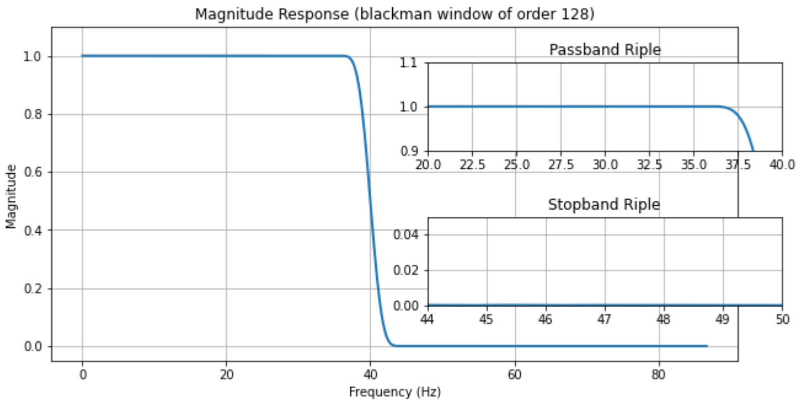


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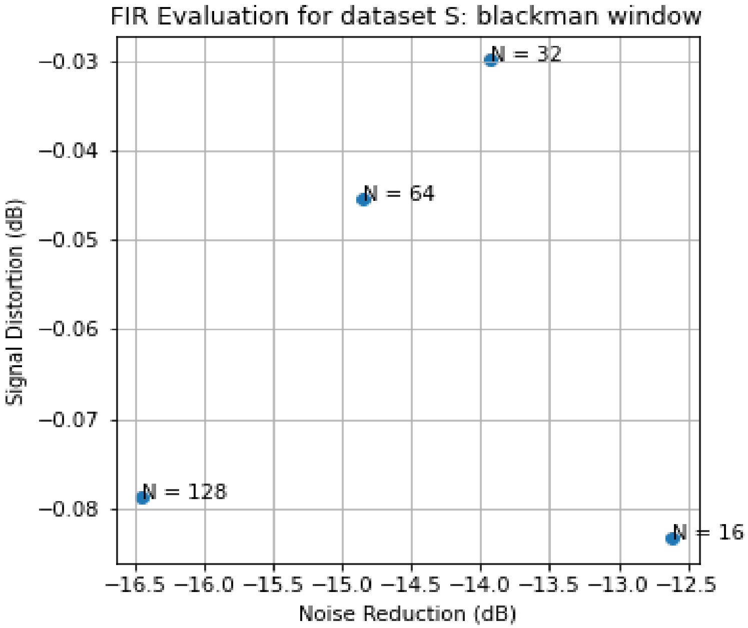
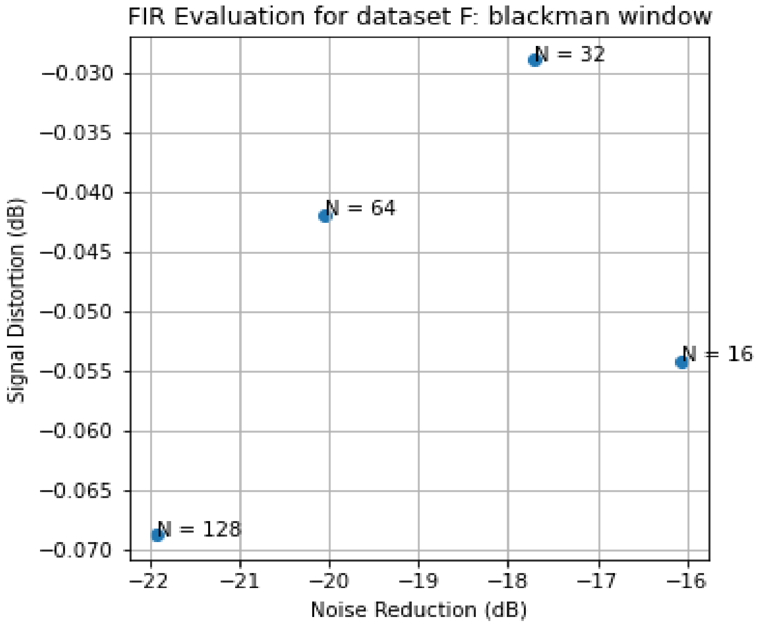
# Analysis

## Data Preprocessing – Data Denoising

### FIR Filtering – Quantitative Analysis of Filter Type and Filter Order




Ictal Signal Filtering



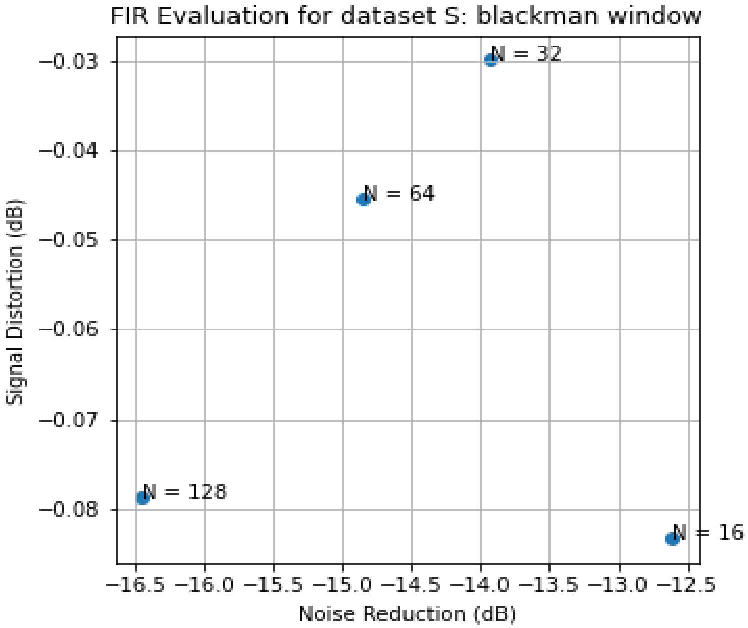

Inter-Ictal Signal Filtering

Evaluation of filter order using quantitative metrics (Blackman Window)

# Analysis

## Data Preprocessing – Data Denoising

### FIR Filtering – Quantitative Analysis of Filter Type and Filter Order

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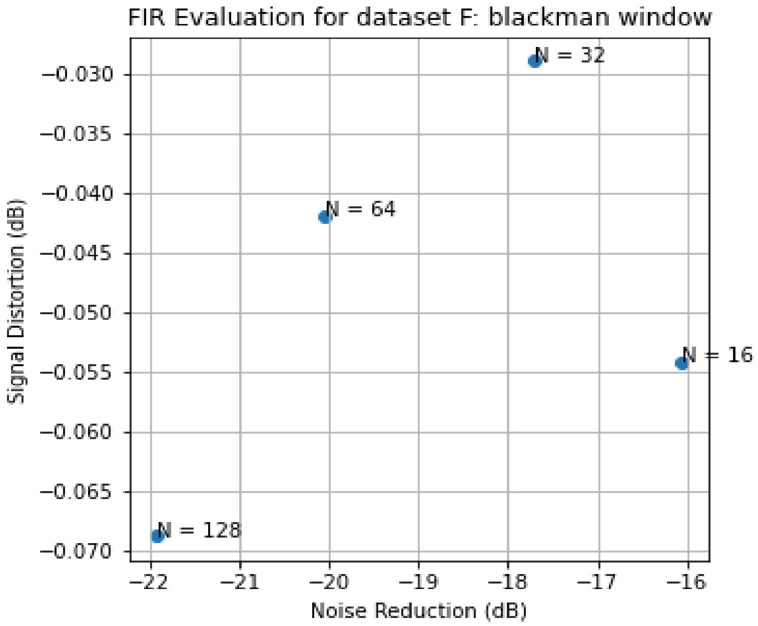


Inter-Ictal Signal Filtering

Evaluation of filter order using quantitative metrics (Blackman Window)

For better performance:

Signal distortion $\cong 0\ dB$

Noise Reduction = Higher negative dB

$n = 64$ is the ideal filter order

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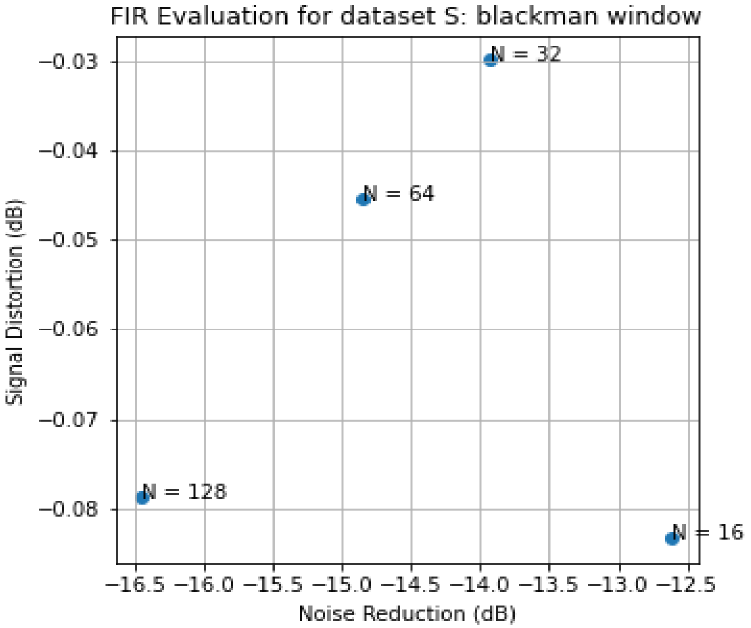


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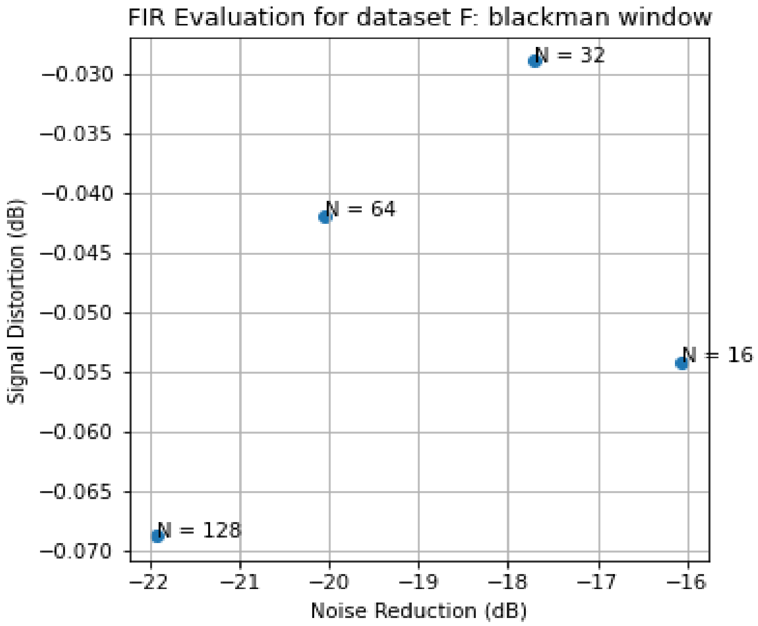


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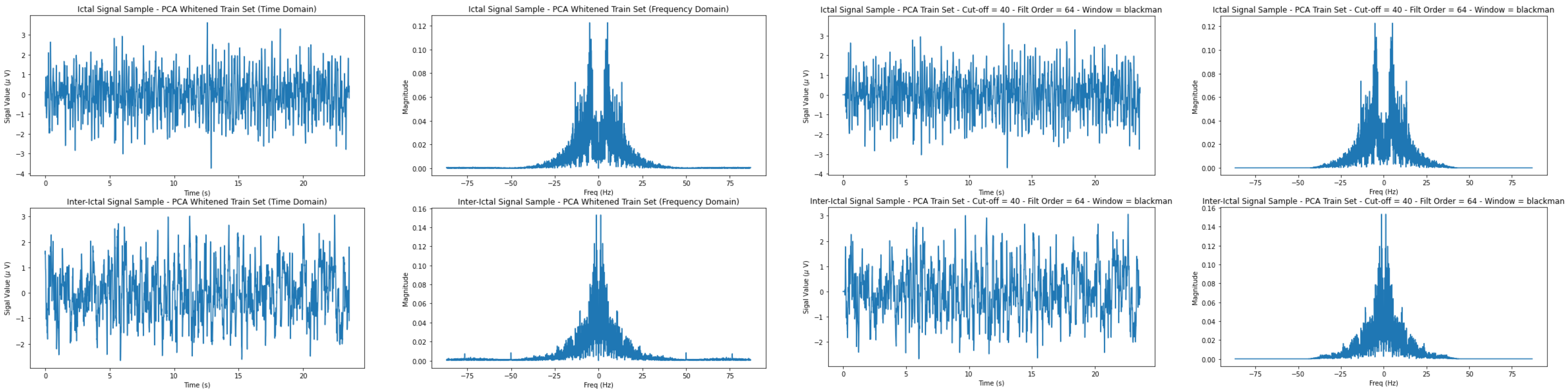
### FIR Filtering




Before Filtering

After Filtering

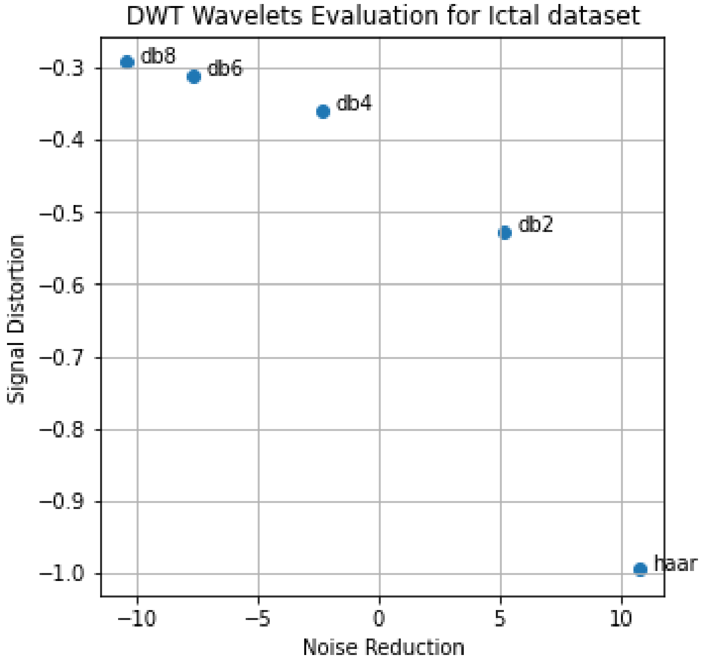
Time domain and Frequency domain comparison of pre-filtered and post-filtered signal sample

Observation: The higher frequency components are sufficiently attenuated.

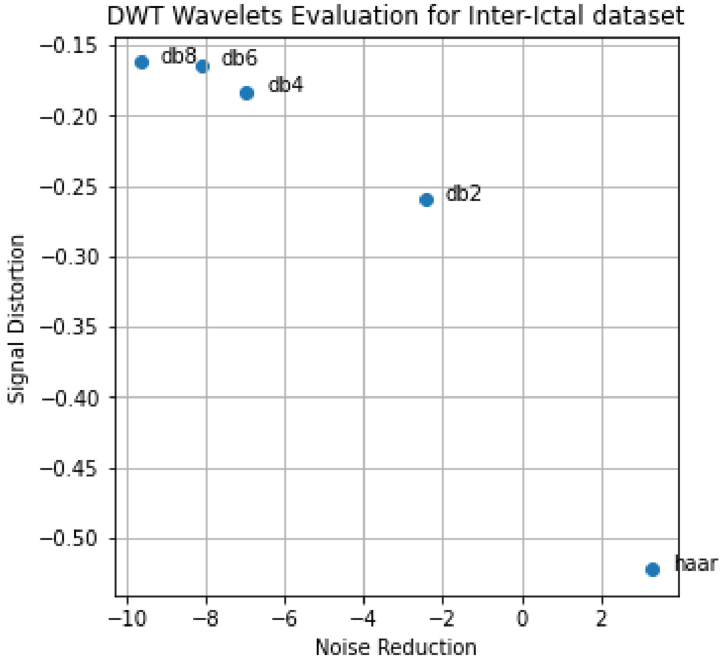
# Analysis

## Data Preprocessing – Data Denoising

### DWT Denoising – Quantitative Analysis




Ictal Signal DWT Filtering

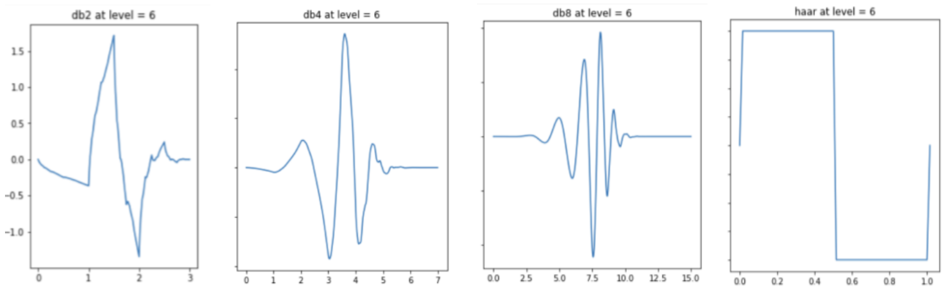



Inter-Ictal Signal DWT Filtering

Evaluation of different wavelet functions at 6-levels

db8 is the best at imposing the lowest signal distortion with the highest noise reduction

Signal distortion is still significant compared to FIR-low passing option selected

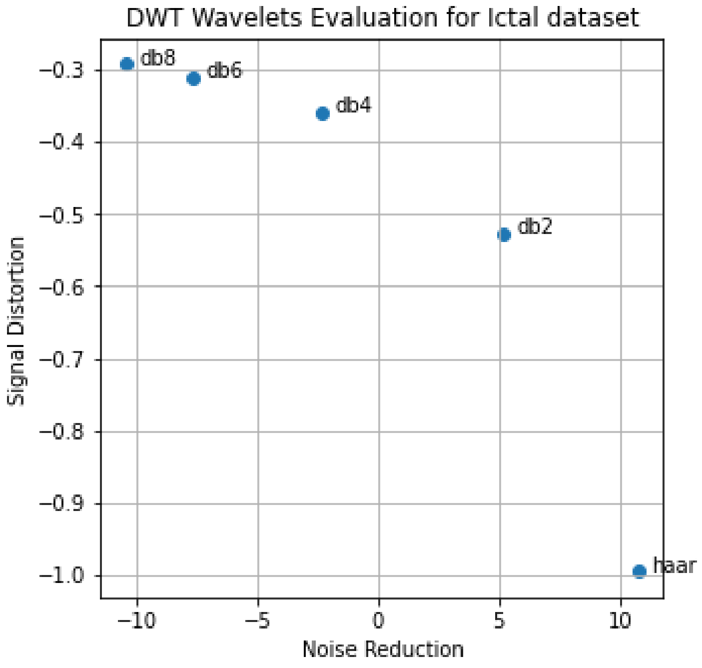



Different wavelet functions used for denoising EEG signals operating at highest resolution

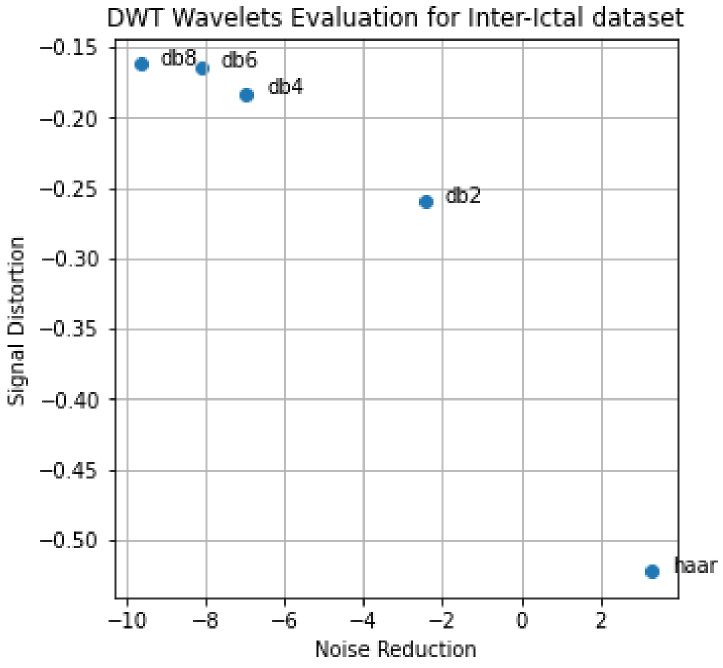
# Analysis

## Data Preprocessing – Data Denoising

### DWT Denoising – Quantitative Analysis




Ictal Signal DWT Filtering

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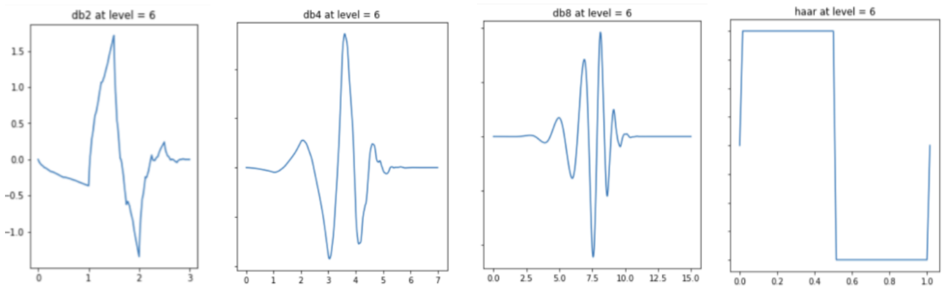


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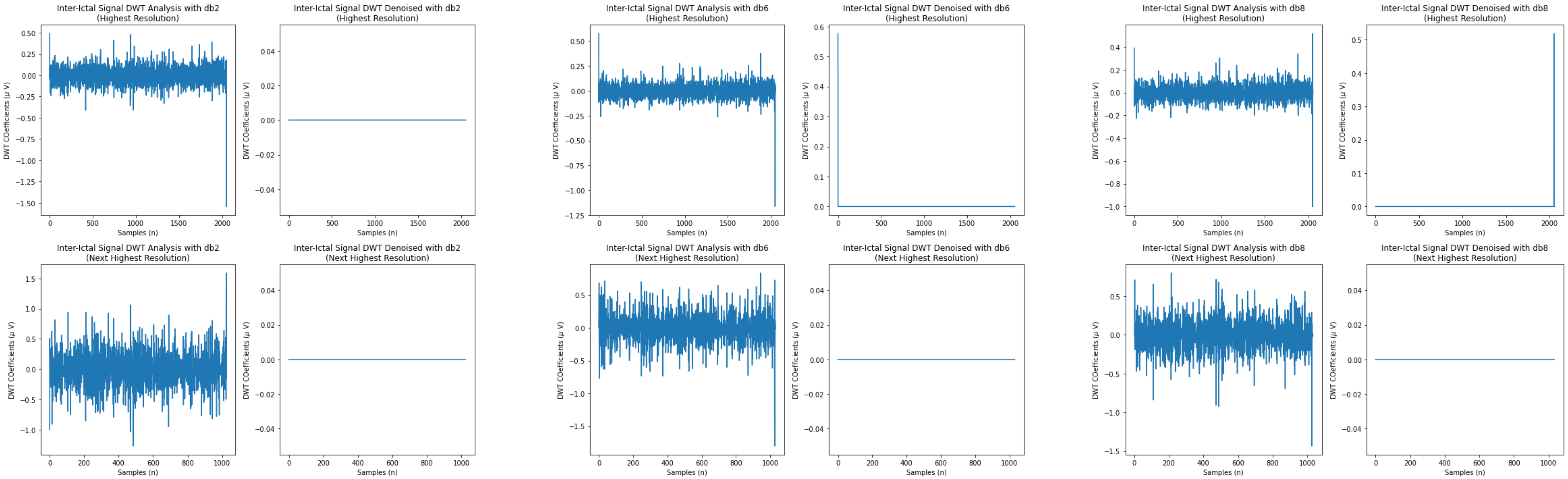
## Data Preprocessing – Data Denoising

### DWT Denoising



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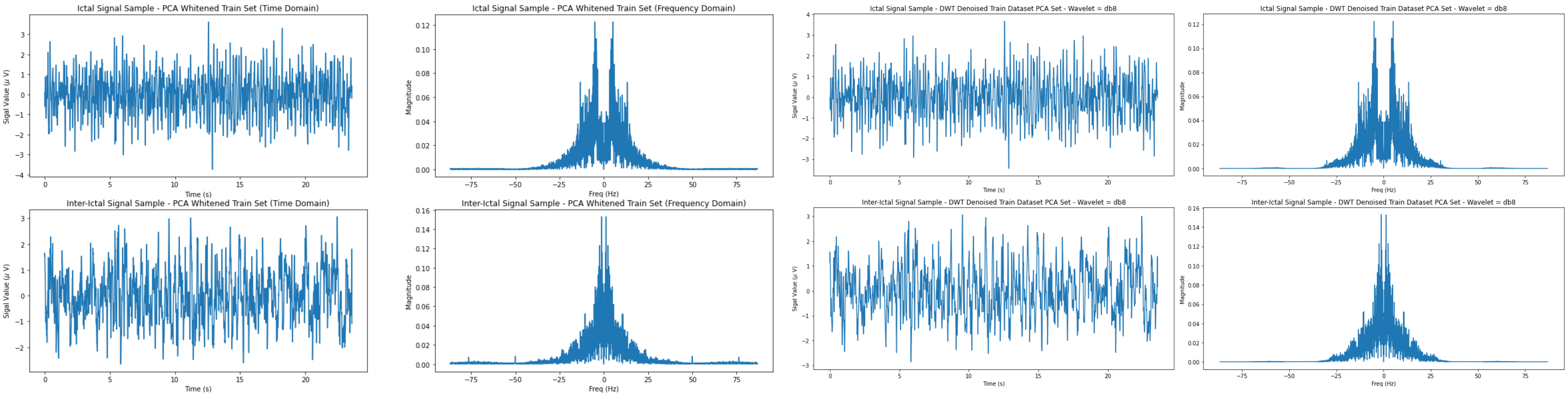
## Data Preprocessing – Data Denoising

### DWT Denoising




Before Filtering

After Filtering

Time domain and Frequency domain comparison of pre-filtered and post-filtered signal sample

Observation: The higher frequency components are sufficiently attenuated but certain components are still present compared to FIR filtering.

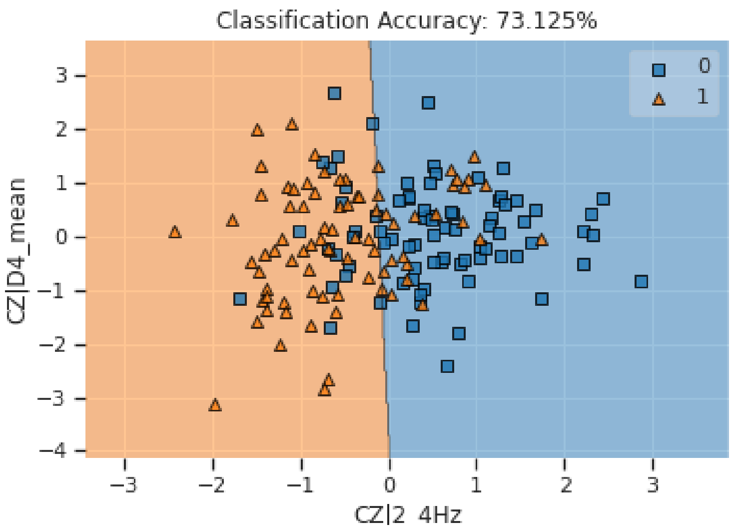
# Analysis

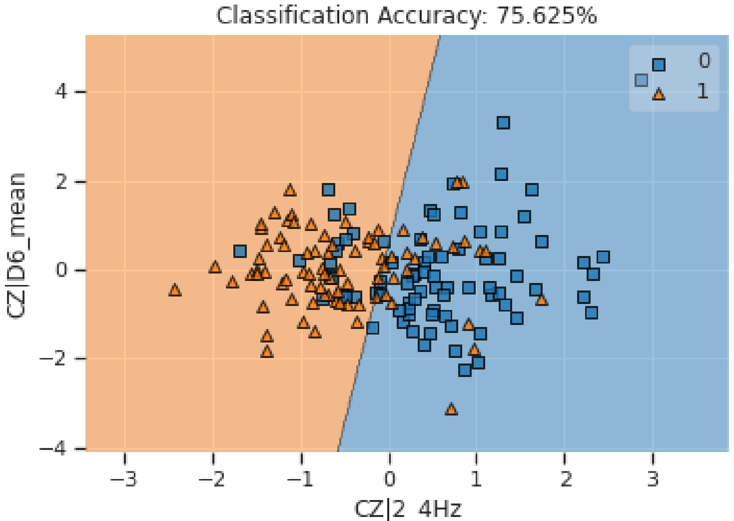
## Feature Engineering – Wavelet Feature Extraction

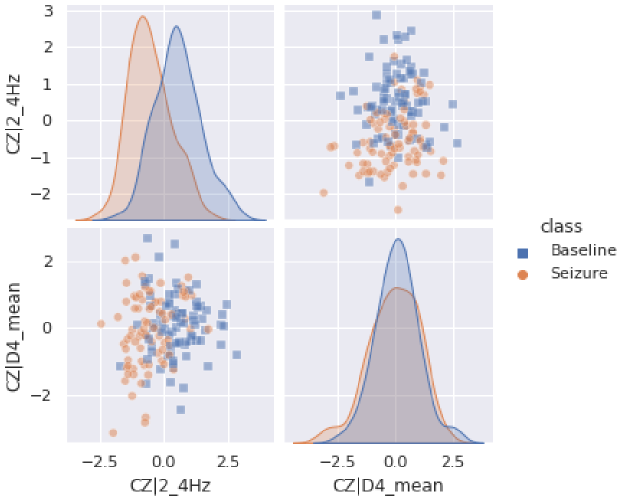
| | Feature Extraction Configurations | | | | | Evaluation Metrics | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Transformation | | Wavelet Function | | | Accuracy | Precision | Specificity | Sensitivity | F1 | AUC |
| | DWT | UDWT | db4 | db6 | Haar | | | | | | |
| **PCA EEG signals** | √ | | √ | | | 0.849 | 0.868 | 0.741 | 0.849 | 0.847 | 0.915 |
| | | √ | √ | | | 0.906 | 0.906 | 0.926 | 0.906 | 0.906 | 0.974 |
| | √ | | | √ | | **0.925** | **0.934** | **1.000** | **0.925** | **0.924** | **0.980** |
| | | √ | | √ | | 0.830 | 0.831 | 0.852 | 0.830 | 0.830 | 0.929 |
| | √ | | | | √ | 0.830 | 0.831 | 0.852 | 0.830 | 0.830 | 0.879 |
| | | √ | | | √ | **0.943** | **0.944** | **0.963** | **0.943** | **0.943** | **0.944** |
| **Original EEG signals** | √ | | √ | | | 0.943 | 0.944 | 0.926 | 0.943 | 0.943 | 0.997 |
| | | √ | √ | | | 0.943 | 0.944 | 0.963 | 0.943 | 0.943 | 0.956 |
| | √ | | | √ | | **1.000** | **1.000** | **1.000** | **1.000** | **1.000** | **1.000** |
| | | √ | | √ | | **1.000** | **1.000** | **1.000** | **1.000** | **1.000** | **1.000** |
| | √ | | | | √ | 0.925 | 0.925 | 0.926 | 0.925 | 0.925 | 0.974 |
| | | √ | | | √ | 0.962 | 0.965 | 1.000 | 0.962 | 0.962 | 0.986 |

# Analysis

## Feature Engineering – Wavelet Feature Extraction



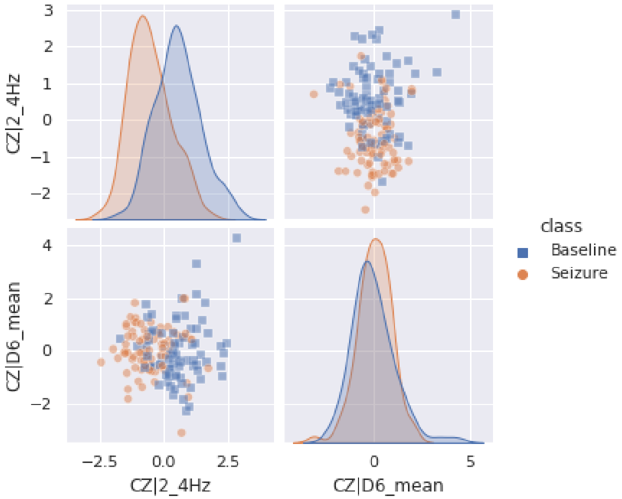




Figure: Classification using feature pairs extracted by DWT using db6 wavelet functions (with pair-plots)

Observations:

With reduced wavelet features:

- Significant reduction in binary classification accuracy.
- Depends on how much overlap distributions of two classes for the selected feature pair

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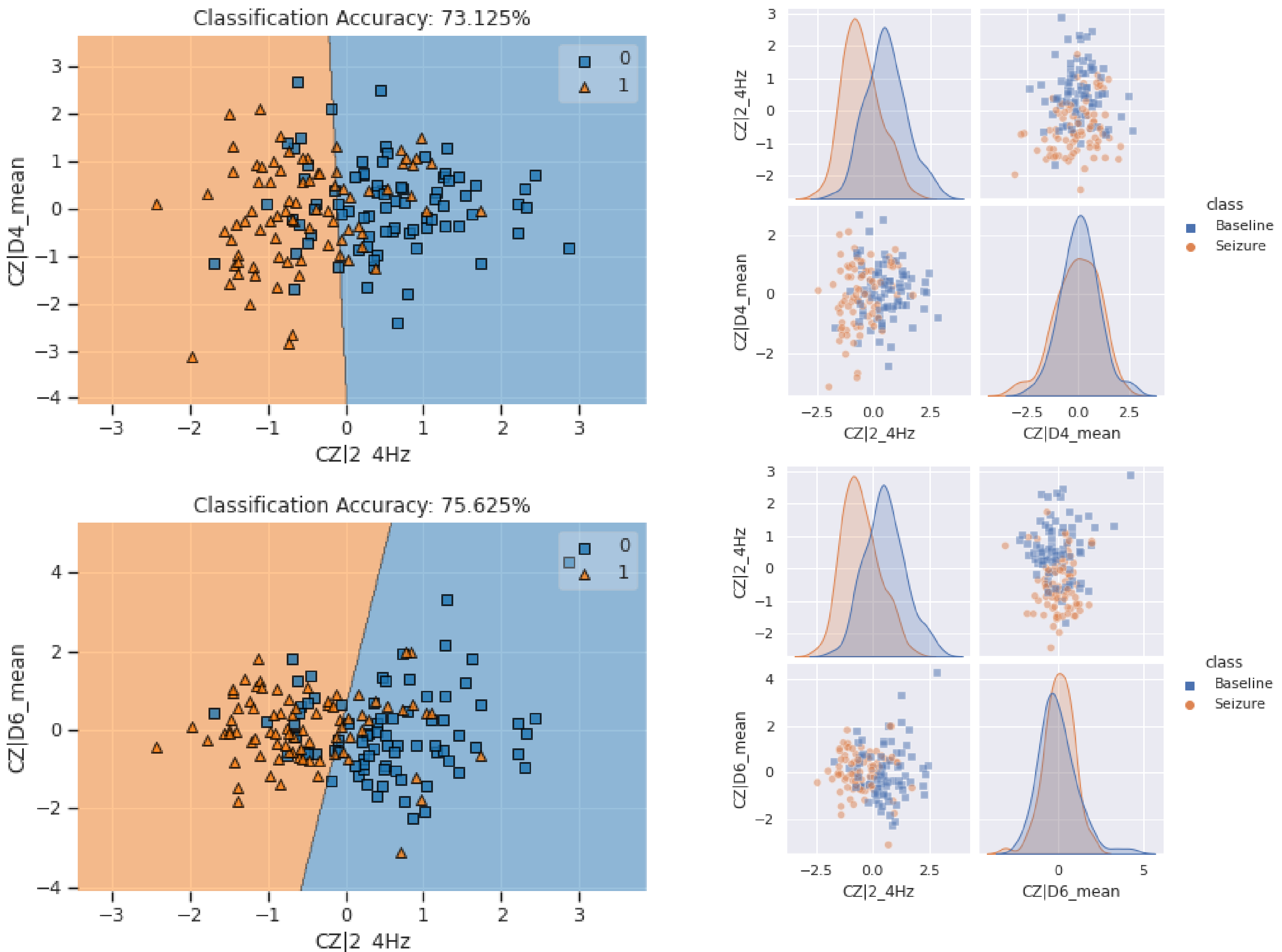


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# Conclusion

- Detrending and whitening may improve the results as a preprocessing step
  - Data is fairly stationary – detrending makes marginal improvement

- PCA whitening causes the final classification results to degrade
  - PCA changes the spectral features of an EEG signal that are extracted from wavelet coefficients
  - May change the nature of the frequency features extracted compared to the original signals.

- Denoising is important
  - FIR filtering is best option compared to DWT-based denoising
  - Should select the correct type of the window and filter order
  - Higher the filter order, sharper transition band and lesser passband ripples - however, this increases filter complexity unnecessarily
  - For this dataset Blackman-Harris window with 64 filter order was sufficient.

- Feature extraction – Best is time-frequency based on literature
  - UWDT is generally best but there is no conclusive evidence in the dataset to that

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# Reference

[1] Tamilia, E., Madsen, J. R., Grant, P. E., Pearl, P. L., & Papadelis, C. (2017). Current and emerging potential of magnetoencephalography in the detection and localization of high-frequency oscillations in epilepsy. *Frontiers in neurology*, *8*, 14.

[2] Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, *64*(6), 061907.

[3] https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/

Other Materials:

a. Lecture Slides
b. Biosignal and Medical Image Processing (Third Edition) Book

# Thank You!