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Removal of ElectroEncephaloGram Signal artifacts and Signal Enhancement using Savitzky–Golay filter and SVM

SandhyaKumari Golla[1]*
[1] Research scholar,
Department of Electronics and communication Engineering,
Koneru Lakshmaiah Education Foundation,
Vijayawada, A.P,INDIA
Suman Maloji[2]
[2]Professor
Department of Electronics and communication Engineering,
Koneru Lakshmaiah Education Foundation,
Vijayawada, A.P,INDIA

* Corresponding author's Email: sandhyakumarigolla@gmail.com,suman.maloji@kluniversity.in

Abstract:

EEG has become the most commonly used signal for diagnosing and treating neurological conditions. These recording are frequently corrupted by various types of noise. Using various signal processing approaches, the artifact is typically removed as a preprocessing task. The Savitzky-Golay filtering approach was proposed in this article for removing noise from EEG signals. It is capable of lowering noise while preserving the shape and height of waveform peaks. The proposed noise reduction approach was tested using real-time EEG recordings of publicly available databases like mental arithmetic data and sleep data .The parameters like Signal to noise ratio (SNR) and mean absolute error (MAE) are used to evaluate the filtered signals. The results shown that the Savitzky-Golay (SG) filtered signals applied to the support vector machine and got good accuracy when compared to the maximum overlap discrete wavelet transform.

Keywords: *ElectroEncephaloGram(EEG), Savitzky-Golay filter, Signal to Noise Ratio(SNR), Mean Absolute Error(MAE)*

1.Introduction:

An Electrocardiographic monitoring system uses the Savitzky-Golay digital differentiator (SGDD) in the difference operation method (DOM) algorithm to detect the QRS complex. By selecting the appropriate window size and polynomial order, the differentiator may successfully reduce 60-Hz noise. The QRS complex within an ECG wave can be found using the difference operation approach, a straightforward and quick methodology[1]. The Savitzky-Golay filter is used in embedded electrocardiographic monitoring platforms to cancel out power line interference. The filter may be implemented in low-cost microcontrollers because of its arithmetical simplicity and use of a few integer coefficients[2]. White noise is effectively reduced by Savitzky Golay filter with smoothing. The investigation of many performance indicators, including SNR, PSNR, Entropy, SD, MSE, frequency spectrum, and convergence, shows that the SG filter with smoothing is more effective at removing noise from ECG signal[3]. The use of an SG smoothing filter depends on the frame length and randomly selected order. In comparison to single-stage SG filters, cascading SG filters have been shown to be a useful option. The maximum number of stages at which SG filtering produced noticeable changes was four[4]. The elimination of motion artefacts from EEG signals was suggested using the wavelet domain optimized Savitzky-Golay (WOSG) filtering method. EEG recordings from multiple publically accessible databases were used to assess the proposed WOSG filtering method. Using a DWT-based multi resolution analysis ,the approximate and detailed sub bands of the motion artifact intermixed EEG signal have been assessed [5]. The Freiburg EEG database contains the ECoG recordings of 18 patients with a total of 80 seizures and 437 hours of interictal recordings.

The proposed patientspecific seizure prediction system uses a classifier to distinguish preictal from interic tal ECoG signals.Preprocessing, feature extraction, classification using SVMs through double cross-validation, and post processing represent a significant portion of the patient-specific approach. The proposed technique extracts spectral power in nine bands from raw, time-differential, space-differential, and time/space-differential ECoG signals using four different feature sets[6].An overview of time frequency (T-F) approaches for signal processing is provided, along with a unique method for classifying and detecting EEG abnormalities based on a combination of signal and image related properties. The T-F representation of the signals is used to extract these properties, which describe the non-stationary nature and multi-component characteristic of EEG data. The signal-related properties, such as the instantaneous frequency, singular value decomposition, and energy-based features, are generated from the T-F representation of EEG signals[7].Relative-Energy (Rel-En), a quick innovative nonlinear filtering technique, is used to reliably extract short-term events from biological signals. We created an algorithm that separates the short- and long-term energy in a signal and outputs a coefficient vector that may be used to magnify the signal and highlight important occurrences.Two filters can be used to implement the suggested algorithm, and it's simple and intuitive to choose its settings. Additionally, Rel-En technique can be applied to other biological signal processing tasks requiring the extraction of short-term events[8].

The proposed distortion metrics were developed while focusing on the distortion of specific neural activity in each rhythm using wavelet subband energy and entropy of the EEG signal. For properly depicting the objective reconstruction loss in each EEG band based on neural activity, weighted signal to noise ratio (WSNR) and weighted correlation coefficient (WCC) were used[9].the adaptive threshold algorithm for the removal of eye movement traces and present a new LMS (Least Mean Square) based algorithm, by using the outlier signal of eye movement as a reference signal and taking the error signal of the LMS system as the estimated EEG signal to achieve a significantly greater signal to noise ratio (SNR)[10].High order statistical or spectral analysis, often known as HOS or HOSA, is capable of assessing non-Gaussian dynamics and is susceptible to Gaussian noise. They also incorporate the phase information, which is lost in the signal's power spectrum. HOS has been employed in wide range of applications as a tool for signal processing, including exploration of interactive oscillators, the analysis of plasmas, and the prediction of the orientation of patterns[11].Relative-Energy (Rel-En), a quick innovative nonlinear filtering approach, is employed to reliably extract short-term events from physiological signals. This approach is thoroughly evaluated using benchmark datasets of three different biomedical applications: imaging photoplethysmography (iPPG) peak detection, EEG K-complex recognition, and ECG QRS-complex detection. The proposed methodology for iPPG peak detection was deployed as a preprocessing step to a fixed threshold algorithm, which vastly enhanced final outcomes[12].

2. Related works:

Electroencephalogram (EEG) signals offer crucial information for locating epileptogenic regions. A crucial step in a successful surgery is the localization of the epileptogenic region using focused EEG data. The automatic identification of focused EEG signals is proposed using a framework based on convolutional neural networks (CNNs). Input EEG signals are converted into Time-Frequency (T-F) representation using the short-time Fourier transform (STFT) on segmented EEG signals[13].To remove muscular or EMG artefacts from multi-channel EEG recordings, multi-channel Singular Spectrum Analysis (MSSA) in the frame of Singular Value Decomposition (SVD) has been used. When compared to the EMG signal, the EEG signal's eigenvectors' frequency variations are relatively minimal. Once the frequencies correlated with EMG signals have really been suppressed and the artifact-free Multi-channel EEG signal has been retrieved, the frequencies associated with EEG signals are realized utilizing peak frequency threshold[14].EEG readings from 40 participants who watched both positive and negative films in the VR-3D and conventional desktop 2D display environments were used to analyze the effects of various emotional films on the audience in these two settings.

The results demonstrated significant differences in alpha and beta band activities between VR and desktop mode, which were replicated in the frontal, central, temporal, and occipital areas[15].The extraction of an EEG signal for the purpose of analyzing data from a drain has been extensively researched, as has the progress of signal process technology and integrated signal conditioning. The paper developed a low-cost circuit for a BCI (brain computer interface) platform to detect EEG signals. The modest circuit employs an active shield driver, a drifting power supply, and a resistance capacitance paired circuit, each of which has remarkable anti-interference properties. This circuit can precisely magnify the faint EEG input and accurately filter out background noise[16].In the instance of non-invasive electroencephalography, graph signal processing (GSP) delivers signal analytical capabilities for directly addresses in irregular domains (EEG). The recently developed method of GraphSlepianfunctions is demonstrated by various for the efficient decoding of motor imagery (MI) brain activity. The specific technique relies on the idea of the graph Fourier transform (GFT).

The informed projections are supplied to a support vector machine (SVM) in a MI-decoding method that combines Graph Slepians, which makes a prediction about the type of expected movement[17].In order to automatically categorize people's emotional states, this study aims to develop a powerful deep feature extraction-based approach. in an effort to find trustworthy deep features. The suggested method uses the acquired features as input to the support vector machine (SVM) algorithm to categorize them into two classes of binary emotions: valence and arousal[18].While many sound sources are present, details relating the user's preferred sound source is not facilitated by noise reduction algorithms in contemporary hearing devices. They can be supplemented with auditory attention decoding (AAD) algorithms, which are using electroencephalography (EEG) sensors to interpret the concentration, to tackle this issue[19].They looked at whether subtly expressed phrases with different connotations might be discerned during electroencephalography (EEG) was being recorded. 30 channel 10-20 system electrodes were employed to record neural activity. The accuracy was significantly increased to 92.46% employing support vector machine-based recursive feature reduction on optimized features[20].

The discrete wavelet transform (DWT) and maximum overlap discrete wavelet transform are two feature extraction algorithms the activity recognition hypothesis takes into account (MODWT). A support vector machine (SVM) classification system is feed the relevant features. The findings reveal an overall precision of 98.81%[21].An analogous strategy for noninvasive electrophysiological testing is Event-Related Potential (ERP). It is capable of transmitting accurate millisecond data of sensory and cognitive processes related to an event or details from a trigger. Three different analysis techniques, including Global Field Power Component Analysis (GFP), ERP Component Analysis, and Brain Topography Analysis, were applied to examine the findings of preprocessing EEG data[22].

The hypothesis of wireless EEG sensor networks (WESNs) makes a conscious effort to circumvent this constraint by interconnecting wide range of these mini-EEG sensors to various parts of the scalp. Similar AAD (Auditory Attention Detection) performance can be obtained utilising WESN-like platforms while still adhering to the rigorous sub - micron requirements for ambulatory EEG[23].To track the characteristic variation pattern, an unique multi-band sub-frame based feature extraction methodology is devised and to classify apnea and non-apnea incidents of an apnea patient in order to discriminate amongst apnea patients and healthy individuals[24].For the purpose of identifying the concentration levels during and after the performance of a cognitive task, a comprehensive examination of EEG signals gathered from individual young adults was undertaken. Entropy indices and the relative performance of the EEG signal in certain frequency bands are also assessed[25].Each EEG signal band provides distinct information about specific neural activity. For precisely expressing the objective reconstruction loss in each band, two robust distortion metrics have been recommended weighted signal to noise ratio (WSNR) and weighted correlation coefficient (WCC)[26].

Due to its shrinking property, the discrete wavelet transform is a suitable option for extracting the features of nonlinear and non - stationary signals such as EEG. The use of the wavelet denoising mechanism to EEG signals assessed during various stages of sleep is investigated systematically[27].Online artifact subspace reconstruction (ASR) and online recursive independent component analysis (ORICA) to remove large amplitude transients have been proposed[28].Variational Mode Extraction - Discrete Wavelet Transform (VME-DWT) performance is compared to that of an Automatic Variational Mode Decomposition (AVMD) and DWT-based methods proposed for suppressing eye blinks in a particular segment of a single EEG channel[29].A computerized algorithm for detecting and removing ECG abnormalities has been proposed.

The automatic distortion detection detects the regularity of the Electrocardiogram artifact, the occurrence of R-spikes, and the inability to link with the EEG signal[30].The utilization of Wavelet Scalograms as input to Artificial Neural Networks (ANN) for the defect analysis of epileptogenic events in Brain activity was investigated[31].Autocorrelation domain feature extraction is employed to classify alcoholic and non-alcoholic individuals. Instead of using traditional narrow spectrum filtering to examine the differences in features of EEG signals captured after exposing alcoholic and non-alcoholic subjects to external stimulation, a high pass IIR filter with zero phase distortion is used, where it preserves the Gamma band as well as all higher frequencies. The reflectivity of the filtered EEG signal are therefore extracted iteratively utilizing the autocorrelation values[32].

A procedure for finding and removing muscle artefacts in protracted EEG recordings using canonical correlation analysis (CCA) and wavelet transform (WT) and results are evaluated in 30 min epochs from scalp EEG recordings collected from three epileptic patients, retaining sensitivity and specificity of 71% and 80%, respectively, for k-means and spectral segmentation[33].The technique enables the analysis and classification of bio-signals with complex interactions, such as EEG signals, which have been heavily influenced by clutter in measurement techniques and a considerable ratio of fluctuation between specific studies in patients. The principal advantage of DDNNs is their measurement property, that enables them to operate with time-dependent variables in EEG signals[34].A new approach for retrieving matrix determinant attributes from evoked potentials signals for accurate processing of motor and mental imagery events[35].Figure(1) represents the block diagram of savitzky-Golay filter.

3.Methodology:

3.1.Savitzky Golay filter:

It has been proposed in 1964 by Abraham Savitzky and Marcel J. E. Golay as a replacement for an ordinary differentiation method as it adds desirable features to the differentiation operation, such as signal and arbitrary noise removal, minimizing the need for classifying stages in hardware that utilizes enormous amounts of energy.

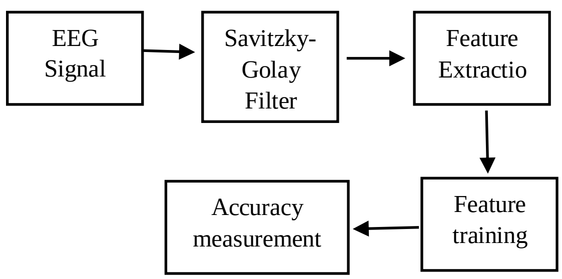

Fig.1. Block diagram of sacitzky-Golay filter

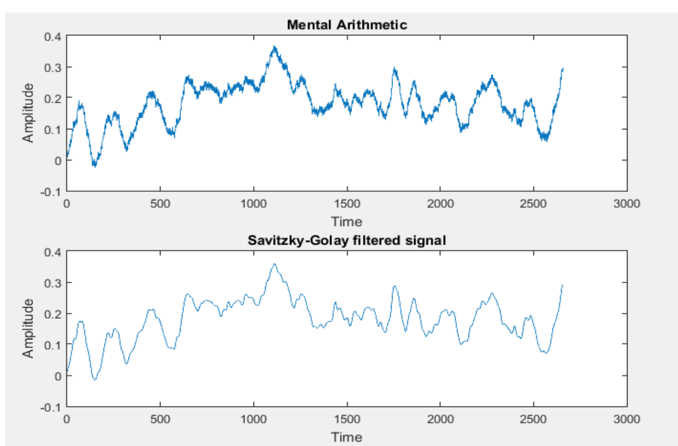

Fig .2. Filtered output of Mental arithmetic data

The filter procedure utilizes a specific set of integer coefficients and intuitive arithmetic. The operation with numerical parameters accelerates arithmetic, making it suitable towards integrated application on a minimal circuit board. The Savitzky-Golay filter SG(k, n) helps to smooth data using a polynomial iteration of the linear regression approach. It generates evenly distributed window of n samples to estimate the normalizedvalue of the window specific point using k-order regression techniques.The normalization property defines that all parameters of a Savitzky-Golay filter have been a ratio of two integer integers. It's an astounding capability for implementations in smart devices that would use an elevated processing unit. To summarize, expanding the pass band implies depreciating the ability to filter Gaussian-distributed signals, emphasizing a commitment between filtering ability and pass band. This dedication is exemplified by the fact that the first-order Savitzky-Golay filter is analogous to the moving average smoothing approach used to reduce random signals.SG filters are originated from the discipline of numerical analysis, they were first examined in the time domain.

The ideal digital differentiator (DD) considerably amplifies noise, especially at high frequencies, a low-pass DD is preferable to a greater alternative. The frequency response of the SGDD is pure imaginary, which is probably close to the frequency response of the ideal DD at low frequencies, according to the anti-symmetry. As a result, the SGDD could be defined as a low DD.A dth degree SGDD, equivalent to the impulse response restriction, precisely retains the phases of the gradient of the input signal up to order d.

$$\sum_n n^i \, y(n) = \sum_n n^i y_{ideal}(n) \qquad (1)$$

Where y(n) and y_{ideal} are the output of the SGDD and the ideal derivative of input signal. The measurement of the noise amplification factor and the best cut-off frequency may support in the selection of the right SGDD to reduce noise amplification while rejecting noise frequencies higher than the cut-off frequency. In this study, mental arithmetic data was analyzed using the Savitzky-Golay filter of order 4, while sleep data

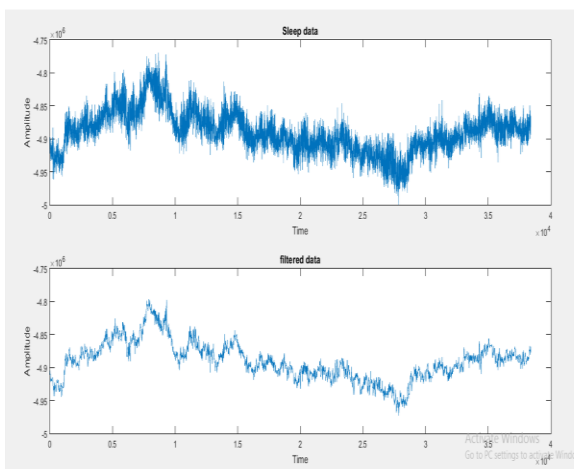

Fig .3. Filtered output of sleep data

was studied using the same order of the SG filter. When compared to Mental arithmetic, the resultant output is a signal with less filtration, and the outcome is not desirable. The results show that the SGDD's correlation and resolution loss is proportionate to the ratio of the cross - section of the signal gradient to the sampling frequency.

Savitzky and Golay proved that the smoothed result obtained by sampling the fitted coefficients at each position is similar to a finite linear combination of the neighborhood set of specified input samples with in approximation duration are integrated by a specific set of weighting coefficients that can be computed once for a given polynomial order N and approximation interval length.SG filtering is applied to a set of digital sample points with the objective of increasing the SNR without decimating the signal's spectral characteristics. Elements of subsequent sample points are furnished with a low order polynomial using the linear method of least squares and algebraic convolution. Figure(2) represents the filtered output of mental arithmetic data and figure(4) represents the filtered sleep data using SG filter.

The output samples can be computed by using discrete convolution of the form

$$y(n) = \sum_{m=n-M}^{n+M} h[n-m]\, x[m] \qquad (2)$$

Linear least squares fitting technique is used to fit a polynomial with an interval d and the convolution coefficients can be represented as,

$$r = \frac{x-\bar{x}}{d} \qquad (3)$$

$$c = (A^T A)^{-1} A^T \qquad (4)$$

3.1.1. Signal to Noise Ratio(SNR):

The signal-to-noise ratio (SNR) is a measure of the fidelity of signal transmission and recognition by both synapses and neurons. It is a non - dimensional proportion of signal power to noise power. SNR can be utilized to measure the quality of electroencephalographic recordings containing noise-affected events[36].Figure(4) is the graphical representation of mental arithmetic data and figure(5) is the graphical representation of sleep data. Table(1) represents the retrieved values of SNR of mental arithmetic data. Table(2) represents the retrieved values of SNR of sleep data.

SNR of unfiltered data	SNR of Cleaned data
3.018	5.112
20.214	21.37
5.285	6.069
13.057	17.575
14.696	18.364
11.063	13.111
10.987	11.758
1.187	2.937
7.219	8.666

Table.1. SNR of Mental arithmetic data

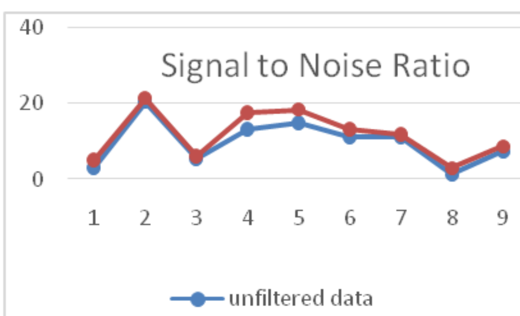

Fig.4. SNR of Mental arithmetic data

The recorded electrical impulses consists of brain signals combined with noise from many other parts of the body, such as heart rate, blinking and eye movement, and other cranial muscle movements. The surrounding in which the EEG data is captured is yet another source for external noise. SNR control measures are grouped into two categories like eradicating external noise sources and classifying internal noise from the signal of interest. The SNR of time-frequency overlapped signals is expressed as ,

$$SNR = \frac{E[(\sum_{i=1}^{N} x_i(t))^2]}{E[n^2(t)]} \qquad (5)$$

SNR of unfiltered data	SNR of Cleaned data
-10.348	-6.026
-5.340	-0.372
8.333	13.242
-2.108	3.843
-5.155	0.677
-12.640	-6.774
-7.571	-2.747
-11.156	-6.890
-1.468	2.785

Table.2. SNR of sleep arithmetic data

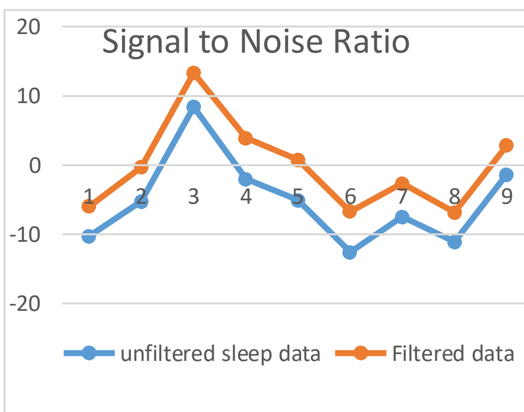

Fig.5. SNR of sleep data

3.1.2.Mean Absolute Error (MAE):

The estimated standard deviation between both the noisy and denoised variables is defined as MAE. In relation, each deviation contributes to MAE in proportion to its absolute value. MAE is calculated by dividing the total number of absolute errors by the sample data. It can be obtained by adding the orders of magnitude of the deviations to obtain the total error, which is then divided by n_i. Figure(3) is the graphical representation of MAE of mental arithmetic data and sleep data.Table(3) represents the values retrieved through Mean Absolute Error.

$$MAE = \frac{\sum_{i=1}^{n} y_i - x_i}{n} \qquad (6)$$

MAE of mental arithmetic data	MAE of sleep arithmetic data
0.0070	8.1e+03
0.0027	8.0e+03
0.0043	8.1e+03
0.0052	7.6e+03
0.0038	7.7e+03
0.0041	7.7e+03
0.0033	7.74e+03
0.0035	6.62e+03
0.0047	6.43e+03

Table.3. MAE of Mental arithmetic and sleep data

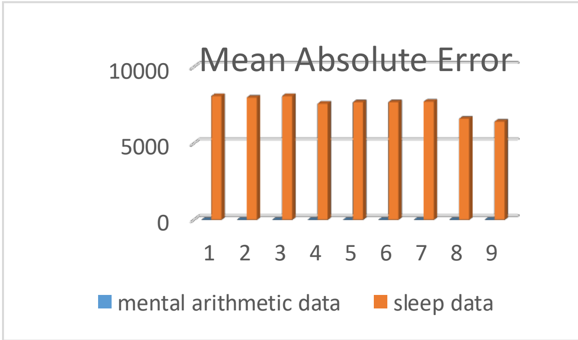

Fig.6. MAE of Mental arithmetic and sleep data

3.2. Support Vector Machine (SVM):

Support Vector Machine, or SVM, is a prominent Supervised Learning algorithm that can be used for both regression and classification problems. The SVM classifier parameters is an important step in establishing an effective system classification. In fact, at least two different parameters must be carefully chosen for setting the kernel and the regularization parameter , where it allows for the compromise between error-based learning and specificity models. Figure(8) represents the algorithm of support vector machine.

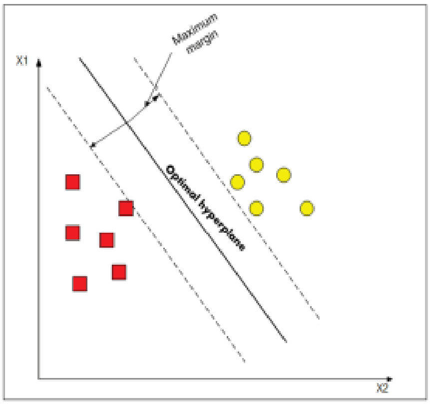

Fig.7. Support Vector Machine

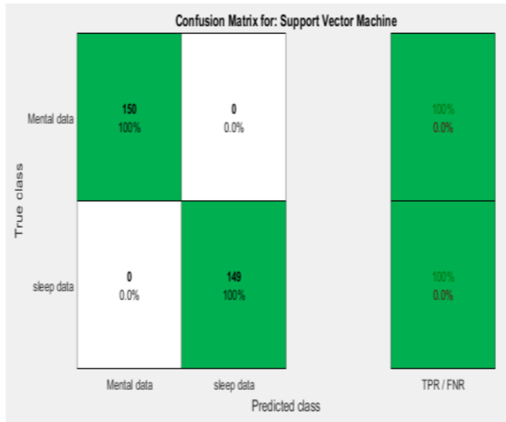

Fig.8. Confusion matrix of SVM

The SVM algorithm's objective is to determine the best line or decision boundary for identifying and classifying n-dimensional space in appropriate category in the long term. SVM selects the intense points that aid in the formation of the hyperplane. Such intense situations are referred to as support vectors, and the technique is known as the Support Vector Machine. The data that has been processed with savitzky-Golay filter is applied to the support vector machine of all the kernels and got good accuracy.Figure(9) represents the confusion matrix of SVM.

4.Conclusion:

The Savitzky-Golay filter has been proposed and tested on Mental arithmetic data and sleep data.The filter is able to denoise the EEG signal without affecting the actual coefficients.The filtered signal was utilized to evaluate parameters such like signal-to-noise ratio and mean absolute error, and retrieved a low mean absolute error and a good signal-to-noise ratio. The extracted features of processed data was trained to an SVM classifier which performed good across all kernels.

5. Conflict of Interest:

There have been no conflicts of interest from among authors. All co-authors have evaluated and approved the manuscript's content. We ensure that the submission is authentic and has not been reviewed by another publisher.

6. Author Contributions:

The first author proposed, designed, performed the experiments, and evaluated. The second author made a significant contribution to the manuscript's development and assessment.

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