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Feature Extraction And Classification Of Eeg Signals Using Neural Network

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ABSTRACT
The use of Electroencephalogram (EEG) or “brain waves” for human-computer interaction is a new and challenging field that has gained momentum in the past few years. In this work different finite impulse response filter (FIR) windowing techniques (Rectangular, Hamming, Hanning, Blackman, Kaiser β= 5,8,12) are used to extract EEG signal to its basic components (Delta wave, Theta wave, Alpha wave, Gamma and Beta wave).The comparison between these windowing methods are done by computing the Fourier transform, power spectrum, SNR values. The features are extracted from the data and applied to classification techniques to identify the accuracy in obtaining the information of the data. In this research, EEG from one subject who performed four tasks has been classified using Radial Basis Function (RBF) and Multi Layer Perceptron (MLP) neural networks. Five data sets with 1000 samples are chosen in order to perform classification techniques. 200 iterations are done to identify the best error rate. These iterations help us to achieve best output. We calculate the elapsed time, confusion matrix, sensitivity, precision, specificity and accuracy for the classified data. The best classification accuracy is approximately 99.66% using the Multi Layer Perceptron technique and the best windowing technique obtained is Kaiser β= 12. The experimental results are performed using MATLAB Tool.
Keywords: Electroencephalography (EEG), Finite Impulse Response, Windowing Methods, SignalFiltering, Neural Networks

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I. INTRODUCTION

Electroencephalography (EEG) data signal consists of electric signal activities on a cerebral cortex with some characteristics, such as nonperiodic, non-standardized pattern, and small voltage amplitude. These attributes evoke EEG signal to be swiftly mixed up with noise and difficult to recognize [1]. Many factors can generate noise and distortions, e.g. room exposure, energeticradiation, heart, muscles, and eyes movement. Noise and other parameters such as a sudden change in signal phase and loss of signal amplitude can briefly stimulate distortion in the signal [2]. Data filtering is used to mitigate noise or distortions in EEG data. Many techniques have been proposed to process data signal filtering, such as Finite Impulse Response (FIR) digital filter. In many cases, a bad filter design can induce signal distortions to occur. Windowing methods are usually employed to extract and repair impulse responses in FIR filter. Many researchers had proposed different windowing methods, but only some can give a good result in filtering EEG data. This paper focuses on comparing four windowing methods to get the best outcome in EEG signal filtering process.

We organized this article as follow: Section II discusses literature reviews, Section III explains the methods used in this research, and Section IV provides results and discussion. Finally, Section Vpresented the conclusion and future works.

II. MOTIVATION

Electroencephalographic (EEG) is ameasurement procedure using electro-medicalequipment to record electrical activities of the brainand its interpretation. Neurons in the cerebralcortex issue electric waves with a minimum voltage(mV) which then passed through an EEG machineto do an amplification process. After it is amplified,the recorded EEG size will be enough to becaptured by the reader's eyes as an alpha, beta, andtheta wave [3]. EEG signal is used to diagnosediseases related to brain and psyche, such asepilepsy, brain tumors, detect the position orlocation of the injured brain and diagnose mentaldisorders.

Many researchers have proposed various methods to filter EEG data. Surface Laplacian (SL) that are spatially located near the electrode whichcurrently being recorded, and to sift out signals thatmay come from outside of the skull. SL filter alsomuffles EEG activities which are common todedicated channels hence increasing the spatialresolution of the recorded signal [4]. However, SLfilter can only be applied to EEG data with thenumber of 64 electrodes or more [5].

Another researcher, Guerrero-Mosquera andVazquez used Independent Component Analysis(ICA) and Recursive Least Squares (RLS) methodto eliminate the eye movement artifacts in EEGdata. The method uses separate electrodes thattightly localized to the eyes, in which register tovertical and horizontal eye movements forextracting a reference signal. This procedureprojects each reference input into ICA domain, and
then RLS algorithm estimates the interference thatmay occur in this data. This proposed methodefficiently rejected artifacts produced by eyesmovements by relying on ICA and RLS adaptivefiltering [6]. Miyazaki et al. also utilized InfiniteImpulse Response (IIR) filter to eliminate theartifacts from EEG data. Their research resultsshowed that the IIR filter can remove artifacts inEEG data quite well. However, IIR has poles that
lead the filter to be unstable [7].

Different with the aforementioned methods, FIRfilter does not require many electrodes and not only
focus on the noise of eye movements. Hence, FIR ismore stable than other filters above. In thisresearch, we utilize FIR filter to process EEG datathat is captured using Emotiv EPOC device with 14electrodes.

III. METHODOLOGY

3.1 Finite Impulse Response (FIR)

Finite Impulse Response (FIR) has a finiteresponse and no poles compare with IIR filter. FIRis more stable than other digital filter andpreferably used by researchers. In general, theoutput of FIR filter y[k] can be expressedmathematically as Equation 1.

$$y[k] = \sum_{n=0}^{M-1} h[n]x[k-n] \qquad (1)$$

where M is the filter length, h[n] is the impulseresponse's coefficient, x[n] is the input filter andy[k] is the output filter.The transfer function of FIR filter isapproximately ideal following the increasing offilter order. Equation 2 expressed this process,where m is the order of the filter, ΔF is thetransition width normalization, Δf is the transitionwidth, and fs is the sampling frequency. Somewindowing types to implement FIR filter areBlackman, Hamming, Hann, and Rectangularwindow. Each windowing type has a different valueof normalized transition width (ΔF)

$$m = \frac{\Delta F}{\Delta f / fs} \qquad (2)$$

FIR filter is usually employed to process thedigital signal, e.g. sound and digital image, to find aclear message without any disruptions. Puspasari etal. implemented FIR filter for pedestrians' locationmonitoring system captured by Global PositioningSystem (GPS). When an unstable GPS received thesignal, FIR filter would remove the noises whichmay occur, such as multipath effect. Beforeapplying FIR filter, the coordinate points of thepedestrian are scattered because of the noise. But,after being processed by FIR, only one coordinate
point was obtained from these distributed data [8].

3.2 Windowing Method

In EEG data processing, we should consider theimpulse response of the data. Finite impulseresponse may generate an excessive ripple in thepass-band and create low stop-band attenuation.Windowing techniques could overcome thisproblem during a filtering process. Given a windowfunction (w[n]) and an impulse response of theideal filter (hd[n]), then the impulse response of theactual filter can be expressed in Equation 3.

$$h[n] = hd[n]*w[n] \qquad (3)$$

Windowing methods employed with FIR filterto mitigate disruptions during filtration process areRectangular, Hamming, Hann and BlackmanWindow.

A. Rectangular Window

Researchers rarely employed the rectangularwindow due to its low stop-band attenuation result.The first lobe of this window has an attenuation of13dB and the narrowest transition region among allwindow methods. Hence, a filter designed usingthis window should have minimum stop-bandattenuation of 21 dB. Coefficient of RectangularWindow is defined as follows:

$$Y[n] = \sum_{k=m1}^{m2} bk\, x[n-k]$$

B. Hamming Window

Hamming window is one of the most popularwindowing methods. A filter designed with theHamming window has minimum stop-bandattenuation of 53dB, which is sufficient for mostimplementations of digital filters. Unlike minimumstop-band attenuation, transition region can bechanged by altering the filter order. The transitionarea will become narrow and minimum stop-bandattenuation remains unchanged as the filter order increases. Coefficient of Hamming Window isdefined as follows:

$$R[n] = \begin{cases} 1 & 0 \ll n \ll l-1 \\ 0 & otherwise \end{cases}$$

C. Hann Window

Researchers usually use Hann window to lessenill effects on frequency characteristic produced bythe final samples of a signal. The first side of a lobein the frequency domain of this window has 31dBof attenuation value, whereas it amounts up to 44dBin the designed filter. The advantage of this windowis its ability to increase the stop-band attenuation ofthe posterior lobes swiftly. Coefficient of HannWindow is defined as follows:

$$W[n]= \begin{cases} 0.5 - 0.5\cos\frac{2\pi n}{1-1} & o \ll n \ll l-1 \\ 0 & otherwise \end{cases}$$

D. Blackman Window

Blackman window is considered as the mostpopular window technique for data signal filtering.Relatively high attenuation value makes thiswindow is very convenient for almost allapplications. The first side of a lobe in the frequency domain of this filter has 51dB ofattenuation value, and the designed filter has stopbandattenuation up to 75dB. Coefficient ofBlackman Window is defined as follows:

$$W[n]= \begin{cases} 0.42 - 0.5\cos\frac{4\pi n}{1-1} 0.08\cos\frac{4\pi n}{1-1} & 0 \ll n \ll 1-1 \\ 0 & otherwise \end{cases}$$

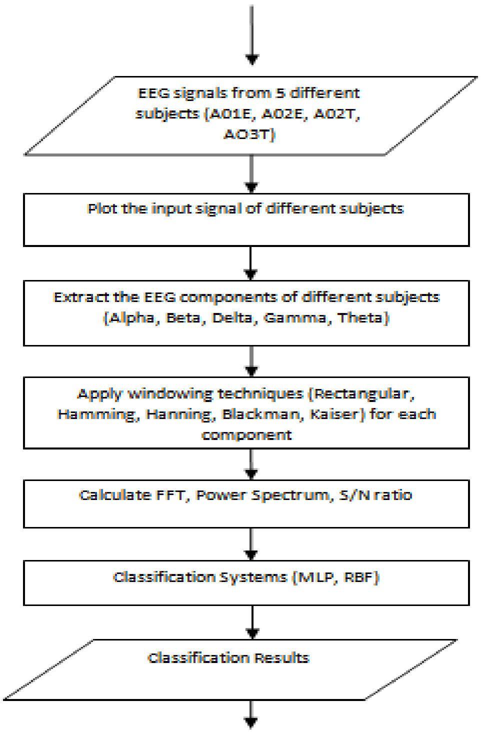

Fig 1. Proposed Method Flow Chart

E. Power Spectrum and Feature Extraction

EEG signals are decomposed into IMFs before furtherprocessing in the frequency domain. The IMF powerspectrum is calculated using FFT algorithm. The featureextraction uses 500 components of the power spectrum, whichequals to 21.2 Hz, since the value is considerably smallbeyond that frequency value. A feature vector is extractedfrom the IMF power spectrum by adding 50 consecutivecomponents for 10 features and 25 consecutive componentsfor 20 features.

F. Classification

In this research we compared the performances of MLP,RBFN, and random forest classifier. The accuracies of thethree classifiers were computed using 10-fold cross validation.MLP consists of the input, several hidden, and outputlayers. The weights of the network are computed using backpropagation algorithm.RBFN comprises three layers, and the hidden layer consistsof neurons with activation functions that work as radial basisfunctions. The neuron output is the value of the functionevaluated at the distance of the input vector and the neuroncentre. The output layer works as perceptron for the learningprocess.

IV. RESULTS:

EEG signal of subject 1 (x-axis- time (sec), y-axis- amplitude (v)).

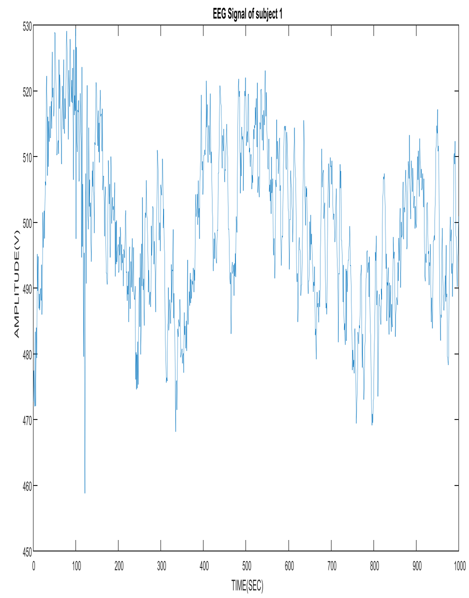

Figure 2: EEG signal of subject 1.

- Extraction of EEG components (alpha, beta, delta, theta, gamma) of subject 1 (x-axis- time (sec), y-axis- amplitude (v)).

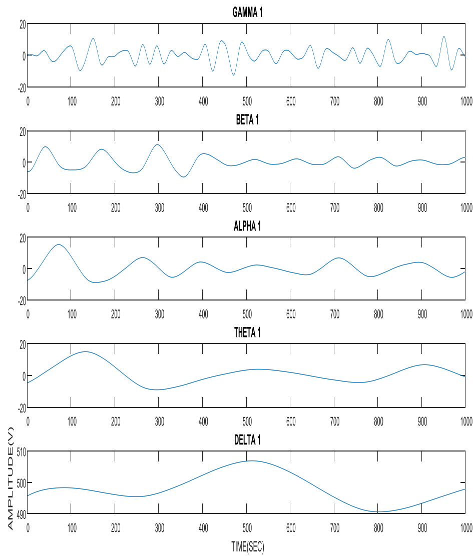

Figure 3: EEG components (alpha, beta, delta, theta and gamma) of subject 1.

Appling windowing techniques (rectangular, hamming, Hanning, Kaiser β= 5, 8, 12, Blackman) to EEG components of subject 1 (x-axis- time (sec), y-axis- amplitude (v)).

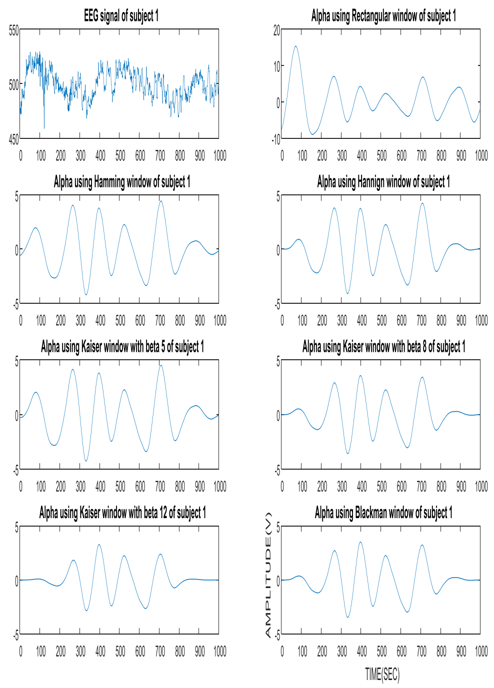

Figure 4: Windowing techniques to Alpha wave of subject 1.

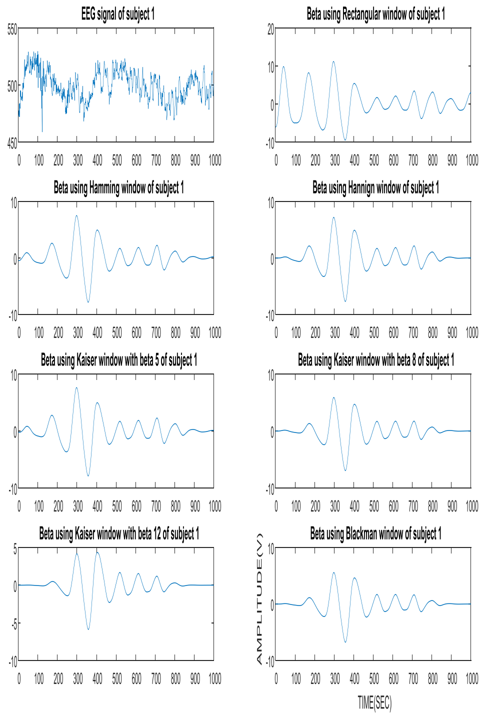

Figure 5: Windowing techniques to Beta wave of subject 1.

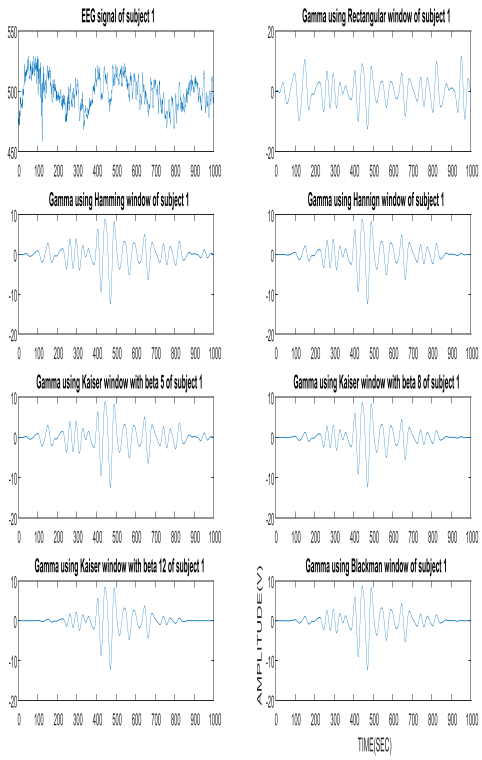

Figure 6: Windowing technique to Gamma wave of subject 1.

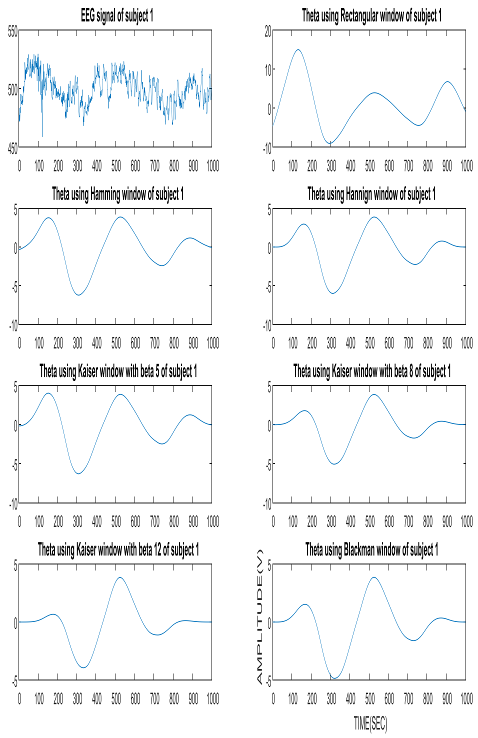

Figure 7: Windowing techniques to Theta wave of subject 1.

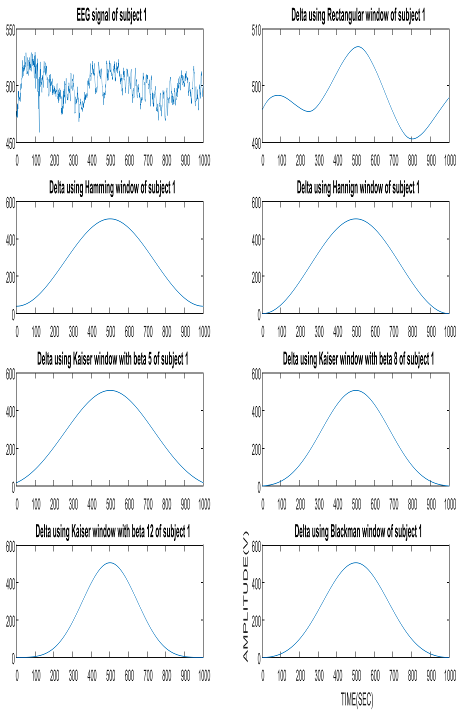

Figure 8: Windowing techniques to Delta wave of subject 1.

SNR values of each EEG wave component after filtered through different windowing techniques.

ALPHA WAVE	SNR VALUES
SNR value for alpha Rectangular Window of subject 1	16.129938
SNR value for alpha Hamming Window of subject 1	46.253262
SNR value for alpha Hanning Window of subject 1	46.261119
SNR value for alpha Kaiser 5 Window of subject 1	46.251532
SNR value for alpha Kaiser 8 Window of subject 1	45.514300
SNR value for alpha Kaiser 12 Window of subject 1	19.490338
SNR value for alpha Blackman Window of subject 1	18.965803

Table 1: SNR values of Alpha wave of subject 1.

BETA WAVE	SNR VALUES
SNR value for Beta Rectangular Window of subject 1	18.402666
SNR value for Beta Hamming Window of subject 1	18.852038
SNR value for Beta Hanning Window of subject 1	18.891380
SNR value for Beta Kaiser 5 Window of subject 1	18.843679
SNR value for Beta Kaiser 8 Window of subject 1	19.636241
SNR value for Beta Kaiser 12 Window of subject 1	19.840126
SNR value for Beta Blackman Window of subject 1	19.665748

Table 3: SNR values of Beta wave of subject 1.

THETA WAVE	SNR VALUES
SNR value for Theta Rectangular Window of subject 1	55.001503
SNR value for Theta Hamming Window of subject 1	56.663659
SNR value for Theta Hanning Window of subject 1	56.908249
SNR value for Theta Kaiser 5 Window of subject 1	56.631603
SNR value for Theta Kaiser 8 Window of subject 1	56.860842
SNR value for Theta Kaiser 12 Window of subject 1	56.673107
SNR value for Theta Blackman Window of subject 1	56.855700

Table 4: SNR values of Theta wave of subject 1.

DELTA WAVE	SNR VALUES
SNR value for Delta Rectangular Window of subject 1	17.570082
SNR value for delta Hamming Window of subject 1	17.572535
SNR value for Delta Hanning Window of subject 1	17.572865
SNR value for Delta Kaiser 5 Window of subject 1	17.572457
SNR value for Delta Kaiser 8 Window of subject 1	17.574566
SNR value for Delta Kaiser 12 Window of subject 1	17.578676
SNR value for Delta Blackman Window of subject 1	17.575071

Table 5: SNR values of Delta wave of subject 1.

GAMMA WAVE	SNR VALUES
SNR value for Gamma Rectangular Window of subject 1	12.954494
SNR value for Gamma Hamming Window of subject 1	13.020581
SNR value for Gamma Hanning Window of subject 1	13.025218
SNR value for Gamma Kaiser 5 Window of subject 1	13.019545
SNR value for Gamma Kaiser 8 Window of subject 1	13.051054
SNR value for Gamma Kaiser 12 Window of subject 1	13.087216
SNR value for Gamma Blackman Window of subject 1	13.057011

Table 6: SNR values of Gamma wave of subject 1.

Confusion Matrix for RBF:
Input – EEG features of 5 different subjects.
Targets – 5 different subjects.

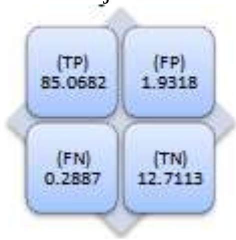

Figure 9: Confusion Matrix of RBF network.

Confusion Matrix for MLP:
Input – EEG features of 5 different subjects.
Targets – 5 different subjects.

Figure 10: Confusion Matrix of MLP network.

Precision using RBF (2): 97.779554
Precision using MLP (1): 99.699699

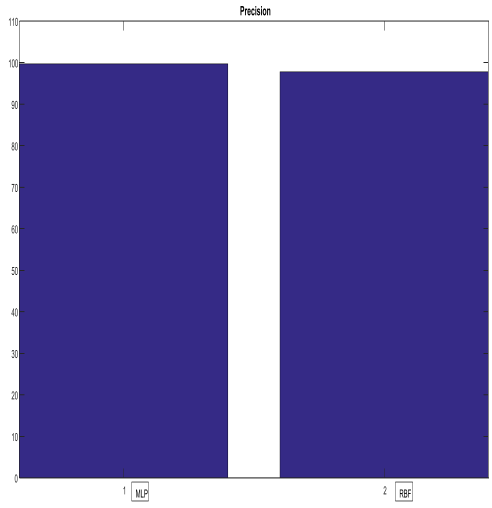

Figure 11: Precision bar graph of MLP, RBF networks.

Sensitivity using RBF (2): 99.661822
Sensitivity using MLP (1): 99.955013

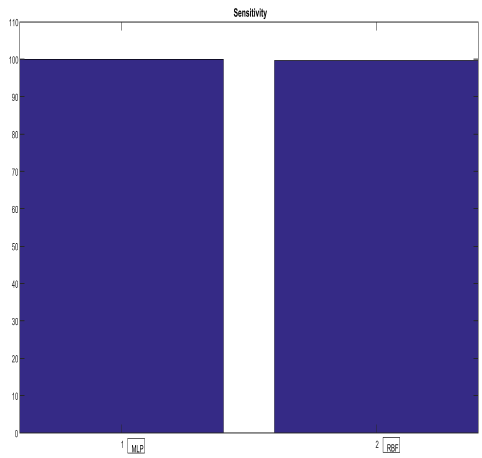

Figure 12: Sensitivity bar graph of MLP, RBF networks.

V. CONCLUSION:

In this study different finite impulse response filter (FIR) windows methods (Rectangular, Hamming, Hanning, Blackman, Kaiser β= 5,8,12) were used to extract EEG signal to its basic components (Delta wave, Theta wave, Alpha wave, Gamma and Beta wave).The comparison between these windowing methods were done by computing the Fourier transform, power spectrum, SNR. The results shown the Best window is Kaiser β= 12 and the resultant signals has been classified using Radial Basis Function (RBF) and Multi Layer Perceptron (MLP) neural networks. We have calculated the elapsed time, confusion matrix, sensitivity, precision, specificity and accuracy for the classified data. The best classification accuracy was approximately 99.66% using the Multi Layer Perceptron.

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