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Research Article

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Design Consideration And Feature Extraction For Unsupervised Ensemble Based EEG Artifacts Eradication And Classification

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ABSTRACT

There is several motion artefacts that might appear in electroencephalography (EEG) data during recording. There were many ensemble based multimode decomposition methods had been designed to eradicate these artifacts. First the true and artefact signals are classified using machine learning (ML) methods. Then paper design and assess the qualitative performance of different unsupervised ensemble algorithms employing EEMD, ICA, EEMD-ICA, as well as EEMD-CCA for the elimination of EEG artefacts. For assessment the district database is taken into account. Actual and artificially created artefact data are also included in the evaluation. The motion artifacts especially ocular Eye blinks (EOG) and muscular (MMG) artifacts are considered for the research. The major challenge is to eradicate high peak eye blinks artifacts. Thus paper proposed wavelet based de noising to improve the signal strength after eradication of the artifacts. The performance is assessed based on the combination of DWT with all these ensemble based methods. The ultimate contribution of the paper is to generate the novel feature set for identification and classification of the EEG artifacts within the EEG signal data. The statistical features with different methods are calculated including PSNR, RMSE, mean, standard deviation, peak to peal difference, the EEMD-CCA-DWT out performs.

Keywords- Machine Learning, EEG signal, Artefact Classification, Basssian Optimization, Motion artifacts removal, EEMD-ICA, EEMD-CCA-DWT, Correlation Filter.

I. INTRODUCTION

EEG signals are critical for detecting brain activity. When compared to other physiological indications, EEG signals perform significantly better. The standard multi 20 electrode system is used for the acquisition of EEG signals form brain. Thus EEG signals contained multiple low and high frequency signals. In general EEG signals suffer from the motion artifacts due to muscular motion or eye blanks. Thus many multi-mode decomposition methods have been studied in past for pre end filtering or artifacts removal. The ultimate aim of this paper is to evaluate the statistical features for these EEG artifacts removal methods. In early days many ensemble based EEG artifacts removal methods were designed viz. Ensemble Empirical Mode Decomposition (EEMD) [1] has challenge of mode mixing, multimode independent component analysis (ICA) [2] suffer from Gaussian nature of artifacts and offer restricted muscular artifacts detection. Later hybrid methods as a combination of EEMD-ICA [3, 4] were designed which had slow convergence. These methods have semi-automatic algorithms and may leads to loss of useful EEG information. Principal Component Analysis,(PCA) via [5] and approach of double blind source separation (BSS) based artifacts removal was presented [6].were used for artifacts removal.

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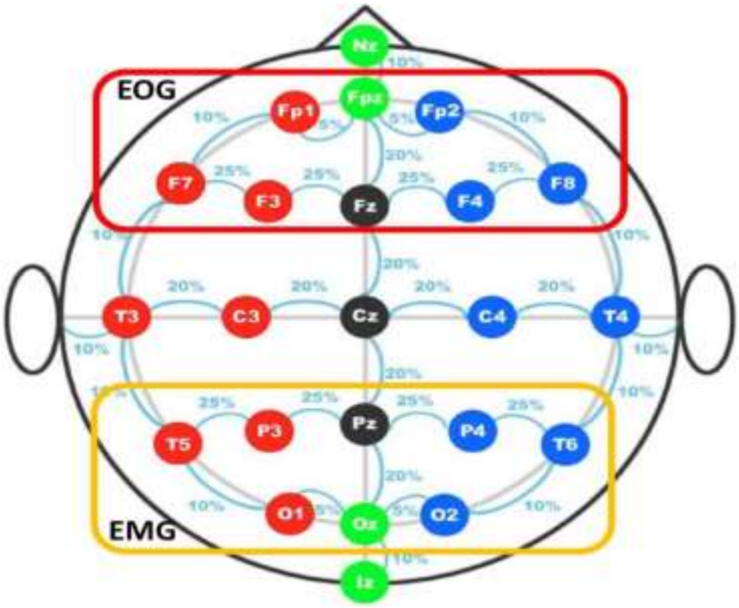
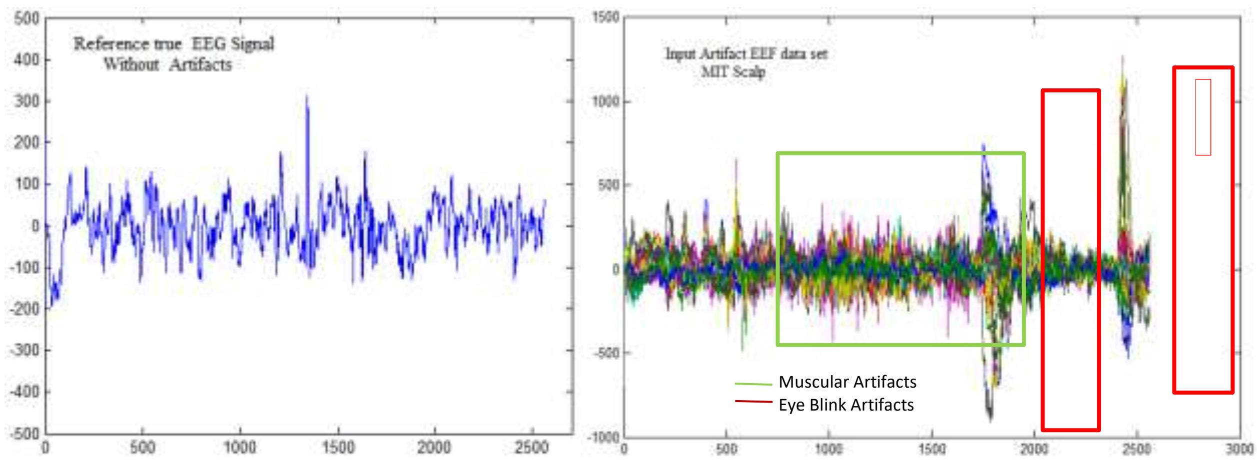


Figure 1 Standard 10-20 EEG signal recording and respective electrode responsible for motion artifacts

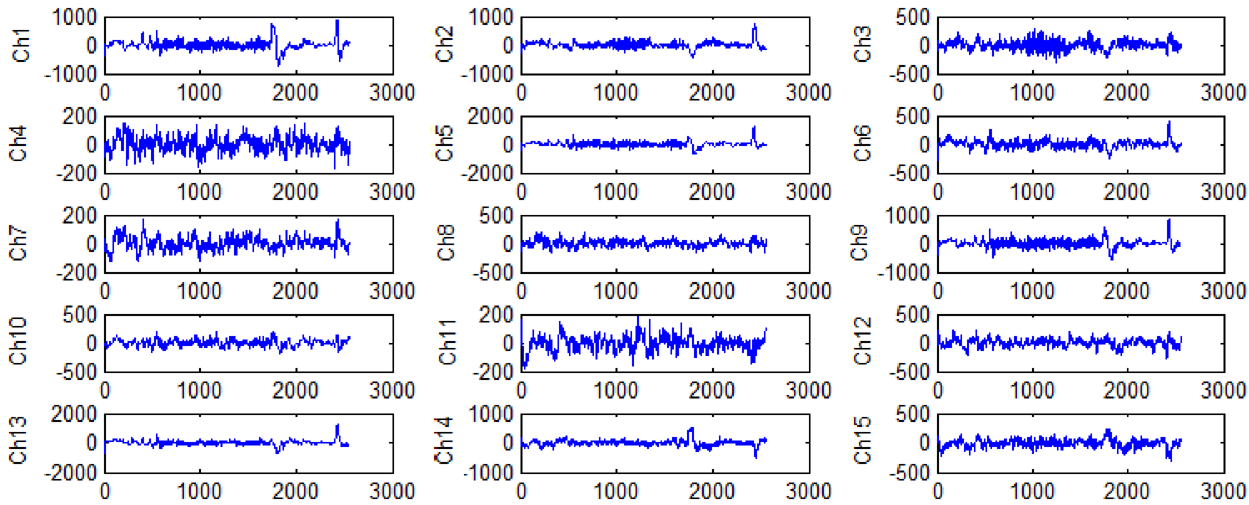
Later performance improvement is offered using modified ICA based artifacts detection methods. A spatial Constraint based ICA (SCICA) with EEMD proposed in [7], fast and efficient artifacts removal method using canonical correlation analysis (CCA) EEMD-CCA is proposed in [8]. A new method of Gaussian elimination based GE-CCA is proposed for EEG artifacts eradication by Vandana [9]. In recent times there are certain deep learning based methods [10] are designed for the achieving the EEG filtering. Thus in this paper our prime concern is to access ensemble based methods for feature extraction to be used for artefacts classification.

The multi-channel EEG data in order to adhere with the global standard of 10–20 channels as shown in the Figure 1, Individual data samples are divided into 16 channels. Figure 1a) displays a first 16 channels of a chb01 01 data online-accessible EEG data set. Signals from EEG are crucial for documenting brain activity. Comparing EEG signals to certain other physiological signs, they perform far better. The EEG signals were obtained by electrodes placed on the individual brain's scalp.

Current techniques employ Empirical Mode Decomposition (EEMD) [1] and Canonical Correlation Analysis (CCA) [2] to eliminate artefacts; Mode mixing, or the incomplete separation of components belonging to distinct scales, which is the main challenge for only EMD, [1] based artifacts removal methods. Furthermore, selecting the right stopping condition can be arbitrary and affect the outcome of the Ensemble-EMD (EEMD) based decomposition process [3]. Before executing EMD, in ensemble based (EEMD) approach white noise is added to the signal in order to alleviate the mode mixing problem. Choosing the right amount of intrinsic mode functions (IMFS) and increasing the complexity as the IMFS rises is the main issue with EEMD.



a) True EEG Reference Channel (Ch18), b) Artifacts data of 23 channels



c) Artifacts data used for classification

Figure 2 Dataset of`23 scalp multichannel MIT Scalp EEG signals with motion artifacts

There are certain methods which have synthetically generated the EEG signal (Roy, Vandana et al) [9] by adding noise of different amplitudes together. Nevertheless, more research and performance improvement in very noisy settings are required. This work proposes an improved ensemble approach for single channel EEG data for eradicating motion artefacts.

1.1. Contribution of work

Paper addressees the problem of EEG artifacts classification and eradication. To get rid of EEG artefacts, numerous ensemble-based multimode decomposition techniques had been developed. First, machine learning (ML) techniques are used to classify the real and artefact signals. A Novel feature extraction approach is presented based on reference signal. Next, paper designs and evaluates the qualitative performance of various unsupervised ensemble algorithms that use EEMD, ICA, EEMD-ICA, and EEMD-CCA to remove EEG artefacts. The district database is considered while making assessments. The examination also includes data from intentionally generated and real artefacts. For the research, motion artefacts are taken into consideration, particularly ocular eye blinks (EOG) and muscular artefacts (MMG). Eliminating high peak eye blinks artefacts is the main task. Therefore, when the artefacts were eliminated, the research suggested using wavelet-based de-noising to increase the signal strength. The performance is evaluated based on SNR and RMSE calculation for different filtering methods using DWT based filtering.

2. Dataset Used for Artifacts Consideration

The true artifacts free reference EEG data as selected Ch18 from the districts EEG datasets is shown in the Figure 2 a). This reference channel is used for the calculation of the relative Peak signal to Noise ratio (PSNR) for the classification of data. The complete EEG data of the 23 channels MIT scalp data are represented in the Figure 2 B). it can be observed from the Figure 2 b) that dataset contains high peak eye blink and dense muscular artifacts data. These are merged with motion artifacts data with 15 channels (Ch1 to Ch15) are merged together as shown in Figure 2 c). Research has proposed to first detect the artifacts or artifacts free EEG from the dataset based on statistical features. The data channels (Ch1 to Ch15 out of 23 channels) are taken which suffer from EEG motion artifacts during acquisition such as eye blink EOG and muscular EMG artifacts. Additionally the Gaussian noise is also present in channels like (Ch4, Ch7, Ch8, Ch11, and Ch15) respectively represent slight small muscular motion. While, channels with more than 1000 mV or up to 2000 mV amplitude represent the high amplitude eye blink signals such as (Ch1. Ch2, Ch5, Ch6, Ch9 and Ch13) respectively in Figure 2. Since the multiple EEG electrodes are used for the acquisition thus all these EEG data consist of multi-band frequency components. Thus after pre pre-processing many decompositions methods may be used for represent multi-channel EEG data before being filtering the data. The Figure 2 clearly shows that not all EEG data has motion artefacts, hence detecting them prior to filtering is critical. Thus for classification problem data can be considered as artifacts free, muscular artifacts, and eye blink artifacts categories.

3. Applications of the EEG Artifacts Detection

EEG data usually records the electrical activity of human brain thus is biologically very useful. There are many versatile application of EEG artifacts detection as shown in Figure 3. The most frequent ones are brain computer interface (BCI), Clinical diagnosis as Epilepsy and sleep disorder. Amongst these the BCI is suitable for robotics and human activity monitoring applications.

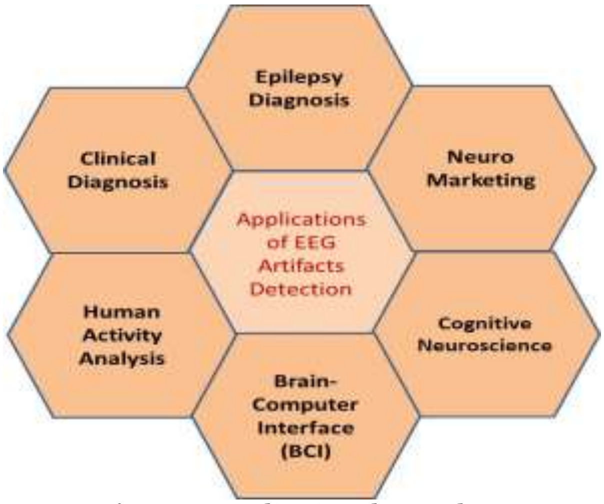


Figure 3 Application cluster chart

Neuro-marketing is a contemporary field that interprets client thinking for marketing purposes. Early detection and classification of EEG artefacts may considerably enhance data interpretation and diagnosis accuracy. EEG signals can also be used to check a person's status during a coma.

4. Related Work

There has been lot of research done in past for EEG artifacts removal and classification. This section has sequentially reviewed the most relevant research works. Jiang, X. et al [1] presented good review of artefact removal methods in there paper. First, they had explored the features of EEG information as well as the many kinds of artefacts. The most recent artifacts removal techniques were then briefly reviewed, followed by a detailed examination. Finally, a comparison of methods is offered to help select the best approach for an instance.

Goh, S. K., et al [2] provided method of independent component analysis (ICA) for EEG signal decompositions. The each component is divided into two vectors by this breakdown: the local vector, which preserves the most material from the distinct EEG data captured by an electrode, and the shared vector, which absorbed redundant artefact information. There formula for an implicit Pareto-based multifaceted optimization trades off un-correlatedness among the local matrices of every element and the resemblance of the present-day vector and the initial vector. They showed that the suggested ICA technique can maximally preserve EEG data whilst eliminating artefacts from an EEG signal. K. Zeng, et al [3] have grouped ensemble based empirical mode decomposition with ICA abbreviated as (EEMD-ICA) method suggested to decompose multimodal neural data, which may be noisy, into internal mode functions (IMFs). The artifactual elements of the IMFs were subsequently separated using separate component analysis (ICA). The strategy was evaluated versus the two most popular techniques for artefact rejection: automated wavelet ICA (AWICA) & classic ICA.

Yang, B. et al [4] had also presented the EMD-ICA based technique: First, EMD is used to break down EEG data from any number of channels into a collection of IMFs functions The input/output matrices of the ICA is made up of these IMFs, each of which may be roughly employed as an input channels. Subsequently, entropy of each ICA is statistical examined in order to figure out whether data has artefacts or not. Artifacts are eliminated and then steps involve feature extraction and EEG data is classified from both sets of data using the supported vector machine (SVM) as method and similar spatial trends (CSP) in order to assess the effectiveness of the suggested approach. Arjon Turnip et al [5] has proposed a flexible principal component analysis (PCA) of iterative minimum squares technique and a band passing filtering for eliminating the artefacts. Eight individuals' genuine EEG recordings were used to evaluate the suggested strategy. Bartels G et al [6] presented a new technique utilising SVM algorithms & blind source separation (BSS) that effortlessly and consistently removes artefacts from EEG. To confirm the correctness of the suggested method, performances were contrasted for prepared and artifacts-contaminated data on a motor imaging task.

Anchal Yadav et al [7] had designed a novel method for removing the ocular artefact combining EEMD and Space Constraints ICA (SCICA). The artifactual EEG data is processed using EEMD to produce IMFs then correlation coefficient is used to distinguish the artifacts and artifacts-free IMFs. In order to get Isolated Component (ICs) and the reverse of the mix matrix, the artifactual IMFs have been included as the input feeds for autonomous component analysis (ICA). Chen, X. et al. [8] proposed a unique combination of EEMD and canonical correlation analysis (CCA) for removing muscular artefacts from EEG data. This strategy can effectively use inter-channel data. The method fared better than cutting-edge methods like EEMD-ICA, CCA, and autonomous component analysis. Additionally, they tested the method using a few-channel EEG that was randomly chosen from a multilingual EEG dataset, and the results were acceptable.

Roy Vandana et al. [9] had addressed motion artefacts generated during the EEG signal collecting process. There artefact removal techniques employ wavelet transformation (WT), ensemble decomposition EEMD, and CCA, to eliminate artefacts. In a highly noisy surroundings, a new method is suggested to further evaluate enhance, and shorten the filter computation period. This novel GECCA technique depends on the approach known as Gaussian elimination, which is intended to remove motion artefacts from EEG signals and is used to calculate correlation values using backslash operations. The GE reduces the computational cost of the CCA method by solving linear equations to determine Eigen values. Employing EEMD-GECCA and wave change, this innovative suggested approach is evaluated against existing artefact reduction strategies.

M. A. Ozdemir, et al. [10] have proposed deep learning (DL) model via bi-direction long-short term memory (BiLSTM), a unique technique for eradicating ocular artefacts is demonstrated in this study. They combined EEG de-noise Net & deep databases for training and testing to evaluate suggested DL models. Additionally, Wavelet Synchro-squeezed transformation (WSST) was used to create highly-localized time-frequency (TF) values, which are subsequently supplied to the Bi-LSTM is net for obtaining characteristics from enhanced events. But method required large EEG data and is also computationally complex.

Shailaja Kotte et al. [11] used an EEG to record brain signals and have reviewed various artifacts eradication methods. Its small magnitude and narrow frequency band makes it easy for external impulsive noise to confuse EEG from the surrounding environment. Incorrect signals were resulted from this and are difficult for the evaluation. Methods like ICA, CCA and along with wavelet are most frequently used in past to eliminate these noises. Chen, Xun et al. [12] have proposed EEMD-CCA for removing muscular artefacts from EEG data. This strategy can effectively utilise inter-channel data. They had evaluated method on three different data sets: real-world, semi-realistic, and artificial. There method fared better than cutting-edge methods like EEMD-ICA, CCA, Mathe, Mariyadasu et al. [13] had provided an overview of current approach used to eliminate physiological artefacts, such as those related to the heart ECG, muscles, and eyes. A summary of data-sets and efficiency metrics used in earlier research for artefact removal were discussed. Each technique viz., wavelet transformation (WT), the (BSS), single spectrum examination (SSA), and independence vector estimation (IVA) were examined along with their benefits and drawbacks. The DWT-BSS, EMD-BSS, unique spectrum estimation - adjustable disturbances canceler (SSA-ANC), SSA-BSS, & EMD-IVA are some of the composite algorithms' were also presented.

Greeshma Joseph et al. [14] had presented the ICA and combination of wavelet packet transform (WPT) as the new techniques were presented. They have concluded that ICA has achieved max of SNR with the WPT-ICA as 14.3959 dB as the performance evaluation. Frølich, L., et al. [15] had used a version of ICA method for reducing muscular EEG artefacts. Aim was to vertically partition the signals with the goal to differentiate artifactual from neuronal origins. Performance is contrasted with linear deconstruction Fourier-ICA and spatio-spectral decompositions. These were found appropriate with three of those most widely used ICA techniques—extended Infomax, FastICA, and TDSEP. We assess the techniques' capacity to eliminate event-locked muscular artefacts while preserving event-related separation in data derived from eighteen individualised foot activities respondents.

Zhenyu Jin et al. [16] have compared numerous artefact elimination methods using transformations, decompositions and filters. Rashmi C R et al. [17] stated that collected electrical brain waves are frequently affected by a variety of artefacts, including cardiac, muscular, and blinking patterns in the eyes. They had presented a comprehensive review to summarize all the approaches that can be used to eliminate physiologic artefacts. A contrast of all the approaches is also covered, along with a discussion of the results of assessment criteria.

Kaur, C. H., et al [18] have employed EEG as an objective analytical instrument to detect depression in its early stages. However, EEG signal processing methods become less accurate due to artefact interference. This paper presents a unique method of de-noising using the wavelet packets transform and EMD with Detrended Changes Analyses (DFA). Meryem Felja et al [19] stated that there were various methods used in literature to eliminate EEG artefacts. This work presents and analyses a novel approach to EEG de-noising that combines wavelet transformations (DWT) with traditional filters.

Roy Vandana et al [20] had addressed the division of the signal's artefact peaks is accomplished via independent component analysis (ICA). Subsequently, a discrete wavelet transformation can be used to transmit signal data at multiple levels until a substantial result is obtained. They widened our search and used the Dual Density Method for the transfer of various tiers. The EEG signal data set that was collected using an external reference was used for analysing the results. It is possible to apply the approach in hospitals because it is parameter-free. V. Krishnaveni et al [21] had aimed to ocular artifacts (OA) for both the low and high frequency parts are adjusted when the wavelet-based EOG rectification technique is used over the whole EEG data.

Olaf Dimigen et al [22] stated that though ICA is frequently employed to reduce these ocular artefacts, many published findings still include residual artefacts and its effectiveness under free seeing settings has not been thoroughly assessed. In this case, I assessed and refined ICA-based corrections for two unrestricted gaze tasks: reading sentences and performing visual search in images. Mahmud, S. et al [23] provided a ML based mufti layer neural network solution for the maximally preserve EEG information while eliminating artefacts from an EEG data.

Velu Prabhakar Kumaravel et al. [24] had presented Neonatal EEG Artefact reduction (NEAR), an EEG artefact reduction pipeline specifically created for neonates. S. Stalin et al. [25] in their study had suppressed additional artefacts before the core motion artefact is identified from one-channel EEG signal employing a support vector machine (SVM). The group decomposition of empirical modes (EEMD) approach is used to abstract from the signal characteristics and perform additional detection. Additionally, the motion artefact elimination is accomplished by the use of the canonical correlation assessment (CCA) filtering technique. Finally, the wavelet transformation (WT) method is used to eliminate the unpredictable nature of any remaining motion artefacts. Liu C, et al. [26] have proposed eliminating one-channel EEG signal artefacts. For the removal of artefacts from single-channel EEG recordings typically combines the blind source segmentation (BSS) method with the decomposition method. For the purpose of removing artefacts from single-channel EEG, ICA and decomposition of empirical modes (EMD) techniques have been combined. The Variational modal deconstruction (VMD) outperforms EMD in terms of the deconstruction impact since EMD is susceptible to modal integrating and lacks a foundation in theory. D. Pancholi,and P. Rawat et al. [27] had proposed a EEG artifacts removal methods for specific application area of the brain computer interface (BCI). They have preseted various methodologies as EEMD, ICA and CCA approaches was used for motion artefact elimination is accomplished by the use of the standard correlation assessment (CCA) filtering technique. Finally, the wavelet transformation (DWT) algorithm was used to eliminate the unpredictable nature of any remaining motion artefacts. Anand Prakash et al. [28] have reviewed artefact removal approaches and their features are the main topic of this review study. To best of my understanding, this assessment comprises multiple works.

R. Rajabioun et al. [29] had first identified any artefacts that may have been present in the collected signals from the EEG, using 1-D Convolutional Neural Networks (CNN), for multi-class EEG artefact detection is presented in their research. In order to optimise operating time, the suggested CNN models remained as straightforward as feasible; nonetheless, in the interim, modelling was sufficiently deep to retrieve relevant artefact characteristics from inputted EEG data. Achraf Djemal et al. [30] has a goal to refute the incorrect conclusions made by the expert, demonstrate accurate EEG signal measurements, and extract only pertinent data form the electroencephalogram (EEG) signal the concept of ICA method. The study includes epilepsy individuals' ages, time measures, seizure kinds, and aberrations for evaluation.

The summary of the related work and evaluation parameters are compared in the Table 1. It is clear from the Table 1 that EEMD-CCA is fatter and offer higher SNR comparatively. The ICA is slow to converge and SNR is also lowered side. The CCA is faster than ICA and using the DWT in combination may achieve significant SNR performance. But on the other side multilevel decompositions may leads to reduction in amplitude.

Table 1 Summary of review work and the parametric evaluation

Authors	Methodology	Parameters
Jiang, X.; et al [1]	Have proposed in literature review of the for artifact removal on EEG.	(LMS) is used to help adaptive filter to upgrade its weight parameter and artifacts eradication.
Sim Kuan Goh et al [2]	Proposed method can automatically isolate artifacts from an EEG signal while preserving maximum EEG information.	Independent Component Analysis was proposed but is relatively slow to converge and noisier too.
K. Zeng et al.[3]	The approach was tested against the classical ICA and the automatic wavelet ICA (AWICA) methods,	SSIM of the EEMD-ICA can almost double that of AWICA and triple that of ICA.
Anchal Yadav et. al [7]	The proposed method is based on EEMD algorithm, in combination to SCICA	Parameters like kurtosis and modified Mean Sample Entropy (MMSE).
Roy, Vandana et al. [9]	Have proposed GE-CCA based method with novel approach for EEG artifact removal. And proposed EEMC-GECCA-SWT as the best.	Concluded that EEMD-CCA-DWT method offer MSE of 69.3283 and stated EEMD-CCA-DWT offer 57.0117% accuracy. But there method of GECCA claims significant improvement offer conventional CCA.
Greeshma Joseph et al. [14]	Have proposed ICA based EEG artifacts removal method along with WPT.	Have achieved 14.3959 dB for WPT-ICA based EEG artifacts elimination. .
Frølich, L., et al [15]	Here we compare three of the most commonly used ICA methods (extended Infomax, FastICA and TDSEP)	Running Fourier-ICA they have used the implementation to run Fourier-ICA with the default parameters. Slightly faster than ICA.
Rashmi C R. et.al. [17]	independent component analysis (ICA) is the most popular single artifact removal method	Scale and translation parameters.
Velu Prabhakar Kumaravel et al [24]	We propose Newborn EEG Artifact Removal (NEAR), a pipeline for EEG artifact removal designed explicitly for human newborns.	ASR cut-off parameter (k), LOF bad channel threshold, ASR parameter k and ASR processing mode.
Shalini Stalin et al [25]	EEG signal using SVM and preceded with further artifacts' suppression. They have used synthetic artifact data and EEMD-CCA for artifact removal.	The concluded that EEMD-CCA-SWT is best approach and applied HHO optimization or performance improvement.
Liu C, et al [26]	Method of artifact removal combining variational mode decomposition (VMD) and second order blind identification (SOBI).	Single-channel EEG signals are decomposed into multi-channel datasets by the VMD method after optimizing parameters. Method has specific uses
D. Pancholi, et al. [27]	They have preseted the review of various EEG artifact elimination method for BCI.	They found that quantitative analysis of the CCA based methods are faster than ICA based. They also concluded that EEMD-CCA-DWT offers better SNR. Additionally CCA-DWT may represent more frequency peaks

Achraf Djemal et al [30]	Independent Component Analysis (ICA) method for a real epileptic EEG dataset will be investigated for artifacts identification and removal.	Electromyography (EMG), Electrocardiography (ECG), and Electrooculography (EOG))

4. ML Methodologies for EEG Processing

Since EEG signals composed of multi frequencies thus there were much decomposition techniques used for EEG signal processing. This method belongs to unsupervised ML based approaches. These methods are EEMD, ICA, CCA and ther hybrid combinations along with transformations like DWT and SWT. This section described these methods sequentially.

4.1 EEMD decomposition of synthetic data

The EEMD have been used for decomposing [27] the signal to multiple intrinsic mode functions (IMF) by adding and the evaluating the Gaussian noise. The output is formed by putting all of the IMFs as well as residual signal together as;

$$y = IMFs = \sum_{j=1}^{l} f_j + p_l \qquad (1)$$

Figure 4 a) illustrates the EEMD decompositions of motion artifacts data at 10 dB SNR noises. It can be seen that as no. of IMF increases the frequency is decreased.

4.2 Independent Component Analysis (ICA)

It is assumed that noise is produced in ICA in a non-orthogonal Gaussian manner. The mathematical framework of the noise integration process utilised during the ICA is as follows;

$$S_{ICA} = A_{N\times M}C + n \qquad (2)$$

Where A is the $N \times M$ size of mixing matrix and n is the additive noise. The signal combination $C = [c_1, c_2, c_j \dots c_N]$ is taken as input to ICA. Since in recent times the hybrid EEMD and ICA combinations were proposed thus C is considered as average $IMFs = y$ taken from the Eq. (1) the ICA algorithm (Roy & Shukla, 2017) are applied. The following independent components results were determined to figure out the total transformation matrices W as:

$$I = W\,X = W\,A\,S_{ICA} \qquad (3)$$

Where, I is the estimated independent components (ICs) and is linearly separable. Method is a BSS-ICA method but lacks the computational accuracy. The Figure 4 b) represents the ICA determined suing the motion artifacts EEG ch1. It can be observed that as the no. increases the IC's has higher frequencies.

4.3 Canonical Correlation Analysis (CCA)

Shailaja Kotte et al. [11] had previously established the Canonical Correlation Analysis (CCA) approach [6]. A BSS-CCA technique was used for determining the correlation between two stochastic processes with many dimensions. Through this methodology, the primary multi-dimensional random elements are handled as a starting point vector, as well as the secondary multidimensional random variables are treated like the first base vector's time-delayed counterpart.. As a consequence, the CCA method uses the data's variability and covariance matrices to determine the linear correlation between the two sets of statistical variables. A pair of pairings, A and B, is supposed to be:

$$\mathrm{B}_v = [\mathrm{b}_{11}, \dots \mathrm{b}_{12}, \dots\dots \mathrm{b}_{1\mathrm{N}}]^{\mathrm{T}} \qquad (4)$$

$$\mathrm{A}_u = [\mathrm{a}_{11}, \dots \mathrm{a}_{12}, \dots\dots \mathrm{a}_{1\mathrm{M}}]^{\mathrm{T}} \qquad (5)$$

Lets that, C_{uu}, C_{vv}, and C_{uv} are the variances of A_u, B_v, and their respective covariance's,. Consequently, the relationship amongst the $\mathrm{A}_u$as well as B_v could be given as;

$$\mathrm{P}^* = \frac{\mathrm{A}_u^{\mathrm{T}} C_{\mathrm{uu}} \mathrm{B}_v}{\sqrt{\mathrm{A}_u^{\mathrm{T}} C_{\mathrm{uu}} \mathrm{A}_u}\sqrt{\mathrm{B}_v^{\mathrm{T}} C_{vv} \mathrm{B}_v}} \qquad (6)$$

In order to achieve the optimum self-correlation, set variable P* as the highest value and as a result, that optimisation may be finished.

$$C_{uu}^{-1} C_{uv} C_{vv}^{-1} C_{vu} A_u = \rho A_v \qquad (7)$$

$$C_{vv}^{-1} C_{vu} C_{uu}^{-1} C_{uv} B_v = \rho B_v \qquad (8)$$

The Eigen values are calculated as having a squared value of P* represented as.

$$\rho = \sqrt{P^*} \qquad (9)$$

These canonical pairs or matches are identified and distinguished by obtaining mutual de-correlation as well as self-correlation among the source systems (R. Rajabioun et al. [20].

4.4 Hybrid EEMD-ICA

The EEMD-ICA approach was first documented by Anchal Yadav et al. [7]. The EEMD technique is used to convert a single system EEG signal into the multi-channel output. Additionally, these acquired IMFs are employed as an output in the ICA sources separation method's second step.. Because the input components were independent, this ICA evaluated them separately in the generated fundamental source signals. The artifacts-containing source signal is eliminated, and the remaining variables are reconstructed, yielding an artifact-free signal.

.4.5 Hybrid EEMD-CCA

Another algorithm is proposed as the combination of the hybrid EEMD-CCA algorithm for improving the efficiency of the artefact removal. The hybrid combination is proposed by Roy Vandana et al [20]. It is stated that CCA is an efficient and fastest algorithm to be used in the real time. The discrete wavelet transform (DWT) is usually combined with EEMD-CCA to improve the SNR performance of the system and make the more robust artifacts removal [27].

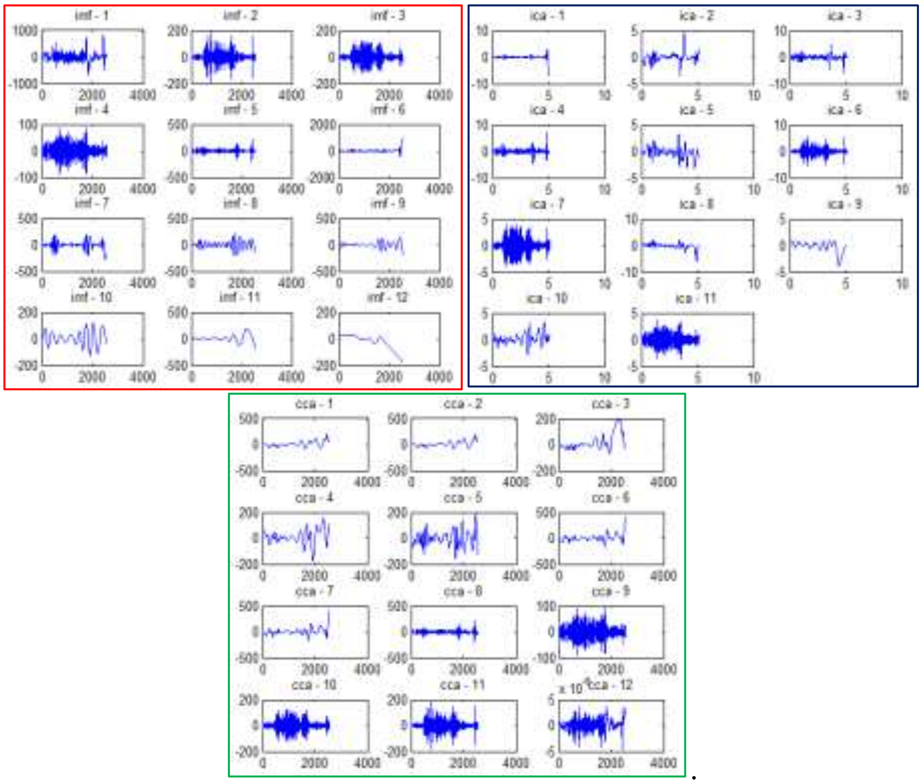


Figure 4. Example of the multi-mode decomposition with a) EEMD decomposition b) EEMD-ICA and C) EEMD-CCA of the Motion artifact data at 10 dB SNR noise plotted for Ch1

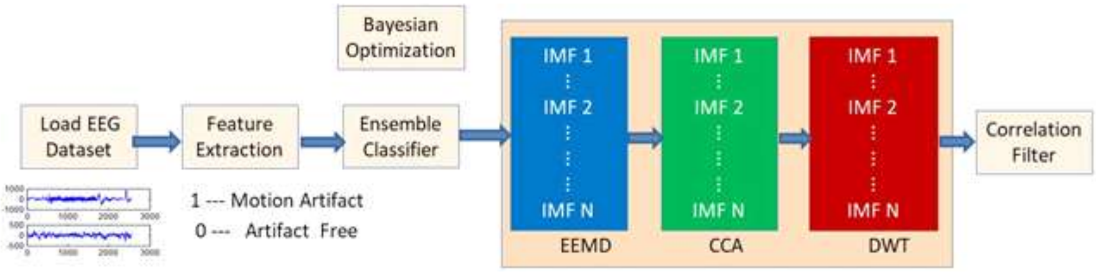


Figure 5 Proposed system block diagram for EEG classification and artifacts eradication

5. Proposed EEG Artifact Classification and Eradication

The research proposed novel feature extraction parameters to classify the EEG artifacts before being processed further. The Ensemble based Bayesian optimization using Decision Tree (DT) is proposed for efficient EEG artifacts classification. The data is classified as artifacts free (0) or with motion artifacts (1) classes. The block diagram of the proposed approach is illustrated in the Figure 4. It can be observed that after classification once the artifacts are detected then the three levels EEMD-CCA-DWT artifacts eradication methodology with Pearson correlation filter is proposed as shown in the Figure 4. Each of the steps involved during the ML based artifacts eradication approach in Figure are clearly briefly describes sequentially. Suppose the artificially noisy input EEG signal may given as;

$$EEG_{art} = EEG_i + A_i + \eta_i \qquad (10)$$

Where, EEG_{art} is the recorded data along with noise and artifacts A_i , and the true EEG_i. Thus the problem of statement is to eradicate the effect of the A_i and noise to recover the close appreciation of the true EEG_i.

The key advantage of using the CCA is that it is faster than ICA approach. Also using CCA preserves the true nature of EEG signal better then the ICA. The DWT is required as combination to further improve the reproduction quality.

5.1. Feature Extraction and Artefact EEG Classification

Paper proposed a new set of extended statistical features calculated to classify EEG artifacts data. The statistical features as, Average, Entropy, Maximum, Minimum are calculated and two unique features as Peak-to-Peak Difference (PDP) and PSNR are additionally calculated to represent the rich set of features. To calculate the PSNR the Ch18 is used as the reference channel and respective PSNR is calculated. Total 16 artifacts channels with 2360 samples each are used for feature representation. The reference channel is considered as ground truth with artifacts free data. Additionally the median and standard deviation of the EEG data are also calculated. The Figure 6 represented the graphical representation of features calculated for the EEG database. It can be observed from the figure 6 a) that if the artifacts are there then Entropy and Average values of the signal are on higher side.

While on the other side the calculated PSNR has the reverse relation and for artifacts data PSNR is low. The mathematical formulations of the features are as follows;

$$Avg = \frac{1}{L}\sum_{i=1}^{L} EEG_i \qquad (11)$$

$$Entropy = E = \frac{1}{p_k}\log(p_k) \qquad (12)$$

The new feature as the PDP is defined as ;

$$PDP = (\max(EEG_i) - \min(EEG_i)) \qquad (13)$$

The PSNR is calculated in terms of the GT reference signal as;

$$PSNR = \frac{1}{L}\frac{EEG_R}{\sum_{i=1}^{L}(EEG_R - EEG_i)^{2}} \qquad (14)$$

The PDP is plotted aghast the EEF signals as shown in the Figure 6.b). It is expected that using the extended feature set with two unique features the accuracy of Artifact classification may improve. The minimum is plotted as absolute minima. As shown in Figure 6.b)

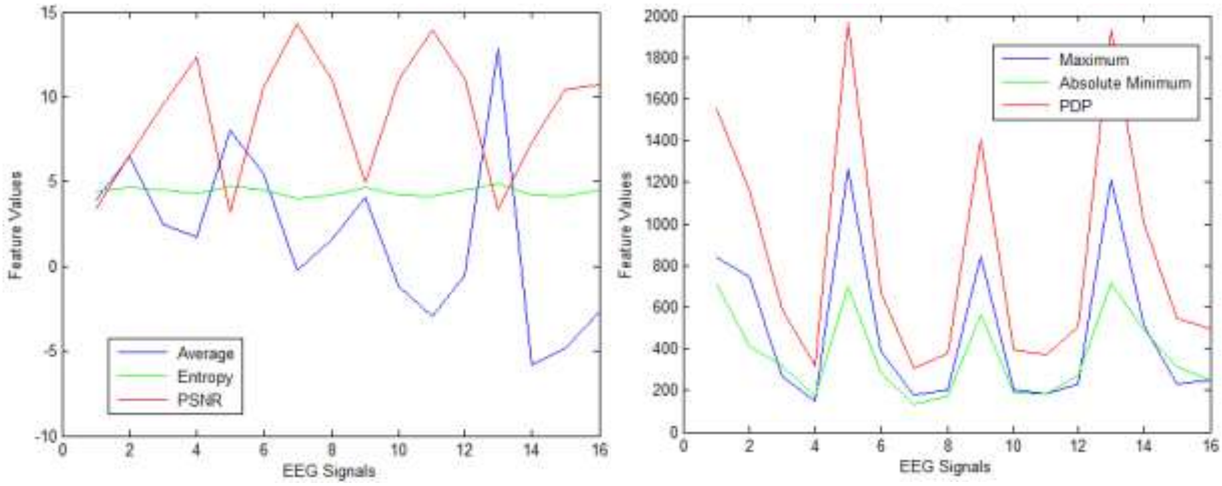


Figure 6 Results of the Feature Extraction, a) set 1 of statistical features b) set 2 of statistical features

6. Results and Evaluations

Paper have preseted the results in two pass first EEG artifacts classification is performed and then the second pass presented the artifacts eradication results.

6.1 Classification Results

In this paper four different classification models are tested/trained and validated. The extracted feature sets are used to predict Motion artifacts as response. For the classification of EEG signals two classes as Artifact free (0) and Motion Artifact (1) are used as the response of EEG data. Paper proposed to subdivide the data into two (2) sub-sets and then cross validation model is applied for the accuracy prediction. Paper proposed to apply the Ensemble optimization model with decision tree using boost ensemble method is finally proposed for performance improvement. Then performance is compared with three other classification models considered are Course SVM, Linear SVM, Logistic Regression (LR),

6.1.1 Model 1: Linear SVM

The first experiment is performed to train and test the EEG artifacts classification using the Linear SVM model using box constrain as unity, the total cost of validation is 2 and training time of the 12.467 sec is achieved for the model. The respective scatter plots and confusion matrix are represented in the Figure 7 a) and Figure 7 b) respectively. In the scatter plots blue dots represents (0) and brown dots are corresponds to artifacts data as (1) and wrong predictions are repressed by X. The accuracy of 87.5 % is achieved as clear from confusion matrix that 33.3 % False Negative Rate (FNR) is achieved for artifacts data class(1).

6.1.2 Model 2: Course Gaussian SVM

Another classifier as Course Gaussian SVM model is trained for the EEG data classifications. Since training time for Linear SVM was higher thus Gaussian kernel based SVM is chosen for the test. The respective scatter plots in Figure 7 c) and confusion matrix are presented in Figure 7 d) respectively. The model used kernel size of 9.8, box constrains as unity, the cost of validation is 4 and training time is reduced to 3.2118 sec. although the model is faster to train but the accuracy for respective EEG data is reduced to only 75% with cross validation model.

Case 1: 6.1.3 Model 3: SVM with Modified Features

Another classifier as linear SVM model is trained using the EEG data but the modified novel features as PDP and PSNR are used for the predictors as the proposed model case 1 of this research**.** In order to improve the prediction accuracy the paper proposed to replace the conventional statistical predictors by the new proposed features or predictor as PDP vs. PSNR.

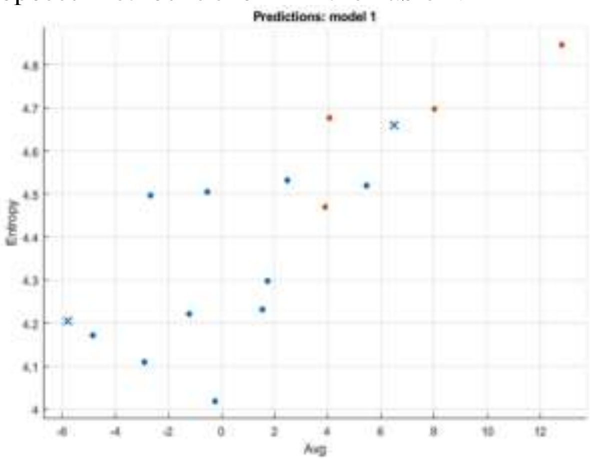
The proposed prediction results of the confusion matrix are presented in the Figure 8. It is observed that the same training time for Linear SVM was capable of enhancing the prediction accuracy from 87.5 to 83.8 %. The respective scatter plots of a proposed case1 in Figure 8 a) and confusion matrix based on modified feature are presented in Figure 8 b) respectively. The use of proposed features offers the improvement of 6.3% accuracy which is considers as significant improvement.

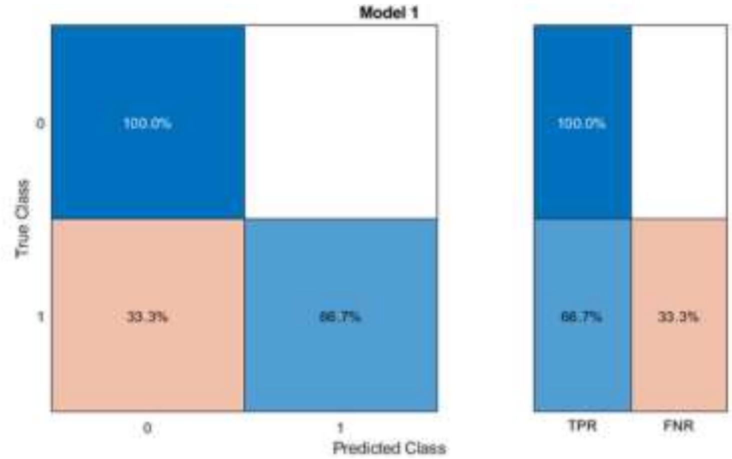
Proposed Case 2: In order to improve the prediction accuracy finally in this research it is proposed to use the ensemble based classifier using the bag ensemble. Bayesian optimisation is an incremental strategy that employs a model to forecast new potential parameters for evaluation. When possible parameter values are scored, their effectiveness mean and variance are anticipated. An acquisition function defines the technique for determining how to employ the statistical features

6.1.4 Model 4: Optimization based Ensemble Classifiers

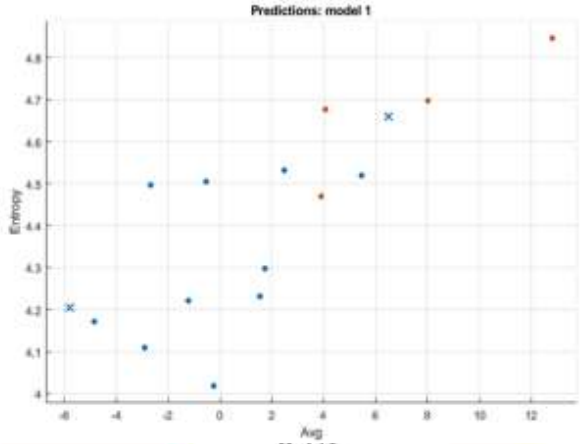
Finally the paper proposed Case 2 to employ the optimization based ensemble classifier or EEG artifacts detection using modified features as PDP and PSNR as predictors. The method proposed Bayesian optimization approach with 10 learners and learning rate of 0.001. The number of splits is 15 and 4 predictor for 30 iterations.

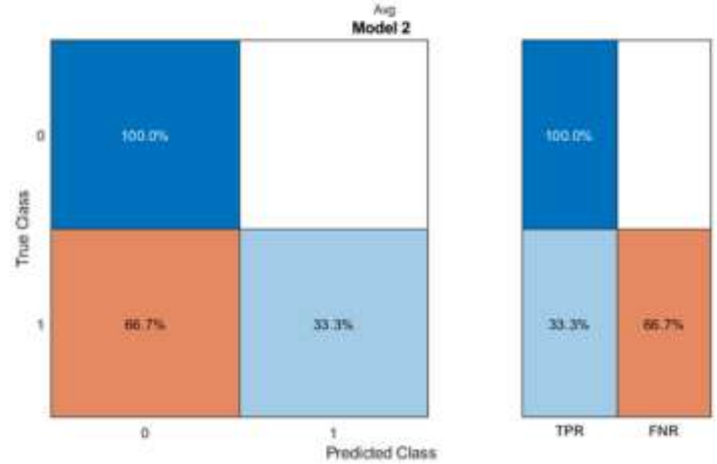
The results of the respective predictors scatter plots are preseted in Figure 8 c) and confusion matrix is presented in Figure 8 d) respectively. The use of proposed Bayesian optimization based classification offers the improvement of 6.2% accuracy and is capable of detecting the EEG artifacts with no false negative. The parametric performance of proposed method is shown in the Table 2.





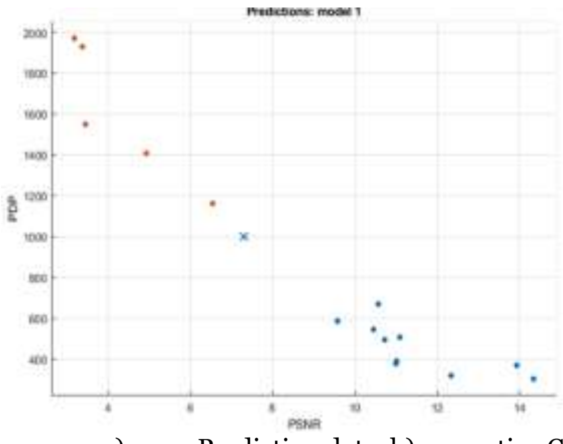
a) Prediction data of Avg vs Entropy b) respective confusion matrices for Linear SVM classifier Model 1

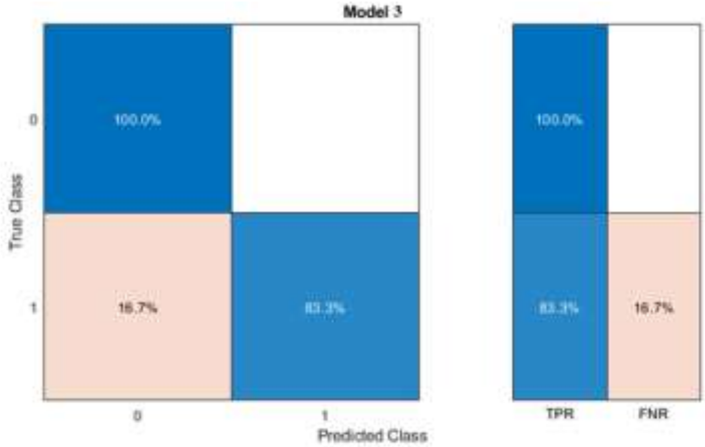




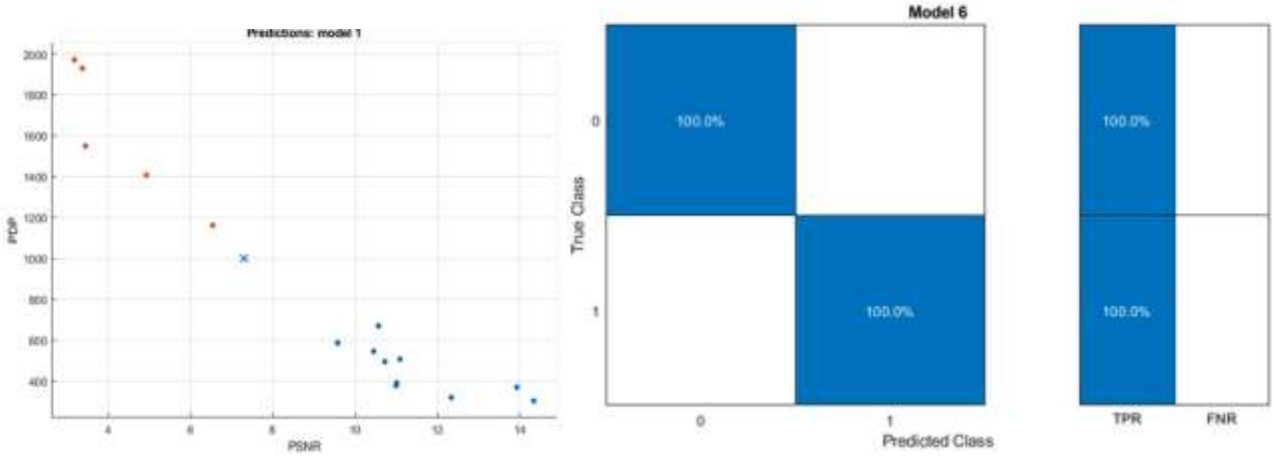
b) Scatter Plot of Avg and Entropy prediction data d) the confusion matrices for Course Gaussian SVM classifier Model 2

Figure 7 results of the SVM based validation of confusion matrix





a) Prediction data b) respective Confusion Matrices for Linear SVM classifier Model 1



c) Prediction new feature scatter data d) respective Confusion Matrices for optimized Ensemble classifier Model 4

Figure 8 results of the classification confusion matrix for the proposed novel features predictors

Table 2 parametric comparison of EEG artifacts classification

Classifiers	Accuracy	False negative rate	Training time
Linear SVM	87.5 %	33.3 %	12.467 sec
Course Gaussian SVM	75 %	66.6 %	2.5543 sec
Logistic Regressions (LR)	93.8 %	16.3 %	21.233 sec
Linear SVM proposed Case 1	93.8 %	16.3 %	12.467 sec
Ensemble Optimized Case2	100 %	0 %	581.25 sec

It can be observed from the Table 2 that the proposed features offer the significant higher accuracy and false negate rate are reduced from 33.5 % to 0 %. The novel features uses as PDP and PSNR makes its significant performance improvement.

It can also be observed from the Table that although using an optimization may improve the accuracy but simultaneously it takes significant higher time of 581.25 sec for training the data comparatively to 12.467 sec for linear SVM. This is limitation for real time performance.

6.2 EEG Artifacts Eradication

Once the artifacts are detected then, paper proposed to eliminate the artifacts from the EEG signals. There are many EEG artifacts eradication methods available. The filtering method must significantly preserve the nature of true EEG signal. Thus paper proposed the combination of EEMD-CCA-DWT in this paper to maintain the shape of the EEG and to achieve the significant SNR performance. The filtering is applied once the artifacts are detected. The initial step is to load the EEG data base to MATLAB envirenment. The set of true EEG and artifact EEG signals are pasedas the input. For the proposed method result evaluation the Ch 7 is considerd as the true EEGdata or the deasired data. The Ch. 1 and Ch 9 of the motion artifacts data are consdered for the results evaluations.

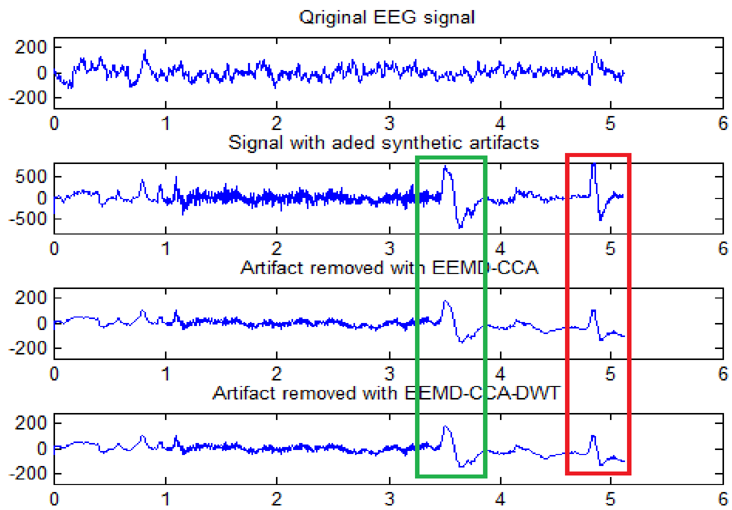


Figure 9 Qualitative comparisons of the EEG artifacts eradication methods for the EEG Ch1 for motion artifacts.

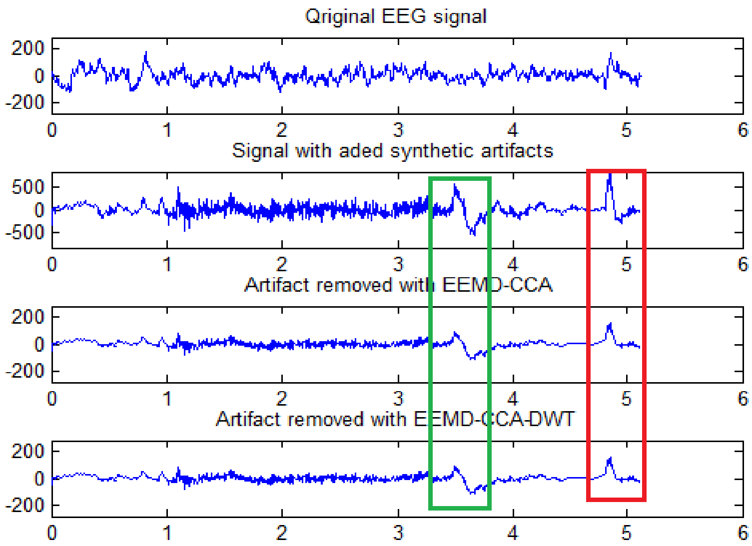


Figure 10 Qualitative comparisons of the EEG artifacts eradication methods for the EEG Ch 9 for motion artifacts

The qualitative comparisons of the EEG artifacts eradication methods are preseted in the Figure 9 for the EEG Ch 1. The magnitude comparsion in the Figure 9 makes it clear that the high peak eyeblink artifacts signals with maximum range of 500 mV is reduced to the desired range of acual true EEG data of 200 mV rage post filtering. This shows the efectivness of the propsoed method. The quanlitative perfromanceof eye blink peaks eredication is marekd with gree and red color box in the Figure coresponding to two eye blink peaks.

Similarly the qualitative comparisons results of the EEG proposed EEMD-CCA-DWT based artifacts eradication methods for the EEG Ch 9 for motion artifacts are represeted in the Figure 10. It can be clearly observ tha the proposed filter significantly maintain the true nature of the EEG data and slo reduce the eye blink peaks significantly.

The quantitatve perfromance of the powere spectral density with two EEG artifact removal methods are preented in the Figure 11. The proposed method EEMD-CCA-DWT significantly have slight improvement in PSD over the EEMD-CCA based method.

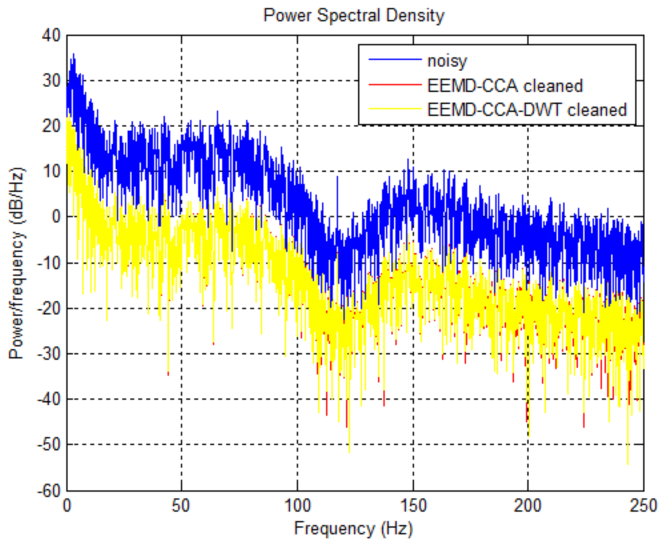


Figure 11 Results of the Power spectral density comparison or EEG filtering methods..

The parametric performance of the methods is compared in terms of the PSNR and MSE. The proposed method significantly improves the artifacts, as error is minimized and PSD too.

Table 3 Quantitative comparison of filtering performance for the EEG Ch 9

Case	RMSE	PSD	PSNR
With artifacts	173.2664	2.3878	--
Artifact free	62.1937	1.0899	11.9156

Results of qualitative comparison with state of art ICA and CCA based method for EEG artifacts eradication using EEMD-ICA-DWT and the proposed EEMD-CCA-DWT filter for the input channels Ch 5 respectively are preseted in the each row of the Figure 12. The artifacts channel is represented in red colour and filtered signal is plotted in blue. It can be observed that proposed EEMD-CCA-DWT method out performs over the EEMD-ICA-DWT. The amplitude is significantly reduced by the proposed method and it also belter preserve the nature of EEG signals too.

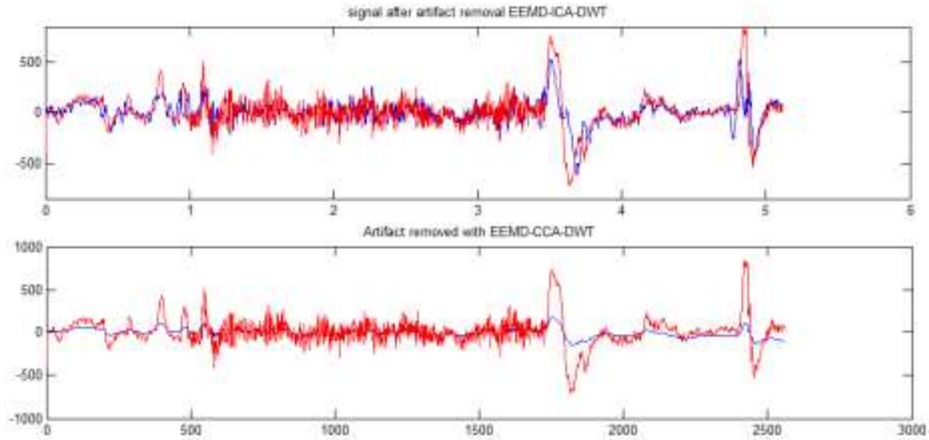


Figure 12: Results comparison of EEG Artifact eradication using EEMD-iCA9DWT and the proposed EEMD-CCA-DWT filter for the input channels CH 1 and Ch 5 respectively in each row.

VII. CONCLUSIONS

First, machine learning (ML) algorithms are used to classify real and artefact signals. The major contribution of the research is to compare the performance of various SVM based classifier. The novel modified feature's as PDP and PSNR are calculated which may significantly increase the accuracy.
It is concluded the proposed predictors with Bayesian optimization based bag Ensemble classifier gives the 100 % accuracy and offers 6.2 % accuracy improvement over SVM classifiers.
The research then designs and evaluates the qualitative performance of various unsupervised ensemble algorithms that use EEMD, ICA-DWT, and proposed EMD-CCA-DWT to eliminate EEG artefacts.

A district's database is used in the assessment process. The examination includes both actual and purposely manufactured artefact data. Motion artefacts, particularly ocular eye blinks (EOG) along with muscle (MMG) artefacts, are considered in the study. The primary problem is to eliminate high-peak eye blink artefacts. Thus, the research offered wavelet-based de noising to boost signal strength after removing artefacts. The performance is evaluated using a combination of DWT and all of the above ensemble-based approaches.
It can be concluded that proposed method minimizes the RMSE significantly from 173.2664 to 62.1937 and also preserved the nature of the EEG signal. First, machine learning (ML) algorithms are used to classify real and artefact signals. The major contribution of the research is to compare the performance of various SVM based classifier. the novel modified feature's as PDP and PSNR are calculated which may significantly increase the accuracy. t is concluded the proposed predictors with Bayesian optimization based bag Ensemble classifier gives the 100 % accuracy and offers 6.2 % accuracy improvement over SVM classifiers. The research then designs and evaluates the qualitative performance of various unsupervised ensemble algorithms that use EEMD, ICA-DWT, EMD-CCA-DWT to eliminate EEG artefacts. A district's database is used in the assessment process. The examination includes both actual and purposely manufactured artefact data. Motion artefacts, particularly ocular eye blinks (EOG) along with muscle (MMG) artefacts, are considered in the study. The primary problem is to eliminate high-peak eye blink artefacts. Thus, the research offered wavelet-based denoising to boost signal strength after removing artefacts. The performance is evaluated using a combination of DWT and all of the above ensemble-based approaches. it can be concluded that proposed method minimizes the RMSE significantly from 173.2664 to 62.1937 and also preserved the nature of the EEG signal.

Although it is also observed that the training time by the proposed ensemble optimization based classifier is higher.

In future use of the neural network based adaptive filter can be used for eliminating the effect of eye blinks artifacts completely. The deep learning based classification can be tested for the large EEG database in future.

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